Development of Novel Techniques for Fetal ECG Extraction in Early Pregnancy

THESIS

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By
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Under the Supervision of
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CERTIFICATE

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This is to certify that the thesis entitled **"Development of Novel Techniques for Fetal ECG Extraction in Early Pregnancy"** and submitted by **R.Swarnalatha** ID No 2005PHXF004P for award of Ph.D. Degree of the Institute, embodies original work done by her under my supervision.

Signature in full of the Supervisor**: ---**

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TITLE OF THE THESIS: Development of Novel Techniques for Fetal ECG Extraction in Early Pregnancy

ABSTRACT:

Congenital heart defects are among the most common birth defects and the leading cause of birth defect-related deaths. Most cardiac defects have some manifestation in the morphology of cardiac electrical signals. The non invasive study of fetal cardiac signals can provide an effective means of monitoring the well-being of the fetal heart. This may be used for the early detection of cardiac abnormalities. The electrocardiogram (ECG) signal is the graphical recording of the electrical potential generated in association with heart activity. It is one of the physiological signals commonly used in clinical aspects. As in adults, the well-being and the status of the fetus can be assessed from a fetal electrocardiogram (FECG) signal.

Non invasive techniques of fetal monitoring are Doppler ultrasound, fetal electrocardiography and fetal magneto cardiography. Among these methods the most commonly used is Doppler ultrasound because it is simple to use and cheap. However this method produces an averaged heart rate and therefore cannot give beat to beat variability. Fetal electrocardiogram offers the advantage of monitoring beat to beat variability. There are many technical problems with non invasive extraction of FECG. The FECG signal is corrupted by different sources of interferences such as maternal electrocardiogram (MECG) maternal electromyogram (MEMG), 50 Hz power line interference and base line wander. The low amplitude of the signals, the different types of noise and overlapping frequencies of mother and fetal ECG make the extraction of FECG a difficult task.

Extraction and analysis of the fetal ECG signal are the primary objectives of electronic fetal monitoring. In extracting the fetal ECG signal, the digital signal processing techniques have played a significant role. The primary assumption is that the abdominal ECG

signal (AECG) is a non linear combination of the maternal ECG, fetal ECG signal and other interference signal. Fetal ECG extraction is from two signals recorded at the thoracic and abdominal areas of the mother's skin. The thoracic ECG (TECG) is assumed to be almost completely maternal whereas the abdominal electrocardiogram is considered to be composite, as it contains both the mother's and fetus ECG signals.

Ten different algorithms have been proposed in this work using three major classifications. They are (i) multi stage adaptive filtering (ii) combination of wavelet and adaptive filtering (iii) combination of soft computing (ANFIS – Adaptive Neuro Fuzzy Inference System) and wavelet.

In multi stage adaptive filtering classification, three different methods have been proposed to extract fetal ECG. These are accomplished by (i) defining the different non linear operators (ii) optimizing the processing algorithms of multi stage adaptive filters (iii) modifying the thoracic signals for optimal maternal ECG cancellation and (iv) suggesting a refining process after the fetal ECG extraction.

In wavelet –adaptive classification, four different methods have been proposed to extract the fetal ECG. This is accomplished by (i) wavelet denoising of the abdominal signal (ii) defining the different non linear operators (iii) modifying the thoracic signals for optimal maternal ECG cancellation and (iv) suggesting a refining process after the fetal ECG extraction.

In soft computing and wavelet classification, three methods have been proposed. This is achieved by (i) ANFIS method (ii) wavelet preprocessing with ANFIS and (iii) ANFIS followed by wavelet post processing methods.

The ten different algorithms were tested with the real abdominal signals and the results were evaluated using the performance parameters. In each classification the best extraction technique was identified. Out of these three identified algorithms in different classifications, it was found that the soft computing with wavelet was more efficient in extracting the fetal ECG.

To test the robustness of the soft computing and wavelets algorithms, further testing and evaluation was done with data sets from 22^{nd} to 40^{th} week of pregnancy, during labour with and without oxytocin administration. Among the soft computing with wavelet techniques, it was found that the ANFIS followed by wavelet post processing is found to be the best extraction method. The accuracy of detection of fetal ECG of this particular technique was found to be 100%.

The accuracy of the three best algorithms from the three different classifications was compared with the other existing techniques. It is concluded that the soft computing followed by wavelet post processing technique was able to extract fetal ECG even during the early stages of pregnancy. Since the morphology of the extracted FECG using this technique remains same, it can be used by the physician to diagnose fetal anomalies.

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbol/ Abbreviation	**Description**
ψ	Mother Wavelet
λ	Forgetting Factor
Ψ	Non Linear Parameter
μ	Learning Parameter
ACC	Accuracy
AECG	Abdominal Electrocardiogram
AI	Artificial Intelligence
ANC	Adaptive Noise Cancellation
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ApEN	Approximate Entropy
AV	Atrio Ventricular
BSS	Blind Source Separation
cA	Coarse Approximation
CCWT	Complex Continuous Wavelet Transform
cD	Coarse Detail
CORR	Correlation coefficient
CTG	Carditocography
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EFM	Electronic Fetal Monitoring

LIST OF SYMBOLS AND ABBREVIATIONS (Contd…)

Symbol/ Abbreviation	Description
EMG	Electromyogram
EP	Electrode Position
FECG	Fetal Electrocardiogram
FHR	Fetal Heart rate
FIR	Finite Impulse Response
FIS	Fuzzy Inference System
FMCG	Fetal Magneto Cardiogram
FN	False Negative
FP	False Positive
FPCG	Fetal PhonoCardiogram
FPGA	Field Programmable Gate Array
GA	Genetic Algorithm
ICA	Independent Component Analysis
IIR	Infinite Impulse Response
LMS	Least Mean Square
MECG	Maternal Electrocardiogram
MEEG	Maternal Electroencephalogram
MEHG	Maternal Electrohystrogram
MEMG	Maternal Electromyogram
MEOG	Maternal Electrooculogram
MF	Membership Function
MHR	Maternal Heart Rate
MP	Matching Pursuits
MRA	Multi Resolution Analysis

LIST OF SYMBOLS AND ABBREVIATIONS (Contd…)

Symbol/ Abbreviation	**Description**
NLMS	Normalized Least Mean Square
NPV	Negative Predictive Value
PPV	Positive Predictive Value
RLS	Recursive Least Square
SA	Sino Atrial
SC	Successive Approximation
SEN	Sensitivity
SNR	Signal to Noise Ratio
SPE	Specificity
SVD	Singular Value Decomposition
TECG	Thoracic Electrocardiogram
TN	True Negative
TP	True Positive
WAF	Wavelet Adaptive Filter
WT	Wavelet Transform

CHAPTER 1
INTRODUCTION

1.1 BACKGROUND OF THE WORK

The electrocardiogram (ECG) signal is one of the most commonly used physiological signals. The activity of the heart can be visualized from an ECG signal obtained by measuring the potential difference of two points on the skin and this ECG can provide valuable cardiac information. The monitoring and analysis of the ECG has been a useful technique for diagnosis of cardiac disease for several decades.

One of the most common birth defects is the defect in the heart and is a leading cause of birth related deaths. Every year about one out of 125 babies are born with some form of congenital heart defects (Minino *et al*., 2007). The defects may be so small that the baby appears healthy for many years after birth or it may be very severe that the life is in danger. Congenital heart defects originate in early stages of pregnancy when the heart is forming and they can affect any function of the heart. Genetic syndrome, inherited disorders and environmental factors such as infections or drug misuse may lead to cardiac anomalies (Pajkrt *et al*., 2004).They can also occur due to specific fetal positioning that chokes the umbilical cord (Zuckerwar *et al*., 1993) The regular monitoring of the fetal heart, fetal ECG and the early detection of any cardiac abnormalities can help the pediatric cardiologist to prescribe proper medications in time, or to consider the necessary precautions to be taken during delivery or after birth.

Fetal electrocardiogram (FECG) monitoring is a technique for obtaining important information about the condition of the fetus in the early stages of pregnancy and before delivery. The well-being and condition of the fetus can be assessed from the fetal ECG. For example, the fetal ECG signal can often reveal important information for an arrhythmia diagnosis. The fetal ECG signal can be obtained from electrical measurements on the maternal abdomen. However, the abdominal ECG signal is composed of a combination of the maternal ECG signal, the fetal ECG signal, and interference signals. As the amplitude of the maternal ECG signal is typically much larger than the fetal ECG signal and the interference signals, ECG signal processing can play a significant role in obtaining a good estimate of the fetal ECG signal.

Non invasive techniques of fetal monitoring are Doppler ultrasound, fetal electrocardiography and fetal magneto cardiography. Among these methods the most commonly used is Doppler ultrasound because it is simple to use and cheap. However this method produces an averaged heart rate and therefore cannot give beat to beat variability (Fukushima *et al*., 1985). Fetal electrocardiogram offers the advantage of monitoring beat to beat variability. There are many technical problems with non invasive extraction of FECG. The FECG signal is corrupted by different sources of interferences such as maternal EMG, 50 Hz power line interference and base line wander. The low amplitude of the signals, the different types of noise and overlapping frequencies of mother and fetal ECG make the extraction of FECG a difficult task (Deam, 1994).

The fetal heart rate variations during pregnancy and labor have been used as an indirect indicator of fetal distress. Observation over longer periods may yield more information about the status of the fetus. The detection of fetal QRS complex from the surface records is very difficult task which is mainly due to overlapping of mothers ECG. The MECG and FECG are partly uncorrelated. Also the MECG signal is very much stronger than the FECG signal embedded in it. The noise in which FECG is embedded is also stronger depending on the gestation age.

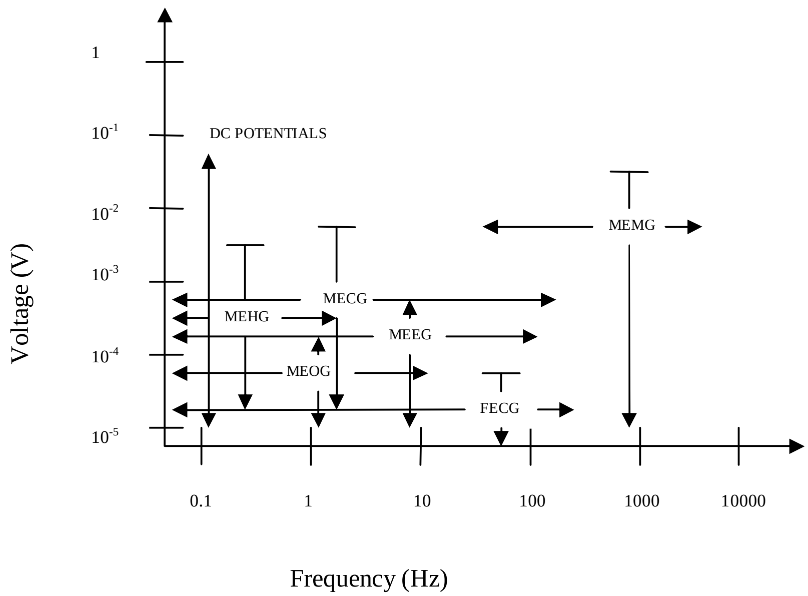

Figure 1.1 The amplitude and frequency range of biosignals that can interfere with fetal cardiac signals

In the Figure 1.1 the labels stand for the maternal electrocardiogram (MECG), electroencephalogram (MEEG), electrohystrogram (MEHG), electrooculogram (MEOG), electromyogram (MEMG) and the fetal ECG (FECG). Note that the amplitude of these signals also depends on the site from which the data is recorded (Devedeux *et al.*, 1993), (Webster, 1998), and (Snowden *et al.*, 2001). The amplitude and frequency range of fetal ECG have been compared with other noises and artifacts. Accordingly, the fetal ECG is much weaker than the other interfering biosignals. Moreover, from the signal processing perspective, there is no specific domain (time, space, frequency, or feature) in which the fetal ECG can be totally separated from the interfering signals. Most of the previous work in this area has been devoted to filtering the fetal cardiac signals. Due to the complexity of the problem there are many issues that require improved signal processing techniques.

Many signal-processing-based techniques were used to extract FECG with various degrees of success. These techniques include adaptive filtering (Widrow *et al.*, 1975), correlation techniques (Abboud *et al.*, 1992), singular value decomposition (Callaerts *et* *al*., 1990), wavelet transform (Mochimaru and Fujimoto, 2002), wavelet transform and pattern matching (Echeverria *et al*., 1996), wavelet analysis method (Datian and Xuemei, 1996), complex continuous wavelet transform (Karvounis *et al*., 2004), orthogonal basis functions (Longini *et al*., 1997), fractals (Richter *et al*., 1998), IIR adaptive filtering combined with genetic algorithms (Kam and Cohen, 1999), frequency tracking (Barros, 2002), real-time signal processing (Ibahimy *et al*., 2003) and Projective filtering techniques (Kotas, 2007). The most recent and most successful method of extractions are blind source separation (Lathauwer *et al*., 2000), independent component analysis (Marossero *et al*., 2003), blind source separation via independent component analysis (Zarzoso et *al*., 1997), and independent component analysis and wavelets (Vigneron *et al*.,2003). Some of the soft computing techniques are categorization process with back propagation and SOM network (Liszka-Hackzell, 1994), neural and fuzzy classifiers technique (Magenes *et al*., 1999) and adaptive linear neural network (Reaz and Wei, 2004), fuzzy logic (Azad, 2000), FIR neural network (Camps *et al*., 2001), dynamic neural network (Camps *et al*., 2004), polynomial network (Assaleh and Nashash., 2005), singular value decomposition and neuro-fuzzy inference system (Zaben and Smadi,2006) and ANFIS (Assaleh, 2007).

Though the BSS and ICA extraction methods considered as the most successful methods, in order to work these techniques properly, it requires multiple leads for collecting several ECG signals. ICA assumes that the composite abdominal signals are obtained via linear mixing of the thoracic signal, fetal components and other interfering signals. The adaptive filters, wavelet transforms and neural networks can use two leads but have their limitations especially when the fetal beats overlap with the QRS wave of the maternal beats. The proposed work extracts the fetal ECG by two lead signals which are the abdominal signal and thoracic signal of the mother's abdomen and thorax region. The proposed work overcomes the limitation of overlapped FECG and MECG signals.

1.2 OBJECTIVES OF THE STUDY

The prime objectives of this research work are;

- To extract the fetal ECG from the maternal abdominal signals recorded from the array of electrodes placed on the maternal abdomen.
- Development of different algorithms to extract fetal ECG.
- Testing of the algorithms with real abdominal signals for different cases.
- Evaluation and analysis of the extracted FECG.
- Comparison of the proposed methods.
- Comparison of the efficient proposed methods with other existing methods.

1.3 METHODOLOGY ADOPTED FOR THE STUDY

The methodologies adopted for this research work to achieve the objectives are:

Phase 1: Development of multi stage adaptive filtering methods

The conventional adaptive filtering methods were incapable of extracting the fetal ECG completely. Thus there is a need to improve and modify the filtering methods to obtain a better quality of fetal ECG. This is achieved by (i) defining the different non linear parameters (ii) optimizing the processing algorithms of multi stage adaptive filters (iii) modifying the thoracic signals for optimal maternal ECG cancellation and (iv) suggesting a refining process after the fetal ECG extraction.

Phase 2: Development of wavelet- adaptive filtering methods

The combination of wavelet and adaptive filtering methods were developed to extract the fetal ECG. This is accomplished by (i) wavelet denoising of the abdominal signal (ii) defining the different non linear parameters (iii) modifying the thoracic signals for optimal maternal ECG cancellation and (iv) suggesting a refining process after the fetal ECG extraction.

Phase 3: Development of soft computing techniques with wavelet

The combinations of soft computing techniques with wavelets were developed to extract the fetal ECG. This is achieved by (i) ANFIS method (ii) wavelet preprocessing with ANFIS and (iii) ANFIS followed by wavelet post processing method.

Phase 4: Testing, evaluation and comparison of the proposed algorithms

All the proposed algorithms were tested with real abdominal signals. The extracted fetal ECG signal was evaluated using performance indices, correlation coefficient and SNR. The better performing methods were identified.

Phase 5: Robust method of fetal ECG extraction

The soft computing with wavelet methods were further tested for the robustness with additional real abdominal signals and results were evaluated for performance indices. The comparison was done between the better proposed methods and the existing methods.

1.4 SCOPE OF THE STUDY

The study is about extracting fetal ECG from composite abdominal signal recorded from the abdomen of the mother during pregnancy. This contains information on the health status of the fetus and which can aid in an early diagnosis of cardiac defects before delivery. Many signal-processing-based techniques were used to extract FECG with various degrees of success. In this research work, different algorithms were developed to have accurate extraction of fetal ECG. The proposed methods should be capable of extracting fetal ECG in the case of overlapping with maternal ECG. It is also required to understand the health status of the fetus during early stages of pregnancy. The proposed algorithms were designed to meet the above requirements. Hence, it is proposed to develop number of algorithms based on different principles of signal processing. The best proposed method can become a diagnostic tool for treatment of fetal arrhythmias.

1.5 ORGANIZATION OF THE THESIS

The research work is presented in seven chapters as follows:

Chapter – 1: In this chapter, the structure of the thesis is presented. This research work deals with the fetal ECG extraction techniques and highlights the importance of the fetal monitoring. The chapter states the objectives of the research followed by the methodology. Ten different extraction algorithms are proposed using adaptive filters, wavelets and ANFIS. The algorithms were tested with real data sets and the results were evaluated.

Chapter – 2: In this chapter, the history of fetal monitoring is presented. The literature survey of the different fetal ECG extraction algorithms were discussed in detail. The research gaps are highlighted by reviewing the existing extraction methods.

Chapter – 3: In this chapter, the multistage adaptive filtering based fetal ECG extraction methods are proposed. Three different methods using multistage adaptive filtering technique with different non linear parameters are proposed. Each method was tested with two sets of different but real abdominal signals. The results were evaluated using the performance parameters. The better adaptive filtering extraction method is highlighted.

Chapter – 4: In this chapter, the combination of wavelet and adaptive filtering methods were developed to extract the fetal ECG. Using this combination, four different methods were proposed along with different non linear parameter. Each method was tested with two sets of different but real abdominal signals. The results are evaluated using the performance indices parameters. The better fetal ECG extraction method is highlighted from the proposed methods.

Chapter - 5 In this chapter, the combinations of soft computing techniques with wavelet were developed to extract the fetal ECG. Three different methods were proposed. The methods were tested with two sets of different but real abdominal signals. The results are evaluated using the performance indices parameters. The better fetal ECG extraction method is highlighted from the proposed methods.

Chapter - 6 In this chapter, further testing of the soft computing and wavelet techniques by the real abdominal signals was done to show the robustness of these methods in early stages of pregnancy. The real abdominal signals are the data sets from 22nd to 40th week and during labour with and without oxytocin administration. The results were evaluated using the performance indices parameters. The best performing method is highlighted.

Chapter - 7 In this chapter, the summary of the ten proposed methods, conclusions, comparison of the proposed methods and comparison of proposed method with existing methods were presented. Future scope of work and the specific contribution of the study are presented.

CHAPTER 2
LITERATURE REVIEW

In this chapter, the state of the art of fetal ECG signal extraction of past and present methods is reviewed. The ECG is a graphical recording of the electrical potentials generated in association with the heart activity. Fetal electrocardiogram (FECG) signal contains potentially precise information that could assist clinicians in making more appropriate and timely decisions before and during labor. The ultimate reason for the interest in FECG signal analysis is in clinical diagnosis and biomedical applications. The extraction and detection of the FECG signal from composite abdominal signals with powerful and advance methodologies are becoming very important requirements in fetal monitoring. FECG is useful to get reliable information on fetal status, the detection of abnormalities and to enable the adoption of measures for assuring fetal wellbeing.

2.1 ELECTROPHYSIOLOGY OF THE FETAL HEART

The prerequisite physiological and electrophysiological aspects of fetal cardiac development and monitoring are presented in this section. Some of these issues are used for explaining the results and conclusions achieved from the extracted FECG from the composite abdominal signals.

2.1.1 FETAL CARDIAC DEVELOPMENT

The heart is the first organ developed in the fetus and undergoes a considerable amount of growth in the very early stages of pregnancy (Jana, 2004). Figure 2.1 shows the fetus and its heart in early stages of pregnancy (Lawrence, 1995). After fertilization, between the three and seven weeks is the most critical period of the fetal cardiac development. The simple heart tube assumes the shape of the four chambered heart. The heart is believed to begin beating by the 22nd day of the life. It can be externally monitored by ultrasound imaging in the 7th to 9th week (Jana, 2004). But only vague images are recordable at this stage. The cardiac waveform and the beat to beat variability of the heart rate are not measurable in ultrasound imaging. So, fetal ECG and the maternal ECG that contains the morphological information of the cardiac activity have received much interest. These signals can be recorded from the maternal abdomen as early as the 21st week after conception (Peters *et al.*, 2001) and (Van Leeuwen *et al.*, 2004).

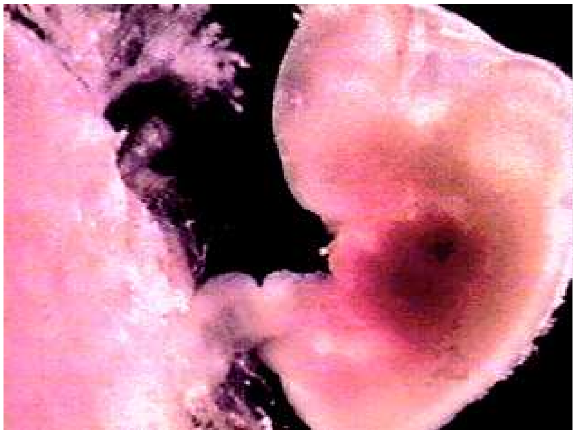

Figure 2.1 The fetus and its heart in the early stages of development

Anatomy of the fetomaternal compartments are shown in Figure 2.2(Lawrence, 1995).The fetus is surrounded by several different anatomical layers with different electrical conductivities (Oostendorp *et al.*, 1989). The highest and lowest conductivity are found in the amniotic fluid and the vernix caseosa. Vernix caseosa is formed over the fetal skin.Both these layers surround the fetus completely. In maternal abdomen compartments, the skin and the subcutaneous fat also have poor conductivity. These two layers which are the interface of the surface electrodes and the internal tissues have considerable influence on the recorded fetal ECG. All of these different tissues and layers form the volume conductor in which the fetal cardiac signals propagates up to the maternal body surface. This volume conductor is not a steady conductor. Its electric conductivity and the geometric shape constantly change throughout gestation. The amniotic fluid, the placenta and the fetus increases its volume in the 20th week onward. This leads to the recordings of the ECG and the MCG using the surface electrodes (Magann, 1997). The very low conductivity vernix caseosa layer is formed between the 28th and 32nd week of gestation (Oostendorp *et al.*, 1989). It electrically shieldes the fetus and makes the recordings very difficult. For normal pregnancies, the layer slowly dissolves in the 37th to 38th week of pregnancy (Stinstra, 2001).

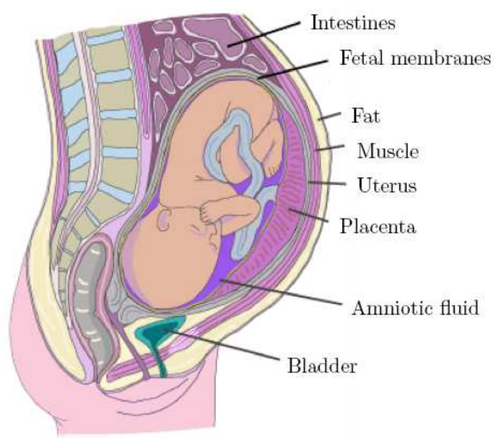

Figure 2.2 The fetomaternal compartments influencing the fetal cardiac surface potentials

During the first two trimesters of pregnancy the fetus does not have a specific presentation and moves about a lot. By the beginning of the third trimester it commonly settles in a head-down position known as the vertex presentation, which is more appropriate for birth (Osei and Faulkner, 1999). However, the fetus may also settle in other, but less-probable, presentations. The presentation of the fetus influences the fetal cardiac signals recorded from the maternal body surface over different leads.

2.1.2 PHYSIOLOGY OF THE FETAL HEART

There are some functional differences between the fetal and adults hearts. After the birth, the right ventricle pumps the blood to the lungs for acquiring oxygen and the left ventricle pumps blood to the body. But for the fetus, the fetal oxygen is supplied by the placenta.The blood is no longer pumped to the lungs. Instead both ventricles pump the blood throughout the body including the lungs (Stinstra, 2001). While the mechanical function of the fetal heart differs from an adult heart, its beat-to-beat electrical activity is rather similar.

2.1.3 FETAL ELECTROCARDIOGRAM

The fetal electrocardiogram was first observed by M.Cremer in 1906 (Deam 1994). The representation of fetal PQRST is (Stinstra, 2001);

- P wave: atrial depolarization. During the next 50ms, only very weak signals are recordable, as it takes some time for the depolarization front to travel through the AV-node. (Ihara *et al*., 2006)
- QRS complex: the ventricular depolarization. The atria is repolarized at the same time; but this repolarization is obscured by the depolarization of the ventricles.
- T wave: the ventricular repolarization.

Though there are similarities between the electrical properties of fetal and adult, the RR interval and morphology are different. The fetal heart beat is almost twice as fast as an adult heartbeat with changes in different stages of fetal cardiac development (Hornberger and Sahn, 2007). Adult and fetal ECG has similar patterns but the relative amplitudes of the fetal complexes undergo considerable changes throughout gestation and even after birth. The most considerable change concerns the T-waves, which are rather weak for fetuses and newborns (Van Leeuwen *et al*., 2004)

2.2 FETAL MONITORING

Fetal electrocardiogram monitoring is a technique for obtaining the important information about the condition of the fetus during pregnancy .The characteristics of the FECG such as heart rate, waveform, and dynamic behavior are convenient in determining the fetal life, fetal development, fetal maturity, and existence of fetal distress or congenital heart disease. Analysis of the fetal heart sound has been used for more than 100 years to find out whether the fetus is alive or not. Pinard´s stethoscope (simple wooden funnel) is still being used for this purpose (Sundstrom *et al.*, 2005). During 1960s the abdominal electrode recordings were providing more information than the simple heart rate (Taylor *et al*., 2003). Electronic fetal monitoring (EFM) was introduced during the 1970s and it has become a useful and significant obstetric tool. It was providing more detailed fetal heart rate analysis and a generally accepted method for fetal surveillance during pregnancy and labor (Amer, 2003). EFM technology is easy to operate and more robust as a result of advances in signal processing techniques. But, to date the EFM cannot provide all the desired information of fetus (Sundstrom *et al*., 2005).

2.2.1 ELECTRONIC FETAL MONITORING

Electronic fetal monitoring uses special equipment to measure the response of the fetal heart rate (FHR). It provides the record that can be read by the doctor or nurse. FHR is a good indicator of stress on the fetus in labor and delivery. Normal heart rate suggests that the fetus is extracting enough oxygen form the woman's bloodstream through the placenta and umbilical cord. But variations in the heart rate can indicate decreased oxygen in the blood and tissues of the fetus, which can lead to potential damage to the brain, central nervous system and organs. In several cases, this can result in death. Electronic fetal monitoring can be external (Non invasive), internal (invasive). The pregnant woman needs to stay in bed during both types of electronic monitoring, but she can move around and find a comfortable position.

2.2.2 INTERNAL ELECTRONIC FETAL MONITORING

This method is also called as the direct or invasive method. The internal monitoring involves the placement of a small plastic device through the cervix. The fetal scalp electrode is placed just beneath the skin of the fetal scalp. The fetal heart rate information is transmitted through the fetal scalp electrode to the fetal monitor. The advantage of the internal fetal monitor is, since the electrode is attached directly to the baby the fetal heart rate is sometimes much clearer and most consistent than the external monitoring device. But the disadvantages are there may be a slight risk of infection and also the scalp electrode may cause a mark or small cut on the baby's head. But this may heals quickly (Chen, 2004).

2.2.3 EXTERNAL ELECTRONIC FETAL MONITORING

This method is also called as indirect or non-invasive method. The external fetal monitoring is done through the skin and it is not meant to be invasive. The electrical signals generated by the fetal heart are measured from multi channel sensitive electrodes placed on the mother's abdomen over conducting jelly (Chen, 2004).This method of recording the fetal ECG from the mother's body without direct contact with the fetus is highly desirable. Some of the external fetal monitoring techniques are:

- Fetoscope
- Fetal Phonocardiogram
- Cardiotocography
- Fetal magnetocardiogram

- Doppler Ultrasound
- Abdominal ECG

Fetoscope: It is a special device like stethoscope. It is placed in the ears of the doctor and the open end is pressed on mother's abdomen. The fetal heart beat can be heard clearly by this method but used less often than the Doppler ultrasound (Peters *et al*., 2001).

Fetal Phonocardiogram (FPCG): It allows the heart sounds and murmurs to be detected by contracting heart. FPCG imparts no energy to the fetus and therefore is inherently safe for long term monitoring. But it was felt to be too susceptible to movement artifacts effects (Bassil *et al.*, 1989).

Cardiotocography (CTG): It is the simultaneous measurement of the fetal heart rate with an ultrasound transducer, and the uterine contractions with a pressure-sensitive transducer (called a tocodynamometer), for measuring the strength and frequency of uterine contractions (Signorini *et al.*, 2003).

Fetal Magnetocardiogram (FMCG): This uses (SQUID) superconducting quantum interference device (Crowe *et al*., 1995).The FMCG is based on the measurement of the magnetic fields produced in association with cardiac electrical activity (Lewis, 2003). The disadvantages of the fetal MCG are the size, cost and complexity of the instrumentation required.

Doppler ultrasound: It is commonly used technique. It is a small device that is pressed against the mother's abdomen. The sound waves are converted in to signals of heart beat by the ultrasound device. The advantage is simple to use and it can be virtually assured that FHR can be obtained (Noguchi *et al*., 1994). The disadvantage is it produces averaged heart rate and cannot give beat to beat variability.The ultrasound transducer involves the procedure of launching 2 MHz signal towards the fetus will be problematic and very uncomfortable (Karvounis *et al*., 2007). So it is not suitable for long periods of FHR monitoring (Ungureanu *et al*., 2005).

Abdominal Electrocardiogram (AECG):

This method has the greater prospect for long term monitoring of FHR and fetal well-being using signal processing techniques. The AECG signal can be used for non invasive FHR determination through the detection of small fetal cardiac potentials from the maternal abdomen surface (Solum *et al.*, 1980). This technique is completely non invasive and unobtrusive. This has comparatively low power requirement and can be used over extended (e.g., 24h) periods. This 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 additional information compared to Doppler ultrasound (Maria *et al*., 2001).

Abdominal Electrocardiogram is recorded by suitably placing the electrodes on the mother's abdomen and recording the combined maternal and fetal ECG. This method monitors the baby's heartbeat by placing a small round ultrasound (high-speed sound waves) disc with ultrasound gel on the mother's abdomen and held in place by a lightweight stretchable band or belt. Uterine contractions are recorded from a pressure-sensitive transducer that is also placed on the abdomen and held by a lightweight stretchable band or belt (Khandpur, 2002).

2.3 AECG OF PREGNANT WOMEN

The AECG of a pregnant woman reflects the mother and fetus heart activity .The ECG signal is measured in two locations (i) the chest and (ii) the abdomen. The typical method of measurement includes 5 abdominal and 3 thoracic recordings (Deam, 1994). The abdominal signals are the composite signals which contain both the maternal ECG and fetal ECG signals where as the thoracic signal contains the maternal ECG signals (Richter *et al.*, 1998). The fetal ECG signal has high heart rate but weaker signal. The maternal ECG signal has lower heart rate than the fetal but a stronger signal.

Figure 2.4 shows the abdominal signals measured in an 8 channel experiment. They have both MECG and FECG along with some high frequency noise. The signals were recorded at a sampling frequency of 250 Hz from 8 electrodes located on a pregnant woman's skin. The real cutaneous electrode recordings for 1000 samples are plotted in Figure 2.3 for different electrode positions (EP2 to EP6). Figure 2.4 shows the signals from the mother's thoracic region (TECG) for three electrode positions (EP7 to EP9). Due to the longer distance between the thorax electrodes and the fetal heart, no FECG heartbeat component can be perceived in this.

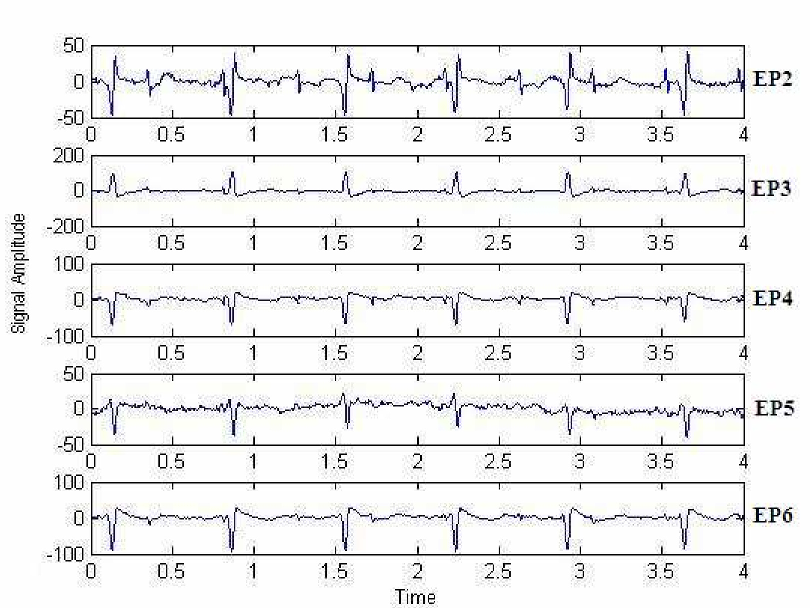

Figure 2.3 Abdominal signals from different electrode positions.

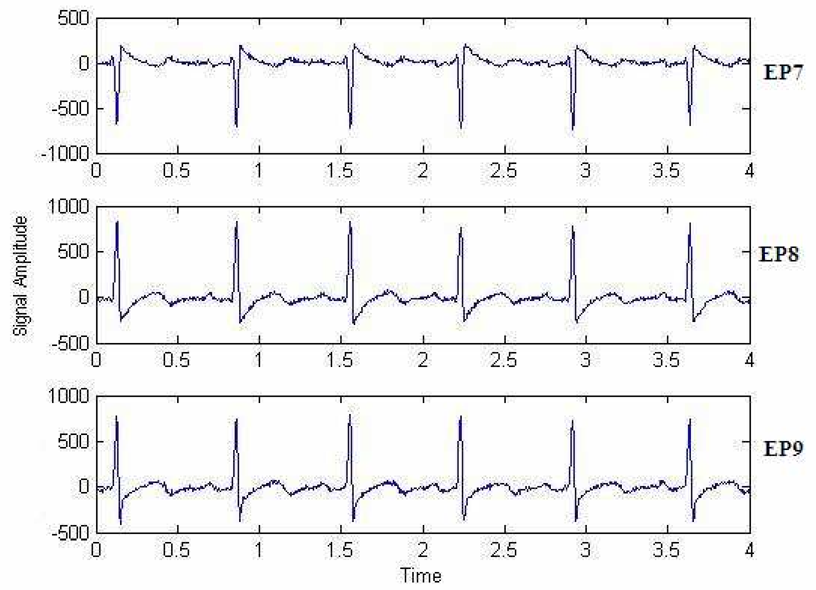

Figure 2.4 MECG signals measured at the thorax region of a pregnant woman.

The maternal ECG signal depends upon the gestational age, the position of the fetus and the positioning of the electrodes (Vrins *et al*., 2004). Fetal heart rate depends upon the fetal activity, hypoxia, placental blood flow, external stimuli, drugs and increases in temperature (Sundstrom *et al*., 2005).

2.3.1 INTERFERENCE AFFECTING THE FECG SIGNAL IN AECG

The FECG exhibits the bandwidth of 0.05 to 10 Hz. The maximum amplitude of the QRS usually oscillates from 100 to 150μV for the maternal recording and up to 60 μV for fetal recording in composite abdominal signal. The energy of the fetal has been estimated to be less than one quarter of the total signals energy (Martinez *et al*., 1997) The FECG signals are disturbed by the electrical noise such as ECG noise. The ECG noise sources are power line interference, muscle contractions, respiration, skin resistance interference and instrumental noise. The electromyogram and electrohysterogram due to uterine contractions can corrupt the fetal ECG signals significantly (Zarzoso *et al*., 1997).

The shape and structure of the FECG signal also depends on the placement of the electrodes, the gestational age and the position of the fetus (Golbach *et al*., 2000). However, there is no standard electrode position identified for optimal FECG acquisition (Vrins *et al*., 2004). All of the above interference and noise make the fetal ECG detection and extraction a difficult process from the composite abdominal signal. The electrical noise which will affect the fetal ECG signals can be categorized in to the following types:

(i) MECG Signal: MECG signal is the most predominant interfering signal with fetal ECG in the abdominal signal. The frequency spectrum of this noise source partially overlaps that of the ECG. Therefore eliminating this noise is an important aspect of fetal ECG extraction (Mazzeo, 1994).

(ii) Power line interference: Power line interference consists of 50 Hz pickup and harmonics. By using low noise electronic amplifiers with high common mode rejection ratio the effect of 50Hz power line interference and the electronic random noise can be eliminated (Assaleh, 2007).

(iii) Maternal muscle noise: The muscle noise is due to maternal movement. It is often from the leg and abdominal muscles and may be picked up from the reference pad from the maternal thigh. EMG activity in the muscles of the abdomen and uterus is the source of this kind of noise. EMG noise can be reduced but not necessarily eliminated with the use of classical low pass filtering techniques (Assaleh, 2007). Sometimes, it will be difficult to identify the EMG signal from the abdominal signal.

(iv) Electrode contact noise: It is the transient interference caused by the loss of contact between the electrode and skin. This disconnects the measurement system from the subjects. The transition may occur only once or may rapidly occur several times in succession.

(v) Motion artefact: There are two main sources for motion artefact which are the electrode interface and electrode cable. The motion artefact can be reduced by proper design of the electronics circuit.

(vi) Inherent noise in electronic equipment: All electronic equipments generate noise. This cannot be eliminated. But it can be reduced by high quality electronic components.

(vii) Ambient noise: The source of this noise is electromagnetic radiation. The surfaces of the human bodies are constantly inundated with electro-magnetic radiation. And it is not virtually possible to avoid exposure to ambient noise on the surface of earth.

(viii) Baseline Drift Interference: Baseline drift interference which is the low frequency components is due to electrode-skin impedance change caused by the respiration and body movement. High pass filters are used to remove the baseline drift (Friesen *et al.*, 1990).

The signal processing algorithms need to remove the (i) MECG from the composite abdominal signals (ii) reduce the effects of the motion artefacts and muscle noise (iii) enhance the FECG for monitoring and analysis purposes.

2.4 FECG SIGNAL DETECTION ALGORITHMS

FECG signal is obtained from the abdominal signal of a pregnant woman that has the potential of being an effective tool for determining the overall condition of the fetus during the delivery. It is used for the detection of pathological phenomena. The detection of FECG is yet a difficult task even when the maternal component of the signal has been reduced. Hence, to observe the FECG some technique should be applied to eliminate the maternal contribution and to improve the SNR (Symonds, 2001).

Several methods have been proposed for detecting and processing the FECG signal from the abdominal signal. The first requirement for performing an untriggered averaging of the FECG is to determine the average FHR. To detect FHR, two fundamental methods can be considered. (i) Peak detection method and (ii) transform method. In the Peak detection method a small segment of the FECG is observed at a time and searched for the fetal R wave. The result of the search in abdominal signal depends on the algorithm used. Due to unpredictable nature of the abdominal signal, the local SNR value fluctuates about the SNR value of the entire signal and might be smaller at sometimes. This may lead to non detection of fetal peaks from the noisy FECG signal. In the second method, a new function of one or more parameters is constructed from the historical signal. Each value of the new function represents a property of the entire signal. At the same time, each value does not depend on the local SNR but the SNR of the entire signal. This leads to detection of FHR even when the FECG signal is obscured by the noise. The peak detection algorithm failed to detect FHR whereas the transform method could detect.

Tal and Akselrod (1989) proposed a discrete Fourier transform method for the detection of FHR from the composite abdominal recordings. The primary application of the proposed method is to simulate FECG signal. The proposed method empowers the detection of FHR from AECG signals where the fetal signal is barely visible. Then the elimination of the MECG from the AECG is performed. They computed a triple parametric transform function by multiplying the signal by their analyzing functions and integrating the result. In general, the method can be applied to handle weak, quasiperiodic, sharp signals of various origins.

Kam and Cohen (1999) proposed two architectures for the detection of FECG. The first architecture is a combination of an IIR adaptive filter and genetic algorithm

(GA). The second one is an independent GA search without the adaptive filter The GA is included whenever the adaptive filter is suspected of reaching local minima. The main disadvantage of an IIR (Infinite Impulse Response) filter is that the error surface is not quadratic but a multimodal surface. Therefore, the presence of the GA forces the algorithm to overcome the local minima and reach the global solution. The quality of the extracted FECG using this IIR–GA adaptive filter is superior to that obtained using the GA alone. The method of combining an adaptive filter with a GA performs effectively, when there are uterine contractions in the ECG data.

Stoughton *et al.*(1990) proposed the adaptive least mean square linear prediction methods. In the presence of background acoustic noise this method was useful for fetal heart tone signature analysis and detection. Adaptive signal-processing methods are presented in support of a noninvasive ambulatory FHR monitor. Successive evaluation of the detected fetal heart tone events are used to determine the instantaneous FHR. The initial investigation has indicated that linear prediction method is feasible for detecting the fetal heart tones in an advanced acoustic FHR monitoring system.

Lai and Shynk (2000) have proposed an adaptive algorithm for detecting and separating the fetal and maternal heart beats. The composite ECG signal is generated by the genesis technologies intrauterine catheter electrode. Using this method the estimation of FHR and MHR are obtained. This method does not require reference signal to cancel the maternal QRS complex and has low computational complexity.

Peters *et al.*(2006) developed an algorithm that calculates the heart rate based on cross-correlation. This algorithm used the multi electrode measurements from the maternal abdomen for fetal monitoring in the early stages of pregnancy. This algorithm is also suitable for monitoring the fetal when the ECG amplitudes are low or the noise levels are high.

2.5 FECG SIGNAL EXTRACTION ALGORITHMS

The fetal ECG signals can be used as indicators for monitoring and assessing the fetus cardiac activities and well-being. There have been several research studies aimed at developing signal processing techniques to extract fetal ECG signals or to suppress other noise components from the composite abdominal signals. The problem of FECG extraction was tackled more than 30 years ago. A variety of techniques that have been applied for fetal ECG signal extraction include adaptive filtering, wavelet transform, ICA (Independent Component Analysis), BSS (Blind Source Separation) and Singular Value Decomposition (SVD). Some artificial intelligence (AI) techniques are Fuzzy logic, neural network, Genetic algorithms (GA) and combinations of fuzzy logic and neural network.

Widrow *et al*.(1975) had addressed the adaptive noise cancellation technique is to remove the interference from the composite abdominal signals. Multiple abdominal signals were used for extraction purpose.

Ferrara and Widrow (1982) had proposed time sequenced adaptive filtering method for the enhancement of the abdominally derived fetal electrocardiograms against background muscle noise. This method requires two or more abdominal channels. The advantage of the adaptive signal enhancing techniques is that the power spectra of the signal and noise need not be known a priori. The result shows that there is substantial improvement in terms of signal distortion when time sequenced filtering is used compared to conventional time invariant filtering.

Widrow and Stearns (1985) proposed the adaptive noise cancellation technique for extracting the fetal ECG by canceling the maternal ECG from the composite abdominal signal. They used two sets of electrodes, one set placed on the abdomen of the mother and the other placed on the chest of the mother. The electrodes placed on the mother's abdomen contain the FECG and MECG whereas the chest electrode contains only the MECG. These two signals form the inputs to the adaptive filters and the error is the extracted FECG. The drawback of this method is, it fails to extract the FECG when it is overlapped with the MECG.

Hamilton (1996) had proposed the comparison between the adaptive filters and non adaptive filters for reduction of power line interference in the ECG. The performance of the two implementations were evaluated with respect to adaptation rate, signal distortion and implementation complexity. The relative effect of adaptive and non adaptive filters was investigated. The result shows that the adaptive implementation of reduction in power line interference is less complex and more effective in removing the noise compared to the non adaptive filters.

Martens *et al*. (2006) had proposed an improved adaptive power line interference canceller for electrocardiography with error filtering and adaptation blocking technique. This method suppresses the fundamental power line interference component and harmonics in ECG recordings and is to be preferred to notch filters. This method would be equally applicable to other types of corrupted signals such as electromyogram (EMG) and the electroencephalogram (EEG) with slight modifications.

Vesal *et al*. (2006) had used classic adaptive noise cancellation technique for non invasive fetal electrocardiogram extraction by including the fetal phonocardiogram as an adaptation trigger. This approach uses additional acoustic modality to detect the temporal occurrence of the fetal heart beats. These estimated periods are used as an adapt- disabled trigger, halting adaptation during a fetal heart beat. Their finding show a better approximation of FECG using a recursive least squares adaptive filters.

Maha Shadaydeh *et al*. (2008) used adaptive volterra filters which are capable of synthesizing the non linear relationship between the mother thoracic signal and the abdominal signal which contains a transformed mother ECG, fetal ECG and other noise elements. They have used a multi sensory noise canceller structure for the extraction purpose. The results provided better estimated FECG waveforms because the adaptive volterra filters used is more capable of representing the complicated relation between the mothers ECG and fetal ECG.

Yanjun *et al*.(2008) used the RLS based adaptive noise cancellation approach to eliminate the maternal ECG and hence to extract FECG. The experimental results have demonstrated that the developed adaptive noise cancellation approach can speed up convergence of the normalized LMS algorithm and is able to tract non stationary FECG. The results show that the RLS ANC algorithm offers more robustness.

The wavelet transform (WT) is an efficient tool for local analysis of non stationary and fast transient signals. The important property of the WT is that it can be implemented by means of discrete time filter bank. The WT represents a very suitable method for the classification of the FECG extraction from the abdominal signal.

Mallat (1989) had developed a procedure to extract the fetal ECG by WT method. There are two stages. The first stage is the preprocessing stage for the suppression of low and high frequency additive noise based on optimal wavelet multiresolution decomposition. The second stage is to cancel the maternal QRS complexes by means of pattern matching and template subtraction. In order to eliminate detail signals that do not have maternal and fetal QRS frequency components and to allow maternal and fetal complex homogenization, the wavelet multiresolution decomposition was used (Abboud and Sadeh, 1989). The homogenization and noise elimination process based on wavelet multiresolution decomposition assure that the maternal QRS complexes on real signal present morphological patterns that can be highly associated with the additive influence of the embedded fetal QRS complex.

The FECG was monitored by calculating the Lipschitz exponent combined with wavelets (Mallat and Hwang, 1992). The main problem with this method is to locate the FECG when it is obscured by the MECG. This was the major drawback, since they had the combinations of the above signals which appeared two or three times in a 10second period. During the uterine contractions the noise contents are more. This leads to set the thresholds on the wavelet coefficients dynamically during the process. This type of denoising may not be optimum since the thresholding of the wavelet coefficients may result in removing the FECG component from the original signal especially during the contractions.

Echeverria *et al*.(1996) had developed a procedure with wavelet analysis and pattern matching for the off line processing of AECG. It is assumed that the signal can be mathematically described by the equations which include the fetal, maternal and Gaussian noise components. These terms are affected by a modulation factor that causes baseline wandering (Bergveld *et al*., 1986).The pattern-matching procedure has an advantage of extraction being specific to every record, giving more robustness to the identification process.

Datian and Xuemei (1996) had proposed the wavelet analysis method for detection of FECG from the AECG signal. The wavelet analysis method was first applied to detect the appearances of the distorted MECG signal and eliminate this signal form the AECG. In some situations even after eliminating the MECG, the FECG was still challenging to extract. This is due to the scale factor of the wavelet base function which can enhance the FECG only with an appropriate value. Using this method the FECG was detected in more efficient way.

Papadimitriou *et al*. (1996) used wavelet transform to denoise the FHR signals. In this method, the transient spikes were removed and the noise was reduced without destroying the high frequency information content of the signal. A noise reduction technique that detects noise components by analyzing the evolution of the WT modulus maxima across scales is adapted to improve the quality of FHR recording. The denoising method eliminates those multiscale maxima which correspond to the noise components. The denoised FHR is reconstructed from the processed maxima by the inverse WT.

Khamene and Negahdaripour (2000) had proposed a biorthogonal quadratic spline wavelet method for extraction of fetal ECG from AECG. This is based on the detection of the singularities obtained from the composite abdominal signal using the modulus maxima in the wavelet domain. Modulus maxima locations of the abdominal signal are used to discriminate between the abdominal and fetal ECG signals. Two approaches have been used. One uses thoracic signal a priori to perform the classification where as in the second approach no thoracic signal was needed. A reconstruction method was utilized to obtain the fetal ECG signal from the detected fetal modulus maxima.

Mochimaru and Fujimoto (2002) also used wavelet-based methods to detect the FECG. They used multiresolution analysis (MRA) to remove the large baseline fluctuations in the signal as well as to remove the noise. MRA was performed on the raw ECG data with 12 levels of decomposition using Daubechies20 wavelet function. Noise removal was accomplished by thresholding the wavelet coefficients at each level.

Karvounis *et al*.(2004) had developed the fetal ECG extraction based on the complex continuous wavelet transform (CCWT) and modulus maxima theory using multichannel MECG recordings. For a nonstationary signal, CCWT can be used to identify stationary sections of the data stream and locate and characterize singularities.

Song *et al.* (2006) had proposed a method where fetal heart sound signals can be detected, denoised, and reconstructed by utilizing wavelet transform based signal-processing approach. This approach improves the signal-to-noise ratio, which allows reliable FHR variation to be estimated under very weak signal environment.

Karvounis *et al*.(2006) had developed a three stage method for FHR extraction based on the time- frequency analysis used for AECG signal processing. In the first stage using time –frequency analysis, the maternal R peaks and fiducial points (QRS onset and offset) are detected and the maternal QRS complexes are eliminated. The second stage locates the positions of the R peak using complex wavelets and pattern matching theory. In the third stage, using histogram based technique the detection of the overlapped fetal R peaks with the maternal QRS is accomplished.

Magalhaes *et al*.(2006) had used approximate entropy with wavelet filtering method (ApEN). This method is suitable in finding the FHR irregularity for fetal risk assessment. ApEn was able to discriminate three categories of behavioral patterns: calm sleep, calm vigilance, and pathological flat-sinusoidal condition. They showed high level of discrimination between normal and pathological FHR tracings.

Some others methods like ICA (Independent Component Analysis), BSS (Blind Source Separation) and Singular Value Decomposition (SVD) are becoming very popular for processing the FECG signal form the AECG.

Kanjilal *et al*.(1997) had proposed the SVD method for fetal ECG extraction by single channel MECG. This method employs the singular value decomposition and analysis based on the singular value ratio spectrum. Using singular value decomposed modes the MECG and FECG components are identified. Then the elimination of MECG and extraction of FECG are achieved through the selective separation of the singular value decomposed components. The important feature of this method is that only one composite MECG signal is required to determine the FECG component. Therefore, the method is numerically robust and computationally efficient.

Lathauwer *et al*.(2000) proposed the emerging technique of ICA to extract the fetal ECG from the multilead potential recordings on the mothers skin which is the classical problem in biomedical engineering. ICA is an ambitious approach. ICA was aimed to reconstruct of the different statistically independent bioelectric source signals, as well as the characteristics of their propagation to the electrodes, which reveals important medical information. It is nonparametric and is not based on pattern averaging, which could hamper the detection and analysis of typical fetal heartbeats.

Barros and Cichocki (2001) had proposed a semi-blind source separation algorithm to extract the fetal ECG from AECG. This algorithm requires a priori information about the autocorrelation function of the primary sources. They did not assume the sources to be statistically independent but they assumed that the sources have a temporal structure and have different autocorrelation functions. The main problem with this method is that if there is FHR variability, a priori estimate of the autocorrelation function of the FECG may not be appropriate for FHR analysis.

Marossero *et al.*(2003) had developed the extraction method by combining the ICA and mermaid algorithm. Minimum Renyi's Mutual Information (Mermaid) was proposed by Hild *et al*.(2001) using BSS technique. Marossero demonstrated the performance of an information theoretic ICA with Mermaid and the performance of the Mermaid algorithm was evaluated. The effectiveness and data efficiency of Mermaid and its superiority over alternative information theoretic BSS algorithms are illustrated.

Ping Gao *et al*.(2003) had combined the SVD and ICA methods to extract the fetal ECG from the mixture of ECG signals from the abdomen of the mother. They mainly applied the blind source separation method using SVD to separate of each component the ICA contributes to the independence of the two components from the mixtures.

Vigneron *et al*.(2003) had also applied the BSS methods for fetal ECG extraction. In this method the fetal ECG was constructed by means of higher order statistical tools for exploiting the non stationary ECG signals with wavelets post processing techniques.

Vrins *et al*.(2004) had applied the BSS technique to extract fetal ECG. In this application the sources are, FECG with MECG, diaphragm and uterus. The mixtures are recorded through electrodes located on the pregnant woman's abdomen.

Burghoff *et al*. (2004) employed the ICA method to separate the fetal and maternal magneto cardiographic signals in twin pregnancy. ICA uses higher-order statistics to decompose the signal into statistical independent components. The results of this method showed that the maternal and fetal components could be separated from each other as well as from other sources of noise and artifacts in the abdominal signal.

Chareonsak *et al*.(2004) had proposed a real-time BSS method that can be used to separate the FECG from the MECG effectively. Najafabadi *et al*. (2005) had employed the ICA method for fetal ECG extraction from the AECG. The results show that ICA works well to extract FECG from AECG even in SNR is -200dB using simulated data. But the performance was drastically decreased in existence of quantification noise.

Lee *et al*.(2005) proposed a new FECG extraction algorithm using a single channel from the abdominal signal. This algorithm is considered into a training and detection step. In a training step, a demixing vector was computed with over determined BSS and fetal beat detection was performed by utilizing the computed demixing vector in the detection step. The algorithm was evaluated with a simulation signal that has diverse heart rates and with real maternal AECG. In all the cases, detection was perfectly achieved.

Some AI techniques are mainly based on neural networks have been proposed for processing FECG signal. Neural network is a computing technique that evolved from mathematical models of neurons and systems of neurons. During recent years, neural networks have become a useful tool for categorization of multivariate data. This kind of technique is very useful for real-time application like FECG signal recording and analysis.

Horner *et al*.(1992) had proposed the genetic algorithm (GA) approach to extract FECG from AECG. This method is based on subtracting the pure MECG from an abdominal signal which contains the FECG and MECG signals. Subtraction via genetic algorithm is supposed to be near optimal rather than a straight subtraction. The disadvantage of the method is needed to get the MECG signals whose shape is similar to the MECG present in the abdominal recordings where the FECG signals also available. Therefore, it needs to be determined exactly where the electrodes need to be placed to pick up the MECG alone.

Liszka-Hackzell (1994) employed the categorization process for the FHR patterns. Digitized data from CTG measurements have been used for categorization of typical heart rate patterns before and during delivery. The backpropagation and SOM (self organizing map) networks were used that can be reliable and agree well with the manual categorization.

Marques *et al*.(1994) proposed a method to determine the FHR using artificial neural networks(ANN). In this method, two baseline determinations methods were suggested with multilayer perception based ANN. The baseline estimation and base line classification were described and compared based on their results. It is found that the base line classification is clearly superior to the corresponding base line estimation method.

Magenes *et al*.(1999) combined the neural and fuzzy classifiers to extract FECG signal from AECG. Using this method, the normal and pathological fetal states were discriminated. Both classifiers are based on linear and non linear indexes extracted from cardiotocographic fetal monitoring. It was observed that the neural and fuzzy classifiers could improve the diagnostic information contained in CTG signals.

Selvan and Srinivasan (2000) had suggested that the combination of adaptive filtering technique with neural network is an efficient technique for processing the abdominal FECG. Real time recurrent learning algorithm is applied for training the neural network. The training converges faster to a lower mean square error and suitable for real time processing as well. The proposed technique performs better than the noise canceller alone or a cascade connection of both noise canceller and signal enhancer.

Azad (2000) had proposed a fuzzy based approach for extraction of FHR. That was the improved scheme for detecting the presence of the QRS complexes from the AECG using a fuzzy detection algorithm. The fuzzy detector incorporates a measure of uncertainty and can conclude that a maternal and fetal ECG is present in the maternal abdominal recordings.

Camps *et al*.(2001) had proposed a method by FIR(Finite Impulse Response) neural network in order to provide highly nonlinear dynamic capabilities to the FECG extraction model. FIR neural network has the noise cancellation techniques as Widrow method. Although the original scheme of Widrow (Widrow *et al*., 1975) considered several reference signals, only one thoracic reference is considered in their proposed method. In this way, all the correlated components (maternal signal) vanish and the FECG register is obtained as the error signal.

Reaz and Wei (2004) proposed FECG extraction based on the adaptive linear neural network. In this method the neural network is trained to cancel out the maternal signal to get the fetal signal alone. The fetal signal is weak under the domination of maternal signal and other noises. The network emulates maternal signal as closely as possible to abdominal signal, thus only the MECG is predicted in the AECG. The main concept of this proposed method is that the network error equals AECG minus MECG, which is the FECG. This method is better than conventional filtering because subtraction was used. It can avoid eliminating desired signal.

Warrick *et al*.(2005) had used the combined tools of signal processing and neural networks to develop the automated technique to detect the FHR patterns of baseline, acceleration and deceleration.

Assaleh (2007) had proposed an adaptive neuro fuzzy logic technique to extract the fetal ECG from the AECG. Using the neuro fuzzy combination the non linearity of the MECG is identified. Then the fetal ECG is extracted by subtracting the aligned version of MECG signal from the abdominal signal.

Some other methods with different techniques for fetal ECG extraction are discussed below.

Mooney *et al*.(1995) had designed a adaptive algorithm based microcomputer controlled data acquisition system capable of accurately capturing the fetal cardiac signal from the maternal transabdominal recordings.

Pieri *et al*.(2001) has proposed the matched filtering technique to extract the fetal ECG from the AECG. Three abdominal leads were used for extraction purpose. The analog preprocessing steps were done then the signal is digitized and further processed by low pass filter, band pass filter. This digital filter stage is followed by a matched filter for further improvement of the SNR. But this method was not yielding satisfactory results.

Laim and Shynk (2002) had used successive cancellation (SC) algorithms for FHR estimation using an intrauterine ECG signal. Intrauterine ECG signal contains the fetal and maternal QRS complexes. The two stage SC algorithms were used to sequentially separate the fetal and maternal heart beat from an intrauterine electrocardiogram signal. The heartbeats are separated consequently in two stages. In each stage a template for fetal or maternal source are initialized and then performs event classification based on a template-matching technique. The template of the stronger source is canceled from the composite ECG signal prior to initialization of the weaker source's template in the second stage. Similarly, beyond the initialization period the classified events of the stronger source are removed before classification of the weaker ones. The postprocessing step improves the classification results by searching for heartbeats that are not detected due to overlapping fetal and maternal complexes or noise corruption.

Ibrahimy *et al*.(2003) had proposed a statistical analysis method for fetal ECG extraction using one abdominal lead recordings. This method performs well for large dataset.

Vasios *et al*.(2003) had proposed the matching pursuits (MP) method to extract the very low frequency periodic components of the complicated FHR fluctuations during labor. This is used to examine the long-term modulation characteristics of the heart rate in relation to the oxygen saturation of fetal arterial blood. The very low frequency range is focused since some of the adaptive responses of the fetus are associated with the long term slowly varying components of the FHR. MP method is sufficiently sensitive to detect abrupt perturbations.

Georgoulas *et al*. (2004) presented an approach to automatic classification of FHR tracings belonging to hypoxic and normal newborns. The classification was performed using a set of parameters extracted from the FHR signal and two hidden Markov models. Their results were satisfactory indicating that the FHR convey much more information than the conventional FHR classification.

Design of application specific integrated circuit for the biomedical instrument has become quite important recently. Various hardware circuits have been implemented to develop FHR monitoring to assess the fetal state thus assuring his well-being during pregnancy period.

Pimentel *et al*. (2001) offered a hardware implementation of a digital compression tool for electrocardiographic signals based on a discrete cosine transform. The platform chosen is a field programmable gate array (FPGA), due to its ease of use and rapid prototyping characteristics.

Charoensak and Sattar (2005) had implemented an efficient FPGE hardware architecture for the realization of a real time BSS. The architecture can be implemented using a low-cost FPGA. The architecture offers a good balance between hardware requirement and separation performance. The FPGA design implements the modified Torkkola's BSS algorithm for audio signals based on ICA technique.

Performance of the extracted FECG was evaluated using the essential parameters proposed by Kohler *et al*. (2002). They are Sensitivity (SEN), Specificity (SPE), Positive Predicted Value (PPV), Negative Predictive Value (NPV) and Accuracy (ACC). TP (True positive) is the total number of positive peaks detected in extracted FECG .TN (True Negative) is the total number of negative peaks detected in extracted FECG. FN (False Negative) when an artefact is detected as negative peak. FP is (False Positive) when an artefact is detected as a positive peak. In addition to the above parameters Correlation Coefficient (CORR) and Signal to Noise ratio (SNR) have also been studied.

2.6 RESEARCH GAPS IDENTIFIED

In view of the literature review, following main research gaps were identified.

(i) BSS and ICA extraction methods though considered as the successful methods, they require multiple leads for collecting several abdominal signals. In this method one can see the remnants of the maternal R wave of the maternal and fetal QRS overlap. The other disadvantage of BSS from cardio pediatrician point of view, that the results were not satisfactory because of the lack of accuracy on the smallest waves. i.e P,O,R,S and T.

(ii) The fetal ECG extraction based on adaptive filters can use two leads but have their limitations especially when the fetal beats overlap with the QRS wave of the maternal beats.

(iii) The fetal ECG extraction based on source separation using wavelet domain introduces the permutation problem which is a known limitations of transform domain BSS particularly for convolute mixtures. The other disadvantage is its limitation when overlapping between the maternal ECG and fetal ECG signals exists.

(iv) Fetal ECG extraction based on neural networks take longer time for training and estimating the thoracic signal from the composite abdominal signal .

(v) Fetal ECG extraction based on fuzzy logic technique is not useful for interference cancellation technique due to its absence of adaptation capability.

The present research aims to overcome the above drawbacks by developing novel techniques and soft computing techniques for FECG extraction. The proposed techniques use two lead (one abdominal and one thoracic) signals to extract FECG.

CHAPTER 3

NOVEL EXTRACTION TECHNIQUES FOR FECG USING MULTI STAGE ADAPTIVE FILTERING

3.1 INTRODUCTION

Suppression of maternal ECG in composite abdominal signal is required to extract the fetal ECG. MECG cancellation is a special case of optimal filtering which can be obtained when the information about the thoracic signal is available. Besides the problem of electrode placement, noise from electromyography activity affects the signal due to the low amplitude signal of fetus. Another interfering signal is maternal ECG which has the intensity 5 to 10 times higher than the FECG (Widrow and Samuel, 1985). The maternal ECG affects all the electrodes which are placed on the chest (thoracic electrode) and those placed on the abdomen (abdominal electrode). Because of the weak nature of the FECG, electrodes placed on the thorax of the pregnant women will hardly record any FECG (Kam and Cohen 1998).If one is able to eliminate the maternal ECG component from the composite abdominal signal, the FECG signal can be obtained.

The best solution for this situation is to use adaptive filters because of the advantage that the coefficients can adjust automatically. Moreover the ECG signals are non stationary in nature. The interfering maternal ECG and 50 Hz pickup can be greatly reduced by the use of adaptive filtering (Widrow *et al.*, 1975) and (Glover, 1977). Once these interferences are removed, the resulting signal contains FECG and the muscle noise. The muscle noise can be reduced by signal enhancement (Ferrara and Widrow, 1981). The adaptive filter output is a best estimate of the fetal ECG component. The thoracic and maternal signals need not be identical in wave shape, but they need to originate from a common source.

In this chapter three new algorithms for FECG signal extraction are proposed. These are named as (1) Method I- FECG Extraction Method (2) Method II-Improved FECG Extraction Method (3) Method - III Novel Method of FECG Extraction.

The testing of the algorithms was done by using data from SISTA/DAISY and Physionet. The data from SISTA/DAISY has abdominal data of 5 channels and thoracic data of 3 channels (De Moor, 2005).

Physionet has 2 channels of thoracic signals and 4 channels of abdominal signals. The database used for the maternal signals is written in European Data Format (EDF). It is provided by PhysioBank the public database of PhysioNet. This database contains a series of 55 multichannel abdominal non-invasive fetal electrocardiogram (FECG) recordings, taken from a single subject between 22 to 40 weeks of pregnancy (Marcelino and Jorge, 1997). The sampling frequencies of Sista data and Physio data are 250Hz and 1KHz.Both of the databases has been transformed to a Matlab readable format for easy extraction, computation, and analysis.

The data from Sista daisy has abdominal data of 5 channels (Channels 2,3,4,5 and 6) and thoracic data of 3 channels (channel 7,8 and 9). Physionet has 2 channels of thoracic signals (channel 2 and 3) and 1 channel of abdominal signal (channel 4). However for extraction of the FECG signal, any one channel of abdominal signal and any one channel of thoracic signal are used. The testing of the algorithms was done with all the combination of abdominal and thoracic signals. In Sista data and physio data any one of the thoracic signal is selected since all the channels have huge maternal signal. For analysis purpose one channel of thoracic signal (channel 7) along with all channels of abdominal signals (channel 2, 3, 4, 5, and 6) were individually analyzed and discussed for Sista data. For physio data, one channel of thoracic signal (channel 2) and one channel of abdominal signal (channel 4) were chosen for analysis. The algorithms have been tested with both the data sets.

For explanation purpose, the combination of abdominal channel 2 and thoracic channel 7 is represented as electrode position 2, 7.In a similar way the other channels are named as 3,7 ; 4,7 ;5,7 and 6,7 for Sista data. For Physio, the combination of abdominal channel 4 and thoracic channel 2 is represented as electrode position 4,2.

The proposed methods detect fetal ECG by preprocessing and denoising of abdominal ECG (AECG) and subsequent cancellation of maternal ECG (MECG) by multi stage adaptive filtering. The thoracic signal (TECG) which is purely of MECG is used to cancel MECG in abdominal signal and the fetal ECG detector extracts the FECG.

The evaluation of these methods with data from Sista Daisy has been presented in sections 3.6.1 to 3.6.3 and analysis in section 3.6.5.1. The evaluation of the methods with physiodata has been presented in section 3.6.4 and analysis in section 3.6.5.2

3.2 DEVELOPMENT OF THE ALGORITHM

A novel technique to extract FECG from the composite abdominal signal has been developed using following methodology:

(i) Preprocessing of maternal ECG

(ii) Multi stage Adaptive maternal cancellation

(iii) Extraction of FECG

3.2.1 PREPROCESSING ALGORITHM

The preprocessing of the abdominal signal is required to remove the DC signal, base line wander and power line interference. Base line wander is caused by the patients breathing or movements during recording (Onaral *et al.*,1984). The frequency range of the baseline wander due to breathing has an upper limit smaller than 1Hz. But when the patient is performing exercise, the upper limit may be larger (Laguna *et al*., 1992).The base line wander is low frequency in nature and EMG noise due to muscular contraction is characterised by high frequency. The band pass filter reduces the influences of muscle noise, 50Hz power interference, T wave interference and baseline wander (Pan and Tompkins, 1985). The Fetal heart rate (FHR) normally lies between 120 and 160 beats min^{-1} (bpm) (Abboud and Sadeh, 1990) which corresponds to fundamental FECG frequency between 2 and 2.7Hz. In pathological cases, the FHR may be outside this range. For fetal bradycardia and for fetal tachycardia the fundamental FECG frequency is around 1.3Hz and 3.3 Hz.

The preprocessing consists of the following steps (Swarnalatha and Prasad, 2007):

(a) Read the abdominal ECG

(b) Separate the high resolution components and low resolution components

(c) Compensate for the phase

(d) Derive the noise component

(e) Separate the noise from the original signal

(f) Reconstruct the signal back

(g) Repeat the entire process iteratively

In preprocessing stage, the high resolution components which are the maternal QRS wave having large amplitude and frequency is separated from the low resolution components of fetal ECG. The separation is done using band pass digital filter. The FIR band pass filter with cut off frequencies from 5Hz to 90Hz is used. The power line interference of 50Hz is also eliminated with this band pass filter. Then the signal is subjected to the Fast Fourier Transform where it decomposes a sequence of values in to components of different frequencies. The compensation for the phase of the signal is done by phase shifting the signal so that the noise signal can be derived. The noise signal thus obtained, is separated from the original signal followed by the Inverse Fast Fourier transform to reconstruct the signal back. The result of the above algorithm for the case of atrial fibrillation and ventricular tachycardia are shown in Figure 3.1 and Figure 3.2. Figure 3.1 (a) is the ECG in ventricular tachyarrhythmia. This ECG signal is processed and the noise component derived is shown in Figure 3.1(b). The reconstructed signal shows more subtle details than the original signal. In both the cases the details seen in the reconstructed ECG are not visible in the original ECG signal.

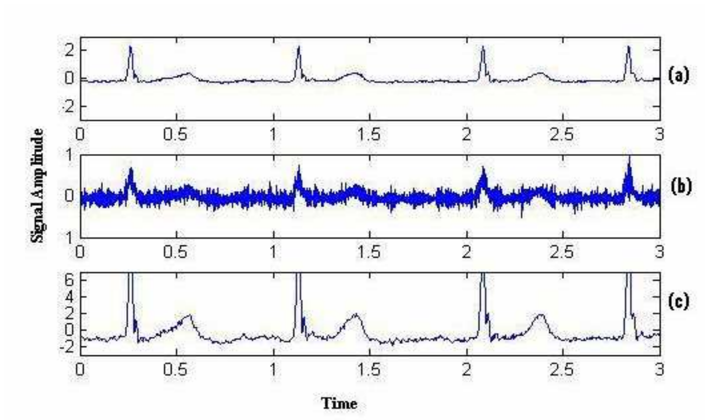

Figure 3.1 (a) ECG in Ventricular tachyarrhythmia, (b) Noise (c) Reconstructed signal

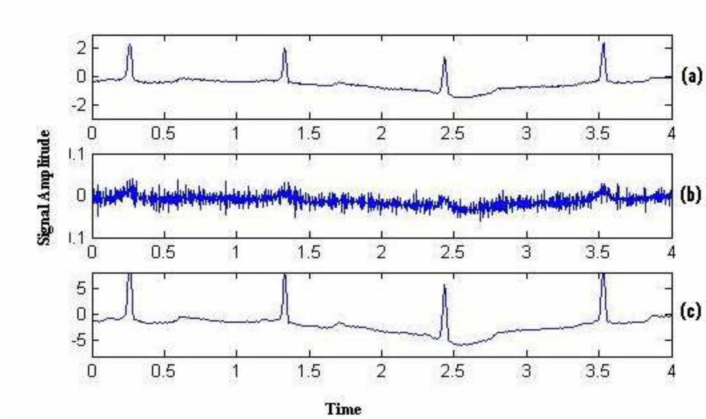

Figure 3.2 (a) ECG in Atrial fibrillation (b) Noise (c) Reconstructed signal

3.2.2 ADAPTIVE MATERNAL CANCELLATION

The subject of adaptive noise canceling was introduced and treated extensively by Widrow (Widrow *et al.*, 1975).Figure 3.3 shows the adaptive method of noise (MECG) cancellation. Here one input signal is the abdominal signal (X_k) which is the mixture of MECG and FECG. In X_k the noise (MECG) is uncorrelated with signal (FECG).

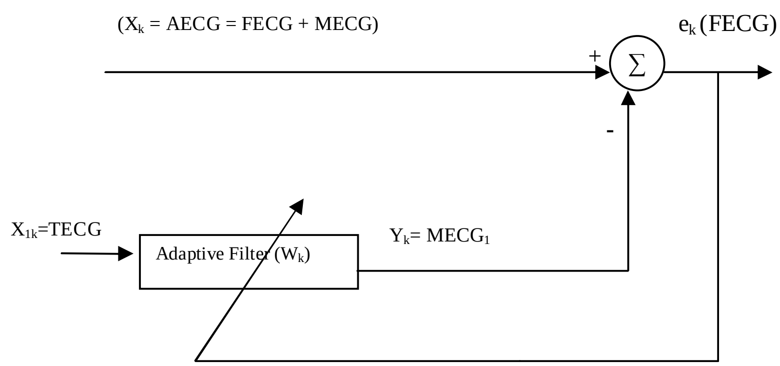

Figure 3.3 Adaptive maternal cancellation

The input signal to the adaptive filter is thoracic signal (TECG) which is uncorrelated to FECG but correlated with MECG. The adaptive filter output Y_k is $MECG_1$. Since $MECG_1$ is generated from TECG it is correlated with MECG but uncorrelated with FECG. The output is the error e_k is given by

$$e_k = FECG + MECG - Y_k \qquad (3.1)$$

The mean square of e_k is obtained as

$$e_k^2 = FECG^2 + (MECG - Y_k)^2 + 2FECG\,(MECG - Y_k) \qquad (3.2)$$

Applying expectations on both sides of the above equation

$$Ee_k^2 = E[FECG^2\,] + E[(MECG - Y_k)^2\,] + 2E[FECG\,(MECG - Y_k)] \qquad (3.3)$$

As FECG is uncorrelated neither with MECG nor with Y_k then 2E [FECG (MECG-Y)]=0

Finally we obtain, $E\,e_k^2 = E\,[FECG^2] + E\,[(MECG - Y_k)^2\,]$ (3.4)

The goal of the adaptive filter is to minimize the mean square error of E [MECG – Y_k]=0

This can be obtained iteratively to give the optimal solution when Y_k= MECG. This result is obtained by the adaptive process without requiring any prior knowledge about the signal and the noise (Widrow and Samuel, 1985). If the properties of noise changes in time and if the frequencies of the signal and the noise overlaps, then the adaptive filtering is chosen. The structure of filter employed for adaptive filtering is invariably finite impulse response because of the inherent stability and mathematical tractability for computation of its coefficients. The filter through an adaptive algorithm readjusts its coefficients W at each time sample, such that the actual filter output is as close to the inference component of the primary input signal as possible in the mean square error (Haykin, 2002). Different algorithms were used for filtering which includes Least Mean square (LMS) and Recursive Least Square (RLS) and normalized least mean square (NLMS). The LMS algorithm is a simple method. It operates by automatically adapting the filter coefficients W so that the instantaneous error signal e_k^2 is minimized. The computations of the weights of LMS are shown in equation 3.5 and 3.6.

$$W_{k+1} = W_k + 2\,\mu\, e_k X_k \tag{3.5}$$

$$e_k = Y_k - W_k^T X_k \tag{3.6}$$

where μ is the learning parameter. LMS algorithm is most effective in terms of computation and storage requirements.The NLMS algorithm is a variant of the LMS algorithm by normalizing with the power of the input. The RLS has the increased complexity, computational cost and fidelity but it minimizes the total error from the beginning to the current value with the forgetting factor λ and it is related to the memory of algorithm. The computations of the weights of are shown in equation 3.7, 3.8 and 3.9.

$$W_k = W_{k-1} + G_k e_k \tag{3.7}$$

where $G_k = P_{k-1} X_k / ά_k$ and $P_k = [X_k^T X_k]^{-1}$; (P_k = Recursive way to compute the inverse matrix, $ά_k$ = priori error)

$$e_k = Y_k - W_{k-1} X_k^T \tag{3.8}$$

$$ά_k = \lambda + X_k^T P_{k-1} X_k \tag{3.9}$$

RLS algorithm has got the superior convergence properties (Emmanuel *et al*., 2002).

3.2.3 BLOCK DIAGRAM OF THE PROPOSED ALGORITHM

The block diagram of the proposed algorithm is shown in Figure 3.4. Fetal ECG detection was done by improving SNR of fetal QRS complex to the other components of the signal using a nonlinear parameter. This reduces the maternal P and T waves. The non linear parameter Ψ is defined as follows.

$$\Psi = DS\ (DS-1) \tag{3.10}$$

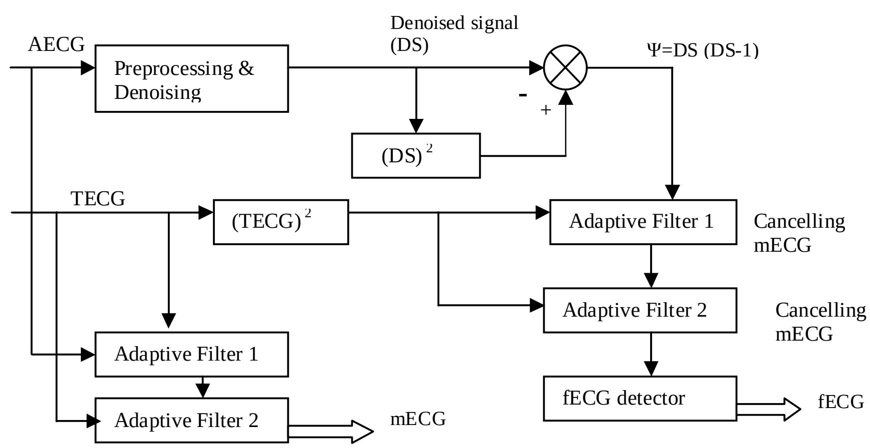

Figure 3.4 Block Diagram of the proposed algorithm

DS is the preprocessed and denoised signal obtained from the original abdominal ECG. The DS signal is squared and then subtracted from DS to obtain Ψ. The advantage of squaring the signal intensifies the slope of the frequency response curve of the derivative and will help in restricting the false positive T waves which is higher than the usual spectral energies (Pan and Tompkins, 1985). The adaptive filter has two input signals. One signal is the thoracic signal and other signal is the non linear operator signal which is the squared denoised signal. The MECG is a quasi periodic signal similar to the FECG. The periodicity of the MECG is usually slower than that of FECG. In abdominal recordings, the MECG amplitude is larger than FECG amplitude. The breathing effects and movements are resulting in changing distance and angle of the electrode with respect to the mother's heart. This leads to a time varying morphology of the MECG. This time variations are not proportional for the P, QRS and T wave because of their different dipole directions (Goldberger and Goldberger, 1994). The MECG cancellation is done by finding an estimate of each MECG complex using scaling procedure. This scaling procedure takes care of the time varying morphology. Adaptive filters are assigned with LMS algorithm in both stages.

Figure 3.5 (a) shows the abdominal signal to be analyzed. Figure 3.5 (b) is the preprocessed signal of the original abdominal signal after reducing the noise. The preprocessed signal is squared. Then, the reconstructed abdominal signal is obtained by adding the preprocessed and the squared signal which is shown in Figure 3.5(d).Figure 3.6(a) is the maternal ECG recorded from thoracic region. In order to reduce the mothers ECG effects on extraction, MECG was eliminated by using two stages of adaptive filtering. The reference signal taken is shown in Figure 3.6(b) which is the squared and scaled thoracic signal .The advantage of this method is that the reference signal need not closely mimic the signal to be cancelled. If such a reference signal could be generated, than this method can be applied where only the mothers ECG is available. The output of the adaptive filter 1 is again adaptive filtered with the squared TECG signal. The output of the adaptive filter 2 is applied to FECG detector to obtain the FECG signal as shown in Fig 3.6(d). The resultant signal depends on the value for the constant of adaptation. After the removal of baseline wander, the power line interference and the MECG, the signal contains FECG combined with EMG interference and measurement noise. The original abdominal signal, extracted FECG by the FECG detector and MECG are shown in Figure 3.7 (a), (b) and (c) for Sista daisy data. Figure 3.8(a) and 3.8(b) are the original signal and extracted FECG for Physio data.

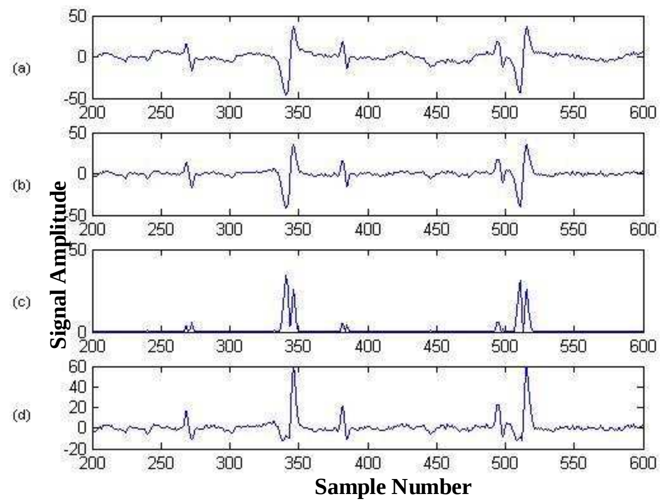

Figure 3.5 (a) Original abdominal ECG (b) Preprocessed signal (c)Square of preprocessed signal (d) signal obtained after adding b and c

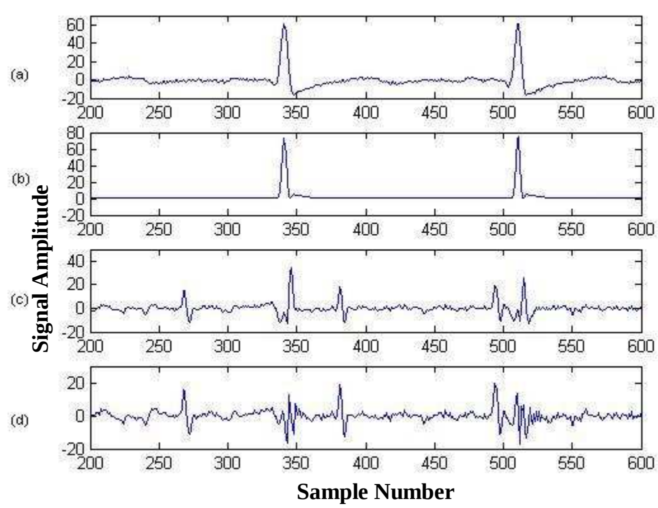

Figure 3.6 (a) Thoracic ECG (b) square of Thoracic ECG (c) Output of Adaptive filter 1 (d) Output of Adaptive filter 2

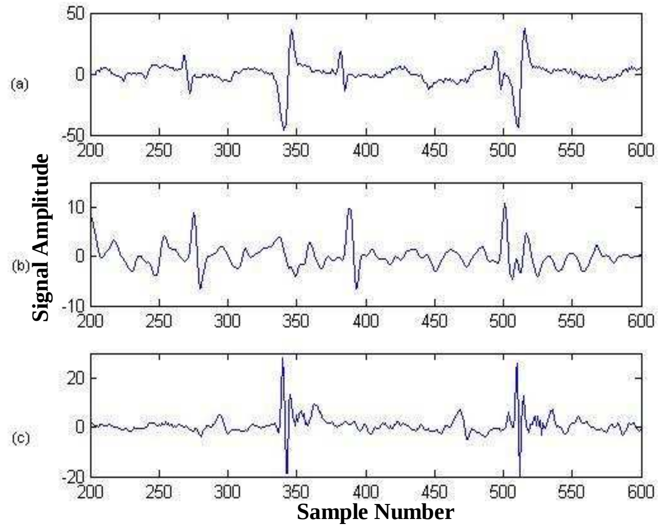

Figure 3.7 (a) Original abdominal ECG (b) Extracted FECG (c) Extracted MECG (Sista)

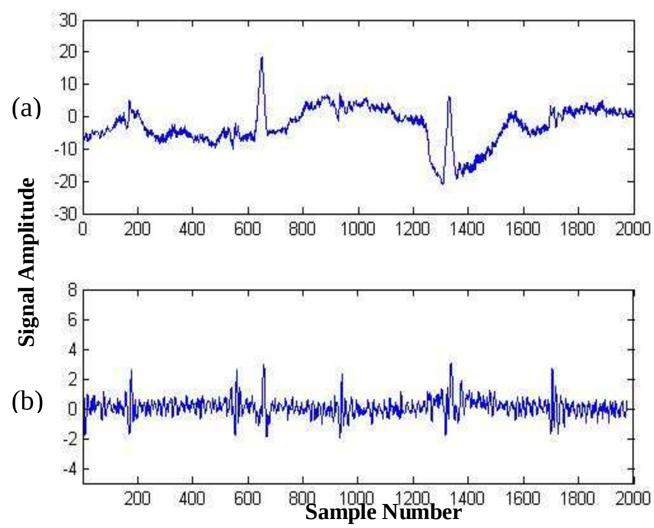

Figure 3.8 (a) Original abdominal ECG (b) Extracted FECG (Physio.net)

The proposed preliminary algorithm was assessed with real composite signal comprising of MECG and FECG. The noise in the FECG signal is due to mother's electromyogram activity. The performance of the method is seen from the extracted waveform centering on R wave peak. The P and T waves can also be seen to some extent.

In order to enhance the quality of the extracted FECG the proposed algorithm, has been refined as presented in the following section.

3.2.4 SELECTION OF PROCESSING ALGORITHMS FOR ADAPTIVE FILTERS

The proposed algorithm is analyzed with different combinations of adaptive processing algorithms to choose the optimum combination to extract the fetal ECG. The different adaptive filter combinations for two stages of adaptive filtering chosen are (i) LMS,LMS (ii) LMS,NLMS (iii)LMS, RLS ((iv)NLMS,LMS (v)NLMS,NLMS (vi) NLMS,RLS (vii) RLS,LMS (viii) RLS,NLMS (ix)RLS,RLS. Figure 3.9(a) is the original abdominal signal. The outputs generated by the combination of adaptive filter 1 as LMS and adaptive filter 2 as LMS, NLMS and RLS are shown in Figures 3.9(b), (c) & (d).

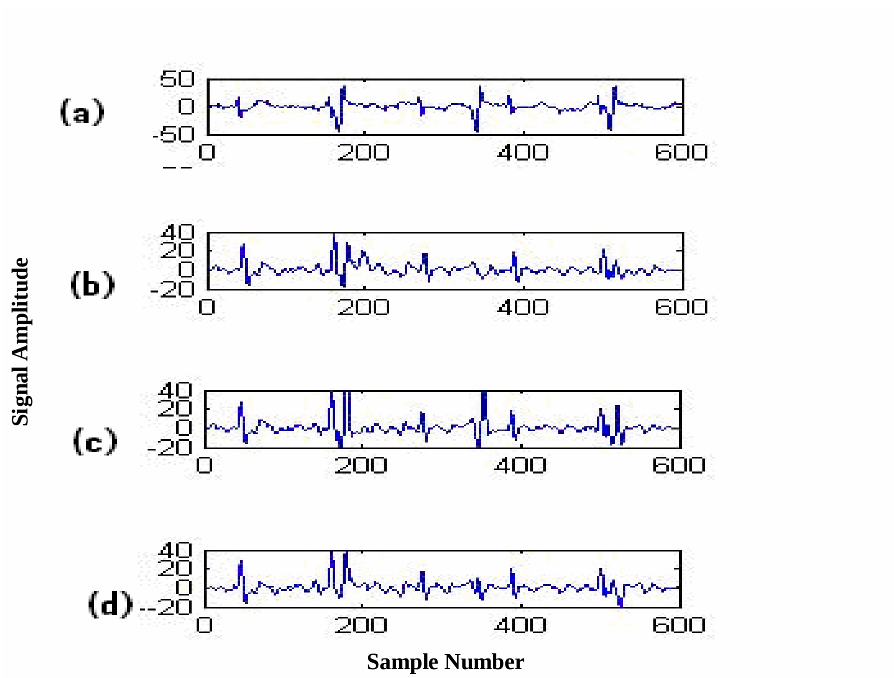

Figure 3.9(a) Abdominal Signal (b) LMS, LMS output (c) LMS, NLMS output (d) LMS, RLS output

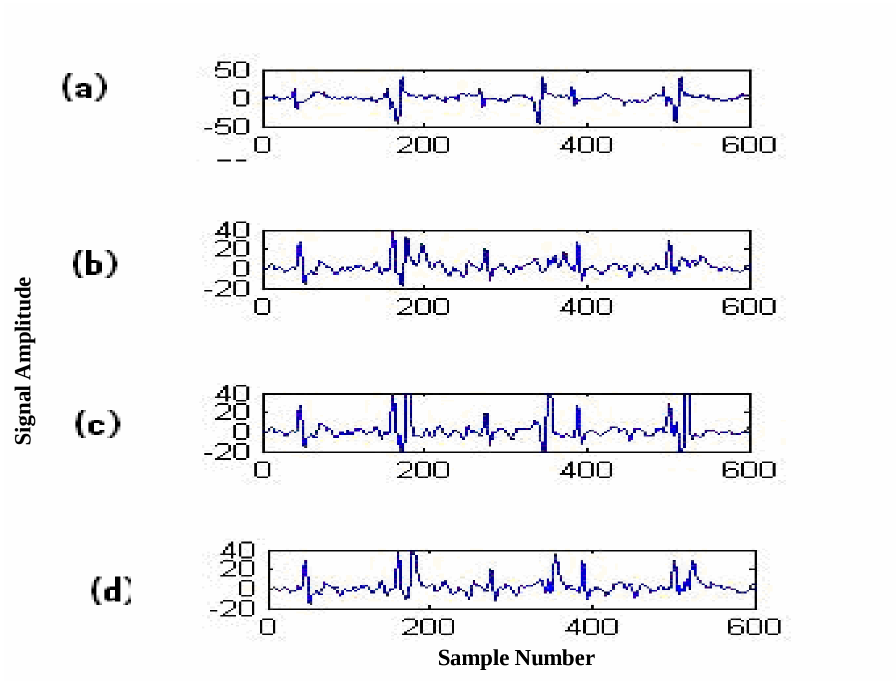

Figure 3.10(a) Abdominal Signal (b) NLMS, LMS output (c) NLMS, NLMS output (d) NLMS, RLS output

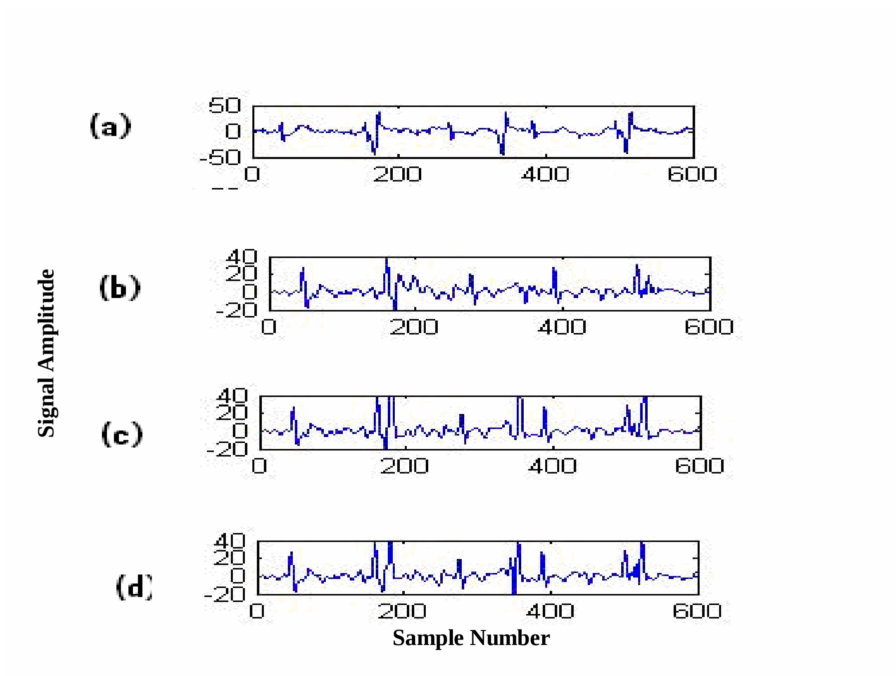

Figure 3.11(a) Abdominal Signal (b) RLS, LMS output (c) RLS, NLMS output (d) RLS, RLS output

Figure 3.10(a) is the original abdominal signal. The outputs generated by the combination of adaptive filter 1 as NLMS and adaptive filter 2 as LMS, NLMS and RLS are shown in Figures 3.10(b), (c) & (d). Figure 3.11(a) is the original abdominal signal. The outputs generated by the combination of adaptive filter 1 as RLS and adaptive filter 2 as LMS, NLMS and RLS are shown in Figures 3.11(b), (c) & (d) .

Optimum Combination of Adaptive filters

Out of 9 possible combinations of the filters tested, the combination with NLMS (Figure 3.10) was not fully suppressing the maternal ECG component. LMS, LMS combination (Figure 3.9) and RLS, LMS (Figure 3.11) combinations were yielding good results. LMS, LMS combination was able to extract fetal ECG completely and suppress the maternal component. However noisy components were present in this method. RLS, LMS was yielding comparatively better result. It is seen that the fetal ECG has significant dominance and maternal ECG is totally suppressed. Thus for further analysis the RLS, LMS combination has been used for two stages of adaptive filters to extract the fetal ECG by the three different methods proposed in this chapter.

3.3 METHOD I - FECG EXTRACTION METHOD

In the earlier extraction algorithm (Swarnalatha and Prasad, 2008) yielded a FECG signal, which was not totally free from maternal components. The method I-FECG extraction method is to extract the fetal ECG by suppressing any other components present in the extracted signal. The extraction of fetal ECG includes the preprocessing of the abdominal signal using the steps explained in section 3.2.1.Then the preprocessed signal is used to develop the non linear parameter Ψ = DS (0.02*DS-1) as shown in Figure 3.12. The adaptive filter has two input signals. One signal is the scaled, squared and again scaled thoracic signal and other signal is the non linear operator signal. Ψ is derived by adding the negative of the denoised signal with the squared and scaled denoised signal. The scaling factor has been determined looking at the amplitude of the squared signal to match with that of the abdominal signal. The scaling factors have been chosen such that the adaptive filters are fine tuned to extract the desired signal. This method can totally avoid thoracic signal being recorded if a replica of thoracic signal can be generated.

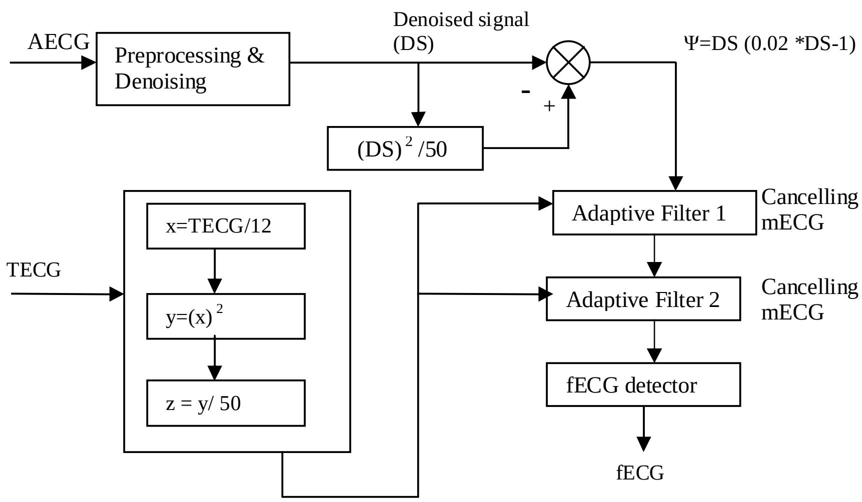

Figure 3.12 Block diagram of the FECG extraction method.

Adaptive filter 1 has the two inputs which are the non linear parameter Ψ and the other from the TECG block. The adaptive filter 1 and adaptive filter 2 uses RLS and LMS combination to cancel the maternal ECG.

3.3.1 METHOD I – FECG EXTRACTION METHOD –RESULTS

The extraction results of method I are shown in Figure 3.13 to Figure 3.17 for Sista data with different electrode positions. Figure 3.18 is the extracted output for Physio data. The visual quality of extracted FECG is seen to be good in this method. The removal of MECG components can be seen clearly from the output. Note that the FECG is extracted even when FECG is overlapped with MECG. It is interesting to note that the algorithm is quite fast in processing the extraction of FECG. The SNR is found to be 11.81, 12.16, 8.55, 20.83 and 8.58 for Sista data for different electrode positions. The SNR for the Physio data is 3.0161.

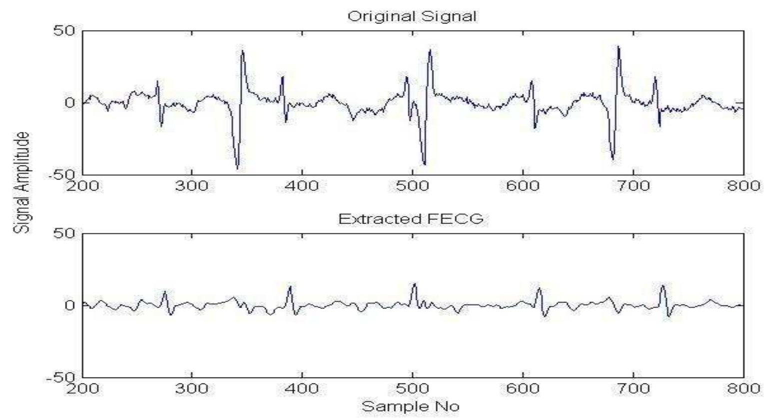

Figure 3.13 FECG extraction- Sista (2, 7)

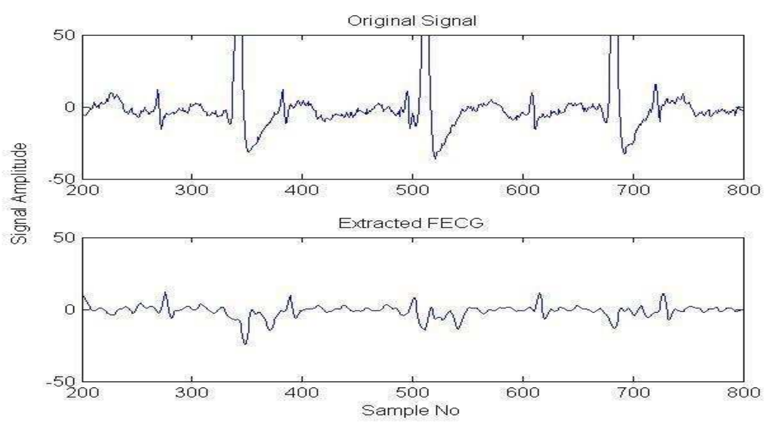

Figure 3.14 FECG extraction- Sista (3, 7)

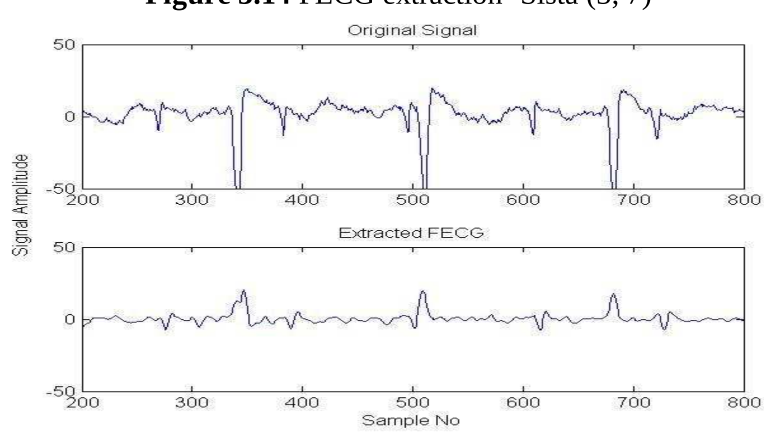

Figure 3.15 FECG extraction-Sista (4, 7)

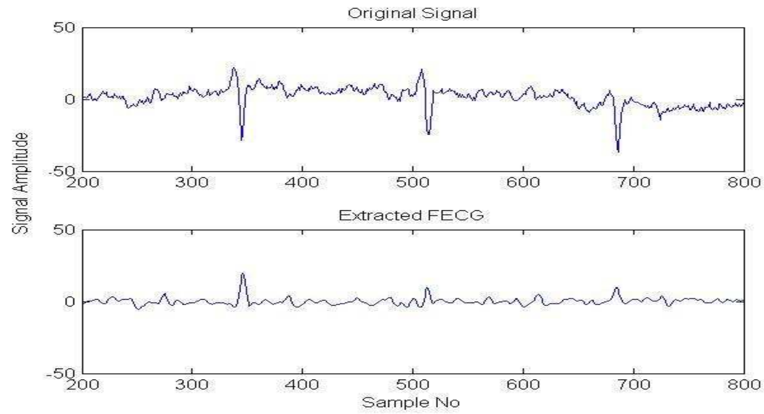

Figure 3.16 FECG extraction- Sista (5, 7)

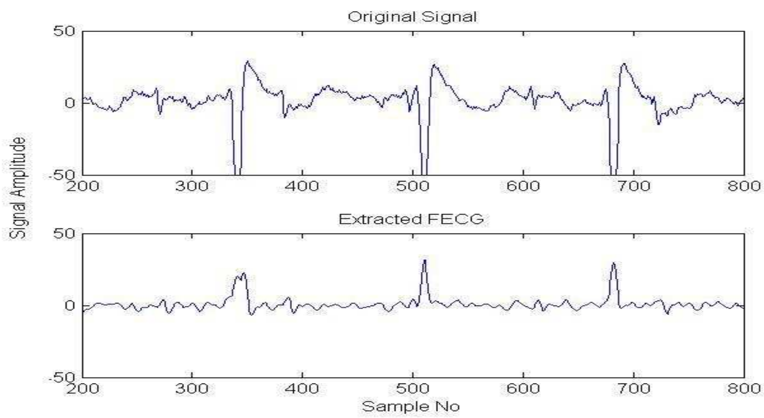

Figure 3.17 FECG extraction-Sista (6, 7)

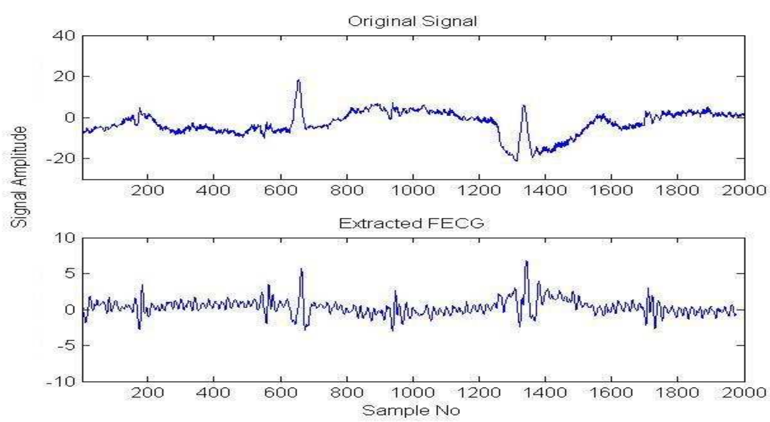

Figure 3.18 FECG extraction-Physio (4,2)

3.4 METHOD II - IMPROVED FECG EXTRACTION METHOD

The method II is the improved FECG extraction method which uses the refinement of the multi stage adaptive filtered signal.The refinement process is proposed to further enhance the quality of the extracted FECG. The block diagram of refinement algorithm is shown in Figure 3.19. In this algorithm, the steps used to refine the extracted FECG are same as the preprocessing methodology discussed in section 3.2.1. This method was yielding a better result than the method I.

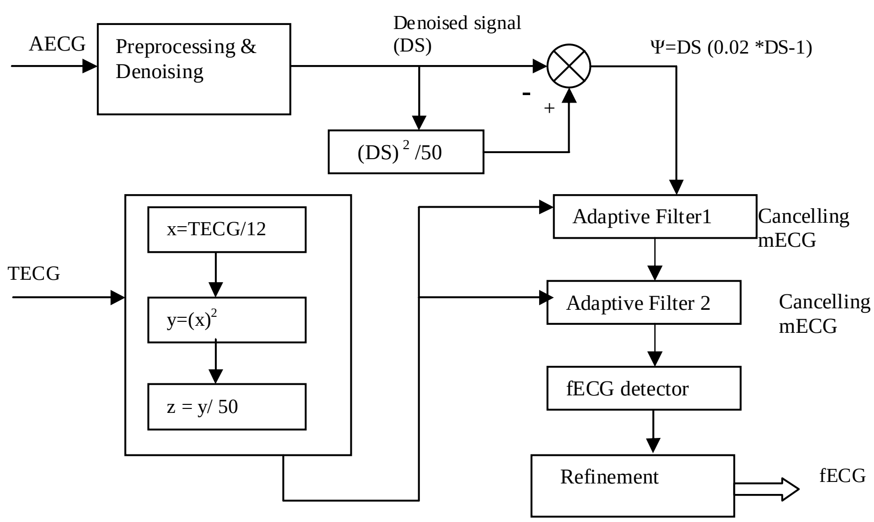

Figure 3.19 Block diagram of the FECG extraction with Refinement

3.4.1 METHOD II - IMPROVED FECG EXTRACTION METHOD - RESULTS

The results of method II are shown in Figure 3.20 to Figure 3.24 for Sista data with different electrode positions. Figure 3.25 is the result of the Physio data.

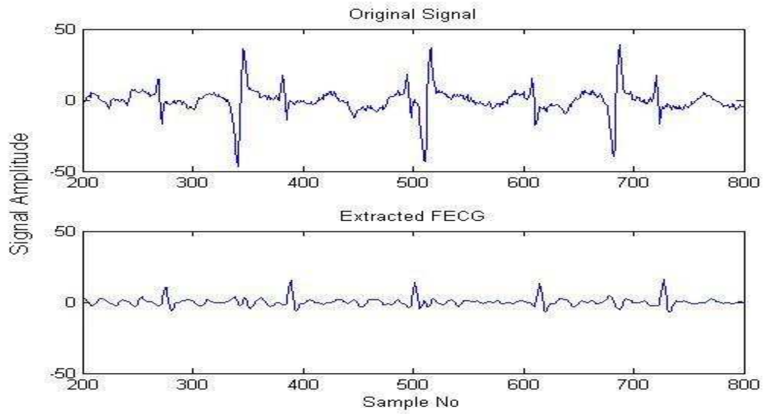

Figure 3.20 Improved FECG extraction-Sista (2, 7)

The extracted FECG shows the QRS complex of the fetal ECG very clearly. The SNR is 19.42, 14.62, 10.29, 21.64 and 9.68 for the Sista data for the different electrode positions. The SNR for the Physio data is 11.9095. These SNR value show the quality of the extracted signal is good compared to method I.

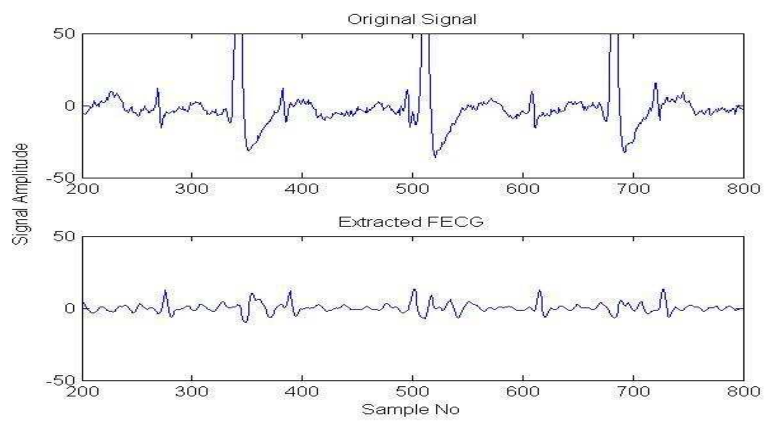

Figure 3.21 Improved FECG extraction-Sista (3, 7)

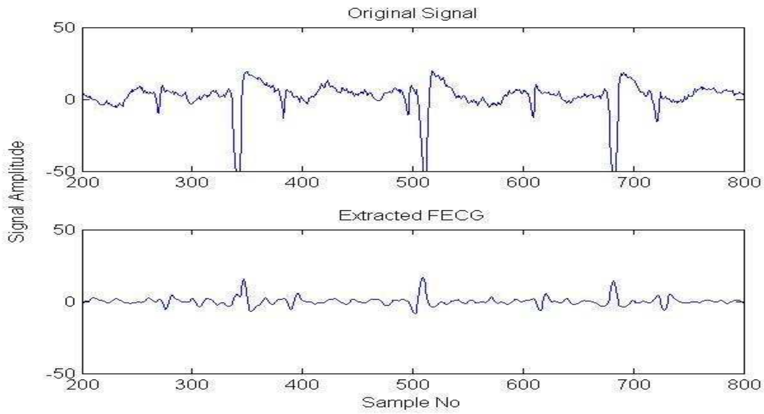

Figure 3.22 Improved FECG extraction- Sista (4, 7)

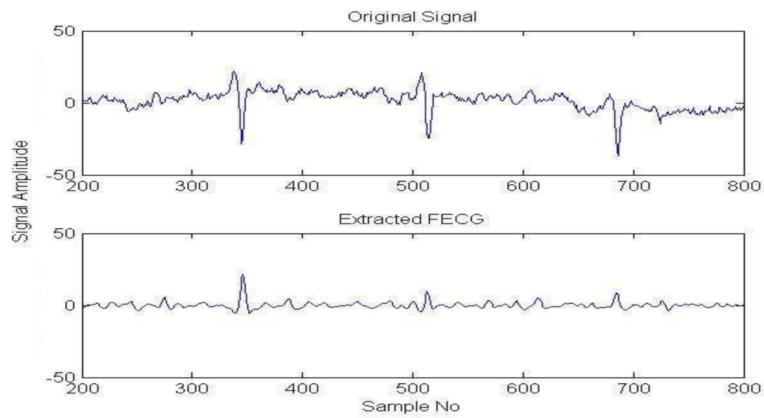

Figure 3.23 Improved FECG extraction- Sista (5, 7)

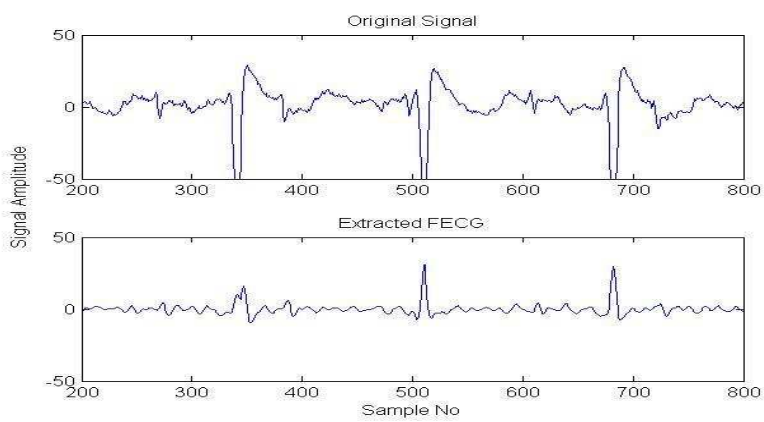

Figure 3.24 Improved FECG extraction-Sista (6, 7)

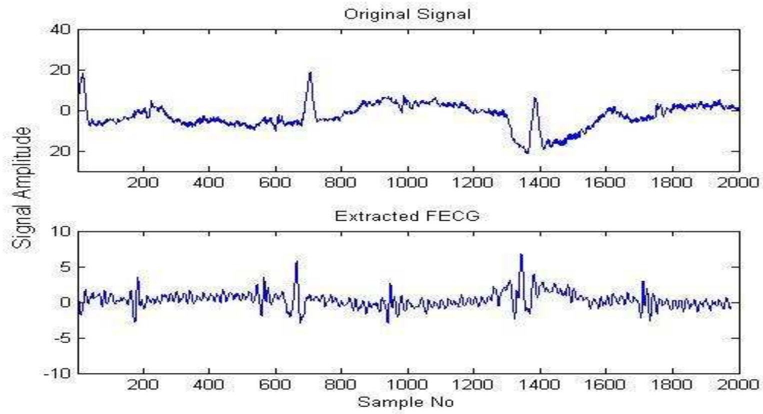

Figure 3.25 Improved FECG extraction- Physio (4,2)

3.5 METHOD III- NOVEL METHOD OF FECG EXTRACTION

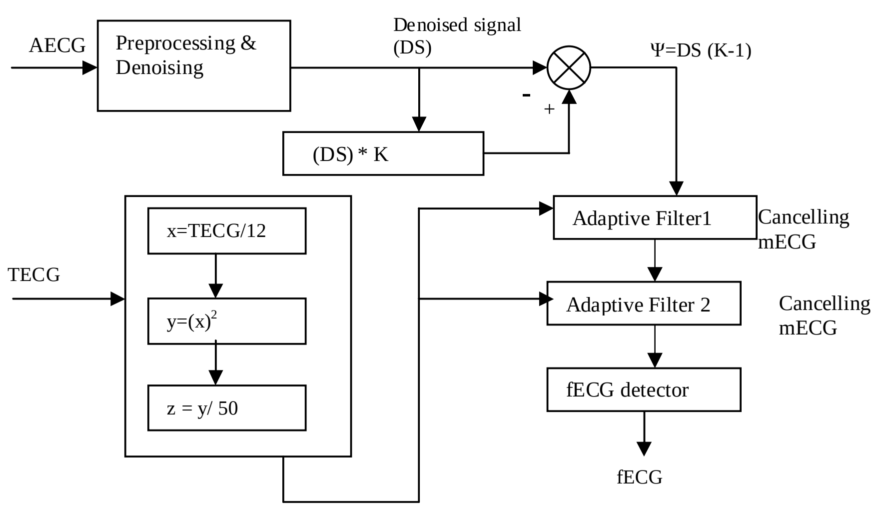

Figure 3.26 Block diagram of the novel method of FECG extraction

Method III is the novel method of FECG extraction. This novel method of FECG extraction uses a non linear parameter Ψ = DS (K-1) and avoids the post refinement after FECG detector as shown in Figure 3.26. Once the preprocessing steps are done for the input signal, the denoised signal is multiplied by factor K. The adaptive filtering in both the stages is done by the new non linear parameter along with the thoracic signal. This new non linear parameter has yielded a better FECG compared to the other proposed methods.

Determination of K value

The K value was determined by studying the variations in the peak magnitude of the power spectral density of the extracted fetal ECG. The power spectral density was studied for different values of K ranging from very small to vary large value. Studying the extracted fetal ECG for different values of K, it was assumed that the quality of extracted fetal ECG is good in the lower ranges of K between 1 and 3. Based on this assumption, the power spectral density for different values of K ranging from 0.2 to 6 was studied. The variations of the peak value (dB/Hz) of the power spectral density for these K values are plotted in Figure 3.27.

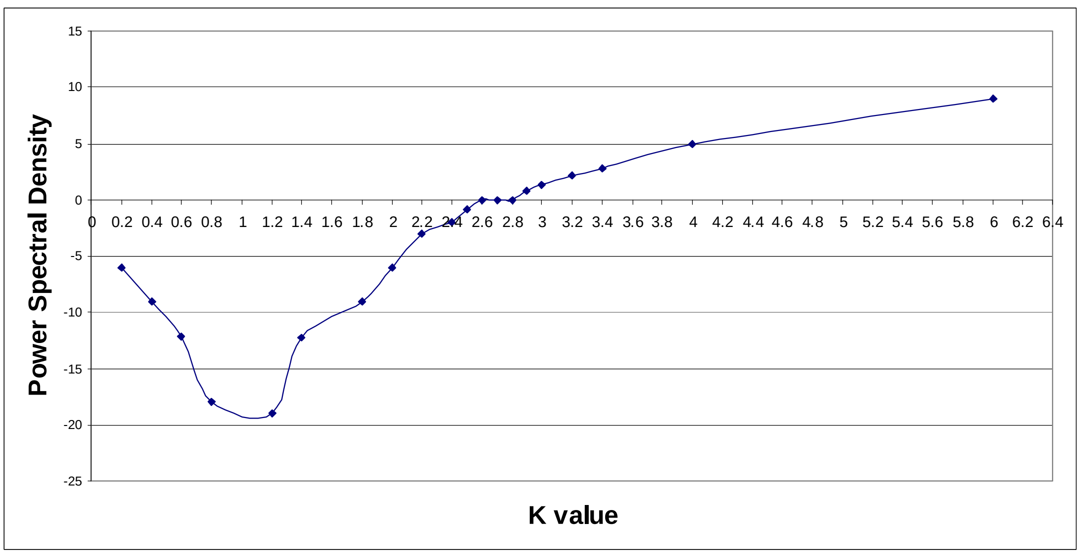

Figure 3.27 Plot of K value versus Power Spectral Density

As the K value increases from 0.2, it reaches a negative peak value (-18db/Hz) at K=1.2. Beyond this it starts rising towards zero db/Hz and reaches 0 db/Hz at K =2.6. The plot remains constant at 0 db/Hz till K=2.8 and then steeply rises after K=2.8. Thus it is observed the plot can be divided in to three regions as K < 2.6, 2.6 <K<2.8 and K>2.8. The plot for K < 2.6 shows uneven variations in the db/Hz value. The region K > 2.8 has steep rise in the value of db/Hz. Only in the region 2.6 <K<2.8 the plot has a constant value of 0 db/Hz. Thus in this region, the K value is not affecting the extraction of fetal ECG. The region below K<2.6 due to its uneven variations is drastically affecting the quality of the extracted fetal ECG. The steep rise of the plot in the region for K>2.8, the extracted fetal ECG is highly corrupted by the maternal ECG and by the other artifacts. Thus the value of K to be chosen should lie between K=2.6 to K=2.8. The value chosen in this work is K =2.6.

3.5.1 METHOD III – NOVEL METHOD OF FECG EXTRACTION – RESULTS

The extraction results of method III are shown in Figure 3.28 to Figure 3.32 for Sista data for different electrode positions. Figure 3.33 is the result of Physio data. The SNR value is 19.98, 17.29, 11.24, 22.45 and 11.51 for Sista data. The SNR for the Physio data is 11.937. The SNR value of this method shows a marked improvement over the earlier two methods. The result clearly shows that the extracted fetal ECG is better than previous methods. It is also seen to be noise free.

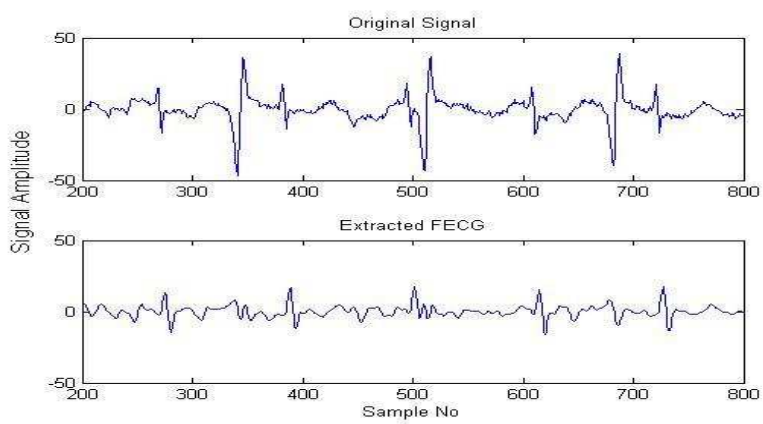

Figure 3.28 Novel method of FECG extraction-Sista (2, 7)

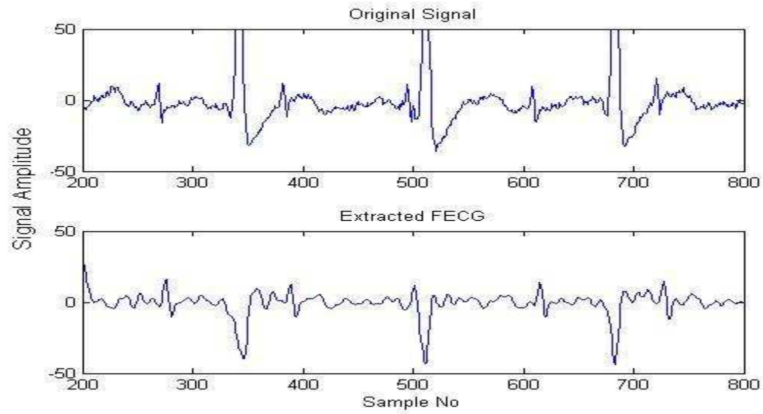

Figure 3.29 Novel method of FECG extraction-Sista (3, 7)

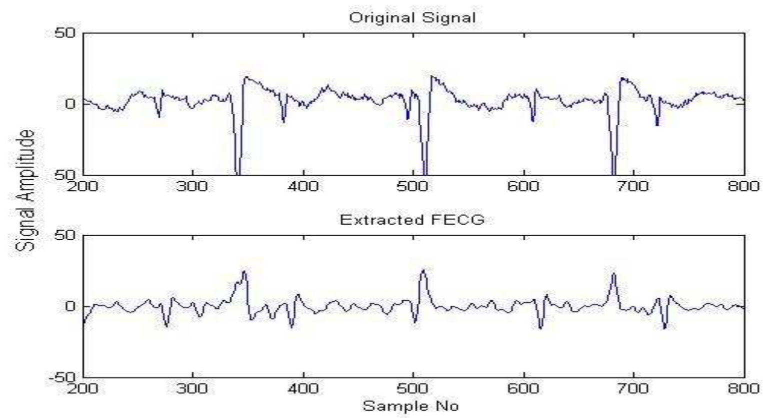

Figure 3.30 Novel method of FECG extraction-Sista (4, 7)

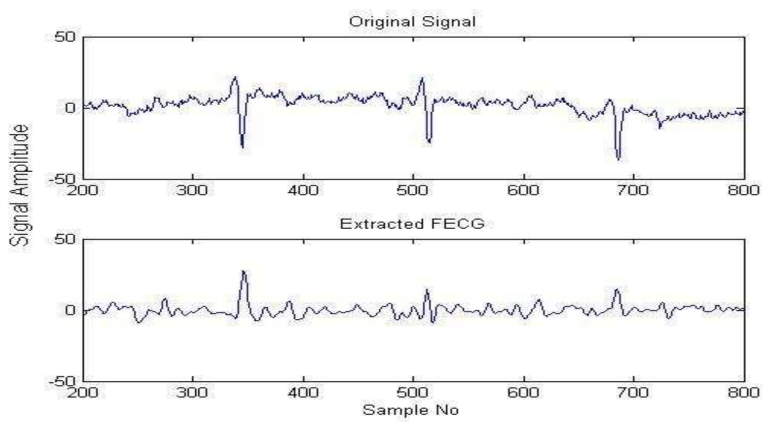

Figure 3.31 Novel method of FECG extraction-Sista (5, 7)

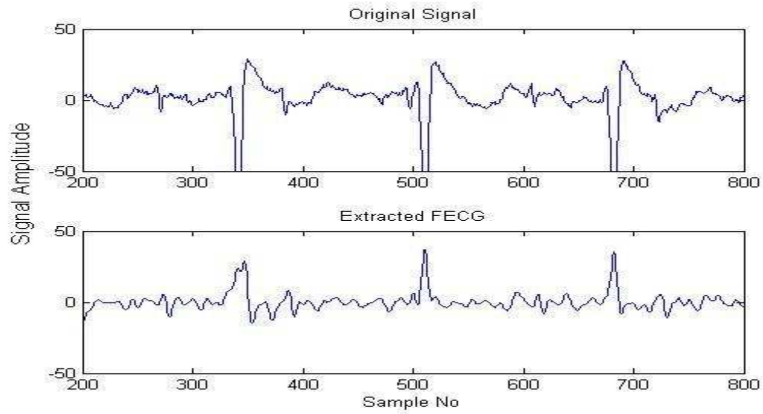

Figure 3.32 Novel method of FECG extraction-Sista (6, 7)

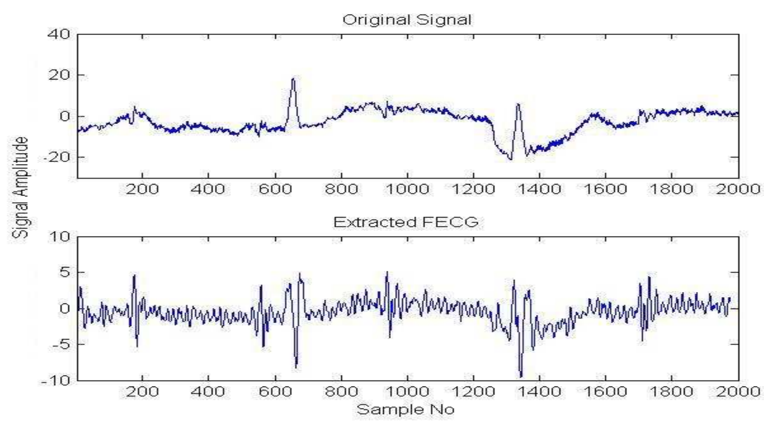

Figure 3.33 Novel method of FECG extraction-Physio (4, 2)

3.6 EVALUATION AND ANALYSIS OF THE PROPOSED METHODS

Evaluation of the proposed algorithms has been done using the following parameters. They are;

1. Sensitivity (SEN) = TP/ (TP+FN)
2. Specificity (SPE) = TN/ (FP+TN)
3. Positive Predictive Value (PPV) = TP/ (TP+FP)
4. Negative Predictive Value (NPV) = TN/ (FN+TN)
5. Accuracy (ACC) = (TP+TN)/ (TP+FP+FN+TN)
6. Correlation coefficient (CORR) - Between the composite abdominal signal and the extracted FECG.

7. Signal to Noise Ratio (SNR) - Signal to noise ratio of the extracted FECG

where TP (True positive) is the total number of positive peaks detected in extracted FECG,TN (True Negative) is the total number of negative peaks detected in extracted FECG, FN (False Negative) when an artefact is detected as negative peak, FP is (False Positive) when an artefact is detected as a positive peak. Sensitivity is related to the positive events correctly detected. Specificity is related to the negative events correctly detected. Positive predictive Value is related to the ability of detecting true positive events. Negative Predictive Value is related to the ability of detecting true negative events. Accuracy is related to total positive and negative events correctly detected. Correlation coefficient is obtained between the composite abdominal signal and the extracted FECG. The correlation value of '1' indicates the high presence of maternal ECG and the value '0' indicates no presence of fetal ECG. The signal to noise ratio is obtained for extracted FECG signal.

In this chapter three different methods of fetal ECG extraction are proposed. All the methods have been tested and evaluated with the same data from Sista data set and Physio data set.

3.6.1 EVALUATION OF METHOD I - FECG EXTRACTION METHOD

The performance of method I tested with data from Sista is shown in Table 3.1. The performance parameter SEN, SPE, PPV, NPV and ACC from electrode position 2, 7 and 3, 7 are seen to have a better performance compared to other electrode positions. Electrode position 4, 7 and 6, 7 are having low signal to noise ratio.In electrode position 4, 7; 5, 7 and 6, 7 the correlation is on the higher side due to presence of maternal ECG in the extracted signal. In electrode position 5, 7 the specificity, PPV, NPV and accuracy are showing a lower value due to the insignificant presence of fetal ECG in the abdominal signal itself. To conclude, the record from electrode position 2,7 have got the best performance as seen from the table 3.1.This is due to large presence of fetal ECG in the extracted output compared to other electrode positions.

Table 3.1 Performance of Method I- FECG extraction method (Sista Data)

Electrode Position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	0.8	1	1	0.84	0.9	0.2024	11.81
3,7	0.72	0.86	0.84	0.75	0.79	0.2814	12.16
4,7	0.43	0.73	0.5	0.67	0.61	0.6220	8.55
5,7	0.75	0.5	0.5	0.5	0.5	0.5301	20.83
6,7	0.63	0.67	0.63	0.67	0.65	0.7199	8.58

3.6.2 EVALUATION OF METHOD II- IMPROVED FECG EXTRACTION METHOD

The performance of method II tested with data from Sista is shown in Table 3.2. The performance parameter SEN, SPE, PPV, NPV and ACC from electrode position 2, 7 and 3, 7 are seen to have a better performance compared to other electrode positions. The SNR is seen to be less in 4, 7 and 6, 7. The correlation is on the higher side in 4, 7 and 6,7 due to large presence of maternal ECG in the extracted signal. The correlation is slightly less in 5, 7 due to less presence of maternal ECG. However, the electrode position 2, 7 and 3, 7 have no presence of maternal ECG and hence the correlation is small.

Table 3.2 Performance of Method II – Improved FECG extraction method (Sista data)

Electrode Position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	0.8	1	1	0.8	0.89	0.1546	19.42
3,7	0.72	0.86	0.84	0.75	0.79	0.2626	14.62
4,7	0.6	0.67	0.7	0.75	0.72	0.5694	10.29
5,7	0.6	0.54	0.6	0.54	0.57	0.4721	21.64
6,7	0.6	0.72	0.75	0.67	0.7	0.7361	9.68

3.6.3 EVALUATION OF METHOD III- NOVEL METHOD OF FECG EXTRACTION

The performance of method III tested with data from Sista is shown in Table 3.3. The elctrode position 2, 7 and 3, 7 are seen to have a better performance compared to other electrode positions with respect to SEN, SPE, PPV, NPV and ACC. In this novel method, SNR is seen to be more in electrode positions 4, 7 and 6, 7 when compared to method I and method II. The correlation is on the higher side in 4, 7 and 6, 7 due to presence of maternal ECG in the extracted signal, where as the correlation is slightly less in 5, 7 due to less presence of maternal ECG.

Table 3.3 Performance of Method III – Novel method of FECG extraction (Sista data)

Electrode Position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	1	0.77	0.89	1	0.89	0.187	19.98
3,7	0.72	0.86	0.83	0.75	0.79	0.2553	17.29
4,7	0.75	0.67	0.75	0.67	0.72	0.5882	11.24
5,7	0.6	0.72	0.67	0.63	0.64	0.4647	22.45
6,7	0.67	0.75	0.75	0.74	0.72	0.6781	11.51

The correlation in position 2, 7 is very good because of no presence of maternal ECG in the extracted fetal ECG. In electrode position 3, 7 even though the correlation is better some presence of maternal ECG is seen in the extracted signal. In over all comparison the electrode position of 2, 7 and 3, 7 are yielding better results compared to other electrode positions.

3.6.4 EVALUATION OF DIFFERENT METHODS FOR PHYSIO DATA

The Physio data has only one electrode position due to one abdominal signal. The different proposed methods are evaluated for this data set only. Hence performance parameters are evaluated method wise. The performance results of method I, method II and method III of FECG extraction are shown in Table 3.4.

Table 3.4 Performance of different methods (Physio data)

Methods	SEN	SPE	PPV	NPV	ACC	CORR	SNR
Method I FECG extraction method	0.64	0.73	0.7	0.67	0.68	0.4236	3.0161
Method II Improved FECG extraction method	0.64	0.73	0.7	0.67	0.68	0.0898	11.9095
Method III Novel method of FECG extraction	0.65	0.88	0.84	0.88	0.8	0.4305	11.937

The method I and method II have the same performance values with respect to SEN, SPE, PPV, NPV and ACC. The correlation in method I and method III are comparable. The method II shows a decrease in the correlation coefficient. This is due to the presence of maternal ECG and probable distortion of the signal due to further refinement. The method II, method III are seen to have large SNR compared to method I. And method III is having the largest value of SNR and performance parameters compared to other methods. This clearly shows that method III is more efficient in extracting fetal ECG than method I and method II.

3.6.5 ANALYSIS OF PROPOSED METHODS

The analysis of FECG extraction for performance parameter SEN, SPE, PPV, NPV, ACC, Correlation coefficient and SNR for method I, method II and method III are shown in section 3.6.5.1 for Sista data and in section 3.6.5.2 for Physio data. The Sista data is analysed with different electrode positions to different performance parameters. The X axis indicates the electrode position and the Y axis indicates the performance parameter. The points in X axis 2, 3, 4, 5 and 6 are equivalent to electrode positions 2, 7;

3, 7 etc. The physio data is analysed with different methods to different performance parameters. From Figure 3.41 to 3.47, the point in X axis 1, 2 and 3 are equivalent to method I, method II and method III.

3.6.5.1 ANALYSIS OF MULTI STAGE ADAPTIVE FILTERING METHODS – SISTA DATA

Figure 3.34 shows the sensitivity plot for method I, II and III. The sensitivity of electrode position for 2, 7 in method III is maximum because of the minimum false negatives detection. In electrode position 5, 7 the method I is having more sensitivity. For 3,7 electrode position all the methods have the same value. In electrode position 4,7 and 6,7 the method III has more sensitivity. To conclude the method III is a better algorithm for extraction of FECG.

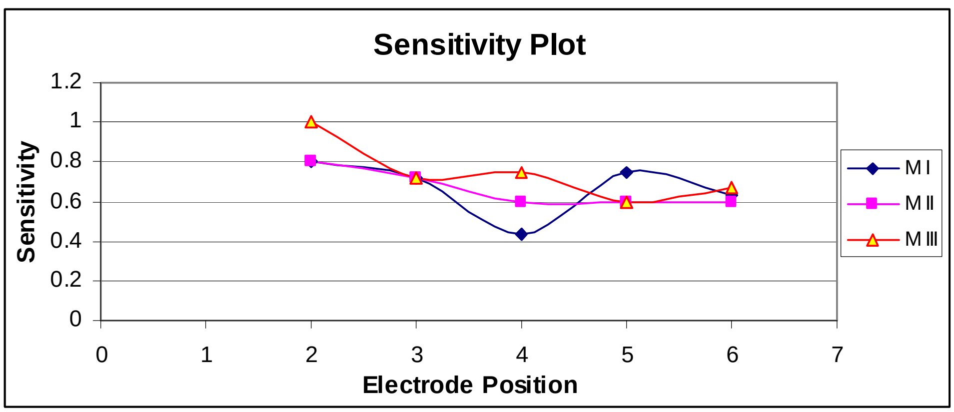

Figure 3.34 Plot of Electrode Position versus Sensitivity – Sista

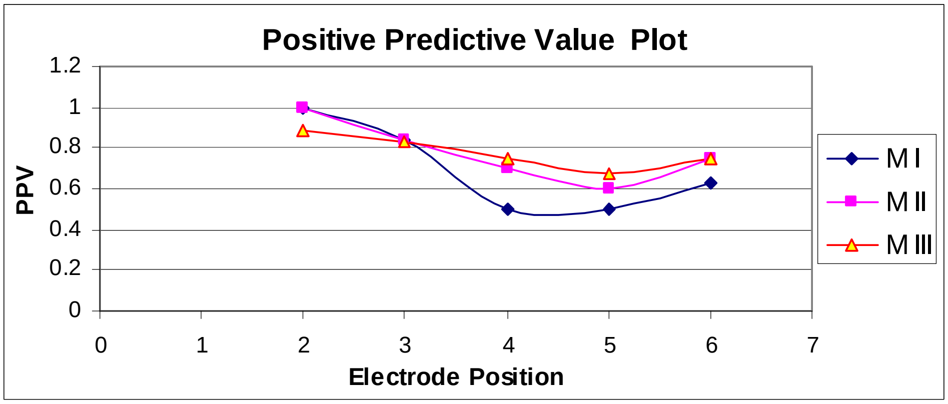

Figure 3.35 Plot of Electrode Position versus Positive Predictive Value -Sista

Figure 3.35 shows the positive predictive plot for method I, II and III. The PPV value is more in method III for electrode positions 4, 7; 5, 7 and 6, 7 because of less detection of false positive peaks. The reason for method III having lower PPV only in electrode position 2,7 is due to more number of false positive detections. In overall, method III performs better for FECG extraction.

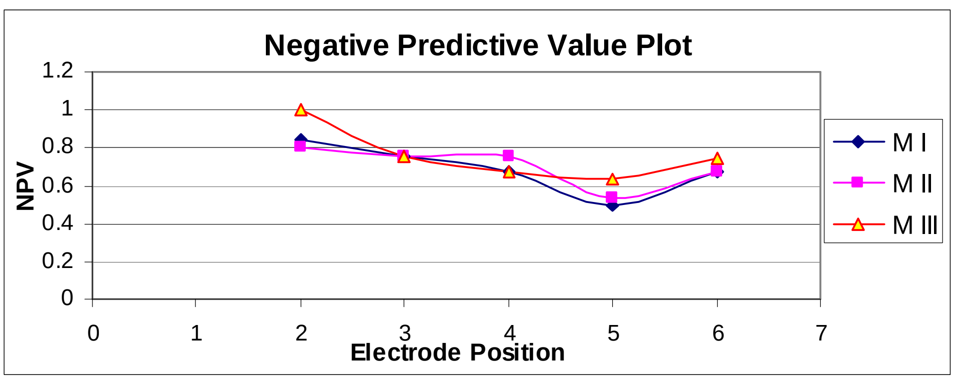

Figure 3.36 Plot of Electrode Position versus Negative predictive value- Sista

Figure 3.36 shows the negative predictive plot for method I, II and III. In method III, the electrode position 4, 7 has least NPV value because of more number of false negatives detections. However in electrode positions 2,7 ; 5,7 and 6,7 the number of false negative detections are less which yields better NPV value. From this analysis, it is concluded that the method III performs better.

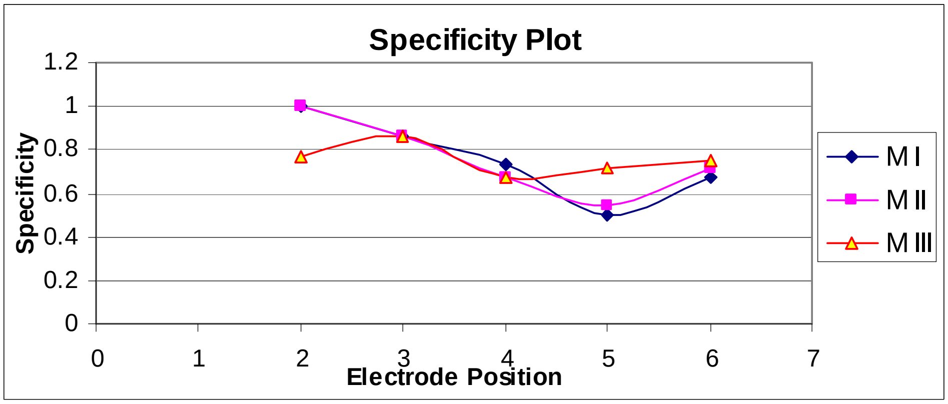

Figure 3.37 Plot of Electrode Position versus Specificity- Sista

Figure 3.37 shows the specificity plot for method I, II and III. In electrode position 2, 7 and 4,7 the specificity in method III is less due to more number of false positive detections. In other electrode positions, method III dominates due to less no of false positive detections.

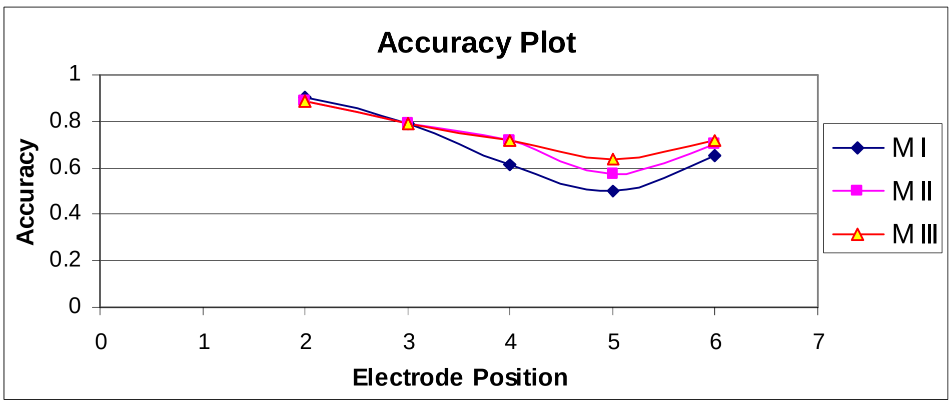

Figure 3.38 Plot of Electrode Position versus Accuracy - Sista

Figure 3.38 shows the accuracy plot for method I, II and III. The accuracy in electrode position 2,7 and 3,7 has the same value for all the methods. In electrode position 4,7 the method II and method III has same but higher than the method I. The accuracy in method III is high for the electrode positions 5,7 and 6,7 are due to the less number of false positive and false negative detection when compared to method I and method II.

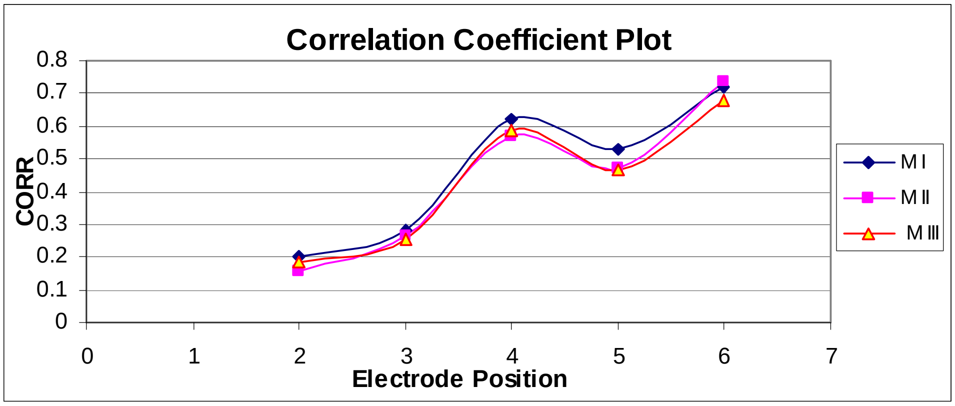

Figure 3.39 Plot of Electrode Position versus Correlation Coefficient - Sista

Figure 3.39 shows the correlation plot for method I, II and III. The correlation coefficient has been calculated between the extracted fetal ECG and the composite abdominal signal containing fetal ECG and maternal ECG. Since the extracted fetal ECG signal should not have any trace of maternal ECG the correlation will be smaller. On comparison of three methods, method III is seen to have lesser correlation coefficient than method I and method II. Thus it is concluded that the method III is better method for extraction of FECG.

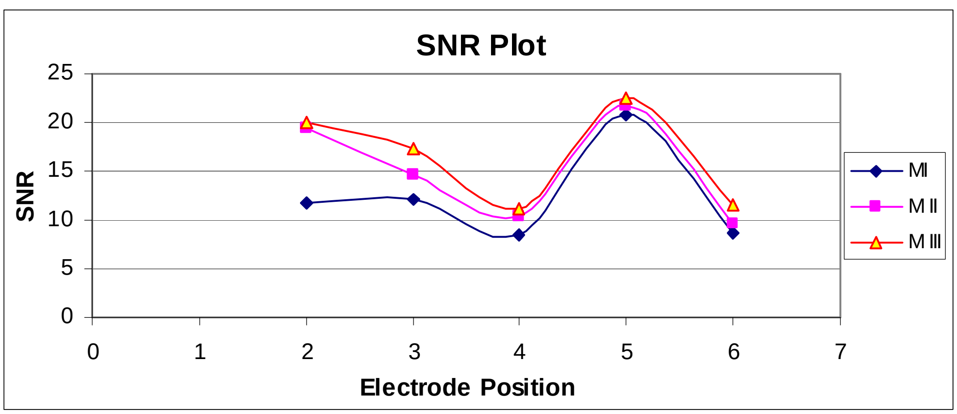

Figure 3.40 Plot of Electrode Position versus SNR - Sista

Figure 3.40 shows the SNR plot for method I, II and III. The SNR is calculated for the extracted fetal ECG. The low SNR in electrode positions 4, 7 and 6, 7 is due to noisy composite abdominal signal. However by comparing all the three methods the SNR is high in method III. Thus it is concluded that the method III is the most suitable method for extraction of FECG.

3.6.5.2 ANALYSIS OF MULTI STAGE ADAPTIVE FILTERING METHODS – PHYSIO DATA

The analysis of FECG extraction for method I, method II and method III are shown for Physio data. The performance parameters are plotted and shown in the Figures 3.41 to 3.47.

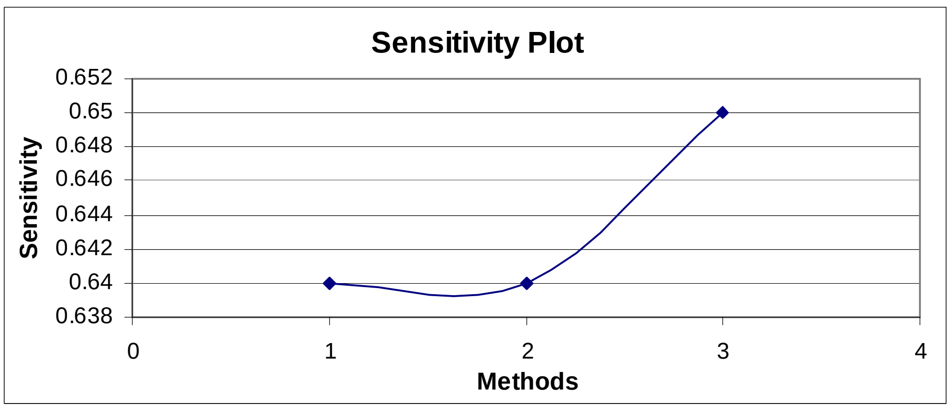

Figure 3.41 Plot of Methods versus Sensitivity- Physio

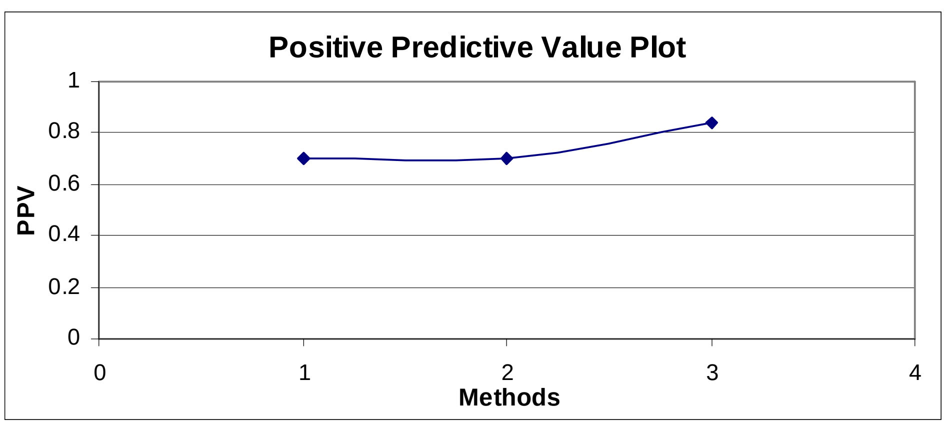

Figure 3.42 Plot of Methods versus Positive Predictive Value- Physio

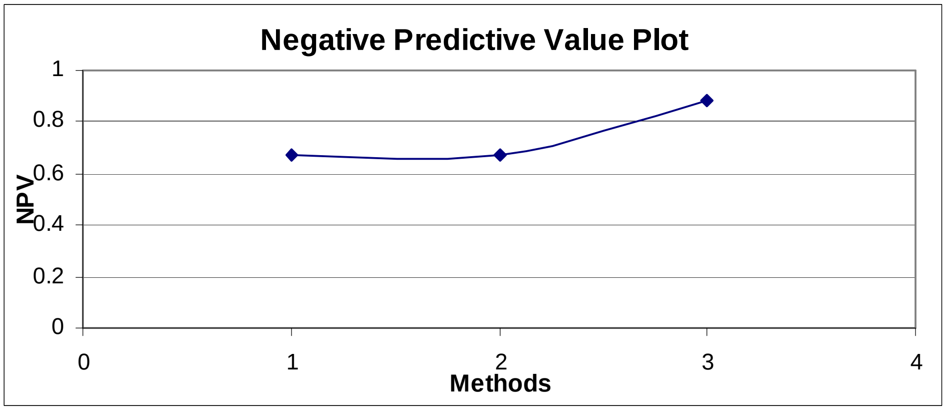

Figure 3.43 Plot of Methods versus Negative Predictive Value- Physio

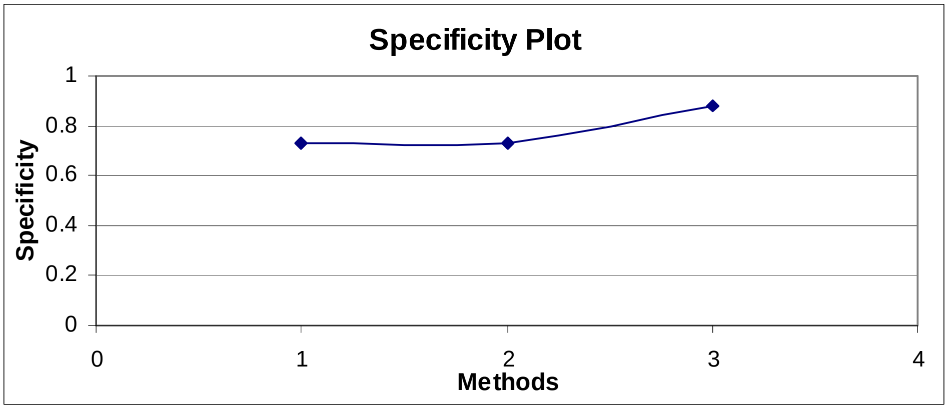

Figure 3.44 Plot of Methods versus Specificity - Physio

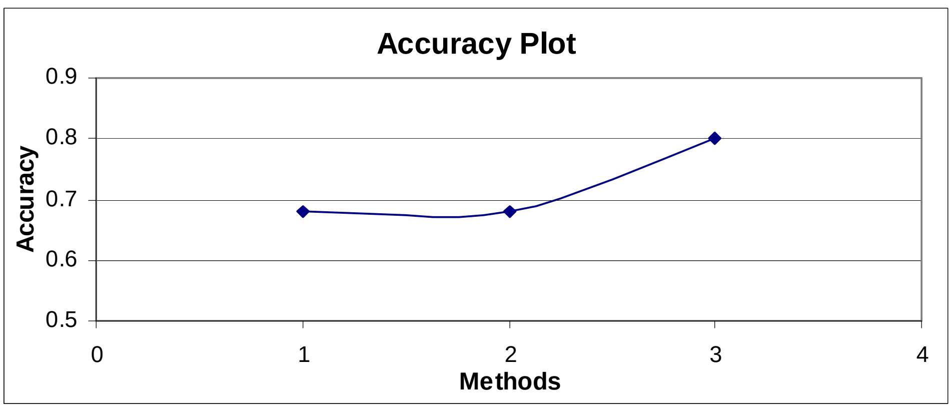

Figure 3.45 Plot of Methods versus Accuracy - Physio

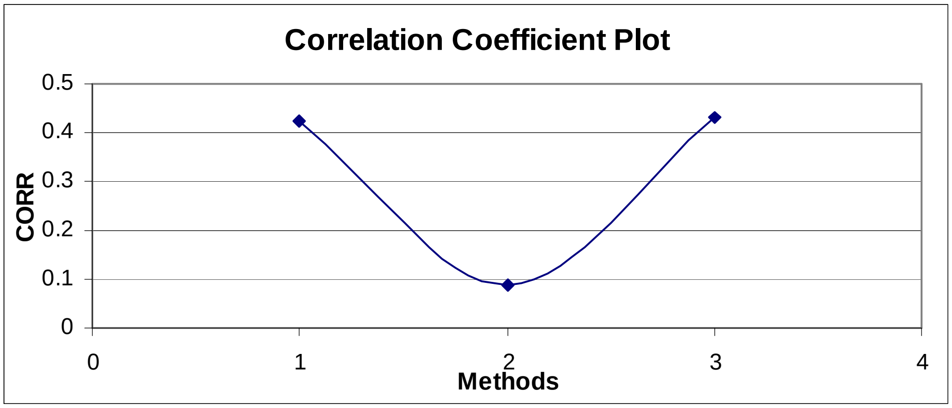

Figure 3.46 Plot of Methods versus Correlation Coefficient- Physio

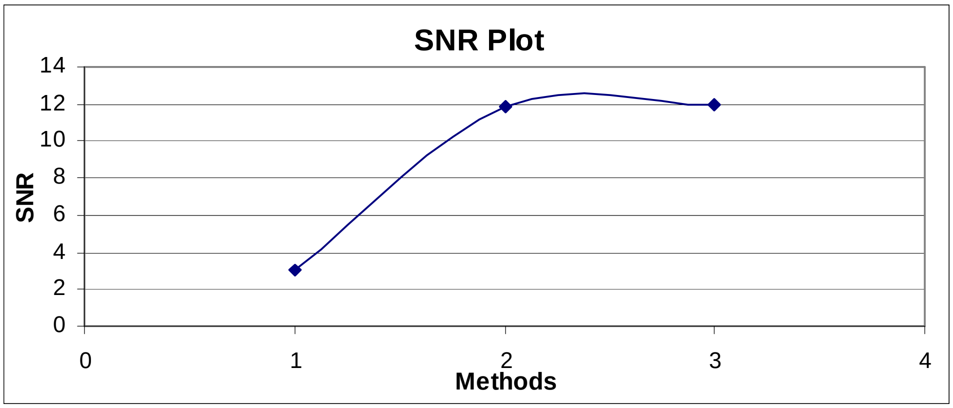

Figure 3.47 Plot of Methods versus SNR- Physio

The results of the performance parameters are as follows:

- Sensitivity is highest in method III.
- PPV is highest in method III.
- NPV is highest in method III.
- Accuracy is highest in method III.
- Specificity is highest in method III.
- Correlation coefficient of the method I and method III are having similar value whereas method II has lower value.
- SNR is highest in method III.

From the above observations it is concluded that method III is the most efficient method for FECG extraction.

3.7 CHAPTER SUMMARY AND CONCLUSION

In this chapter, three methods of FECG extraction from composite abdominal signal using multi stage adaptive filtering is proposed. The methods are (1) FECG Extraction Method (2) Improved FECG Extraction Method (3) Novel Method of FECG Extraction. The algorithms of the three methods have been tested with the same data sets from Sista and Physio. The performance of these methods is evaluated using the parameters sensitivity, specificity, positive predictive value, negative predictive value, accuracy, correlation coefficient and SNR. The evaluation and analysis show that all the methods are performing well. However by comparing all the performance parameters, method III – Novel method of FECG extraction seen to be more efficient and produces a high quality of FECG signal. The position of the electrode also plays a significant role in the quality of the signal to have better extraction. And it is found that the electrode position 2, 7 yields the best quality of FECG signal using method III.

CHAPTER 4

NEW EXTRACTION TECHNIQUES FOR FECG USING WAVELET- ADAPTIVE FILTERS

4.1 INTRODUCTION

Physiological measurements used for diagnostic purposes are frequently characterized by non stationary time behaviour. For these patterns, time-frequency representations are desirable. The Wavelet transform is an efficient mathematical tool for local analysis of fast transient signals and non stationary signals. It represents a very suitable method for classification of FECG signals from the abdominal ECG signal. It allows the use of long time interval analysis and yields more precise low-frequency information and short time interval analysis yields the high-frequency information. There are large number of wavelet transforms which includes Haar, Daubechies, Biorthogonal, Coiflets and Symmlet. The shape of the wavelet can be selected and it can be matched to the shapes of components embedded in the signal to be analyzed (Daubechis I., 1992). There is no absolute way to choose a certain wavelet. The choice of the wavelet transform depends upon the application. Selecting a wavelet function which closely matches the signal to be processed is very important in the wavelet applications.

4.1.1 WAVELET TRANSFORM

The wavelet transform is a time-scale representation technique (Mallat and Hwang, 1992). Computing the wavelet transform consists of breaking up a signal in to shifted and scaled versions of an original (mother) wavelet which is similar to the Fourier transform which breaks up the original in to sinusoids of different frequencies. Wavelet transform describes a signal by using correlation with translation and dilation of a function called as mother wavelet. The continuous wavelet transform (CWT) is defined as the sum over all times of the continuous signal f(t) multiplied by scaled, shifted versions of the mother wavelet ψ((t-τ)/s) as shown in equation 4.1(Mallat,1998).

$$CWT(s,\tau) = \frac{1}{\sqrt{s}} \int f(t)\psi\left(\frac{t-\tau}{s}\right)dt \tag{4.1}$$

The parameter s is the scale factor (dilation parameter) that compresses the mother wavelet and τ is the translation of the mother wavelet along the time axis. The CWT can be considered as a correlation of f(t) with the mother wavelet .Higher correlation exists if f(t) and mother wavelet show higher similarity. An original mother wavelet is chosen from a predefined set of wavelets. Otherwise, a custom wavelet can be constructed. The wavelet is then stepped through the signal, multiplied with the signal at every time instant of interest and integrated to yield a wavelet coefficient. The scale of the wavelet is then changed to compress or dilate it. The new wavelet undergoes the same process of stepping through the signal, multiplication and integration to yield wavelet coefficients. This process is repeated for the set of scales chosen.

The discrete wavelet transform (DWT) computes coefficients for a dyadic scale sequence. This means that the wavelet coefficients are only calculated for scales based on the power of two. DWT is defined by splitting f(t) in to smaller non over lapping parts f_i(t), taking a finite number of scales N and down sampling the discrete wavelet coefficients samples to M, the number of samples of f_i(t), as shown in equation 4.2

$$DWT_i(s,\tau,N) = \left\langle \sum_{j=1}^{N} \sum_{k=1}^{N} CWT_i(s_j,\tau_k) \right\rangle \Downarrow N \tag{4.2}$$

The computational time is highly reduced in DWT compared to CWT because the coefficients are not calculated for every scale and integration is replaced by summation, which is more easily implemented. The DWT is a batch method, which analyses a finitelength, time-domain signal at different frequency bands with different resolutions by successive decomposition in to coarse approximation (cA) and coarse detail (cD). The approximation is the high scale, low frequency components of the signal and the details are the low scale, high frequency components. The 5 level wavelet decomposition structure is shown in Figure 4.1. 'S' is the signal.cA_1 to cA_5 are the 5 levels of coarse approximations and cD_1 to cD_5 are the detail information's.

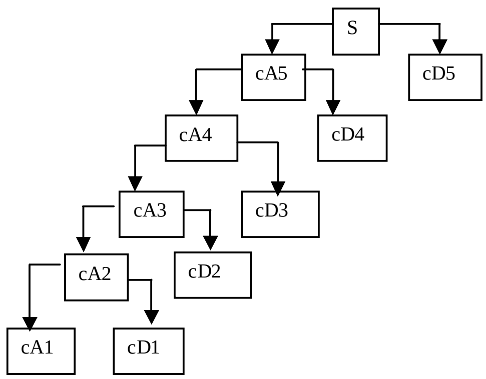

Figure 4.1 5-Level wavelet decomposition

4.1.2 WAVELET DENOISING

Wavelet denoising is based on the assumption that the random errors in a signal are present over the entire coefficient. But the deterministic changes are getting captured in a small number of large coefficients. The wavelet denoising method consists of applying DWT to the original signal, thersholding the detail and approximation coefficients and inversing the threshold coefficients to obtain the time domain denoised data (Paraschiv- Ionescu *et al.*, 2002). Denoising was performed by two different criterions named as hard thresholding and soft thresholding. In hard thresholding, wavelet coefficients on some or all scales that are below a certain threshold are believed to be noise and they are set to be zero. In soft thresholding, in addition to hard thresholding coefficients on all coefficients above this threshold are reduced by the value of the threshold.

The wavelets are used as a decomposition and denoising tool (Najumnissa and Shenbagadevi, 2008). The performance of the wavelet denoising depends upon the type of wavelet transform, type of the wavelet, thersholding rule and the number of decomposition levels. The steps for denoising are;

1. Decompose the signal – Choose a wavelet, choose level 'n'. Compute the wavelet decomposition of the signal's' at level 'n'.
2. After the wavelet decomposition, the wavelet coefficients are modified and then the reconstruction takes place.
3. Reconstruction of the signal - Compute wavelet reconstruction using the original approximation coefficients of level'n' and the modified coefficients of level from '1 to n'.

4.1.3 DESIGN OF EXTRACTION SYSTEM

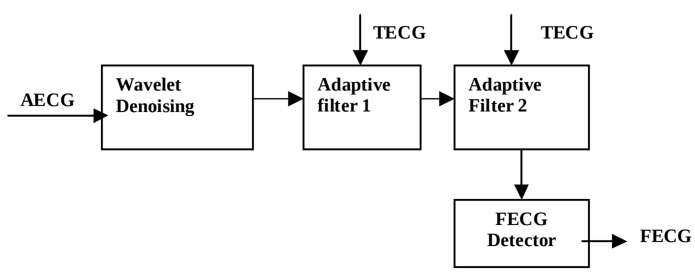

Figure 4.2 The design of the extraction system

The design of the extraction system is shown in Figure 4.2. In this wavelet denoising, the decomposition and reconstruction were performed by coiflets wavelet because the wavelet functions belonging to this family have a similar shape of FECG. And also the energy spectrum is concentrated around low frequencies (Mahmoodabadil *et* *al*., 2005). The properties of coiflets wavelet are good for this application because it reduces the noise and provides high resolution output. The number of level of decomposition was set as 5. The denoised signal is reconstructed by the approximation and the processed details. The approximation and details were processed by soft Stein's unbiased risk estimate (SURE) thresholding rule. The approximation and detail information of the composite abdominal signal is shown in Figure 4.3.

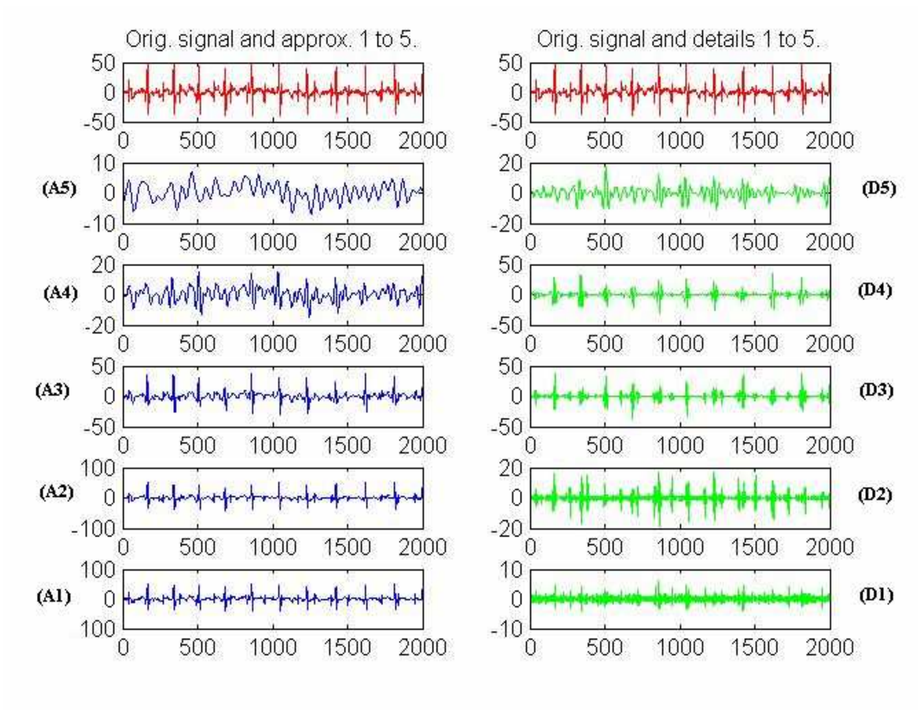

Figure 4.3.Decomposition of the composite abdominal signal

In this method only the approximation coefficients are retained as the signal carries useful information. This signal is used for further extraction procedure of FECG. The information of the level of approximation is selected by visual inspection. The denoised signal is the input to the two stage adaptive filtering system. The adaptive filter1 uses the RLS algorithm and the adaptive filter 2 uses LMS algorithm as justified in section 3.2.4. The output of the second stage adaptive filter forms the input to the FECG detector.

In this chapter four new algorithms for FECG signal extraction are introduced using wavelet and adaptive filtering techniques. These are named as Wavelet Adaptive Methods (WAF). The types are;

1) WAF Method I

2) WAF Method II

3) WAF Method III

4) WAF Method IV

These algorithms were tested using data from Sista and Physio for different electrode positions as mentioned in section 3.1.

4.2 WAF METHOD I

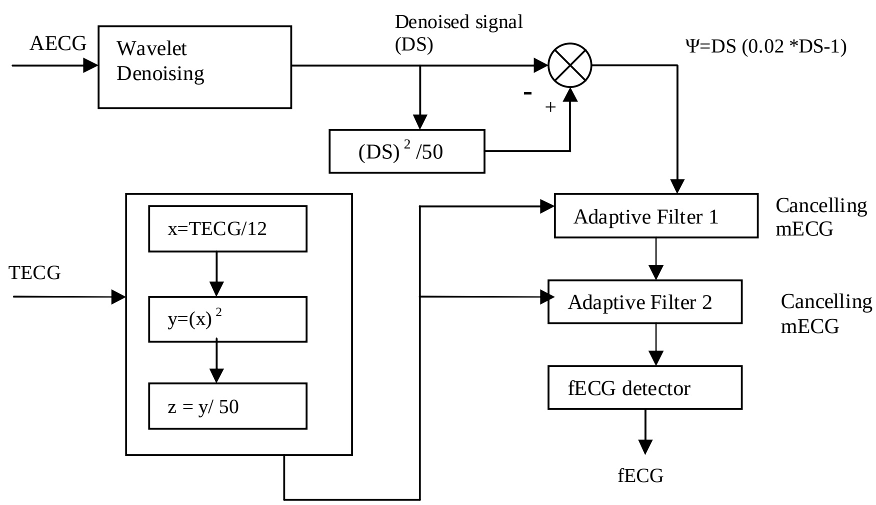

Figure 4.4 Block diagram of the WAF -Method I

The block diagram of the proposed algorithm of WAF method I is shown in Figure 4.4.The objective of the algorithm is to extract the fetal ECG by suppressing the maternal ECG and noise from the signal. The abdominal signal is subjected to wavelet with 5 levels of denoising. The final approximation coefficient is taken as the denoised abdominal signal which is represented as DS. The DS is squared and scaled and added to original denoised signal to derive the non linear parameter Ψ. The fetal ECG extraction is done using this non linear operator defined as $\Psi = DS\ (0.02*DS-1)$.

The adaptive filter has the following two input signals.

(1) The scaled, squared and scaled thoracic signal.

(2) The non linear operator signal Ψ.

The adaptive filters 1 and 2 are trained to cancel the MECG from the composite abdominal signal. The RLS, LMS combination has been used for two stages of adaptive filtering. The error signal from the adaptive filter2 is the desired fetal ECG signal which is further processed by FECG detector to extract the fetal ECG which is totally free from maternal ECG signals. The results for Sista data and Physio data are shown in section 4.2.1

4.2.1 WAF METHOD I – RESULTS

The proposed Method I uses wavelet denoising and non linear parameter Ψ=DS(0.02 *DS-1) to extract fetal ECG. The extraction results are shown from Figure 4.5 to Figure 4.9 for Sista data and Figure 4.10 is the extracted output for Pysiodata. The visual inspection shows the suppression of maternal ECG in electrode position 2, 7 and partial presence of maternal ECG in other channels. The SNR is found to be 24.20, 14.85, 24.31, 22.96, and 28.14 for sista data and 34.86 for physio data. This method has significantly improved the SNR in all the data sets when compared to the adaptive method I as discussed in section 3.3.1.

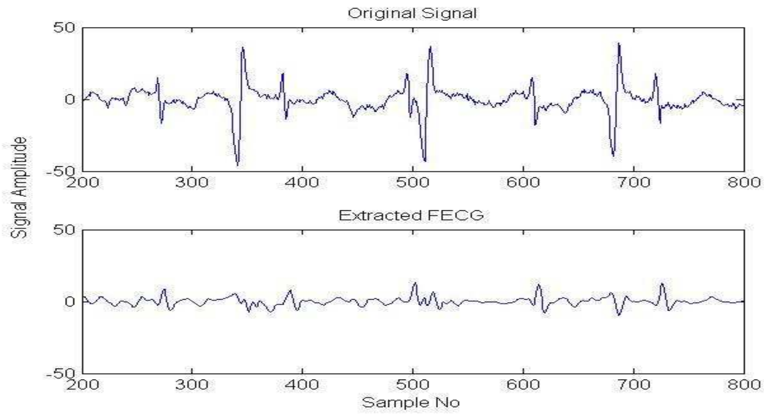

Figure 4.5 WAF method I – Sista (2, 7)

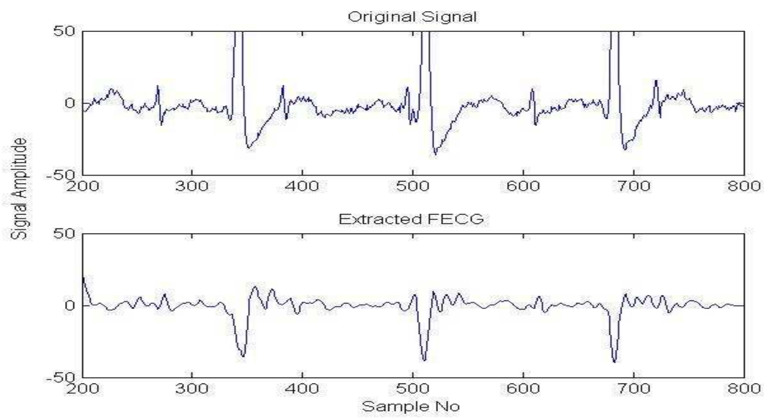

Figure 4.6 WAF method I – Sista (3, 7)

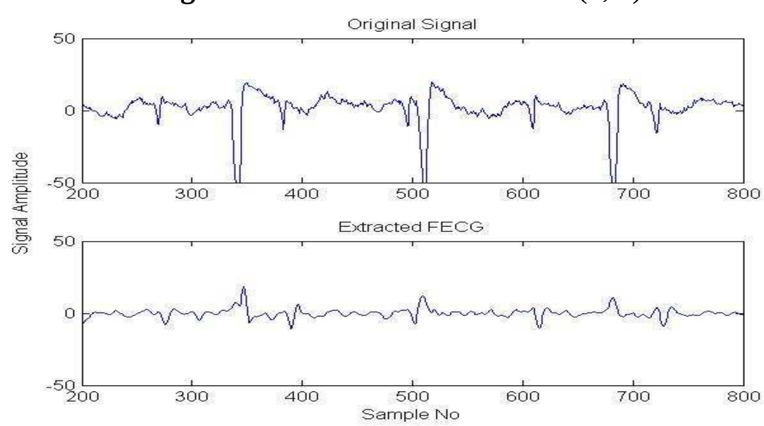

Figure 4.7 WAF method I – Sista (4, 7)

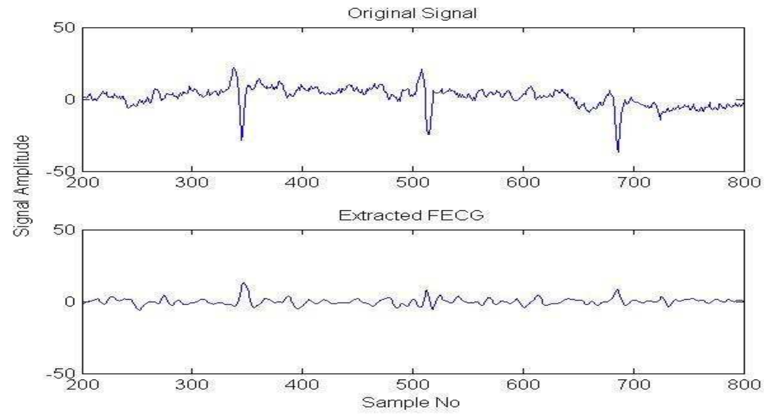

Figure 4.8 WAF method I – Sista (5, 7)

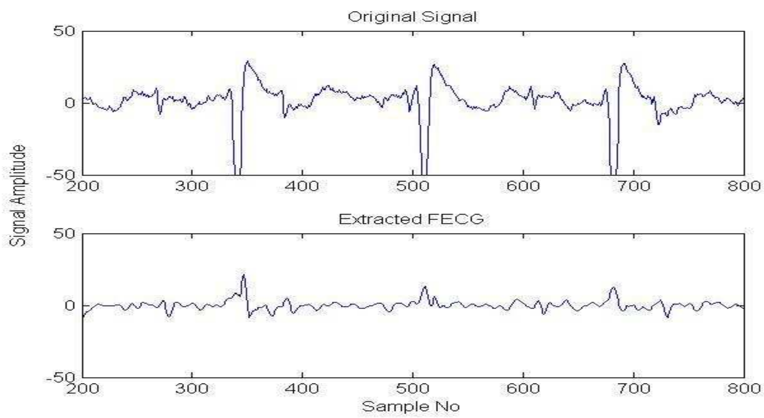

Figure 4.9 WAF method I – Sista (6, 7)

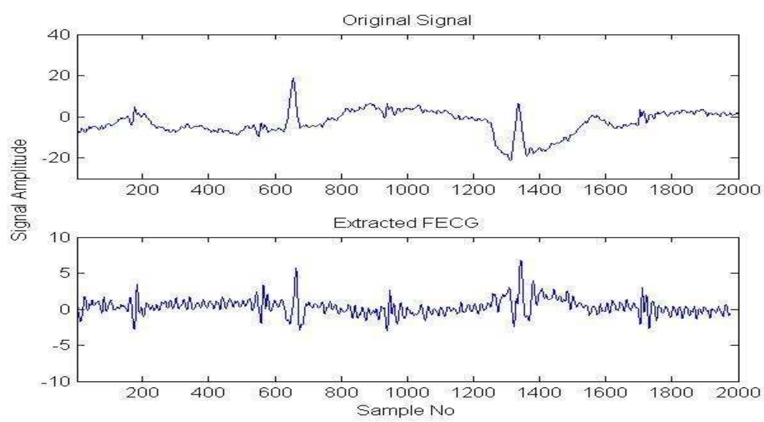

Figure 4.10 WAF method I **–** Physio (4,2)

4.3 WAF METHOD II

The block diagram of WAF method II of fetal ECG extraction with refinement technique is shown in Figure 4.11.

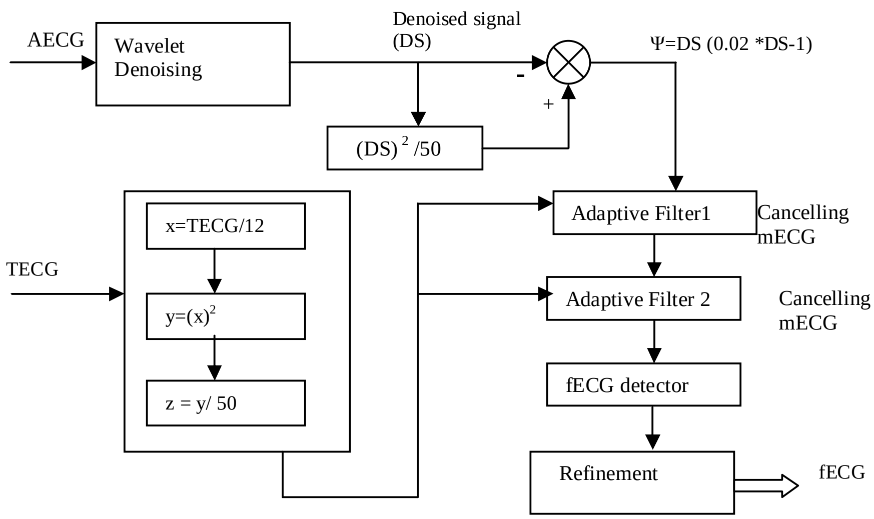

Figure 4.11 Block diagram of the WAF with refinement -Method II

The refinement is done for further improvising the quality of the FECG. The extracted FECG signal from method I is further post processed. The post processing steps are (i) reading the extracted FECG signal, (ii) separating the high/low resolution components (iii) compensating for the phase (iv) deriving the noise component (v) separating the noise from the signal (vi) reconstructing the signal. This reconstructed signal is the extracted FECG signal. This WAF method II was yielding a better result than the WAF method I. The refinement results are shown in section 4.3.1 for Sista and Physio data.

4.3.1 WAF METHOD II – RESULTS

The proposed WAF method II uses wavelet denoising and non linear parameter Ψ=DS (0.02 *DS-1) along with refinement. The extraction results are shown from Figure 4.12 to Figure 4.16 for Sista data and Figure 4.17 is the extracted output for Physio data. The visual inspection shows the suppression of maternal ECG. The SNR is found to be 26.5, 13.77, 26.78, 26.22, and 31.39 for Sista data and 43.81 for Physio data. This method has significantly improved the SNR in all the data sets when compared to the WAF method I and adaptive method II. The extracted signal is clean and the effect of the artifacts related spikes were suppressed.

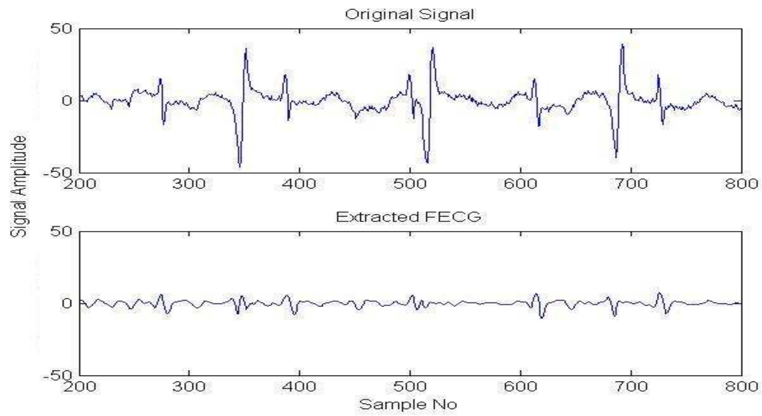

Figure 4.12 WAF method II – Sista (2, 7)

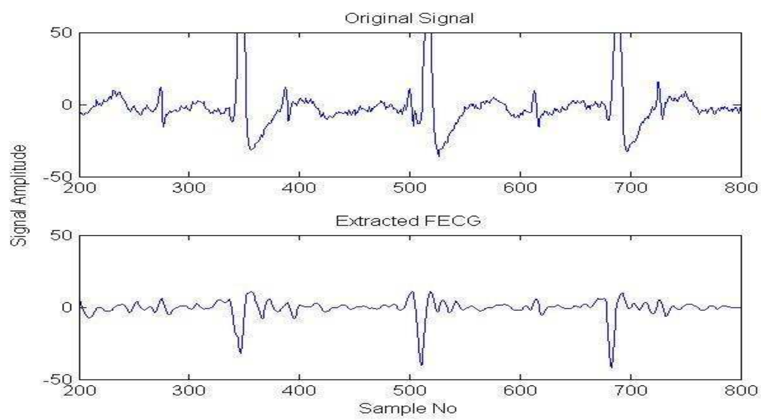

Figure 4.13 WAF method II – Sista (3, 7)

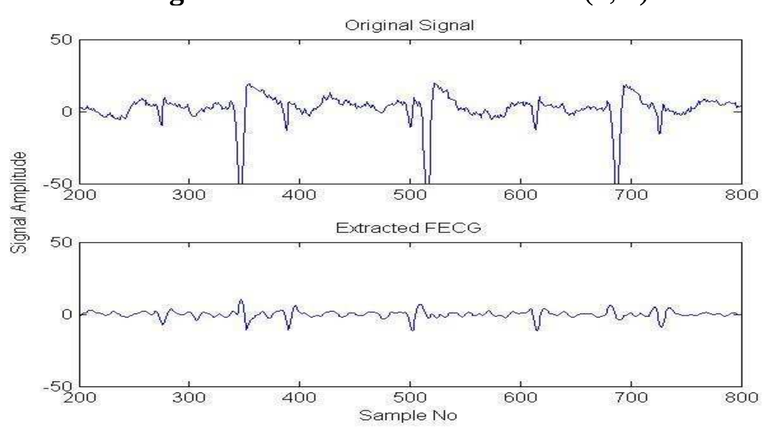

Figure 4.14 WAF method II – Sista (4, 7)

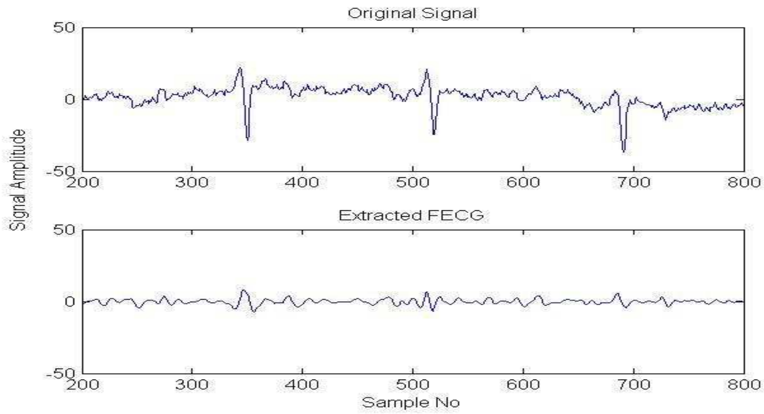

Figure 4.15 WAF method II – Sista (5, 7)

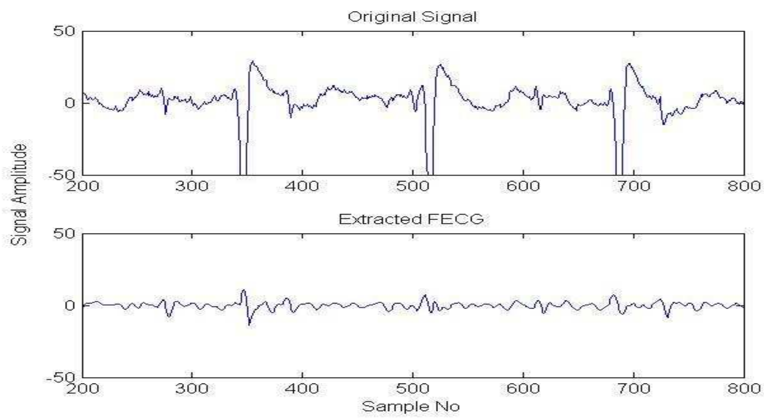

Figure 4.16 WAF method II – Sista (6, 7)

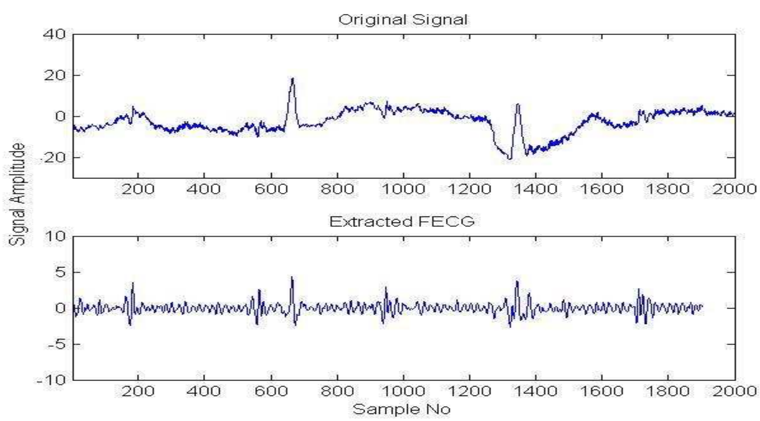

Figure 4.17 WAF method II – Physio (4,2)

4.4 WAF METHOD III

The block diagram of WAF method III is shown in Figure 4.18. In this method, the abdominal signal is denoised and multiplied by factor K to derive a new non linear parameter ψ. This non linear parameter ψ is defined as ψ = DS (K-1). The K value is fixed to be 2.6 using the procedure adopted as discussed in section 3.5. The thoracic signal remains the same as discussed in WAF method I and WAF method II. The results are shown in section 4.4.1

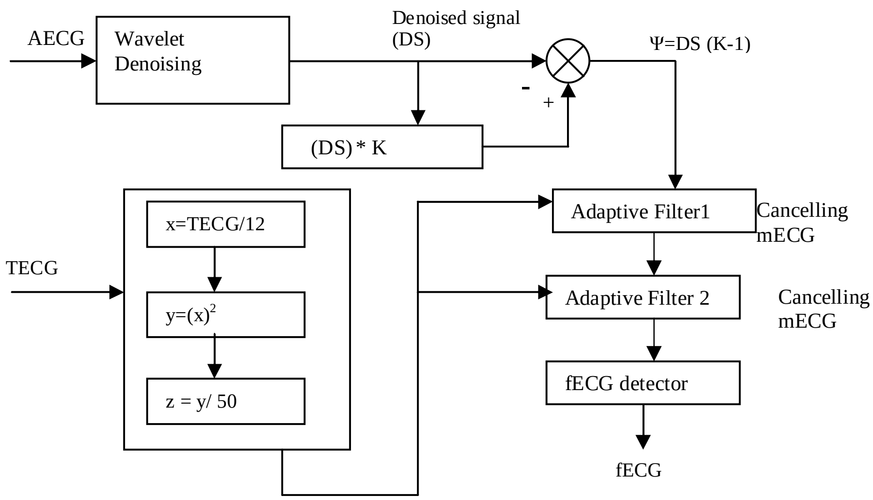

Figure 4.18 Block diagram of the WAF -method III

4.4.1 WAF METHOD III – RESULTS

The WAF method III uses wavelet denoising and non linear parameter ψ=DS(K-1) to extract fetal ECG. The extraction results are shown from Figure 4.19 to Figure 4.23 for Sista data and Figure 4.24 is the extracted output for Physio data. The results show that the performance was inferior to WAF method I and WAF method II. This is due to the presence of maternal ECG in the extracted signal. Even by changing the value of K linearly, the algorithm failed to suppress the maternal ECG completely. The SNR is seen to be 14.18, 11.84, 11.99, 12.34, and 14.78 for sista data and 26.13 are for the physio data. The SNR is seen to be less in method III when compared to WAF method I and method II.

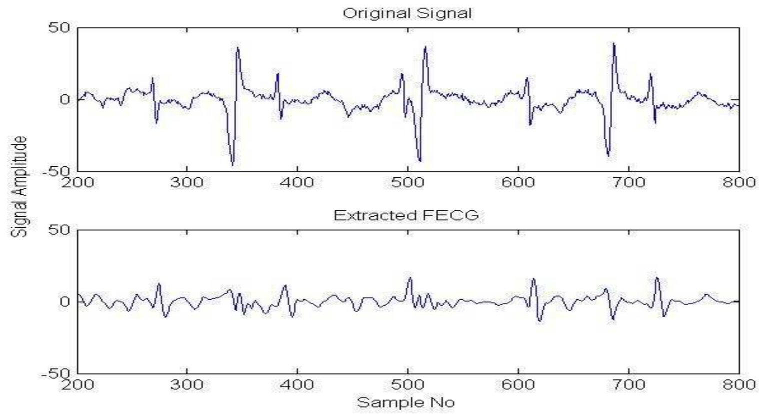

Figure 4.19 WAF method III – Sista (2, 7)

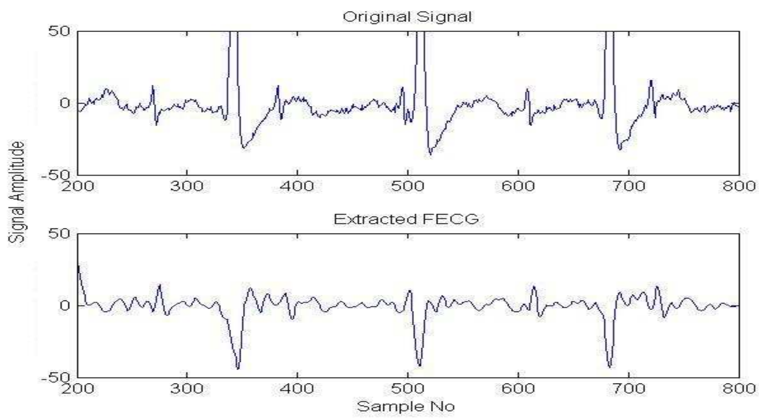

Figure 4.20 WAF method III – Sista (3, 7)

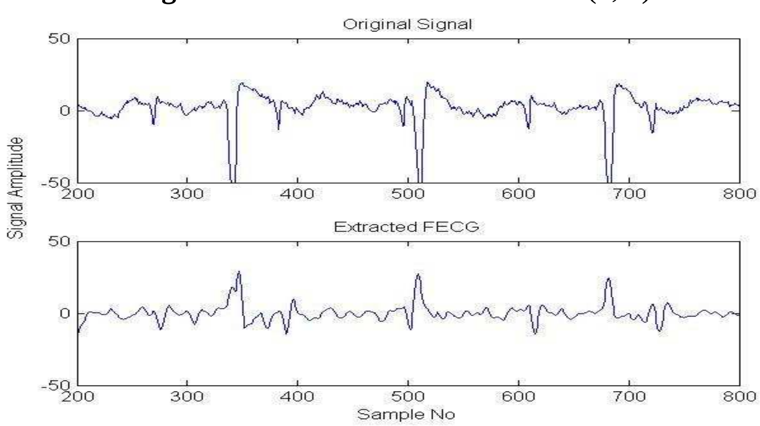

Figure 4.21 WAF method III – Sista (4, 7)

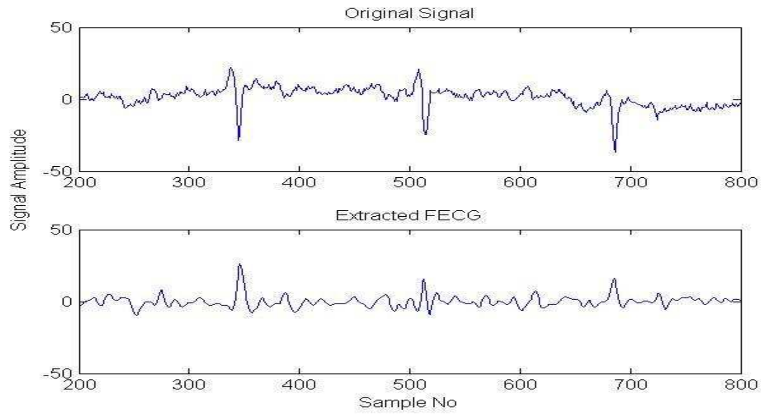

Figure 4.22 WAF method III – Sista (5, 7)

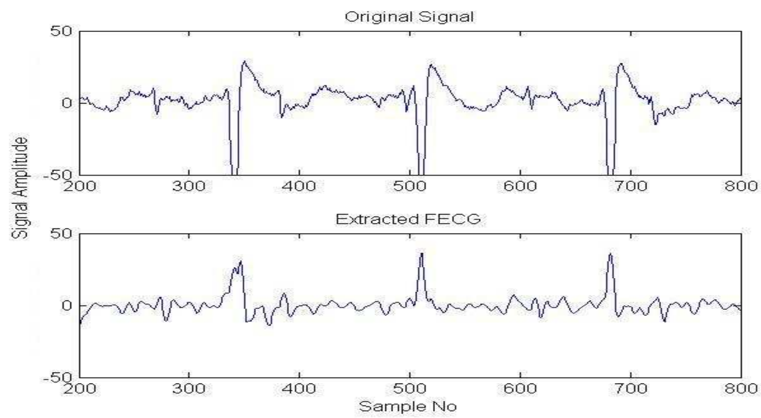

Figure 4.23 WAF method III – Sista (6, 7)

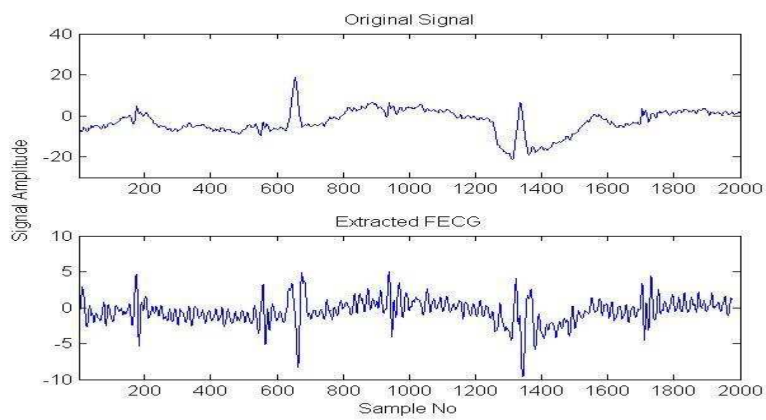

Figure 4.24 WAF method III – Physio (4,2)

4.5 WAF METHOD IV

The block diagram of WAF method IV is shown in Figure 4.25.To overcome the disadvantage of WAF method III, the WAF method IV was proposed. In this method, the denoised signal remains same as in method III. Since the algorithm failed to suppress the maternal ECG even by changing the value of K linearly, the thoracic signal has now been modified. The thoracic signal is now scaled, then considered as a second order quadratic function and again scaled to improve the extraction. The signal extracted by this technique is better than the WAF method III. However this method is found to be inferior to WAF method II. The results of this method are shown in section 4.5.1.

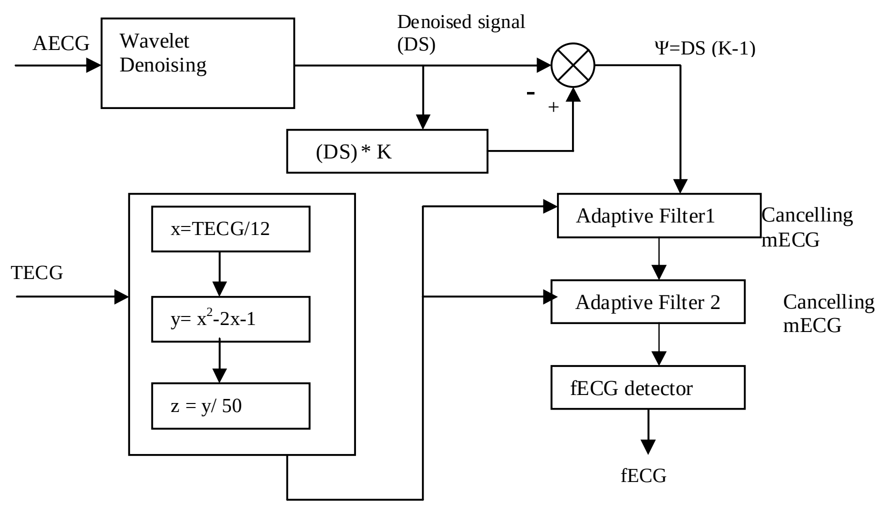

Figure 4.25 Block diagram of the WAF -method IV

4.5.1 WAF METHOD IV – RESULTS

The WAF method IV uses wavelet denoising and non linear parameter Ψ=DS(K-1) along with the modified thoracic signal to extract fetal ECG. The extraction results are shown from Figure 4.26 to Figure 4.30 for Sista data and Figure 4.31 is the extracted output for Physio data. The SNR is seen to be 14.35, 12.15, 12.01, 12.03 and 14.82 for Sista data and 31.73 are for the Physio data. The SNR is increased by this technique which is better than the WAF method III. However this method is found to be inferior to WAF method II.

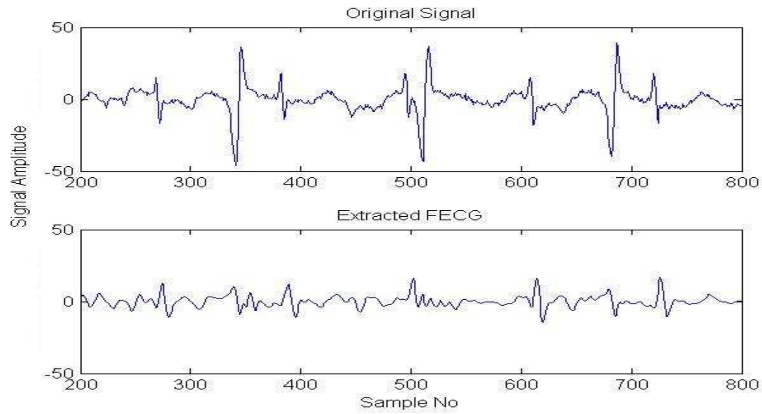

Figure 4.26 WAF method IV – Sista (2, 7)

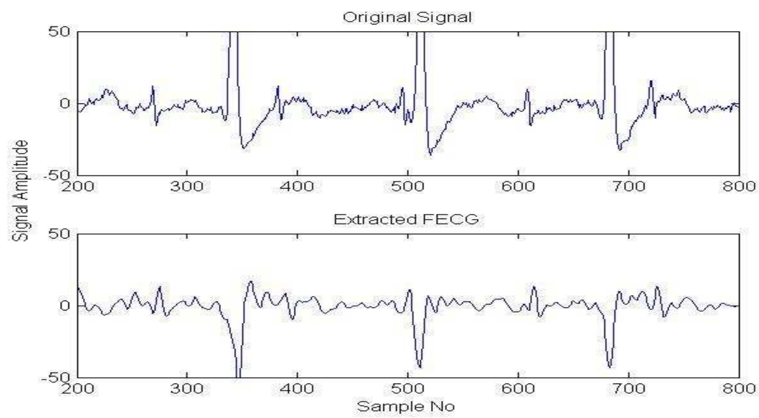

Figure 4.27 WAF method IV – Sista (3, 7)

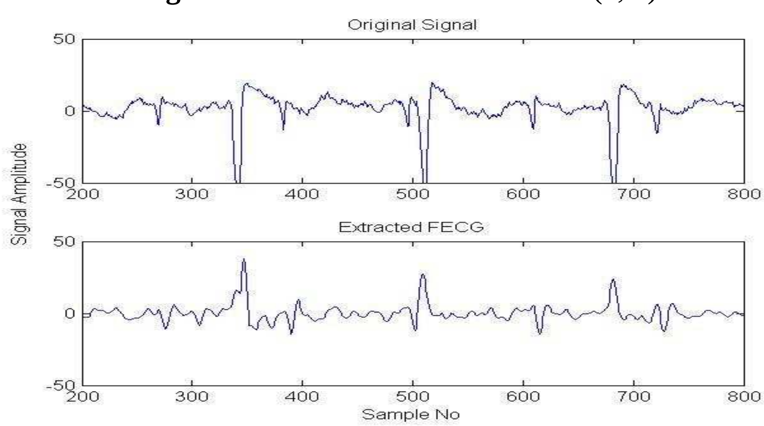

Figure 4.28 WAF method IV – Sista (4, 7)

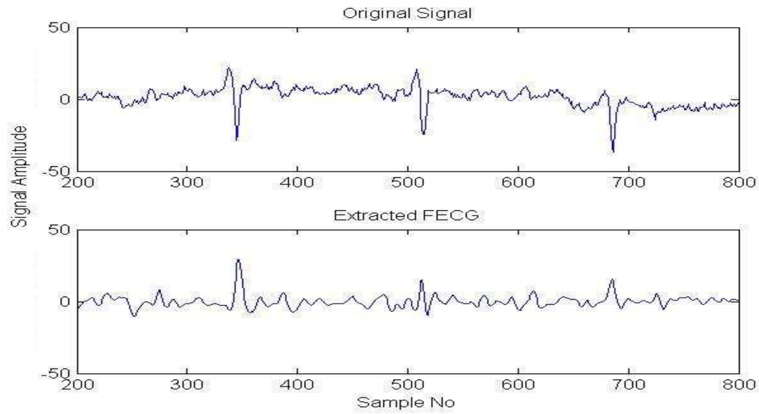

Figure 4.29 WAF method IV – Sista (5, 7)

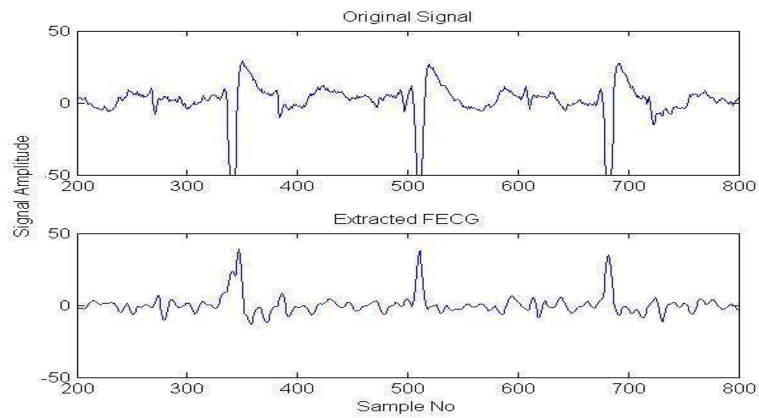

Figure 4.30 WAF method IV – Sista (6, 7)

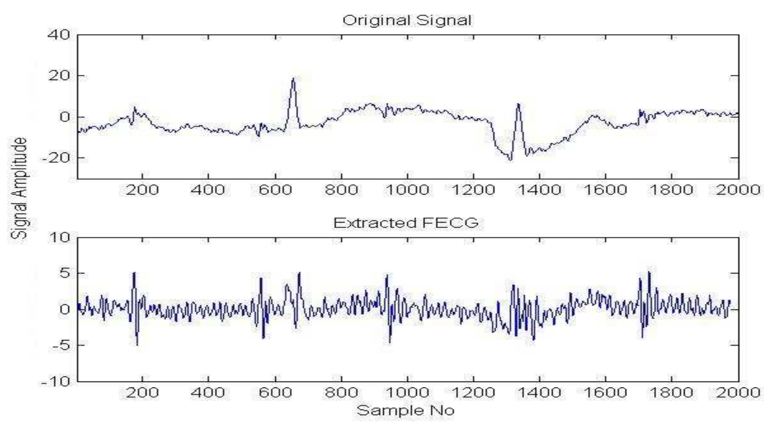

Figure 4.31 WAF method IV – Physio (4,2)

4.6 EVALUATION AND ANALYSIS OF THE PROPOSED METHODS

In this work four different methods of fetal ECG extraction are presented. They are (1) WAF method I

(2) WAF method II

(3) WAF method III

(4) WAF method IV

The methods have been tested with the same data. The performance evaluation has been done by the following parameters. Sensitivity (SEN), Specificity (SPE), Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy (ACC), Correlation Coefficient (CORR) and Signal to Noise ratio (SNR) as mentioned in section 3.6.

4.6.1 EVALUATION OF WAF METHOD I

The performance of WAF method I tested with data from Sista is shown in Table 4.1. The performance parameters SEN, SPE, PPV, NPV and ACC from electrode position 2, 7; 3,7 and 4, 7 are seen to have a better performance compared to 5, 7 and 6, 7. In electrode position 5, 7 the specificity, PPV, NPV and accuracy is showing a lower value due to the insignificant presence of fetal ECG in the abdominal signal itself. In electrode position 6,7 the magnitude of maternal ECG is very large compared to fetal ECG which leads to poor value of the performance parameters.

Table 4.1 Performance of WAF Method I(Sista data)

Electrode position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	0.67	1	1	0.75	0.83	0.1851	24.2001
3,7	0.78	0.67	0.7	0.75	0.72	0.7618	14.8498
4,7	0.67	0.7	0.67	0.7	0.68	0.4810	24.3144
5,7	0.6	0.55	0.57	0.5	0.55	0.4039	22.9610
6,7	0.67	0.58	0.57	0.5	0.55	0.4969	28.1437

However, in terms of SNR the electrode position 2,7; 4, 7 and 6, 7 are having higher value compared to 3, 7 and 5, 7. In electrode position 3, 7 the correlation is on the higher side due to presence of maternal ECG in the extracted signal. To conclude, the record from electrode position of 2,7 have got the best performance indices as seen from the table 4.1.

4.6.2 EVALUATION OF WAF METHOD II

The performance of WAF method II tested with data from Sista is shown in Table 4.2. The performance parameters SEN, SPE, PPV, NPV and ACC for all the electrode position are seen to have a better performance compared to WAF method I. However in method II, the SNR is seen to be less in 3, 7. This may be due to the noisy maternal ECG present in the extracted FECG. In electrode positions 4, 7 and 5, 7 has similar correlation and SNR. The electrode position 6,7 has got high SNR and medium correlation. The lowest correlation is seen in electrode position 2, 7 and this is due to the absence of maternal ECG in the extracted FECG.

Table 4.2 Performance of WAF Method II(Sista data)

Electrode position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	0.8	1	1	0.83	0.9	0.165	26.5029
3,7	0.72	0.88	0.83	0.7	0.75	0.7586	13.7762
4,7	0.75	0.75	0.75	0.75	0.75	0.3718	26.7895
5,7	0.78	0.67	0.68	0.67	0.68	0.3473	26.2162
6,7	0.67	0.75	0.75	0.67	0.71	0.4055	31.3970

4.6.3 EVALUATION OF WAF METHOD III

The performance of WAF method III tested with data from Sista is shown in Table 4.3. The electrode position 2, 7 is seen to have a better performance compared to other electrode positions with respect to SEN, SPE, PPV, NPV and ACC. In this WAF method III, SNR is seen to be more for electrode position 2, 7 and 6, 7 when compared to other electrode positions. The correlation coefficient is highest in 3, 7 compared to all other electrode positions due to presence of maternal ECG in the extracted signal. The electrode position 2, 7 has less correlation coefficient due to good extraction of fetal ECG. Thus the electrode position of 2, 7 is yielding better results in WAF method III compared to other electrode positions. However, the overall performance of WAF method III is slightly inferior to WAF method I and WAF method II.

Table 4.3 Performance of WAF Method III (Sista data)

Electrode position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	0.79	1	1	0.7	0.79	0.2369	14.1796
3,7	0.7	0.7	0.7	0.7	0.7	0.7144	11.8368
4,7	0.75	0.63	0.67	0.71	0.69	0.592	11.9924
5,7	0.57	0.64	0.62	0.64	0.61	0.4751	12.3430
6,7	0.67	0.67	0.67	0.67	0.67	0.6883	14.7873

4.6.4 EVALUATION OF WAF METHOD IV

Table 4.4 Performance of WAF Method IV (Sista data)

Electrode position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	0.67	1	1	0.72	0.82	0.2711	14.3583
3,7	0.63	0.6	0.72	0.6	0.62	0.6929	12.1589
4,7	0.7	0.67	0.7	0.67	0.69	0.5684	12.0124
5,7	0.67	0.6	0.67	0.6	0.64	0.4491	12.0341
6,7	0.67	0.67	0.67	0.67	0.67	0.6673	14.8282

The performance of WAF method IV tested with data from Sista is shown in Table 4.4. The performance indices, correlation and SNR show a slight improvement in WAF method IV over WAF method III. This is due to modification done in the thoracic signal as is shown in section 4.5. However, the results are inferior to WAF method I and WAF method II.

4.6.5 EVALUATION OF DIFFERENT METHODS FOR PHYSIO DATA

The performance of WAF method I, WAF method II, WAF method III and WAF method IV for FECG extraction were tested with data from Physio and the results are shown in Table 4.5.

Table 4.5 Performance of different methods (Physio data)

Method	SEN	SPE	PPV	NPV	ACC	CORR	SNR
WAF Method I	0.67	0.78	0.75	0.7	0.72	0.4246	34.8517
WAF Method II	0.75	0.75	0.75	0.75	0.75	0.2582	43.806
WAF Method III	0.6	0.72	0.75	0.67	0.7	0.4873	26.1316
WAF Method IV	0.68	0.67	0.7	0.75	0.73	0.3118	31.7337

The WAF method I, WAF method III and WAF method IV have comparable correlation factor and performance indices. In terms of SNR the method I has the higher value compared to method III and method IV. WAF method II shows constant value of performance indices, high SNR and low correlation factor. These values indicate that the WAF method II performs very well for the case of Physio data.

4.6.6 ANALYSIS OF WAF METHODS

The analysis of FECG extraction for performance parameter SEN, SPE, PPV, NPV, ACC, Correlation and SNR for WAF method I, WAF method II, WAF method III and WAF method IV are shown in section 4.6.6.1 for Sista data and in section 4.6.6.2 for Physio data.

4.6.6.1 ANALYSIS OF WAF METHODS – SISTA DATA

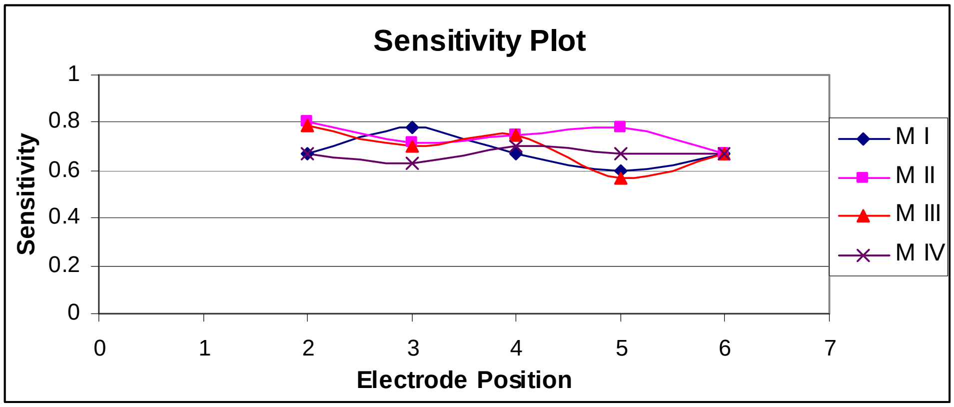

Figure 4.32 Plot of Electrode Position versus Sensitivity - Sista

Figure 4.32 shows the sensitivity plot for all WAF methods. The sensitivity of electrode position for 3, 7 in method I is high because of the minimum false negatives detection. For 6, 7 electrode position all the methods have the same value. In electrode position 2,7; 4,7 and 5,7 the method II has more sensitivity due to less number of false positive and false negative detections. Hence to conclude the WAF method II is having higher sensitivity compared to the other three methods for extraction of FECG.

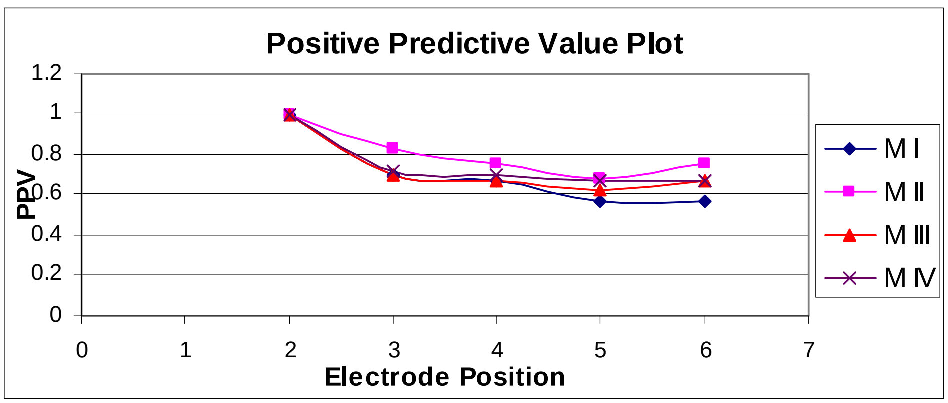

Figure 4.33 Plot of Electrode Position versus Positive Predictive Value- Sista

Figure 4.33 shows the positive predictive plot for all WAF methods .The PPV value is more in WAF method II for electrode positions 3, 7; 4, 7; 5,7 and 6, 7 because of less false positive peaks detection. In electrode position 2, 7 all the four methods have the similar value. Overall, WAF method II has better PPV value compared to other WAF methods of FECG extraction.

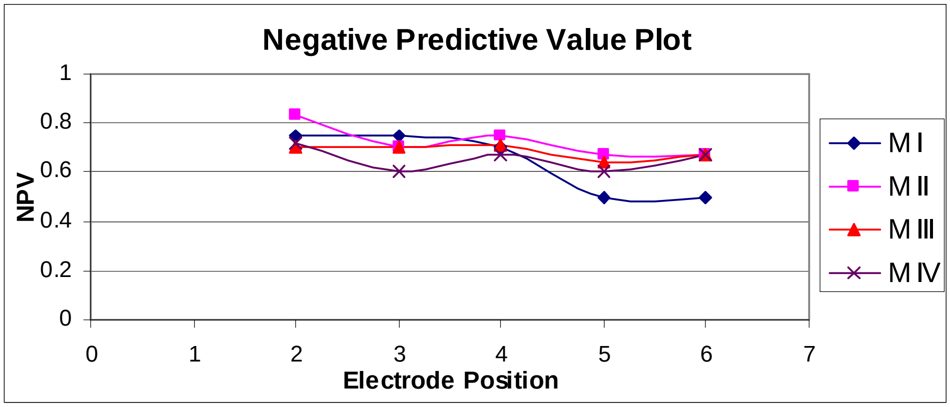

Figure 4.34 Plot of Electrode Position versus Negative Predictive Value- Sista

Figure 4.34 shows the negative predictive plot for all WAF methods. It is seen from the plot that in electrode position 3, 7 the NPV is more for WAF method I due to less number of negative false detections. In method I, the electrode position 5, 7 has least NPV value because of more number of false negatives detections. The WAF method II has higher value of NPV in all electrode positions except 3, 7. This is due to less number of false detections in the electrode positions 2,7; 4,7 ; 5,7 and 6,7 and more number false detection in 3,7. From this analysis, it is concluded that the WAF method II performs better than the other WAF methods.

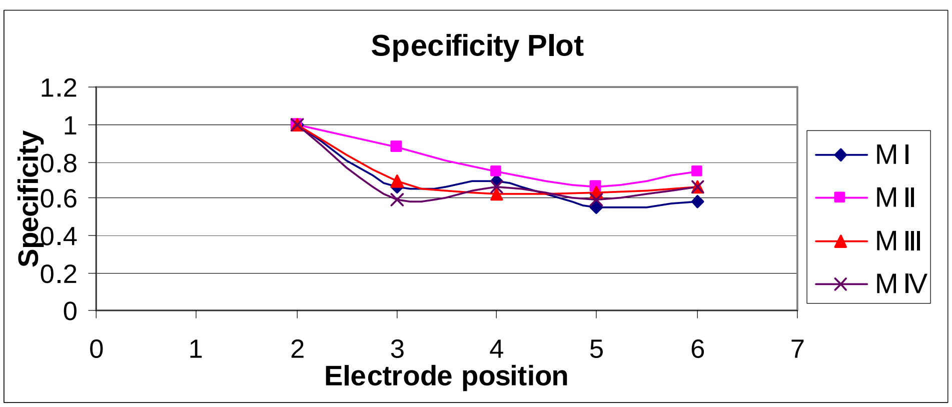

Figure 4.35 Plot of Electrode Position versus Specificity- Sista

Figure 4.35 shows the specificity plot for all WAF methods. WAF method IV shows lowest value of specificity for electrode position 3, 7. This is due to presence of maternal ECG leading to more false positive detections. In all the electrode positions the WAF method II indicates high value of specificity due to less no of false positive detections. The specificity is higher in WAF method II compared to all the other WAF methods.

Figure 4.36 shows the accuracy plot for all WAF methods. In electrode position 3,7 WAF method IV shows least value of accuracy due to more number of false positive and false negative detections. This is due to the presence of maternal ECG in the extracted signal. WAF method I show less accuracy in the case of electrode position 5, 7 and 6, 7. This is due to significant presence of maternal ECG. The accuracy in WAF method II is high for all the electrode positions due to the less number of false positive and false negative detections. Thus WAF method II is the better method for fetal ECG extraction in case of accuracy.

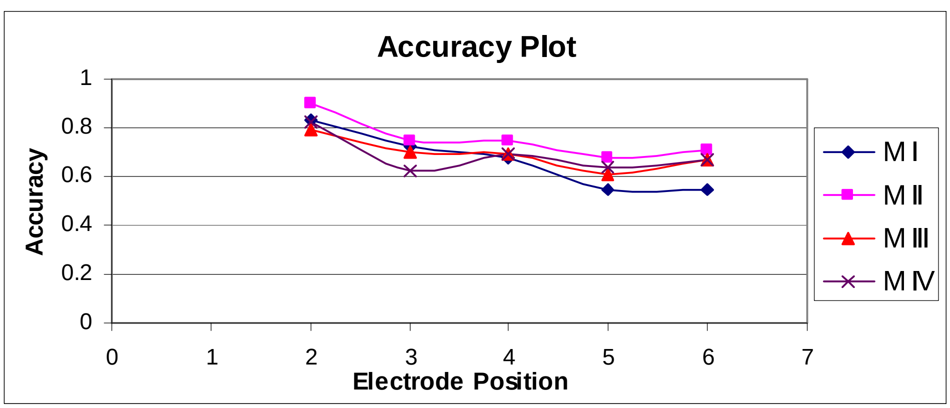

Figure 4.36 Plot of Electrode Position versus Accuracy - Sista

Figure 4.37 shows the correlation plot for all the WAF methods. The correlation coefficient has been calculated between the extracted fetal ECG and the composite abdominal signal containing fetal ECG and maternal ECG. Since the extracted fetal ECG signal should not have any trace of maternal ECG the correlation will be smaller.

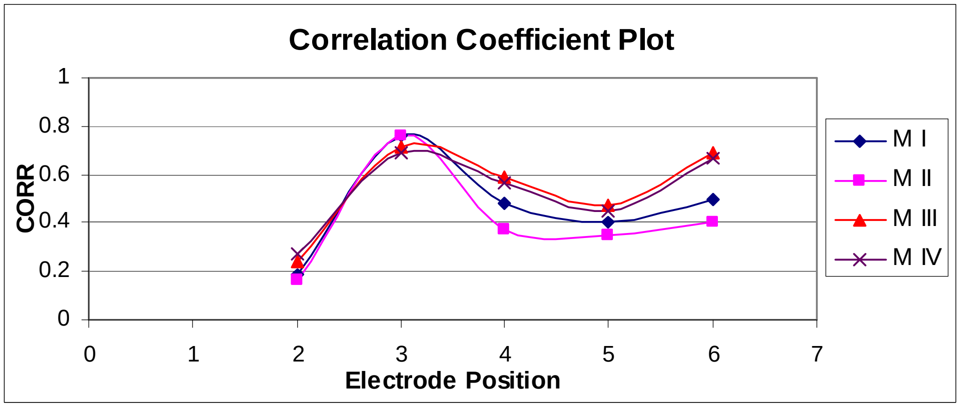

Figure 4.37 Plot of Electrode Position versus Correlation Coefficient- Sista

In all the WAF methods, electrode position 3, 7 shows the higher correlation coefficient. This is because of the magnitude of the maternal ECG is very large compared to the magnitude of fetal ECG in the recorded abdominal signal. This leads to large presence of maternal ECG in the extracted signal. In comparison of the four WAF methods, method II is seen to have lesser correlation coefficient than the other methods. Thus it is concluded that the WAF method II is better method for extraction of FECG.

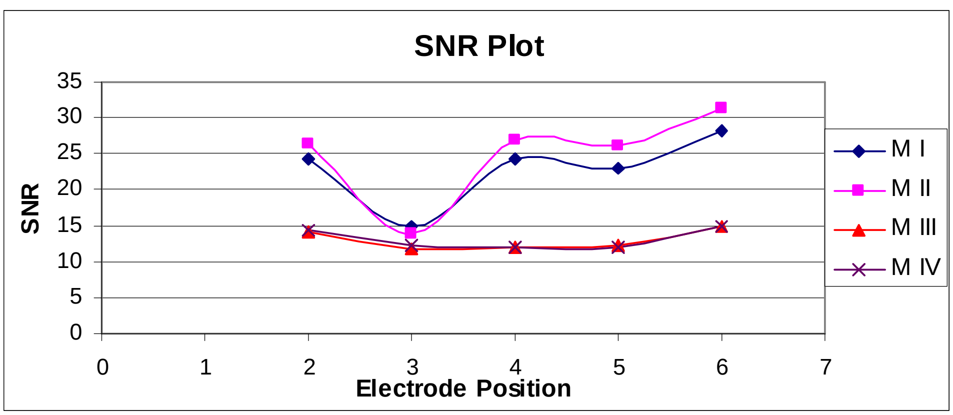

Figure 4.38 Plot of Electrode Position versus SNR -Sista

Figure 4.38 shows the SNR plot for all WAF methods. The SNR is calculated for the extracted fetal ECG. For all the electrode positions WAF method III and method IV have similar values of SNR due to presence of maternal ECG. Only in the case of electrode position 3, 7 WAF method I has high SNR compared to WAF method II. In the case of electrode positions 2, 7; 4, 7; 5, 7 and 6, 7 SNR is higher in WAF method II compared to all other methods. Thus it is concluded that the WAF method II is the most suitable method for extraction of FECG.

4.6.6.2 ANALYSIS OF WAF METHODS – PHYSIO DATA

The analysis of FECG extraction for WAF method I, WAF method II, WAF method III and WAF method IV are shown for Physio data. The performance parameters are plotted and shown in the Figures 4.39 to 4.45.

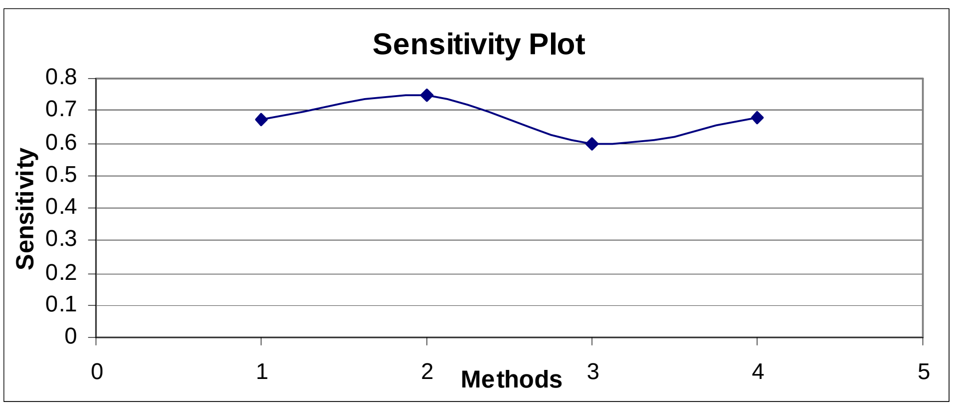

Figure 4.39 Plot of Methods versus Sensitivity- Physio

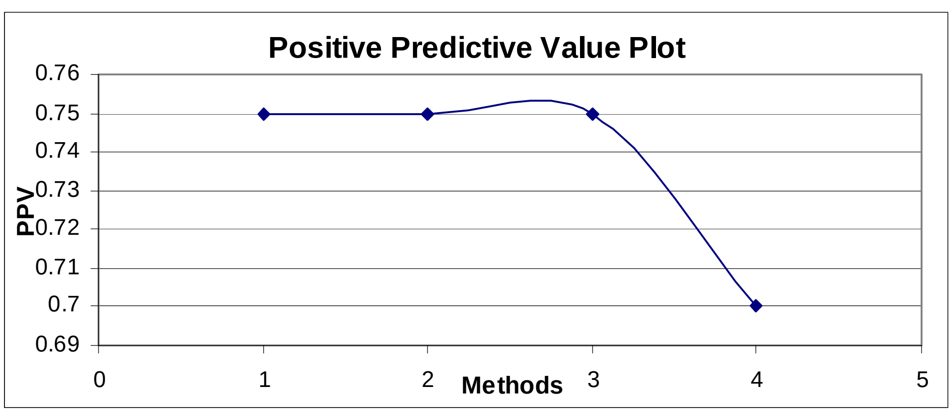

Figure 4.40 Plot of Methods versus Positive Predictive Value-Physio

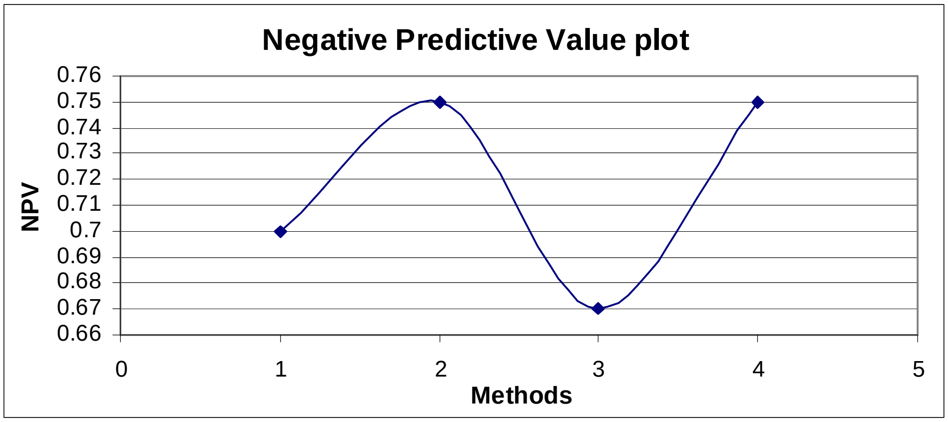

Figure 4.41 Plot of Methods versus Negative Predictive Value-Physio

Figure 4.42 Plot of Methods versus Specificity - Physio

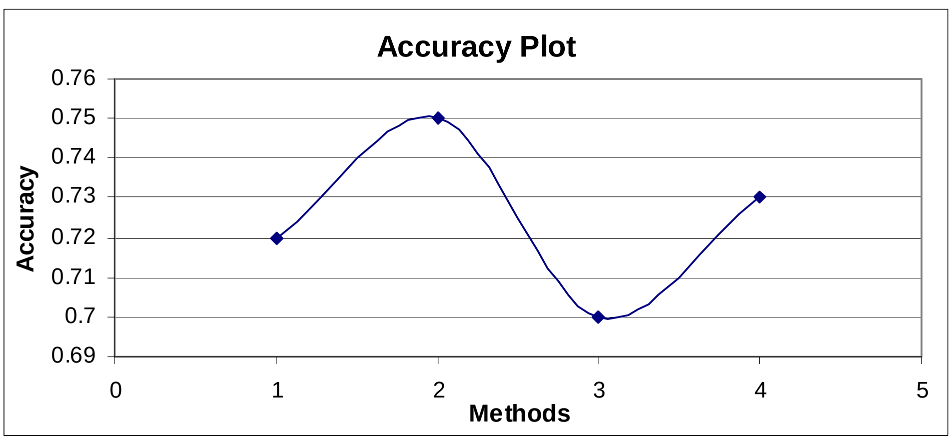

Figure 4.43 Plot of Methods versus Accuracy-Physio

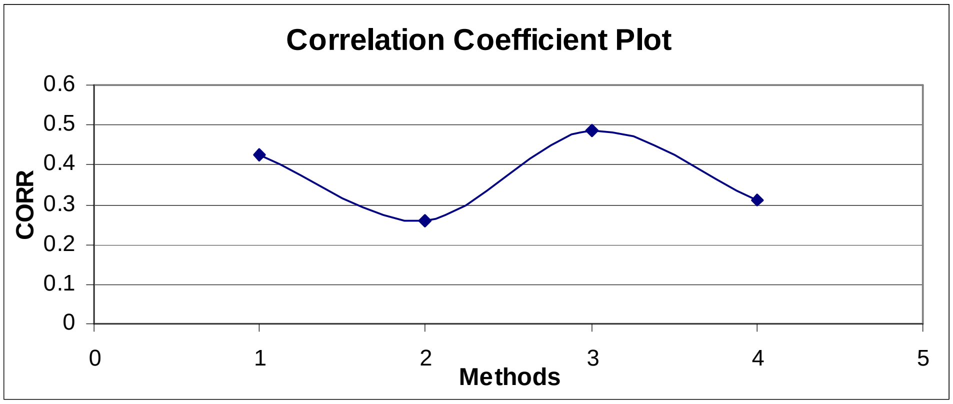

Figure 4.44 Plot of Methods versus Correlation Coefficient- Physio

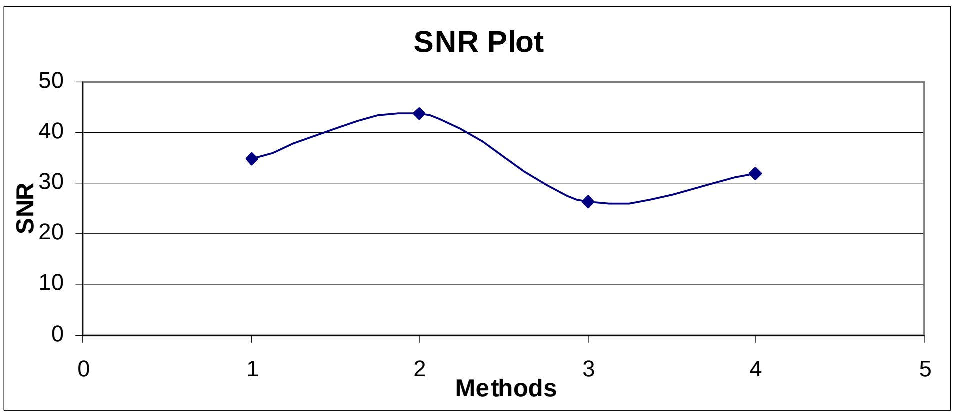

Figure 4.45 Plot of Methods versus SNR- Physio

The results of the performance parameters are as follows:

- The Sensitivity for all the methods is seen to vary between 0.6 to 0.8 with WAF method II having highest value.
- The positive predictive value is seen to be similar in method I, II and III. It falls to a lower value in method IV.
- The negative predictive value is seen to oscillate with methods II and IV having higher values. Method III has the lowest value.
- The specificity value gradually decreases from method I to method IV. This is due to large number of false positive detections.

- The Accuracy is oscillating with method II having highest accuracy and method III having lowest accuracy.
- The correlation coefficient is showing an oscillatory nature with method II having lowest value and method III having highest value.
- The SNR also shows the oscillating nature with method II having the highest value and method III having the lowest value.

From the above observations of the performance parameter indices, except in specificity method II performs better. Thus it is concluded that WAF method II is the efficient method for FECG extraction.

4.7 CHAPTER SUMMARY AND CONCLUSION

In this chapter, the four methods of FECG extraction using WAF are proposed. They are:

(i). WAF METHOD I - FECG extraction which uses wavelet denoising and non linear parameter Ψ=DS (0.02 *DS-1).

(ii) WAF METHOD II - FECG extraction which uses wavelet denoising and non linear parameter Ψ=DS (0.02*DS-1) along with refinement after FECG detector.

(iii) WAF METHOD III - FECG extraction which uses wavelet denoising and non linear parameter Ψ = DS (K-1).

(iv) WAF METHOD IV - FECG extraction which uses wavelet denoising and non linear parameter Ψ= DS (K-1) along with the modified thoracic signal.

The algorithms of the four methods have been tested with the same data sets from Sista and Physio. The performance of these methods is evaluated using the parameters sensitivity, specificity, positive predictive value, negative predictive value, accuracy, correlation coefficient and SNR. The evaluation and analysis show that WAF method I and WAF method II are performing well. However by comparing all the parameters, WAF method II is seen to be more efficient and produces a high quality of FECG signal. Even in these methods of extractions, it is seen that the position of the electrode plays a significant role in the quality of the signal. It is found that the electrode position 2, 7 yielded the best quality of FECG signal using WAF method II.

CHAPTER 5

FECG EXTRACTION USING COMBINATION OF WAVELET AND SOFT COMPUTING TECHNIQUES

5.1 INTRODUCTION

Over the last few decades, neural networks and fuzzy systems have established their reputation as an alternative approaches to signal processing. Both have certain advantages. However, their applicability has some weakness of the individual models. The advantage of neural networks is to recognize the patterns and adapt themselves to cope with changing environment. Fuzzy inference systems incorporate human knowledge and perform inferencing and decision making. Adaptive Neuro Fuzzy Inference system (ANFIS) takes the advantages of the combination of neural networks and fuzzy logic. This artificial intelligence technique called ANFIS is used to estimate the maternal ECG present in the abdominal signal of a pregnant woman. Then the FECG is extracted by subtracting the estimated MECG from the abdominal signal.

In this chapter, a new method of combining the hybrid soft computing technique called ANFIS along with wavelets is proposed to estimate the maternal electrocardiogram (MECG) and to extract the FECG signal from the mother's abdominal electrocardiogram (AECG). Three methods have been proposed namely (1) Method I- FECG extraction using ANFIS (2) Method II- FECG extraction using wavelet preprocessing and ANFIS (3) Method III- FECG extraction using ANFIS followed by wavelet post processing. The results obtained by three methods were analyzed in terms of signal to noise ratio, correlation coefficients and with performance indices. All the proposed methods were able to successfully remove the artifacts and extract the desired FECG signal. These algorithms were tested using data from Sista and Physio as mentioned in section 3.1.

5.1.1 ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

Adaptive neuro fuzzy inference system (ANFIS) was originally presented by Jang (Jang, 1993). It has an architecture and learning procedure for the Fuzzy Inference System (FIS) that uses a neural network learning algorithm for constructing a set of fuzzy if-then rules with appropriate membership functions (MFs) from the specified input–output pairs. This procedure of developing a FIS using the framework of adaptive neural networks is called an adaptive neuro fuzzy inference system. ANFIS has the advantages of easy implementation and learning ability by combining the neural networks with fuzzy inference system (Jang *et al.*, 1997). There are two methods that ANFIS learning employs for updating membership function parameters: (1) back propagation for all parameters (a steepest descent method), and (2) a hybrid method consisting of back propagation for the parameters associated with the input membership functions and least squares estimation for the parameters associated with the output membership functions. As a result, the training error decreases, at least locally, throughout the learning process. Therefore, the more the initial membership functions resemble the optimal ones, the easier it will be for the model parameter training to converge. Human expertise about the target system to be modeled may aid in setting up these initial membership function parameters in the FIS structure (Jang, 1993). The type of fuzzy model uses fuzzy inputs and rules but its outputs are non-fuzzy sets. (Takagi and Sugeno, 1985).

For simplicity, assume that the fuzzy inference system has two inputs x and y and one output z. A first-order Takagi and Sugeno fuzzy model has the following rules,

Rule1: If x is A1 and y is B1, then f1 = p1x + q1y + r1 (5.1)

Rule2: If x is A2 and y is B2, then f2 = p2x + q2y + r2 (5.2)

Here, ‘x is A1 and y is B1’ and ‘x is A2 and y is B2’ are called as the premise section (non linear section), while ‘f1 = p1x + q1y + r1’and ‘f2 = p2x + q2y + r2’ are called as the consequent section (linear section). i.e p1, p2, q1, q2, r1, r2 are linear parameters and A1, A2, B1, B2 are non linear parameter. The corresponding equivalent ANFIS architecture is shown in Figure 5.1(Jang, 1993).

5.1.2 ANFIS ARCHITECTURE

ANFIS is a multilayer feed forward network. The system architecture consists of five layers namely; fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer. The circular nodes represent the fixed nodes whereas the square nodes represent the nodes which have parameters to be learnt. The following section discusses in depth the relationship between the input and output of each layer in ANFIS.

Layer 1: It is the fuzzy layer .Every node i in this layer is an adaptive node with a node function. $O_{l,i}$ is the output of the ith node of the layer l .

$$O_{l,i} = \mu_{Ai}(x) \text{ for } i = 1, 2, \qquad \text{or}$$

$$O_{l,i} = \mu_{Bi-2}(y) \text{ for } i = 3, 4 \tag{5.3}$$

x (or y) is the input node i and Ai (or Bi−2) is a linguistic label associated with this node. Therefore $O_{1,i}$ is the membership grade of a fuzzy set (A1,A2,B1,B2).In this work, bell shaped membership functions(MF) are chosen .

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b}} \tag{5.4}$$

ai, bi, ci are the premise parameter set to be learnt.

Layer 2: It is the product layer that consists of two nodes labeled as Π. The output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{Ai}(x)*\mu_{Bi}(y) \quad i = 1, 2 \tag{5.5}$$

Each node represents the firing strength of the rule. w_1, w_2 are the weight functions of the next layer.

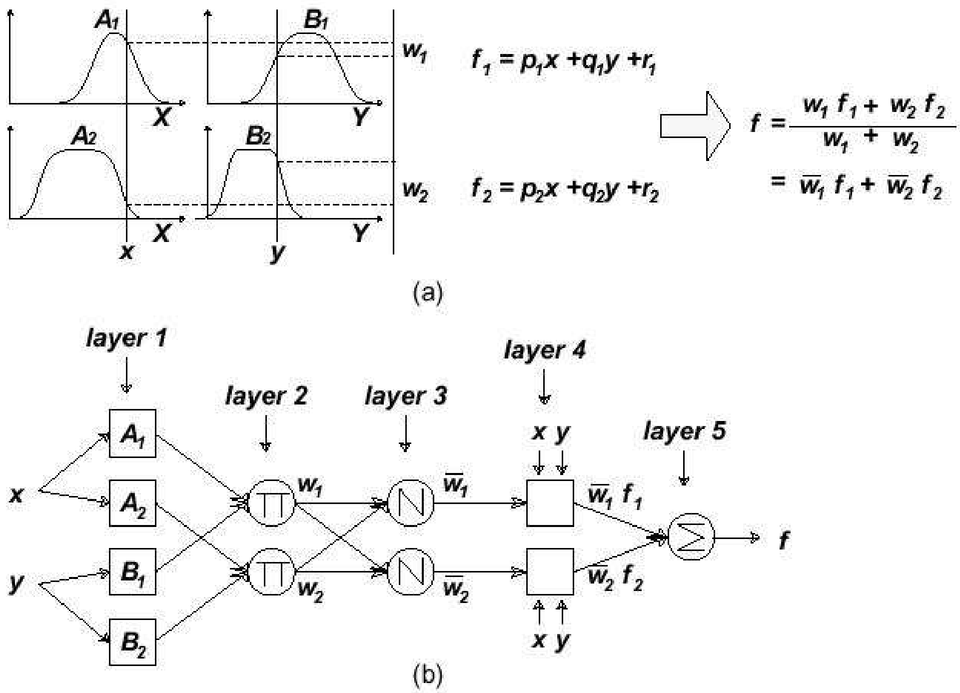

Figure 5.1 (a) First-order Sugeno fuzzy model (b) corresponding ANFIS architecture.

Layer 3: It is the normalized layer. Every node in this layer is a fixed node labeled as Norm. Its function is to normalize the weight function with the following condition, where $O_{3,i}$ denotes the Layer 3 output .

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \tag{5.6}$$

Outputs are called normalized firing strengths.

Layer 4: It is the defuzzy layer. Every node i in this layer is an adaptive node. The defuzzy relationship between the input and output of this layer is defined below, where $O_{4,i}$ denotes the layer 4 output .

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i \left(p_i x + q_i y + r_i \right) \tag{5.7}$$

$\overline{w}_i$ is the normalized firing strength from layer 3. p_i, q_i, r_i denote the linear parameters which are also called consequent parameters of the node.

Layer 5: It is the total output layer, whose node is labeled as sum, which computes the overall output as the summation of all incoming signals. The result can be written as follows where as $O_{5,i}$ denotes the layer 5 output .

$$Overalloutput = O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \text{i=1,2} \tag{5.8}$$

5.1.3 HYBRID LEARNING ALGORITHM

The ANFIS can be trained by a hybrid learning algorithm which combines the gradient descent method and least square method. Each epoch of hybrid learning consists of forward pass and backward pass. In the forward pass the algorithm uses least-squares method to identify the consequent parameters on the layer 4.In the backward pass the errors are propagated backward and the premise parameters are updated by gradient descent (Jang and Gulley, 1995).The total parameter set is divided in to three. They are;

S = set of total parameters

S1 = set of premise (non linear) parameters.

S2 = set of consequent (linear) parameters.

Table 5.1 shows the passes in the hybrid learning algorithm for ANFIS. In forward pass, S1 is unmodified and S2 is computed using a Least Squared Error (LSE) algorithm (Off-line Learning). i.e The forward pass propagates the input vector through the network layer by layer.

Table 5.1 Two passes in the hybrid learning algorithm for ANFIS

Parameters	Forward Pass	Backward Pass
S1 - Premise Parameters (a_i, b_i, c_i)	Fixed	Gradient Descent
S2- Consequent Parameters (p_i, q_i, r_i)	Least Squares estimator	Fixed
Signals	Node Outputs	Error signals

This process is repeated for all the training data entries and the error measurement is obtained. In backward pass, S2 is unmodified and S1 is computed using a gradient descent algorithm usually Back propagation. i.e the error is sent back through the network in a similar manner to back propagation and premise parameters are updated by gradient descent after the back pass. The mathematical analysis of the hybrid learning algorithm was discussed by Jang (Jang, 1993).The hybrid learning rules not only decrease the dimensions of the search space in the gradient method, but also accelerate convergence. In other words, it can speed up the training process, and it is more accurate and efficient than the conventional decent scheme.

5.1.4 MECG CANCELLATION USING ANFIS

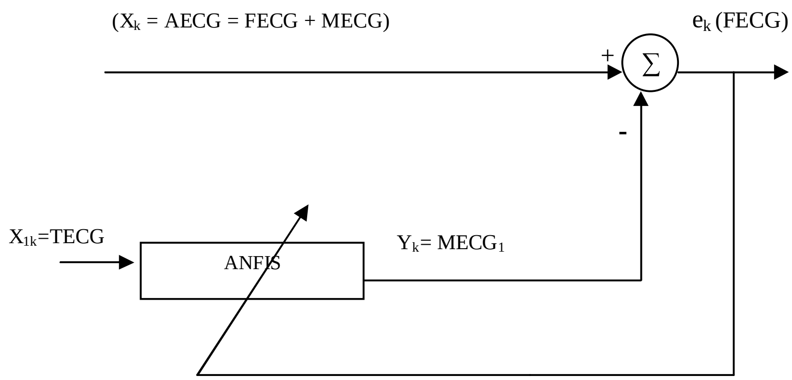

Figure 5.2 Adaptive Noise Cancellation using ANFIS

Figure 5.2 shows the block diagram of the maternal ECG cancellation using ANFIS.Here one input signal is the abdominal signal (X_k) which is the mixture of MECG and FECG. In this the noise (MECG) is uncorrelated with signal (FECG). The other input signal is thoracic signal (TECG) which is uncorrelated to FECG but correlated with MECG. The ANFIS output Y_k is $MECG_1$ which is the estimated thoracic signal by ANFIS. Since $MECG_1$ is generated from TECG it is correlated with MECG but uncorrelated with FECG. When MECG and $MECG_1$ are close to each other, these two get cancelled and we get the estimated output signal e_k which is the required signal FECG. The three different methods of extractions suggested in this chapter use the MECG cancellation technique.

5.2 METHOD I- FECG EXTRACTION USING ANFIS

Method I is the fetal ECG extraction technique using ANFIS. The block diagram of this method is shown in Figure 5.3.

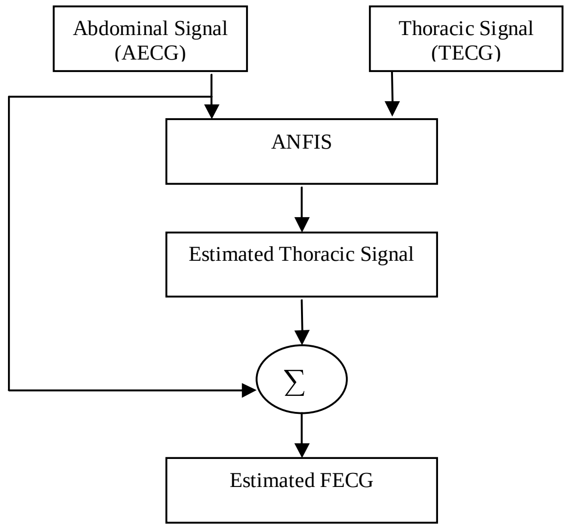

Figure 5.3 FECG extraction using ANFIS

The inputs to the ANFIS are (i) abdominal signal (MECG +FECG) acting as the reference signal (2) thoracic signal (TECG) acting as the desired signal. These two signals act as the training pair for ANFIS training. The ANFIS uses hybrid learning technique to calculate the linear, non linear parameters. Hybrid rule decreases the dimension of the search space in the gradient method and also cuts down the convergence time. Also the ANFIS is a multilayer network, gradient method learning rule is used to tune the parameters in the hidden layer. The parameters in the output layer can be identified by the least squares method. Once the designated epoch is reached or the goal is reached, it stops training and gives the estimated thoracic signal.

Now, the output of the ANFIS is the estimated thoracic signal present in the abdominal signal. The error between the estimated thoracic signal and the abdominal signal gives the FECG. Real data was used to illustrate the effectiveness of the proposed method in extracting FECG signals. The training and learning procedure is needed only one time. Thus the computational complexity can be reduced. The ANFIS converts the fuzzy inference engine in to an adaptive network that learns the relationship between the inputs and outputs.

5.2.1 FIS STRUCTURE

The basic structure of a Fuzzy Inference System (FIS) maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output. In a conventional fuzzy inference system, an expert who is familiar with the target system to be modeled determines the number of rules. In cases where there are no experts available, the number of membership functions assigned to each input is chosen empirically. Also, the fuzzy inference system is applied to modeling systems whose rule structure is essentially predetermined by the user's interpretation of the characteristics of the variables in the model. Selecting the membership function and an appropriate number of membership functions is essential for improving the convergence speed of the ANFIS algorithm.

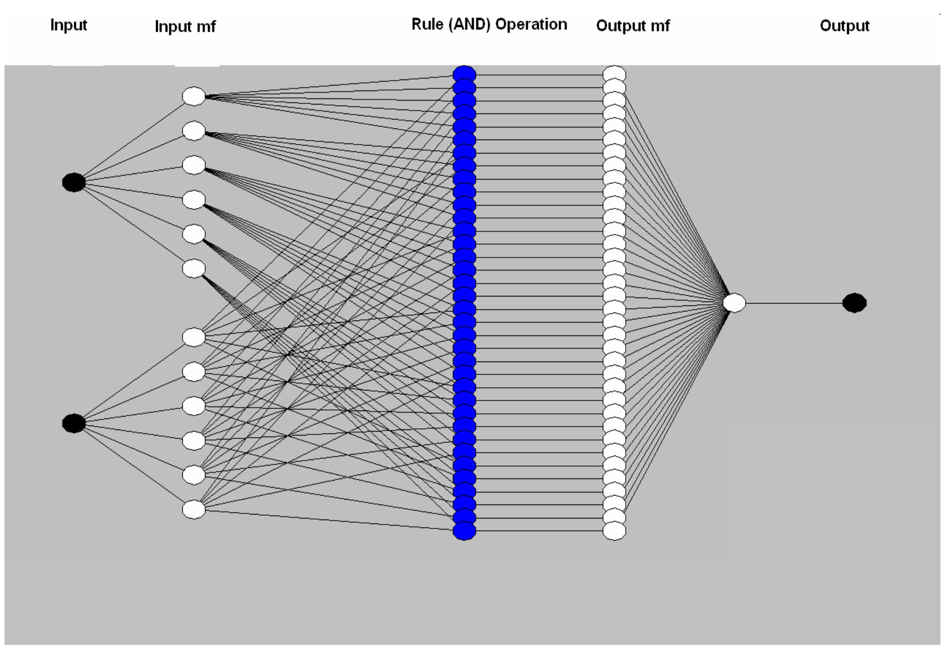

Figure 5.4 ANFIS structure

In this analysis, the generalized bell shape (gbellmf) is used for ANFIS training. The number of membership function for each input variable is determined by a trial and error process. Since the Sugeno type fuzzy model is used, the defuzzification is not required at the output. The structure of ANFIS used for extraction of FECG is shown in Figure 5.4.There are two inputs in the input layer. Fuzzification is done by layer1 (inputmf) which has 6 membership functions to each input. Totally 36 fuzzy rules are used in layer 2 (Rule). Layer 3 is the normalizing layer which is not included in this architecture. Layer 4 is the defuzzification layer (outmf). Layer 5 is the summation layer. Two inputs, 6 membership functions generating 36 fuzzy rules yielded 101 nodes, 108 consequent parameters and 36 premise parameters are used for training data pair of 601 samples.

5.2.2 METHOD I - FECG EXTRACTION USING ANFIS – RESULTS

The fetal ECG extraction was done using ANFIS as shown in Figure 5.3. The outputs of this method for different channels are shown from Figures 5.5 to 5.9 for Sista data. Figure 5.10 is the extracted output for Physio data. Figure 5.5 shows the abdominal ECG, estimated thoracic signal and the extracted fetal ECG using ANFIS method. The estimated thoracic ECG is closely following the maternal ECG which is present in the abdominal ECG signal. The estimated TECG is seen to resemble the maternal ECG present in the abdominal signal. The FECG is obtained as the error signal between the estimated TECG and the AECG. The extracted FECG shows the total absence of MECG.

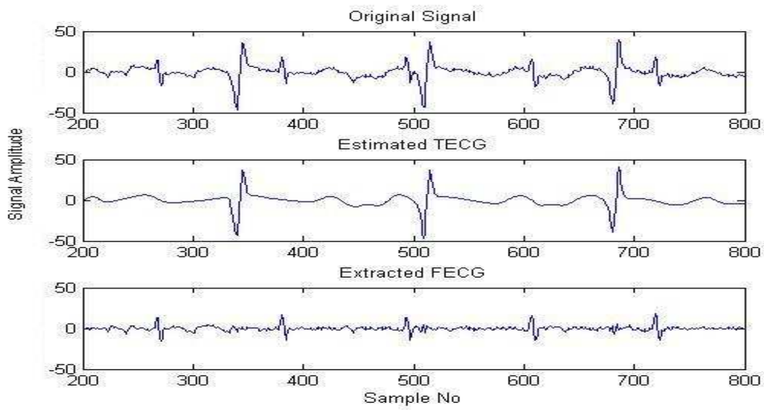

Figure 5.5 FECG extraction using ANFIS – Sista (2, 7)

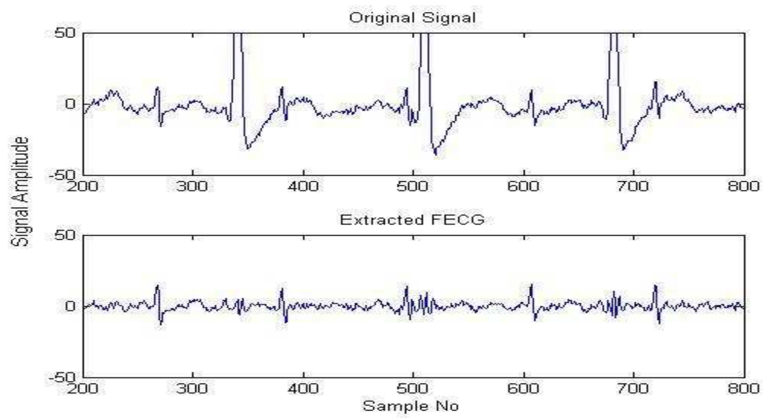

Figure 5.6 FECG extraction using ANFIS – Sista (3, 7)

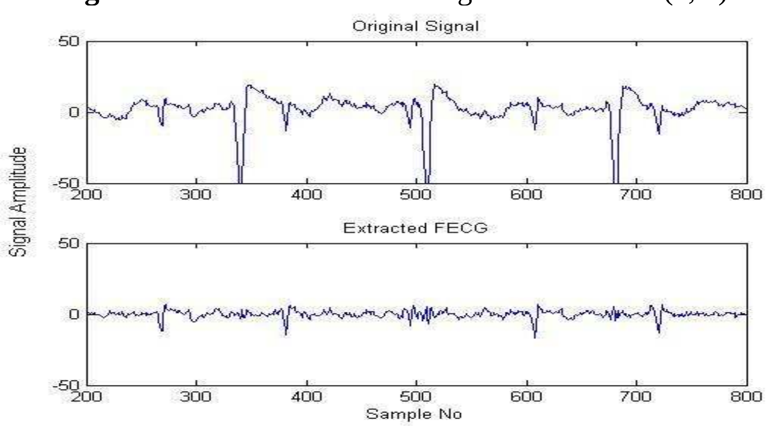

Figure 5.7 FECG extraction using ANFIS – Sista (4, 7)

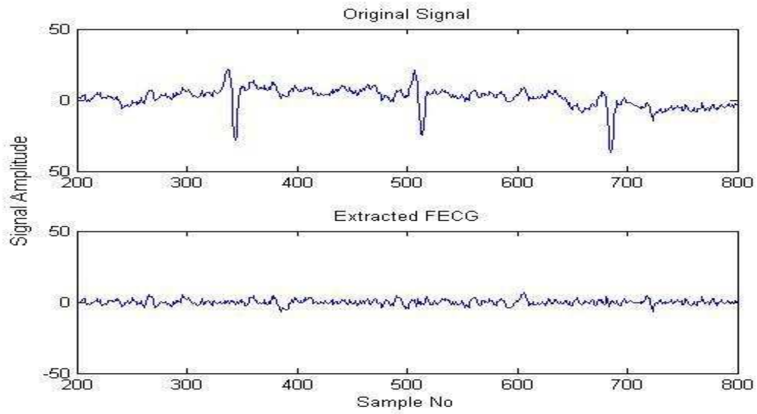

Figure 5.8 FECG extraction using ANFIS – Sista (5, 7)

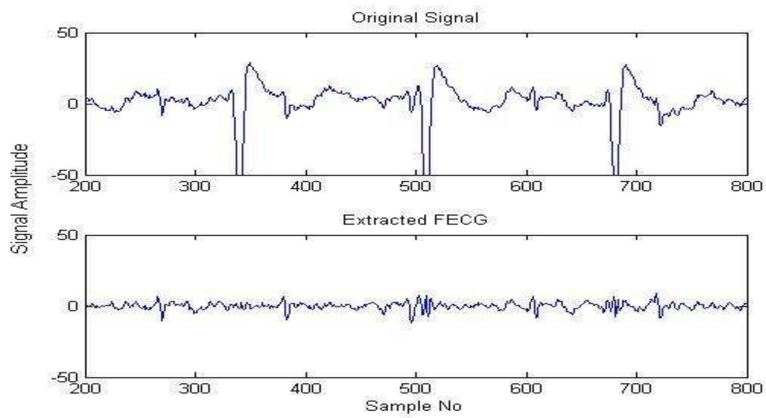

Figure 5.9 FECG extraction using ANFIS – Sista (6, 7)

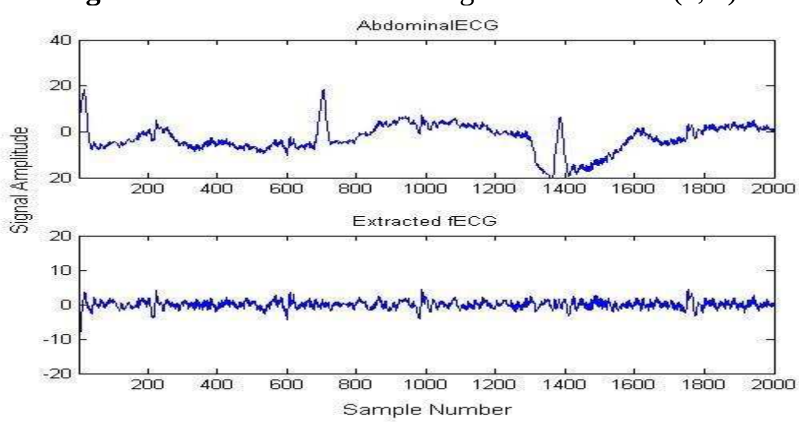

Figure 5.10 FECG extraction using ANFIS – Physio (4,2)

5.3 METHOD II- FECG EXTRACTION USING WAVELET AND ANFIS

In method II, the abdominal ECG is first wavelet preprocessed as shown in Figure 5.11.The wavelet preprocessing includes wavelet decomposition and reconstruction. The wavelet decomposition and reconstruction were performed by coiflets wavelet and only the approximation coefficients are retained as a signal carrying the useful information. The number of levels of decomposition was chosen as 5.

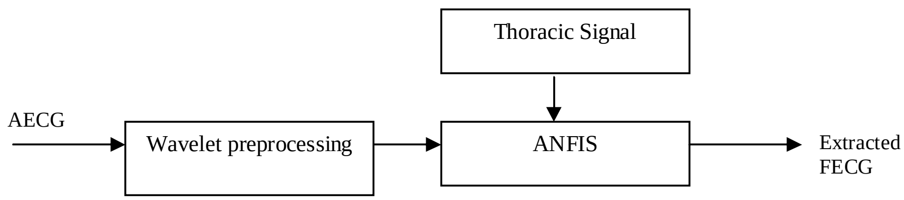

Figure 5.11 FECG extraction using Wavelet and ANFIS

The property of coiflets wavelet is good for this application because it reduces the noise and provides high resolution output. Also the chosen wavelet has a shape similar to FECG. The approximation coefficient is taken as a noise free abdominal signal which is one of the inputs to ANFIS and the other input is the thoracic signal. The output of ANFIS is the extracted fetal ECG.

5.3.1 METHOD II- FECG EXTRACTION USING WAVELET AND ANFIS – RESULTS

The abdominal ECG is decomposed in to 5 levels using wavelet transforms. The denoised AECG is chosen as the input to the ANFIS as shown in Figure 5.11. The outputs of this method for different channels are shown from Figures 5.12 to 5.16 for Sista data and Figure 5.17 is for Physio data. The FECG is obtained as the error signal between the estimated TECG and the wavelet denoised abdominal AECG. The results show that the extracted FECG along with noisy signal present in the positions of MECG.

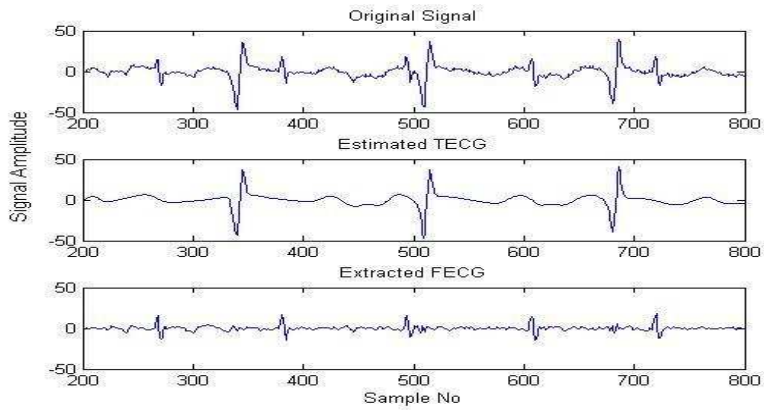

Figure 5.12 FECG extraction using Wavelet and ANFIS – Sista (2, 7)

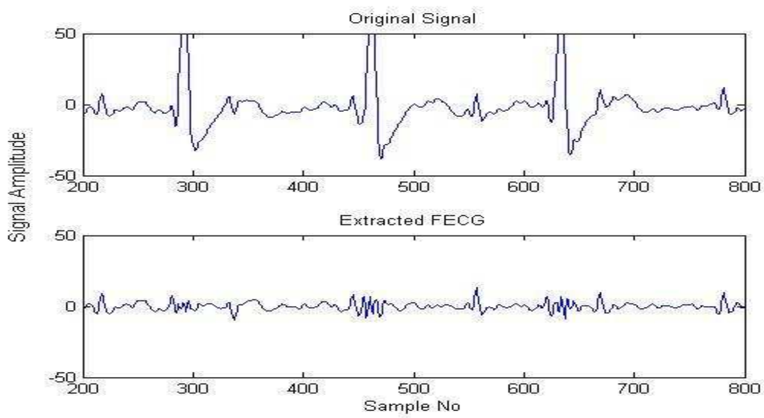

Figure 5.13 FECG extraction using Wavelet and ANFIS – Sista (3, 7)

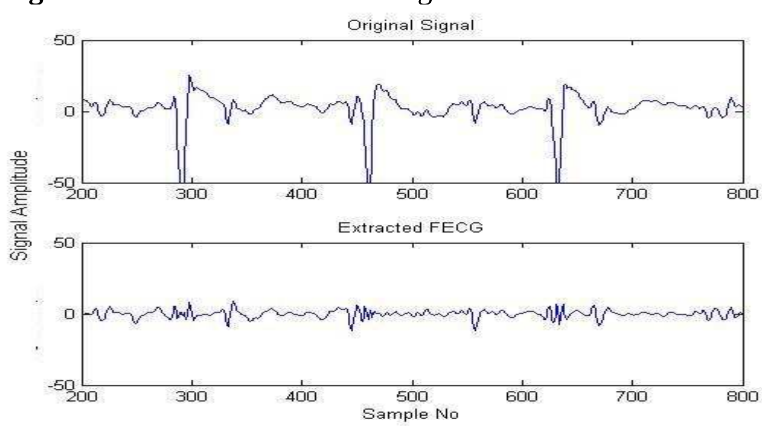

Figure 5.14 FECG extraction using Wavelet and ANFIS – Sista (4, 7)

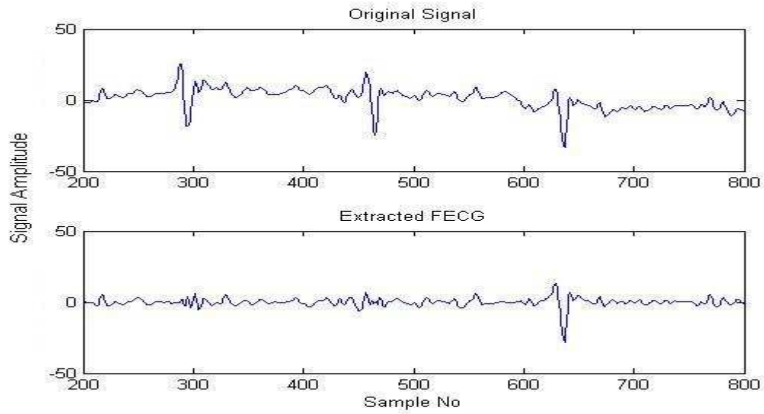

Figure 5.15 FECG extraction using Wavelet and ANFIS – Sista (5, 7)

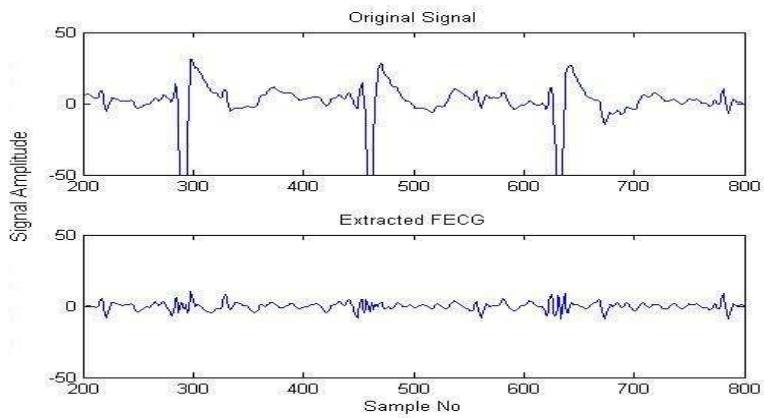

Figure 5.16 FECG extraction using Wavelet and ANFIS – Sista (6, 7)

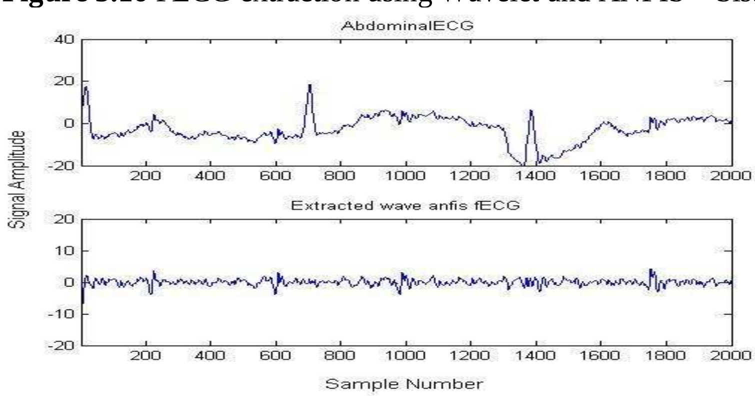

Figure 5.17 FECG extraction using Wavelet and ANFIS – Physio (4,2)

5.4 METHOD III - FECG EXTRACTION USING ANFIS AND WAVELET

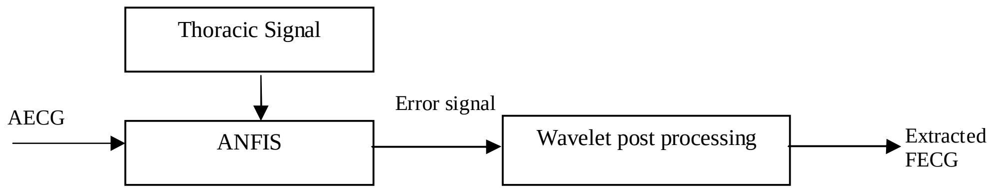

Figure 5.18 FECG extraction using ANFIS and Wavelet

In this method, the inputs to the ANFIS are the abdominal signal and the thoracic signal. The error signal is the FECG signal. And it is decomposed to 5 levels using coiflet wavelet as shown in Figure 5.18.The approximation coefficient is taken as a noise free FECG signal which is the output from the wavelet post processing block. The extracted FECG of this method for different channels are shown in section 5.4.1

5.4.1 METHOD III- FECG EXTRACTION USING ANFIS AND WAVELET – RESULTS

The fetal ECG extraction was done using ANFIS with wavelet post processing as shown in Figure 5.18. The outputs of this method for different channels are shown from Figures 5.19 to 5.23 for Sista data and Figure 5.24 is for Physio data. The FECG is obtained as the error signal between the estimated TECG and the AECG. This signal is further processed by wavelets. The extracted FECG is decomposed in to 5 levels. The results clearly show that the extracted FECG is noise free.

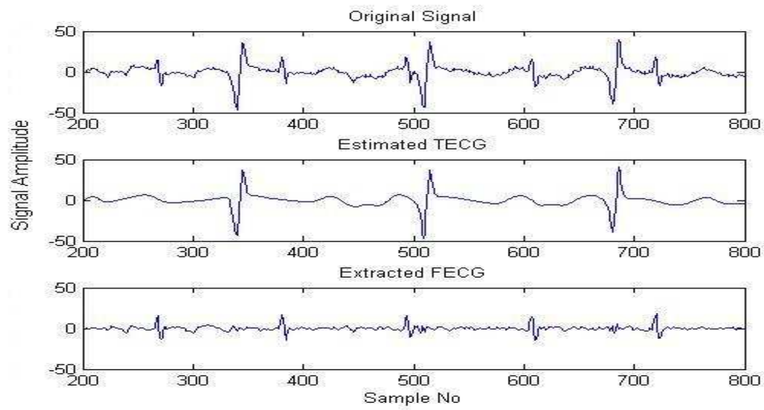

Figure 5.19 FECG extraction using ANFIS and Wavelet – Sista (2, 7)

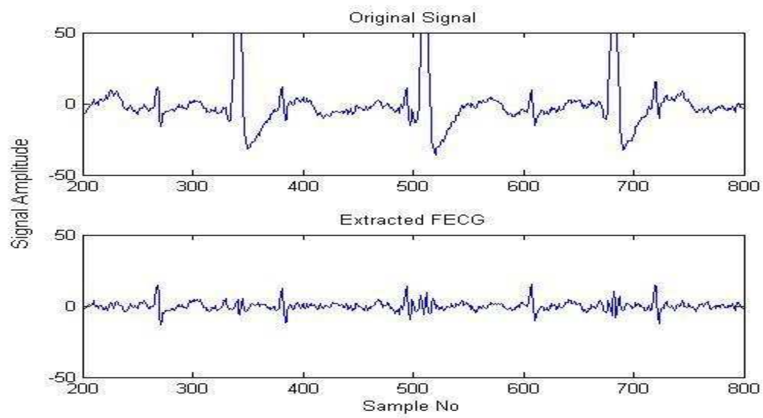

Figure 5.20 FECG extraction using ANFIS and Wavelet– Sista (3, 7)

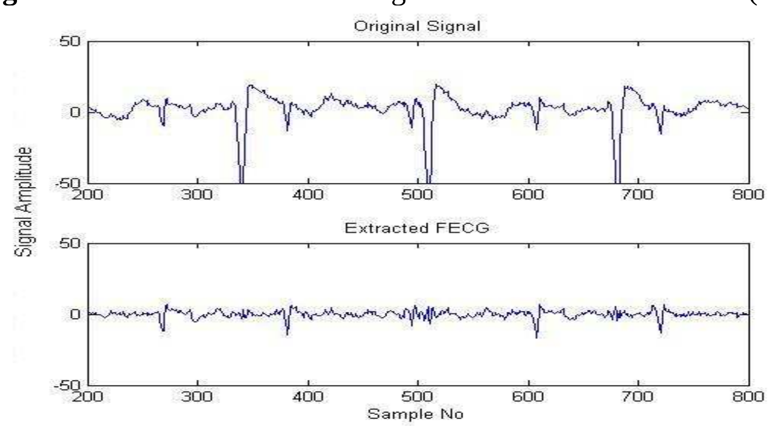

Figure 5.21 FECG extraction using ANFIS and Wavelet – Sista (4, 7)

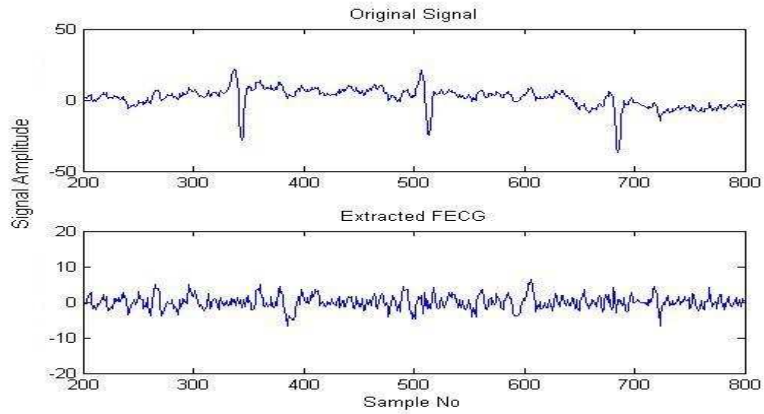

Figure 5.22 FECG extraction using ANFIS and Wavelet– Sista (5, 7)

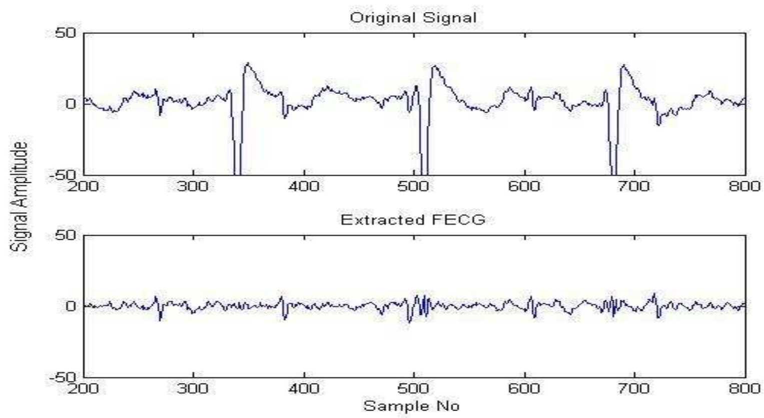

Figure 5.23 FECG extraction using ANFIS and Wavelet – Sista (6, 7)

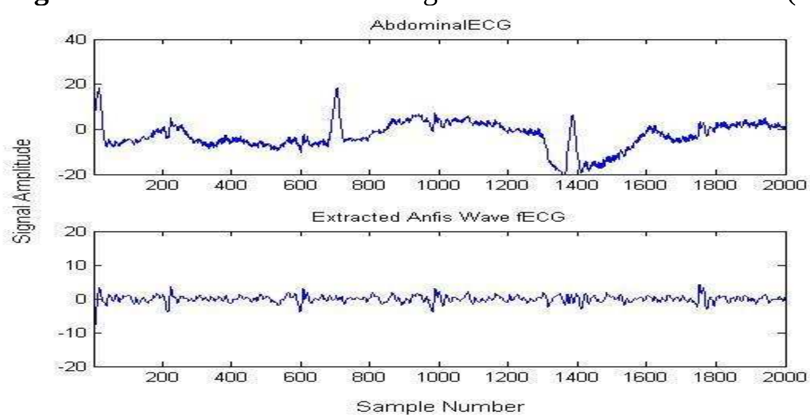

Figure 5.24 FECG extraction using ANFIS and Wavelet – Physio (4,2)

5.5 EVALUATION AND ANALYSIS OF THE PROPOSED METHODS

The extraction of FECG was done using the following methods.

(1) Method I- FECG extraction using ANFIS

(2) Method II- FECG extraction using wavelet preprocessing and ANFIS

(3) Method III- FECG extraction using ANFIS followed by wavelet post processing.

The methods have been tested with the same data. The performance evaluation has been done by the following parameters. Sensitivity (SEN), Specificity (SPE),Positive Predictive Value (PPV),Negative Predictive Value (NPV),Accuracy (ACC),Correlation Coefficient (CORR) and Signal to Noise ratio (SNR) as mentioned in section 3.6.

5.5.1 EVALUATION OF METHOD I-FECG EXTRACTION USING ANFIS

Table 5.2 Performance of method I- FECG extraction using ANFIS (Sista Data)

Electrode position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	1	1	1	1	1	0.3888	28.6781
3,7	0.78	0.75	0.78	0.75	0.77	0.1922	26.4579
4,7	0.8	0.8	0.8	0.8	0.8	0.2508	25.5271
5,7	0.67	0.7	0.73	0.64	0.68	0.2882	19.9250
6,7	0.73	0.73	0.73	0.73	0.73	0.1846	23.4564

The performance of ANFIS method I tested with data from Sista is shown in Table 5.2. The performance parameter SEN, SPE, PPV, NPV and ACC from electrode position 2, 7 and 4, 7 are seen to have a good performance compared to other electrode positions. The performance in electrode position 5, 7 is lower to other electrode positions due to less magnitude of the extracted fetal ECG. In electrode position 6, 7 the dominance of maternal ECG is very large compared to fetal ECG which leads to lower value of the performance parameter but better than electrode position 5, 7. However in terms of SNR the entire electrode positions except 5, 7 have larger value. The correlation coefficient in all the electrode positions has significant values suggesting a good presence of fetal ECG and absence of maternal ECG. In electrode position 5, 7 the sensitivity, NPV and accuracy is showing a slightly lower value due to the insignificant presence of fetal ECG in the abdominal signal. To conclude, the record from electrode position of 2, 7 have got the best performance indices.

5.5.2 EVALUATION OF METHOD II – FECG EXTRACTION USING WAVELET AND ANFIS

The performance of wavelet and ANFIS tested with data from Sista is shown in Table 5.3. In electrode position 2,7 ; 4,7 and 5,7 have better performance compared to 3,7 and 6,7. The electrode positions 2, 7 have the same performance in method I and method II. However, the electrode position 3, 7 and 6, 7 is inferior to method I. In method I and method II, for electrode position 4, 7 have the similar performance.

Table 5.3 Performance of method II – FECG extraction using wavelet and ANFIS (Sista Data)

Electrode position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	1	1	1	1	1	0.3132	39.3100
3,7	0.67	0.67	0.67	0.67	0.67	0.1589	38.2865
4,7	0.75	0.8	0.75	0.8	0.78	0.2258	38.8842
5,7	0.72	0.8	0.83	0.67	0.75	0.4168	55.1830
6,7	0.67	0.64	0.73	0.64	0.69	0.1733	34.1679

Electrode position 5, 7 is better in method II. The correlation coefficient for all electrode positions except 5, 7 have slightly decreased value in method II compared to method I. The decrease in correlation factor is due to the increased presence of fetal ECG. The SNR is increased in all the electrode positions indicating that method II can suppress noise in the extracted FECG than method I.

5.5.3 EVALUATION OF METHOD III – FECG EXTRACTION USING ANFIS AND WAVELET

In electrode position 2,7 all the performance parameters are good and same as method I and method II. In all other electrode positions, the performance parameters are similar to method I and method III. Method III seems to be superior to method II in all the cases.

Table 5.4 Performance of method III –FECG extraction using ANFIS and Wavelet (Sista Data)

Electrode position	SEN	SPE	PPV	NPV	ACC	CORR	SNR
2,7	1	1	1	1	1	0.3816	120.404
3,7	0.75	0.72	0.75	0.72	0.74	0.1875	124.005
4,7	1	0.8	0.75	1	0.88	0.2466	121.402
5,7	0.67	0.75	0.8	0.6	0.7	0.2761	115.622
6,7	0.7	0.7	0.7	0.7	0.7	0.1853	114.347

The performance of ANFIS followed by wavelet post processing method tested with data from Sista is shown in Table 5.4. The correlation coefficients in all the electrode positions are slightly higher than method II and lower than method I. This indicates the good quality of the extracted FECG. In terms of SNR, this method shows a drastic increase compared to method I and method II. This is because of the ability of the algorithm to filter out the noise components after the soft computing stage. In over all comparison, the electrode position of 2, 7 yields the best results compared to other electrode positions in all the methods. This shows that the position 2, 7 is the optimum position for recording abdominal ECG. To conclude, method III - ANFIS and wavelet post processing method is capable of extracting fetal ECG in whatever may be the electrode position.

5.5.4 EVALUATION OF DIFFERENT METHODS FOR PHYSIO DATA

The performance of method I- ANFIS extraction method, method II- wavelet and ANFIS extraction method, method III- ANFIS and wavelet extraction method were tested with data from Physio and the results are shown in Table 5.5. By comparing the performance parameters and correlation coefficient method II and method III are having similar values. This is due to minimum number of false positive and false negative detections. Method II and method III are performing better than method I. In terms of SNR there is gradual increase of the value from method I to method III. Hence to conclude for physio data, ANFIS and wavelet post processing method is the best method for fetal ECG extraction.

Table 5.5 Performance of different methods (Physio data)

Method	SEN	SPE	PPV	NPV	ACC	CORR	SNR
Method I ANFIS	1	0.64	0.67	1	0.79	0.2706	15.2725
Method II Wavelet and ANFIS extraction method	1	0.8	0.84	1	0.9	0.1935	36.8038
Method III ANFIS and wavelet extraction method	1	0.8	0.84	1	0.9	0.1962	43.6143

5.5.5 ANALYSIS OF PROPOSED METHODS

The analysis of FECG extraction for performance parameter SEN, SPE, PPV, NPV, ACC, Correlation and SNR for (1) ANFIS –method I (2) wavelet preprocessing followed by ANFIS - method II (3) ANFIS followed by wavelet post processing - method III are shown in section 5.5.5.1 for Sista data and 5.5.5.2 for Physio data.

5.5.5.1 ANALYSIS OF ANFIS METHODS – SISTA DATA

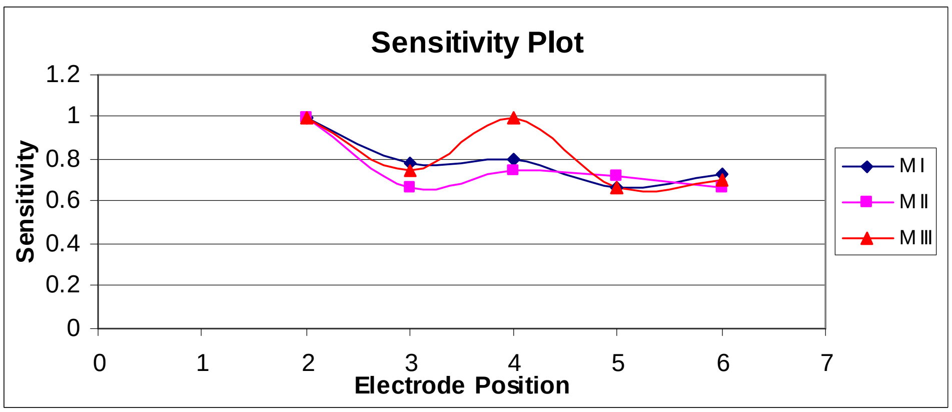

Figure 5.25 Plot of Electrode Position versus Sensitivity- Sista

Figure 5.25 shows the sensitivity plot for ANFIS methods with different electrode positions. The sensitivity of electrode position for 3, 7 in method I is high because of the minimum false negatives detection compared to method II and method III. For 6, 7 electrode position, all the methods have the similar value. In electrode position 4, 7 method III shows the highest sensitivity because of no false detections. And in all the other electrode positions, method III is having similar performance as method II. Hence to conclude method II and method III have similar performance with respect to sensitivity.

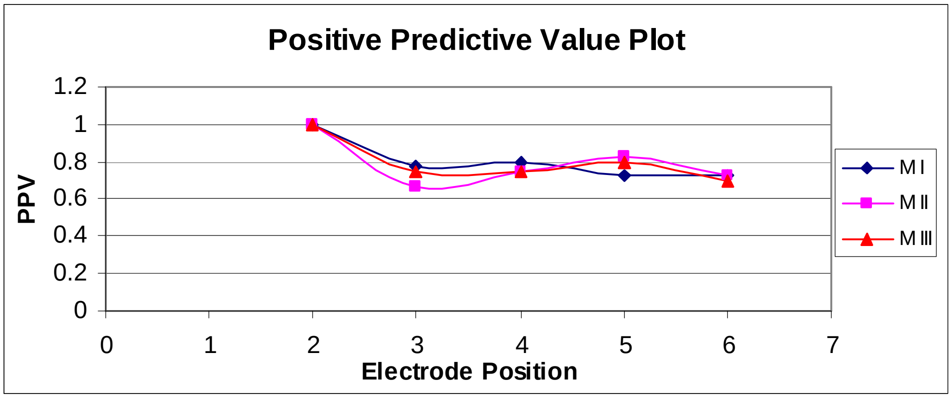

Figure 5.26 Plot of Electrode Position versus Positive Predictive Value-Sista

Figure 5.26 shows the positive predictive plot for ANFIS methods with different electrode positions. The PPV value is same and high for all electrode positions except 3, 7 in method II and method III. This is due to less detection of false positive peaks. In electrode position 3, 7, method II has smaller value of PPV. This is due to the presence of maternal ECG in the extracted signal and its magnitude is comparable to that of fetal ECG magnitude. In electrode position 3, 7 the PPV value in method III is slightly higher than method II because the magnitude of the fetal ECG in the extracted signal is much higher.

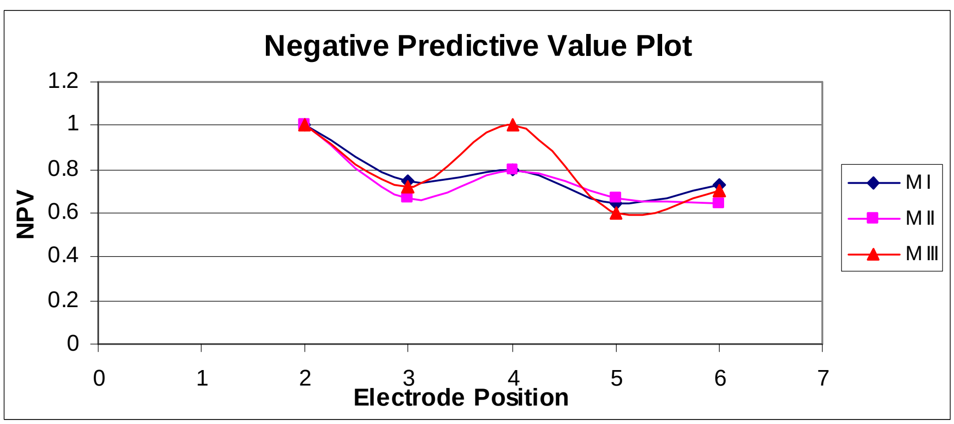

Figure 5.27 Plot of Electrode Position versus Negative Predictive Value - Sista

Figure 5.27 shows the negative predictive plot for ANFIS methods with different electrode positions. It is seen from the plot that all the methods are performing equally well in all electrode positions except in 4, 7. In the case of electrode position 4, 7 the method III was showing a better performance because of the excellent quality of the extracted signal which is due to minimum number of false negative detections.

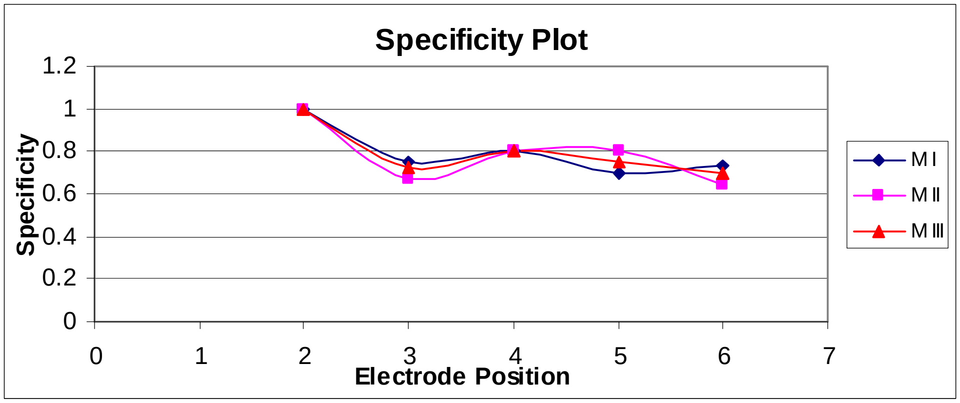

Figure 5.28 Plot of Electrode Position versus Specificity- Sista

Figure 5.28 shows the specificity plot for ANFIS methods with different electrode positions. The specificity value is similar for all the methods in electrode positions 2, 7 and 4, 7. Electrode position 3, 7 and 6, 7 have similar behavior. In electrode position 5, 7, method II shows a higher value compared to other methods. The trend is similar in all the methods.

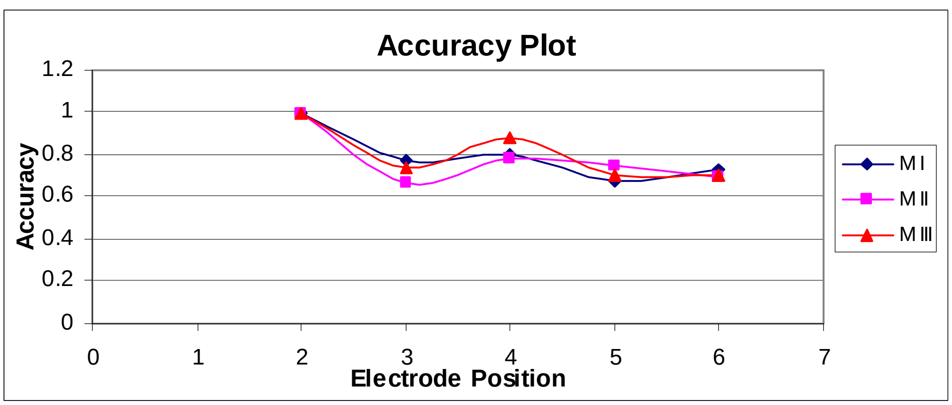

Figure 5.29 Plot of Electrode Position versus Accuracy –Sista

Figure 5.29 shows the accuracy plot for ANFIS methods with different positions. It is seen from the plot that in electrode positions 2, 7 has the highest accuracy value in all the methods because of the good quality of the signal and also there are no false detections. In electrode position 2,7 and 6, 7 all the methods have similar behavior. In 4, 7, method III has got the highest value. In electrode position 3, 7 and 5, 7 the method III maintains the same trend where as the other methods are changing the values. Considering the average performance in 3, 7 and 5, 7 and good performance in the other positions it is concluded that the accuracy is higher in method III.

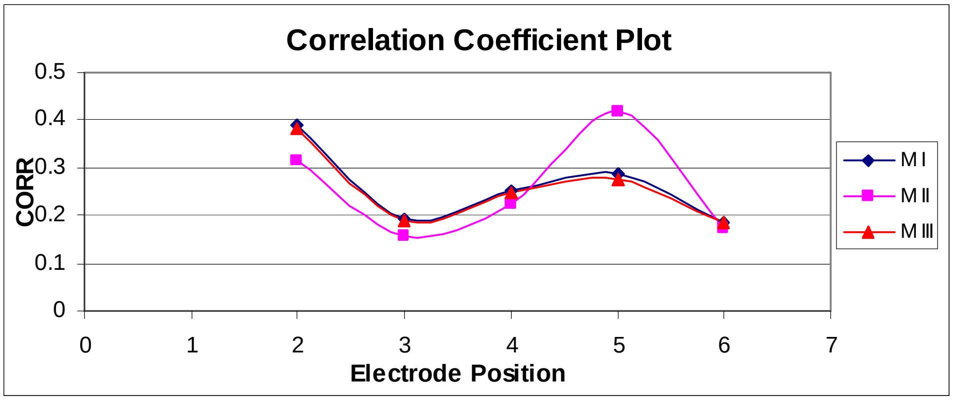

Figure 5.30 Plot of Electrode Position versus Correlation Coefficient-Sista

Figure 5.30 shows the correlation coefficient plot for ANFIS methods with different electrode positions. All the methods satisfy the criteria for good extraction based on the values of correlation coefficient. This means all the ANFIS methods are capable of extracting fetal ECG with either no or very minimal presence of maternal ECG. It is seen from the plot that the correlation coefficient shows method I and method III have the similar behavior in all the electrode positions. The method II has an alternating behavior having small and large values of correlation. To conclude with respect to correlation coefficient the method I and method III have the desired performance characteristics.

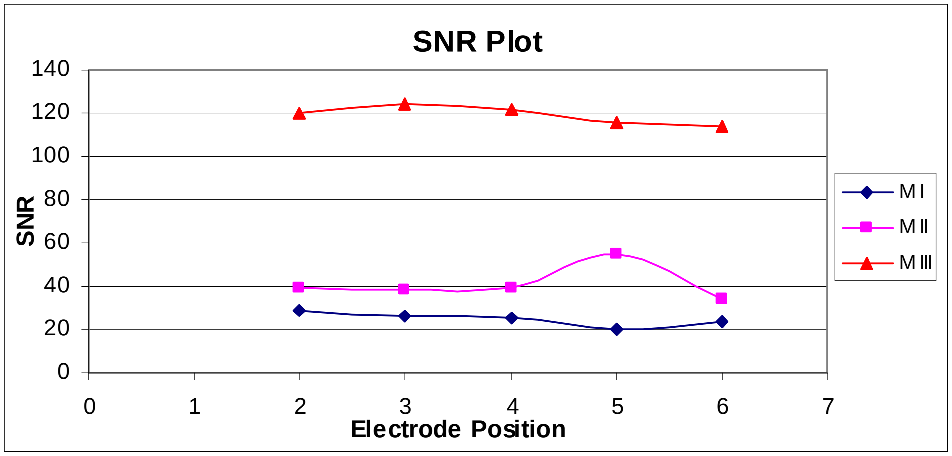

Figure 5.31 Plot of Electrode Position versus SNR- Sista

Figure 5.31 shows the SNR plot for ANFIS methods with different electrode positions. The SNR is calculated for the extracted fetal ECG. It is very clearly seen from the plot that the method I has the lower value and method III has the higher value. In method III the SNR is high due to, the extracted fetal ECG is further denoised using wavelets.

By comparing the performance indices for all the electrode positions, it is observed that the method II and method III have an improved and similar behavior compared to method I. However, by comparing the correlation coefficient and SNR, it is concluded that the method III is performing better in extracting fetal ECG than the other two methods.

5.5.5.2 ANALYSIS OF ANFIS METHODS – PHYSIO DATA

The analysis of FECG extraction for all the ANFIS methods for Physio data are discussed in this section. The performance parameters are plotted for different methods and shown in Figures 5.32 to 5.38.

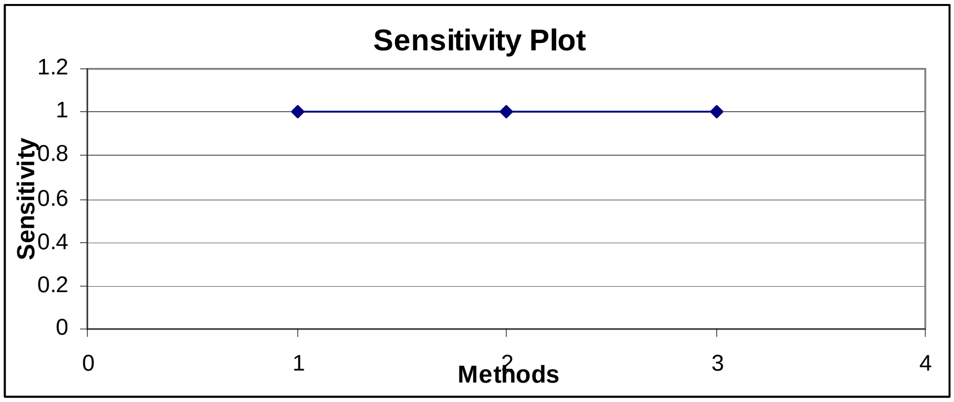

Figure 5.32 Plot of Methods versus Sensitivity-Physio

Figure 5.32 shows the sensitivity plot for different methods for physio data. All the three methods show highest sensitivity. This is due complete extraction of fetal ECG from abdominal signal and no false detections made by the methods. Thus, in terms of sensitivity all the methods are performing equally well.

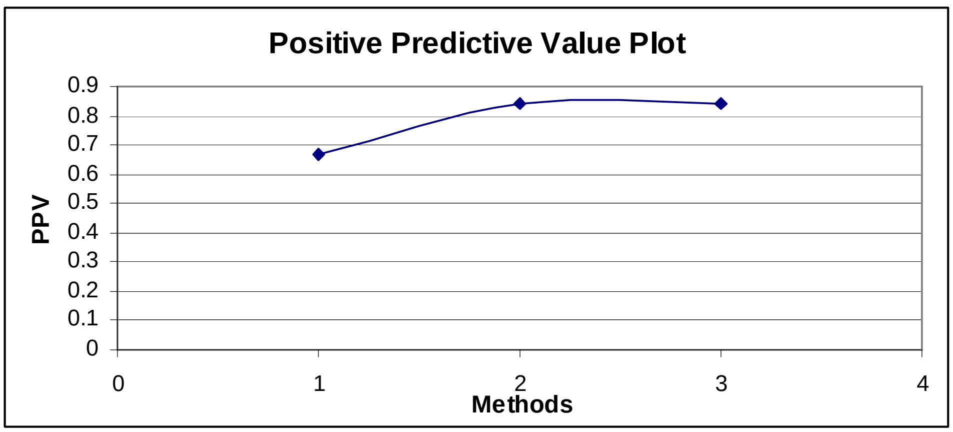

Figure 5.33 Plot of Methods versus Positive Predictive Value-Physio

Figure 5.33 shows the positive predictive plot for different methods for physio data. The plot shows the gradual increases in PPV value from method I to method II. However, the method II and method III have the same value. This is due to less false positive detections. Hence in terms of PPV, method II and method III have similar capabilities of extraction for Physio data.

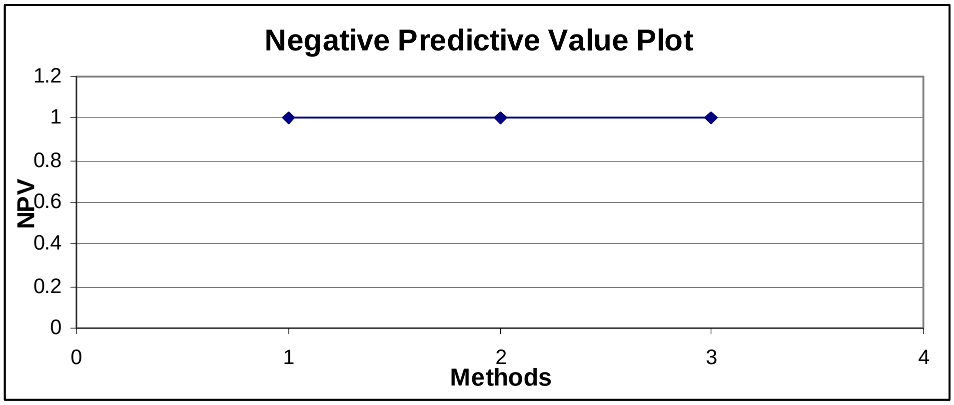

Figure 5.34 Plot of Methods versus Negative Predictive Value- Physio

Figure 5.34 shows the negative predictive plot for different methods for physio data. All the three methods show highest NPV value. This is due complete extraction of fetal ECG from abdominal signal and no false negative detections made by the methods. Thus, in terms of NPV all the methods are performing equally well.

Figure 5.35 Plot of Methods versus Specificity – Physio

Figure 5.35 shows the specificity plot for different methods for physio data. The plot shows the gradual increases in specificity value from method I to method II. However, the method II and method III have the same value. This is due to less false positive detections. Hence in terms of specificity, method II and method III have similar capabilities of extraction for physio data.

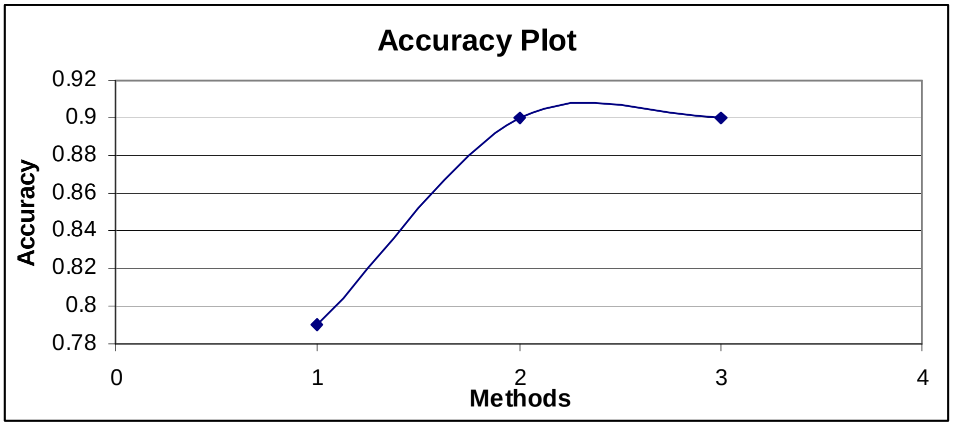

Figure 5.36 Plot of Methods versus Accuracy – Physio

Figure 5.36 shows the accuracy plot for different methods for physio data. It is seen from the plot that the accuracy increases from method I to method II. Method II and method III are having the same value. This plot indicates that method II and method III are able to fully extract the fetal ECG with no or minimal false positive and false negative detections.

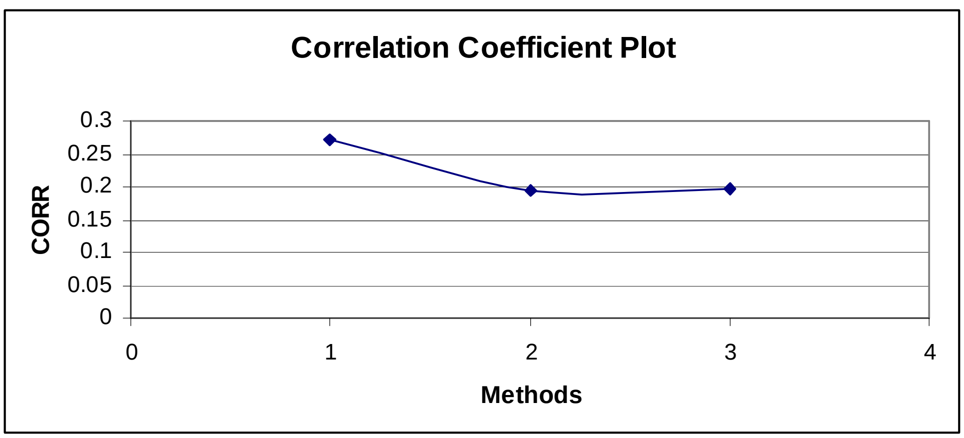

Figure 5.37 Plot of Methods versus Correlation Coefficient-Physio

Figure 5.37 shows the correlation coefficient plot for different methods for physio data. The correlation is seen to decrease from method I to method III. This indicates complete fetal ECG extraction from the abdominal signal with no presence of maternal ECG. Hence it is concluded that the method II and method III have similar extraction capabilities.

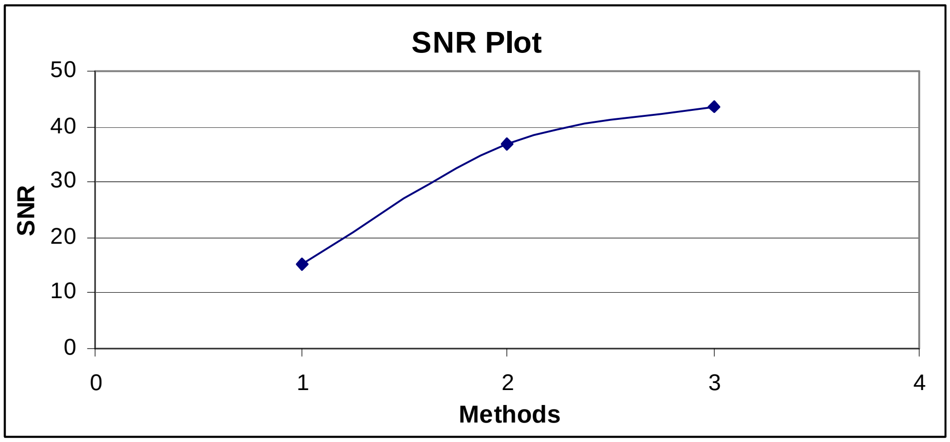

Figure 5.38 Plot of Methods versus SNR- Physio

Figure 5.38 shows the SNR plot for different methods for physio data. The plot shows the gradual increase of SNR from method I to method III. From this it is concluded that the method III is able to extract the fetal ECG with minimum noise. Hence by comparing the performance indices, correlation coefficient and SNR it is concluded that the method III- ANFIS followed by wavelet post processing was yielding a good extraction.

5.6 CHAPTER SUMMARY AND CONCLUSION

In this chapter three methods were suggested by combining the soft computing technique with wavelets. They are:

(1) Method I- FECG extraction using ANFIS

(2) Method II- FECG extraction using wavelet preprocessing and ANFIS

(3) Method III- FECG extraction using ANFIS followed by wavelet post processing.

The algorithms of the three methods have been tested with the same data sets from Sista and Physio. The advantages of these methods are it requires only one abdominal signal and one thoracic signal for FECG extraction. This is done by applying ANFIS to identify the non linear relationship between the maternal component in the abdominal ECG and the thoracic ECG which is assumed to have no fetal component in it. The FECG can be extracted by subtracting the MECG signal from the abdominal signal. The mathematical analysis is very less because of the qualitative aspects of the artificial intelligence. The performance of these methods is evaluated using the parameters sensitivity, specificity, positive predictive value, negative predictive value, accuracy, correlation coefficient and SNR. The case of overlapping of FECG with MECG is seen at sample 500 in electrode position 2,7 for Sista data. The proposed methods are able to extract FECG present in the abdominal signal even if the fetal signal is overlapped with maternal signal. Thus the extracted FECG is the actual FECG present in the abdominal signal. The visual quality of the extracted signal is seen to be better in wavelet post processed extraction. The electrode positions 2, 7; 3, 7; 4, 7; and 6, 7 the wavelet post processed technique shows considerable improvement in performance indices for Sista data. However in electrode position 5, 7 the performance indices show a marked decrease in values. This may be due to insignificant presence of FECG in the abdominal signal.

The evaluation and analysis show that the performance indices and the correlation coefficient are very similar in method II and method III for both the data sets. In terms of SNR method III out performs method II in both the data sets. This may be due to the loss of quality of the extracted FECG in method II and may be the result of losing some FECG information from the composite signal. Hence it is concluded that method III- ANFIS followed by wavelet post processing is the best method for fetal ECG extraction from the abdominal signal. The visual quality indicates that the extracted FECG is of superior quality compared to other methods.

CHAPTER 6

SOFT COMPUTING EXTRACTION TECHNIQUES DURING EARLY STAGES OF PREGNANCY AND LABOR

6.1 INTRODUCTION

In the previous chapters (3, 4 & 5), several methods were proposed to extract fetal ECG from the composite abdominal signal. They are; FECG Extraction method, Improved FECG Extraction Method ,Novel Method of FECG Extraction ,WAF Method I,WAF Method II,WAF Method III,WAF Method IV,ANFIS method of extraction, wavelet preprocessing followed by ANFIS and ANFIS followed by wavelet post processing. All the above methods were tested with the same set of data from Sista daisy and Physio. Out of these methods, soft computing techniques were yielding better performance and extraction. To confirm the extraction capabilities, these ANFIS techniques were further tested with the data during the pregnancy period from 22nd to 40th week, and data during labor before and after oxytocin administration. The extraction of FECG was done using the following methods in this chapter. They are; (1) Method I-FECG extraction using ANFIS (2) Method II- FECG extraction using wavelet preprocessing and ANFIS (3) Method III-FECG extraction using ANFIS followed by wavelet post processing. The algorithms were discussed in detail in Chapter 5.The testing and evaluation of the algorithms was done using data sets from 6 patients. They are

- CASE I: data set from gestation age 22nd to 40th week with sampling frequency of 1KHz.
- CASE II: Normal pregnancy data set with the sampling frequency of 250Hz.

- CASE III: 40^{th} week data set for normal pregnancy with sampling frequency of 1 KHz.
- CASE IV: 37^{th} week data set from a sport woman having no risk of pregnancy and sampling frequency is 250Hz.
- CASE V: Data set during labor with no oxytocin administration and sampling frequency of 400Hz.
- CASE VI: Data set during labor, after oxytocin administration with sampling frequency of 400 Hz.

6.2 RESULTS OF CASE I

Case I is data set from gestation age 22^{nd} to 40^{th} week with sampling frequency of 1KHz. The table 6.1 presents the number of recorded signals for each week of gestation age. The testing of algorithms was done for all the recorded signals. The analysis and evaluation were presented for one recorded signal for each week of gestation.

Table 6.1 Gestation weeks and number of recorded signals – Case I

Weeks of gestation	Number of recorded signals
22	8
23	7
24	4
25	2
27	1
29	2
30	3
31	3
32	3
33	4
34	1
35	3
37	2
38	6
39	4
40	2

Three weeks of data sets are chosen to show the extraction capabilities of the algorithms during the progression of pregnancy. The beginning week (22nd), the middle week (33rd) and end week (39th) of the gestation ages are selected from the available data set. The results of these three weeks of gestation age are shown in this section.

The abdominal signal and the extracted signal of the 22nd week are shown from Figure 6.1 to Figure 6.3 for the three proposed methods. In this week the abdominal signal is seen to be very noisy. The magnitude of the fetal ECG is very small compared to the maternal ECG in the abdominal signal. The fetal ECG in the abdominal signal is not dominantly seen. However, the three proposed algorithms were able to extract all the fetal ECG components. In Figure 6.1, in addition to the fetal ECG maternal EMG signal along with noise is present. The fetal ECG is more visible in Figure 6.2 and Figure 6.3. However, the ANFIS and wavelet post processed method is seen to be less noisy.

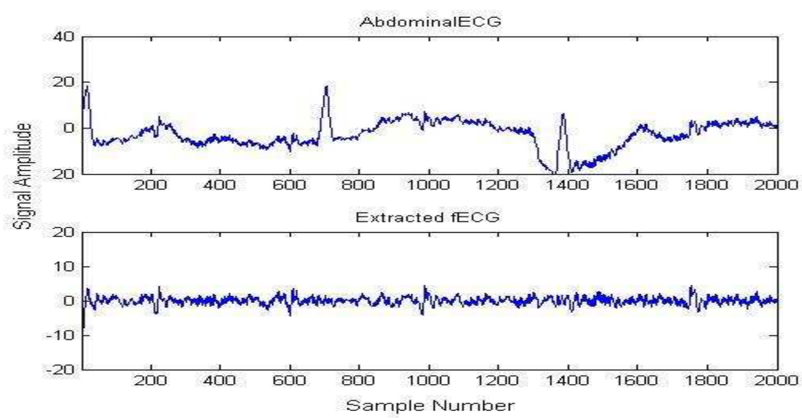

Figure 6.1 FECG extraction using ANFIS – 22nd week data- Case I

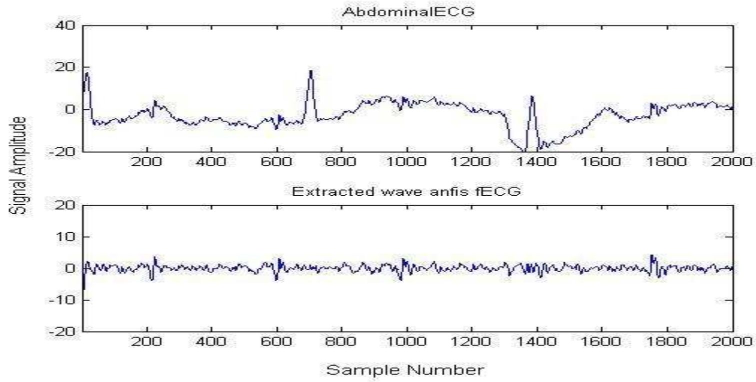

Figure 6.2 FECG extraction using Wavelet and ANFIS –22nd week data- Case I

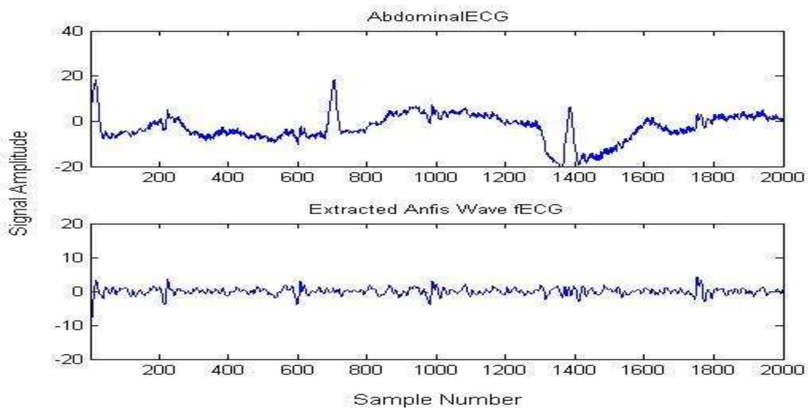

Figure 6.3 FECG extraction using ANFIS and Wavelet –22nd week data -Case I

The abdominal signal and the extracted signal of the 33rd week are shown from Figure 6.4 to 6.6 for the three proposed methods. The abdominal signal in this week has strong maternal ECG. This is due to increased uterine contractions and the fetal ECG is not clearly visible in the abdominal signal. However, the fetal ECG is visible in the extracted signal. It is seen from the extracted output that the noise components are gradually eliminated.

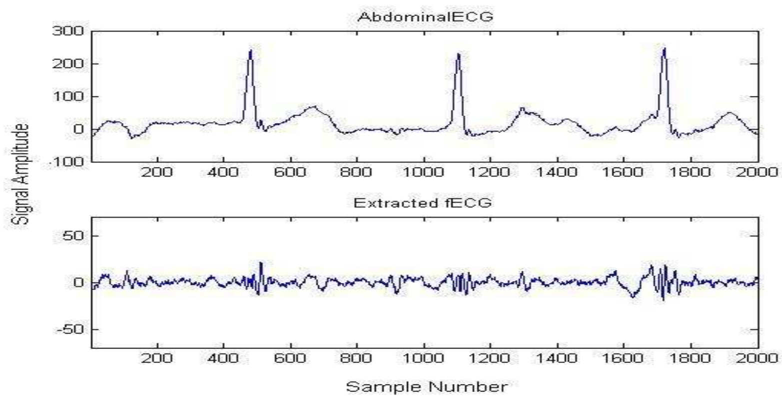

Figure 6.4 FECG extraction using ANFIS – 33rd week data- Case I

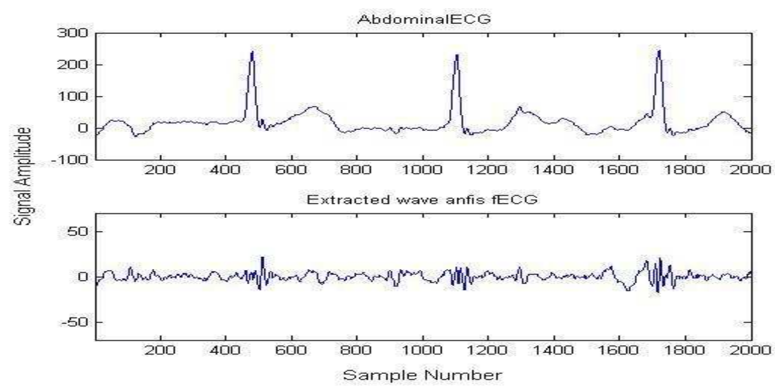

Figure 6.5 FECG extraction using Wavelet and ANFIS - 33rd week data- Case I

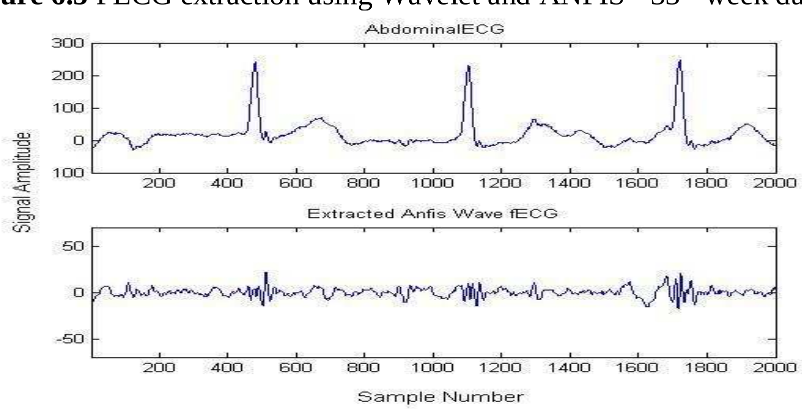

Figure 6.6 FECG extraction using ANFIS and Wavelet –33rd week data- Case I

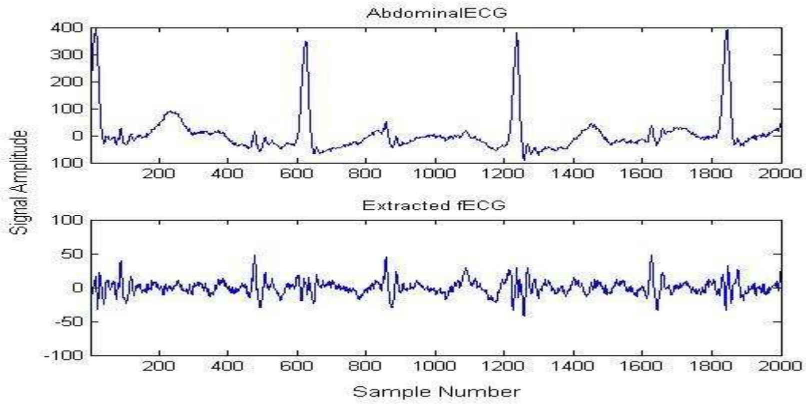

Figure 6.7 FECG extraction using ANFIS – 39th week data -Case I

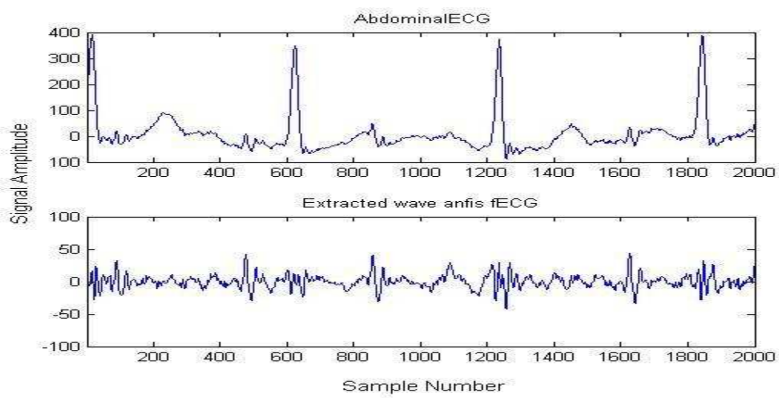

Figure 6.8 FECG extraction using Wavelet and ANFIS –39th week data -Case I

The abdominal signal and the extracted signal of the 39th week are shown from Figure 6.7 to 6.9 for the three proposed methods. During this week the abdominal signal shows strong presence of fetal ECG along with the large magnitude of maternal ECG. The large magnitude of maternal ECG is due to the strong uterine contractions nearing the delivery period. The strong presence of the fetal ECG in the abdominal signal is due to the full growth of the fetus nearing the delivery period. Out of the three proposed methods, the ANFIS and wavelet post processed method shows clear extraction of fetal ECG.

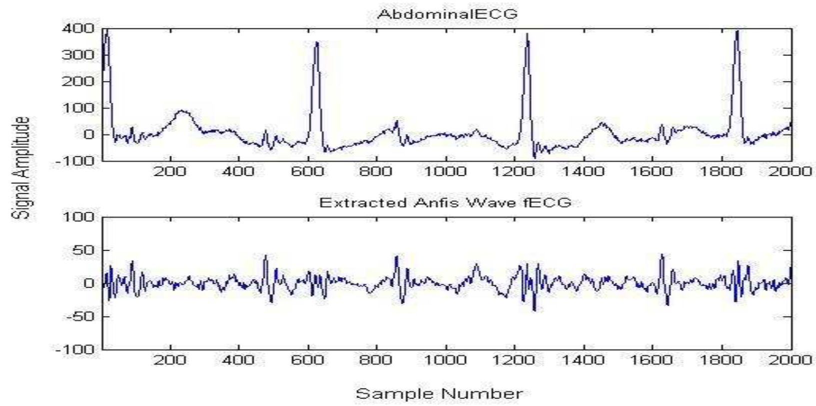

Figure 6.9 FECG extraction using ANFIS and Wavelet –39th week data -Case I

The recordings at 28 -32 weeks of gestation show a decrease in the magnitude of fetal ECG in the abdominal signal. This is caused by the presence of the vernix caseosa, a fatty and isolating layer which appears around 28 weeks and starts deteriorating around 32 weeks of gestation. Difficulties in obtaining the fetal heart rate in this period have been reported by several authors. (Bergveld et al 1986, Oestendorp et al 1989, Taylor et al 2003). The week wise performance evaluation for different gestation weeks are shown in Section 6.8.1

6.3 RESULTS OF CASE II

Case II is the normal pregnancy data set with a sampling frequency of 250Hz. Figure 6.10 shows the abdominal ECG and the extracted fetal ECG using ANFIS method. The FECG is extracted by canceling the thoracic ECG signal from the abdominal ECG signal. In Figure 6.11, the results of FECG extraction using wavelets and ANFIS are shown. In this method there is a oscillatory phenomenon present in the position of maternal ECG in the extracted signal. Such a phenomenon is insignificant in ANFIS followed by wavelet post processing method as shown in Figure 6.12 where the extracted FECG is also noise free. Figure 6.10 to Figure 6.12 shows the total absence of MECG in the extracted FECG. The overlapping of FECG with MECG is seen in the abdominal signal. The proposed methods were able to extract FECG even when, FECG is overlapping with the maternal ECG. Thus the extracted FECG is the actual FECG present in the abdominal signal. The visual quality of the extracted signal is seen to be better in ANFIS & wavelet post processed extraction method.

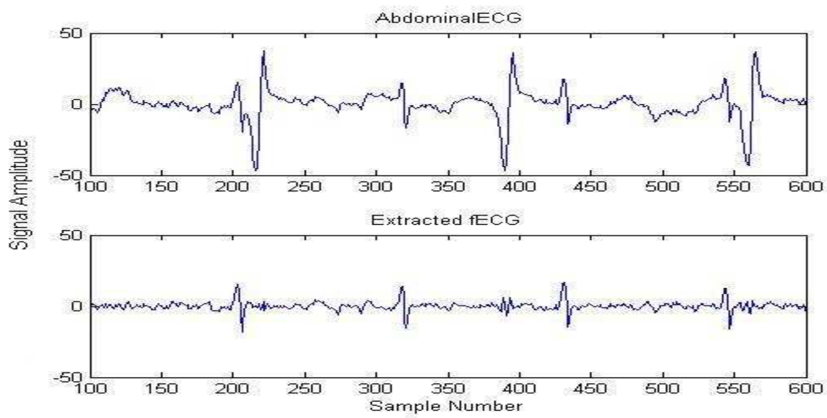

Figure 6.10 FECG extraction using ANFIS – Case II

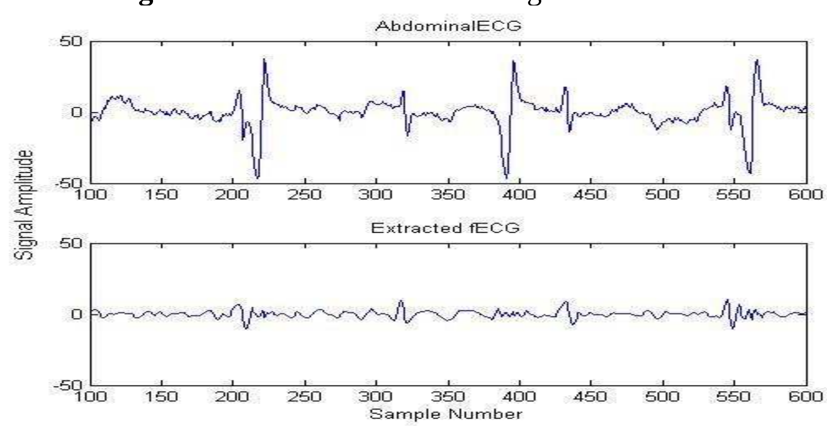

Figure 6.11 FECG extraction using Wavelet and ANFIS – Case II

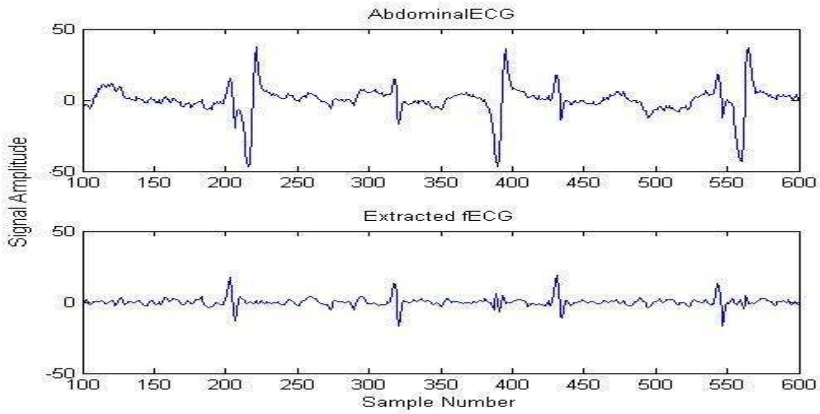

Figure 6.12 FECG extraction using ANFIS and Wavelet – Case II

6.4 RESULTS OF CASE III

Case III is the 40^{th} week data set with a sampling frequency of 1KHz. Figure 6.13 shows the abdominal signal which has very large magnitude of maternal ECG compared to fetal ECG present in the composite abdominal signal. The recorded signal has higher magnitude and large variations due to large contraction of uterus nearing the delivery time. The different methods used in this work are able to suppress maternal ECG and extract fetal ECG even in the presence of large P and T waves as shown in Figures 6.13 to 6.15 The visual quality of extracted FECG shows gradual decrease in noise content from Figure 6.13 to Figure 6.15 with significant presence of fetal ECG.

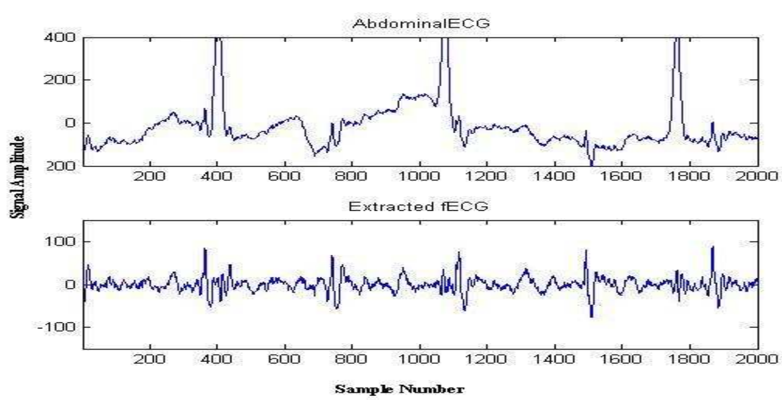

Figure 6.13 FECG extraction using ANFIS – Case III

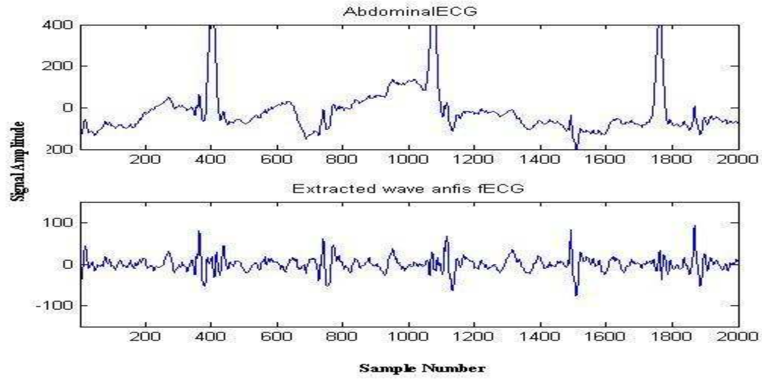

Figure 6.14 FECG extraction using Wavelet and ANFIS – Case III

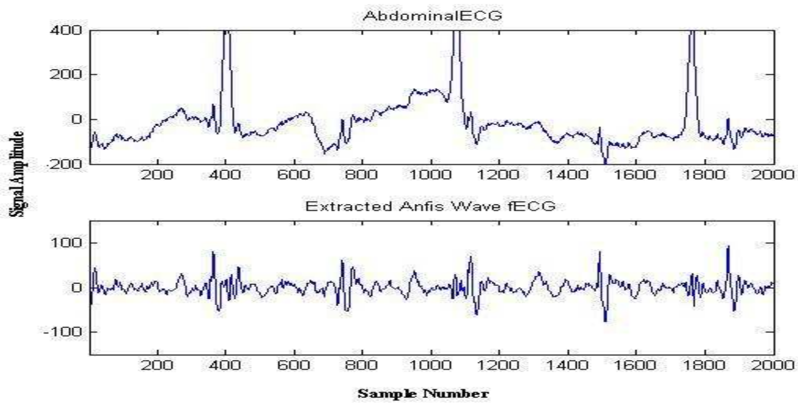

Figure 6.15 FECG extraction using ANFIS and Wavelet – Case III

6.5 RESULTS OF CASE IV

Case IV is the 37th week data set from a sport woman having no risk of pregnancy and with sampling frequency of 250Hz. In this case the abdominal signal shows no overlapping between the fetal ECG and maternal ECG. Also the numbers of FECG components present in the signal are more compared to previous data sets. The proposed methods are able to extract all the fetal ECG present in the composite abdominal signal as shown in Figures 6.16 to 6.18. The FECG is the dominant component in extracted signal.

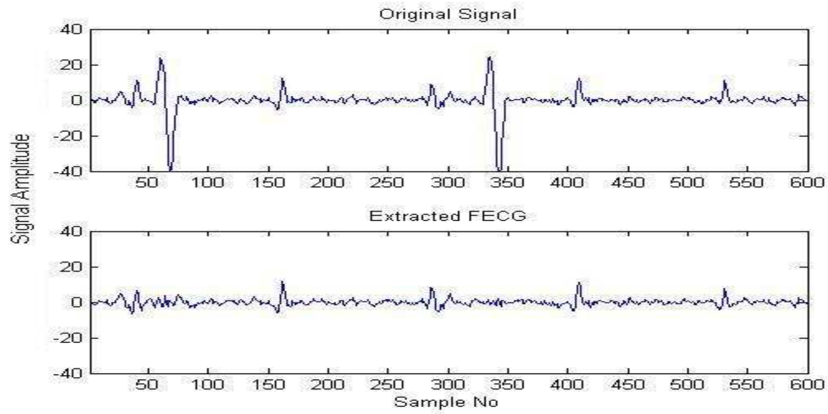

Figure 6.16 FECG extraction using ANFIS – Case IV

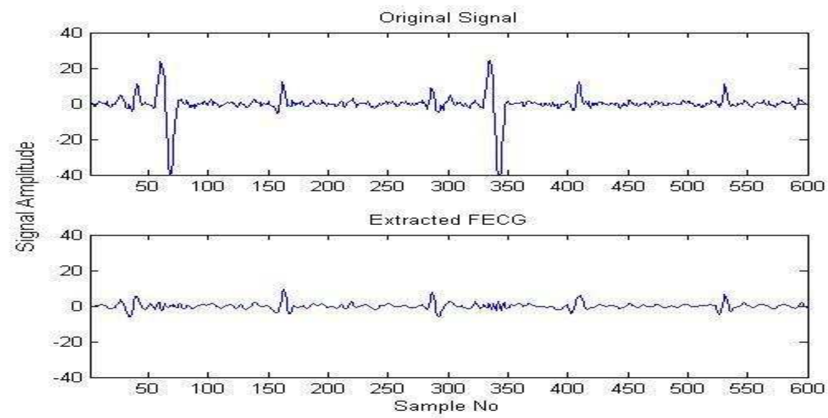

Figure 6.17 FECG extraction using Wavelet and ANFIS – Case IV

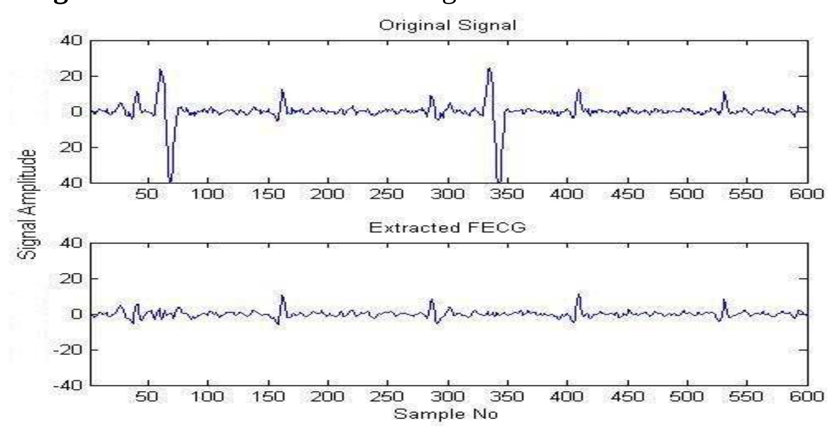

Figure 6.18 FECG extraction using ANFIS and Wavelet – Case IV

6.6 RESULTS OF CASE V

Case V is the data set which is recorded during labor without oxytocin administration with sampling frequency of 400 Hz. All the methods were able to extract FECG successfully and suppress the maternal ECG to a very large extent as shown in Figures 6.19 to 6.21 The visual quality of the extracted signal in Figure 6.19 and Figure 6.21 are similar. However in Figure 6.20 there is a small presence of maternal ECG at sample number 950 in the extracted FECG signal.

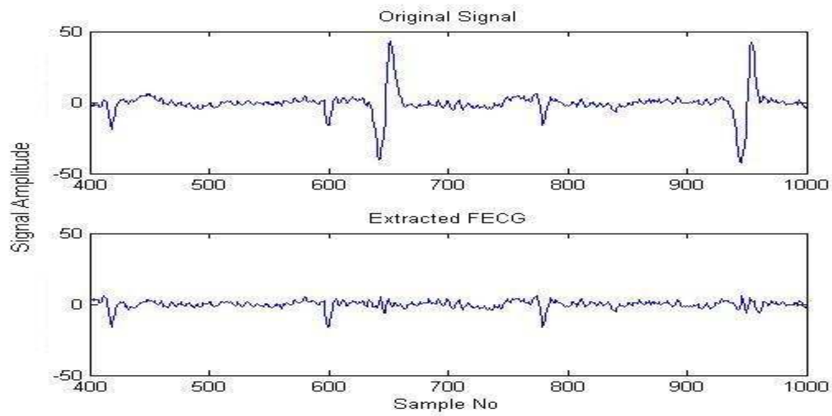

Figure 6.19 FECG extraction using ANFIS – Case V

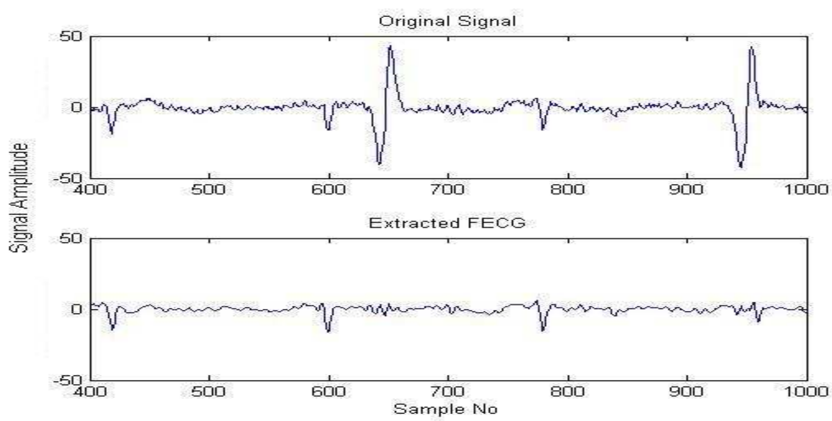

Figure 6.20 FECG extraction using Wavelet and ANFIS – Case V

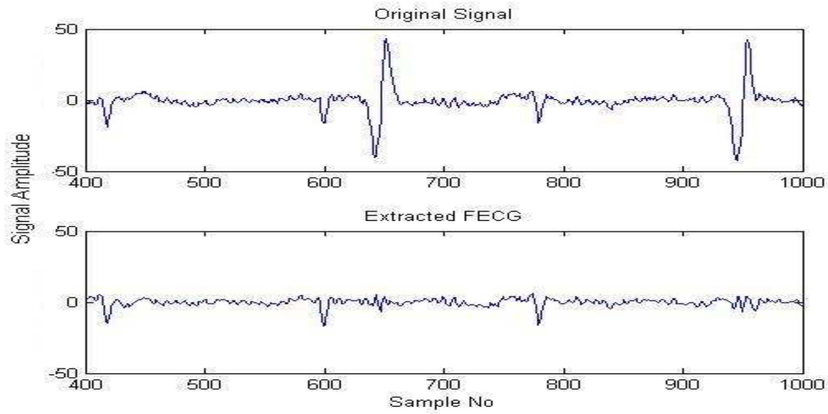

Figure 6.21 FECG extraction using ANFIS and Wavelet – Case V

6.7 RESULTS OF CASE VI

Case VI is the data set which is recorded during labor, after oxytocin administration with sampling frequency of 400 Hz. The recorded abdominal signal has higher magnitude and large variations due to large contraction caused by oxytocin administration. The signal at sample 700 is overlapped with large maternal ECG followed by followed by large T wave. Even in such situation, the overlapped FECG was extracted. The algorithms are able to extract even if the baseline has fluctuations due to the uterine contractions. The visual quality of extracted FECG shows gradual decrease in noise content as seen from Figures 6.22 to 6.24.

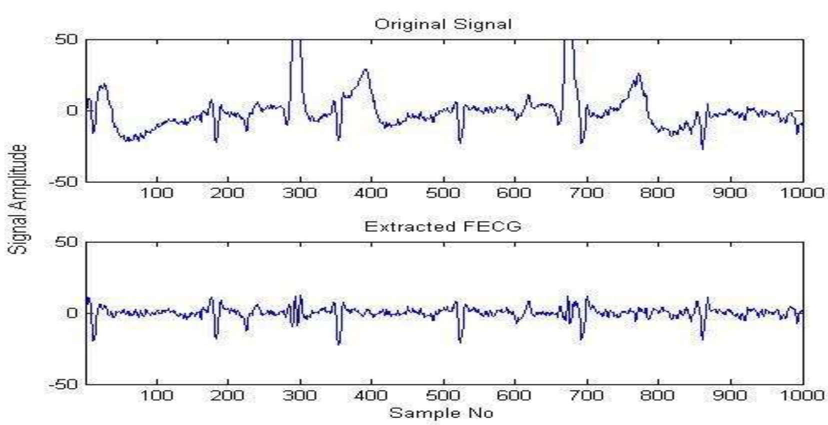

Figure 6.22 FECG extraction using ANFIS – Case VI

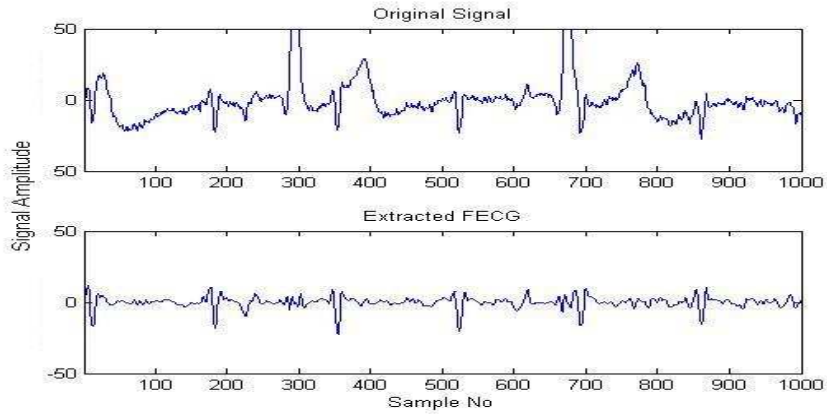

Figure 6.23 FECG extraction using Wavelet and ANFIS – Case VI

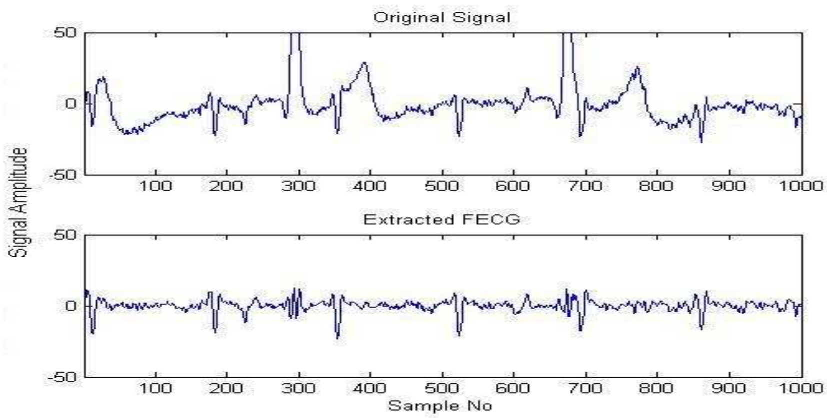

Figure 6.24 FECG extraction using ANFIS and Wavelet – Case VI

6.8 EVALUATION AND ANALYSIS OF THE DIFFERENT CASES WITH THE PROPOSED METHODS

The proposed methods have been analyzed for the quality of extracted FECG. The parameters used to assess the quality of the FECG are signal to noise ratio (SNR), correlation coefficients (CORR) and performance indices as mentioned in section 3.6.

6.8.1 EVALUATION AND ANALYSIS OF CASE I

Table 6.2 Week wise Performance Evaluation for ANFIS method – Case I

Week	SEN	SPE	PPV	NPV	ACC	CORR	SNR
22	0.86	0.72	0.75	0.84	0.79	0.2706	15.2723
23	0.69	0.63	0.65	0.67	0.666	0.1484	19.9865
24	0.77	0.54	0.63	0.7	0.66	0.1586	38.0658
25	0.86	0.5	0.63	0.78	0.68	0.1408	13.5391
27	0.62	0.62	0.62	0.62	0.62	0.1136	20.1669
29	0.59	0.71	0.67	0.71	0.65	0.0768	36.2712
30	0.57	0.79	0.73	0.65	0.68	0.158	43.3239
31	0.67	0.56	0.6	0.63	0.61	0.1058	42.8171
32	0.67	0.61	0.64	0.65	0.64	0.1539	45.6173
33	0.92	0.42	0.62	0.84	0.67	0.1111	31.0299
34	0.58	0.75	0.7	0.64	0.67	0.1125	34.2874
35	0.6	0.67	0.64	0.63	0.64	0.0922	45.5558
37	0.65	0.67	0.65	0.65	0.68	0.0882	43.6325
38	0.64	0.91	0.88	0.72	0.77	0.1305	42.3448
39	0.57	1	1	0.7	0.79	0.124	37.4008
40	0.83	1	1	0.86	0.92	0.1482	39.1487

The week wise performance evaluation is shown from Table 6.2 to 6.4 for different methods of Case I. The plots of the above parameters are shown from Figures 6.25 to 6.31 with respect to gestation weeks.

Table 6.3 Week wise Performance Evaluation for Wavelet and ANFIS method – Case I

Week	SEN	SPE	PPV	NPV	ACC	CORR	SNR
22	0.8	1	1	0.84	0.9	0.1935	36.8042
23	0.73	0.6	0.64	0.69	0.66	0.1247	48.7634
24	1	0.67	0.75	1	0.84	0.1536	65.9958
25	0.79	0.57	0.65	0.73	0.68	0.1038	31.1383
27	0.62	0.62	0.62	0.62	0.64	0.099	35.5483
29	0.59	0.71	0.67	0.71	0.65	0.0736	62.3414
30	0.6	0.9	0.86	0.69	0.75	0.154	79.3182
31	0.58	0.75	0.7	0.64	0.67	0.1031	66.5387
32	0.72	0.65	0.67	0.69	0.68	0.1487	72.3639
33	0.91	0.46	0.63	0.84	0.68	0.1059	62.626
34	0.55	0.82	0.75	0.64	0.68	0.106	62.994
35	0.64	0.64	0.64	0.64	0.64	0.0906	66.6977
37	0.85	0.57	0.65	0.8	0.71	0.0864	70.7803
38	0.7	0.9	0.88	0.82	0.8	0.1277	69.334
39	0.57	1	1	0.7	0.79	0.1184	62.5112
40	0.83	1	1	0.86	0.92	0.1437	68.852

Table 6.4 Week wise Performance Evaluation for ANFIS and Wavelet method – Case I

Week	SEN	SPE	PPV	NPV	ACC	CORR	SNR
22	0.83	0.83	0.83	0.83	0.83	0.1962	43.6144
23	0.55	0.91	0.86	0.67	0.73	0.1262	53.5337
24	1	0.8	0.84	1	0.9	0.1542	79.1955
25	0.92	0.5	0.65	0.88	0.71	0.0953	50.714
27	0.62	0.62	0.62	0.62	0.62	0.1032	53.7831
29	0.62	0.77	0.62	0.67	0.69	0.0737	93.1423
30	0.67	0.89	0.88	0.73	0.78	0.1541	99.3541
31	0.6	0.8	0.75	0.67	0.7	0.1039	100.9372
32	0.83	0.58	0.67	0.72	0.71	0.1488	101.6783
33	0.91	0.45	0.63	0.83	0.68	0.1062	72.1489
34	0.75	0.75	0.75	0.75	0.75	0.1069	73.2829
35	0.67	0.67	0.67	0.67	0.67	0.0906	99.0459
37	0.91	0.58	0.67	0.88	0.74	0.0864	93.8987
38	0.7	0.9	0.8	0.75	0.8	0.128	81.8657
39	0.67	1	1	0.75	0.83	0.1182	79.6384
40	1	1	1	1	1	0.1443	77.7112

Figure 6.25 shows the sensitivity plot for different methods of Case I. It is seen from the plot that the sensitivity is higher in all the weeks from 22nd to 25th and from 32nd to 40th. The period from 27th to 32nd week shows less sensitivity because of vernix caseosa, a fatty and isolating layer which deteriorates the detection process.

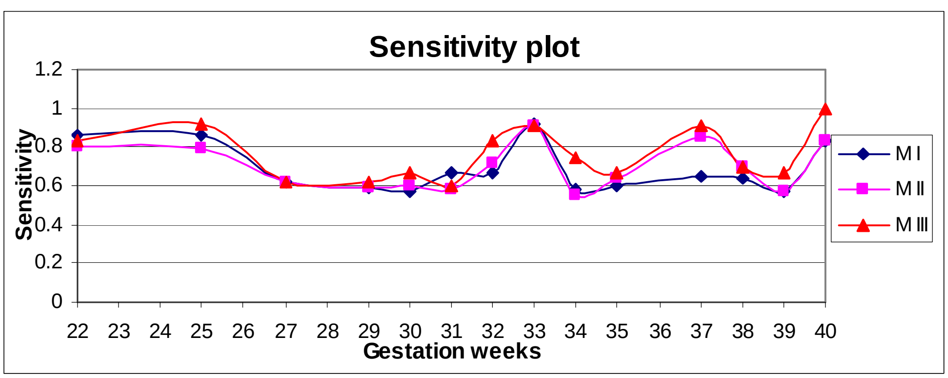

Figure 6.25 Plot of Gestation weeks versus Sensitivity – Case I

The quality of the recorded signal, during different weeks determines the sensitivity. Even though the signal is weak in 22nd week all the methods are able to extract fetal ECG totally. The change in the trend of sensitivity in all the three methods looks similar. The sensitivity is lower in the ANFIS method and higher in ANFIS and wavelet method. This confirms that the ANFIS wavelet processing method is suitable method for extraction.

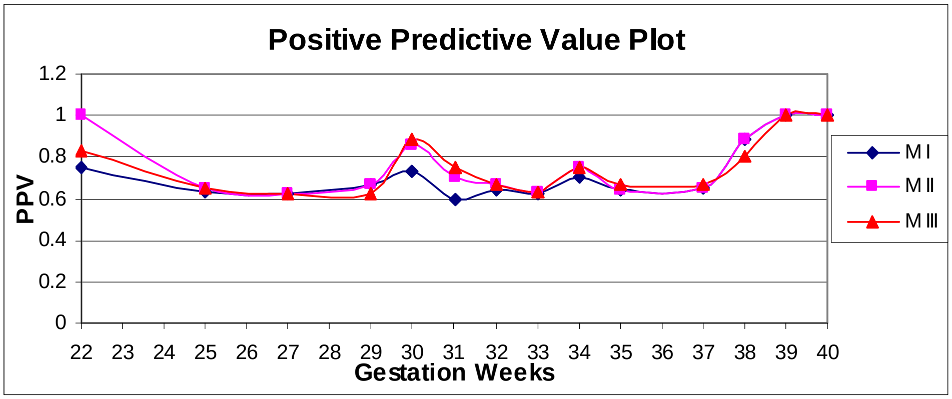

Figure 6.26 Plot of Gestation weeks versus Positive Predictive Value – Case I

Figure 6.26 shows the positive predictive plot for different methods of Case I. In all the three methods the change in the trend is same. Eventhough the signal is weak in 22nd week, method II is able to extract fetal ECG totally thus giving the PPV value of 1. However, method III is also successful in extracting of fetal ECG with the value of 0.8.During the gestation week from 27th to 32nd week the method II and method III is able to extract in better way than the method I. The PPV plot shows that the method II and method III has the similar behavior except in few weeks. In 40th week, all the methods were able to extract the fetal ECG because of the large magnitude of fetal ECG. To conclude, the method II and method III are performing equally well with respect to PPV.

Figure 6.27 shows the negative predictive plot for different methods of Case I. All the methods were able to extract the fetal ECG in the 22nd week because of the less noisy abdominal signal. This is due to less uterine activity. As the gestation weeks increases the noise in the abdominal signal also increases. As gestation age increases, the NPV value is higher in the method II and method III compared to method I. However, the NPV value is smaller during 27th to 32 week because of the quality of the signal itself. It is seen from the plot that the ANFIS followed by wavelet is yielding a better extraction.

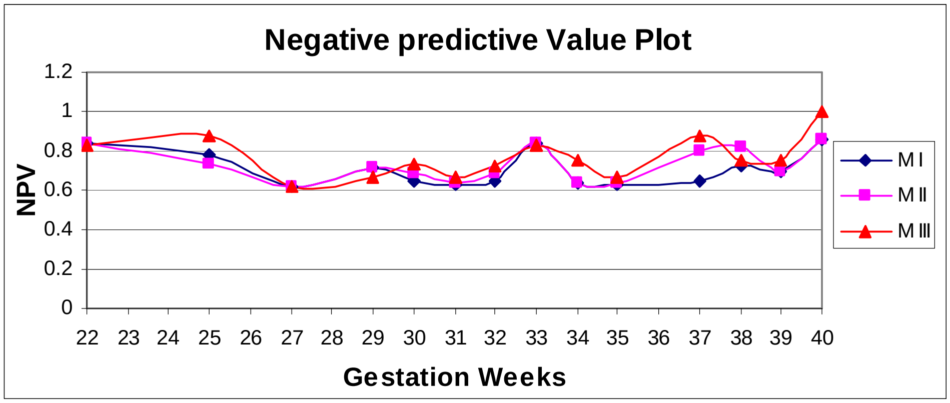

Figure 6.27 Plot of Gestation weeks versus Negative Predictive Value – Case I

Figure 6.28 shows the specificity plot for different methods of Case I. As seen from the plot, the method II is performing very well at 22nd week by no false negative detections. All the methods are performing equally well from 38th week onwards. Even, during the onset of vernix caseosa the methods were able to extract fetal ECG with minimum number of false negative detections seen by the increased value of specificity. To conclude method II and method III are performing well with respect to specificity.

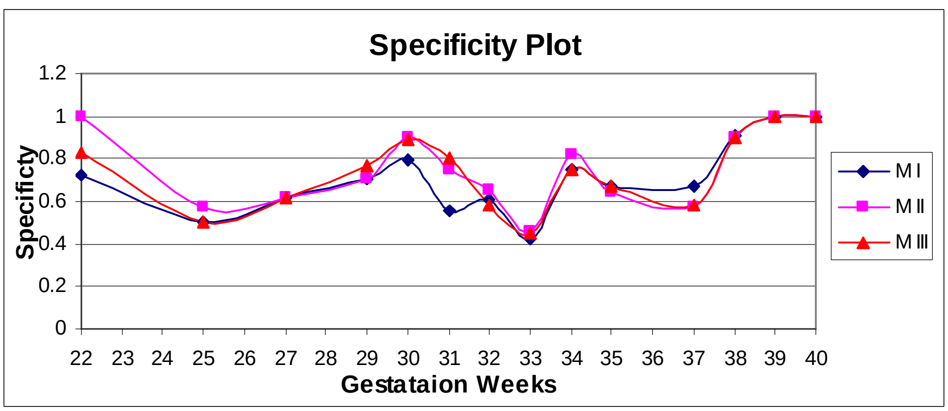

Figure 6.28 Plot of Gestation weeks versus Specificity – Case I

Figure 6.29 shows the accuracy plot for different methods of Case I. It is seen from the plot all the methods are in similar trend with very slight differences. The accuracy value is higher in 22nd and 40th week because of no false detections being made. The weeks during the onset of vernix caseosa show lesser value of accuracy due to some false detection because of the quality of the original signal. It is concluded that the method III is performing better.

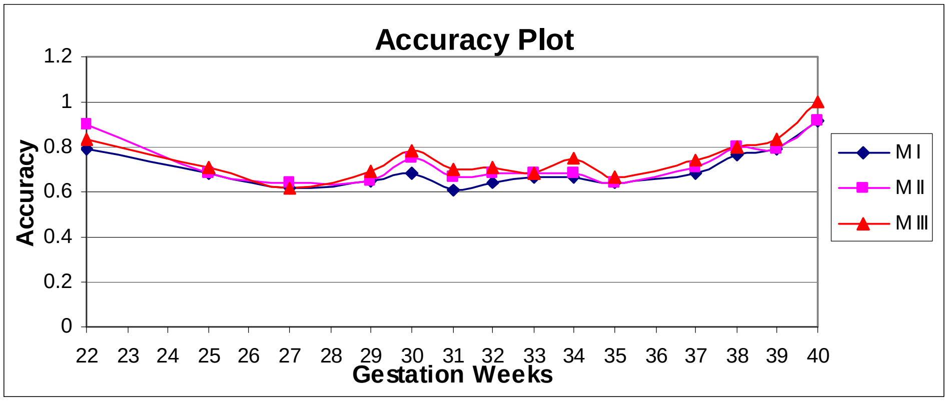

Figure 6.29 Plot of Gestation weeks versus Accuracy – Case I

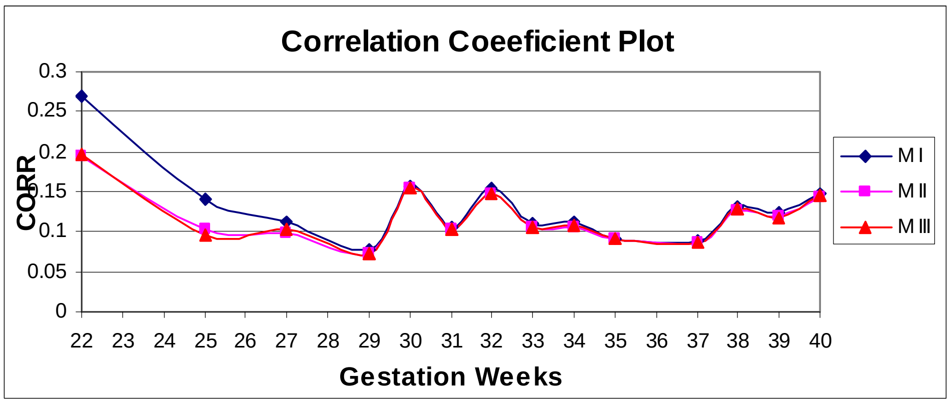

Figure 6.30 Plot of Gestation weeks versus Correlation Coefficient – Case I

Figure 6.30 shows the correlation coefficient plot for different methods of Case I. During the 22nd week the correlation coefficient is seen to be smaller in method II and method III. From 29th week onwards all the three methods have the same behavior. It is seen that the method II and method III are capable of extracting fetal ECG during early stages pregnancy. However, the correlation coefficient value has increased from 29th week to 33rd week due to the vernix caseosa which affects the quality of the signal. In terms of correlation coefficient it is concluded that method II and method III are equally extracting the fetal ECG.

Figure 6.31 shows the SNR plot for different methods of Case I. It is very clear from the plot that the SNR value for method III is higher than the other two methods in all gestation weeks. The trend of SNR is similar in all the cases.

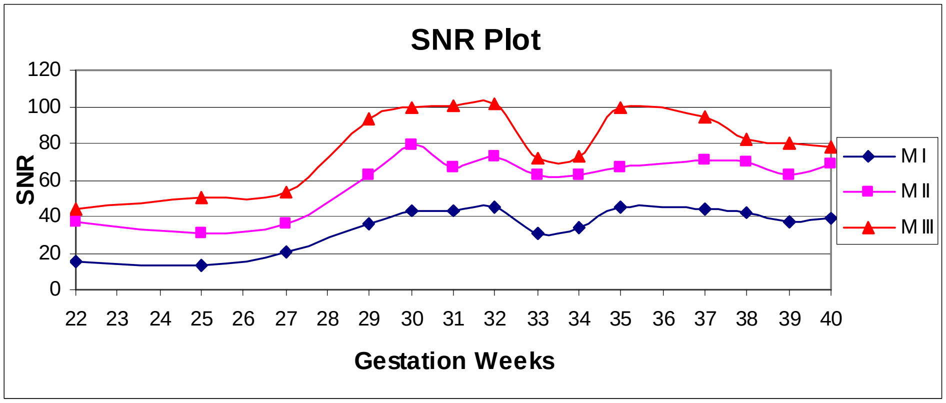

Figure 6.31 Plot of Gestation weeks versus SNR – Case I

By comparing all the performance indices and correlation coefficient it is concluded that method II and method III are the efficient methods for extracting the fetal ECG from the abdominal signal. On comparing SNR the method III performs better than method II. The visual quality of the extracted signal in this method also justifies the same. Hence it is concluded that ANFIS followed by wavelet is a superior method for fetal ECG extraction.

6.8.2 EVALUATION AND ANALYSIS OF CASE II

The performance indices, correlation coefficient and SNR were done for case II with the three different methods. The results are shown in table 6.5. For all the three methods the performance indices have the same value. This indicates that all the methods could detect fetal ECG completely without any false detection.

Table 6.5 Performance Evaluation for Case II

METHODS	SEN	SPE	PPV	NPV	ACC	CORR	SNR
Method I- ANFIS	1	1	1	1	1	0.3888	28.6781
Method II- Wavelet preprocessing & ANFIS	1	1	1	1	1	0.3132	39.3100
Method III- ANFIS & wavelet post processing	1	1	1	1	1	0.3816	120.404

The correlation is seen to be similar in method I and method III as shown in Figure 6.32. However, method II has a low value suggesting better extraction. Figure 6.33 shows the drastic increase in SNR in method III compared other two methods.

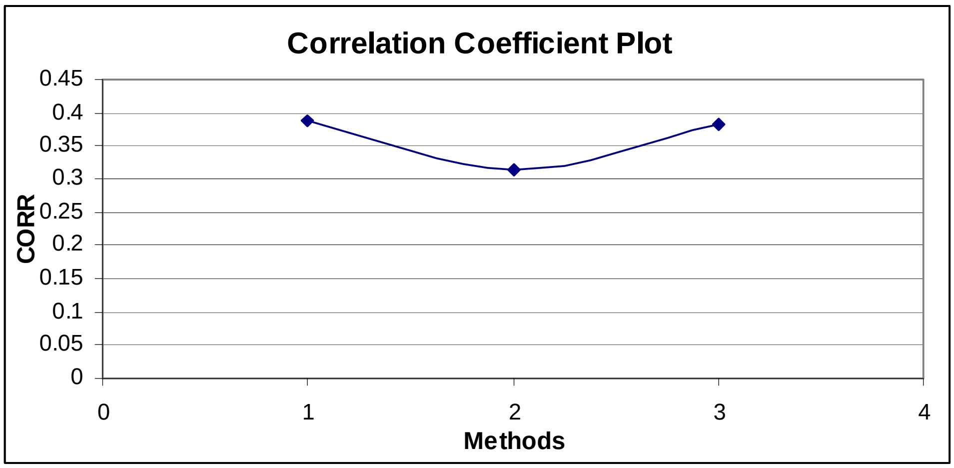

Figure 6.32 Plot of Methods versus Correlation Coefficient – Case II

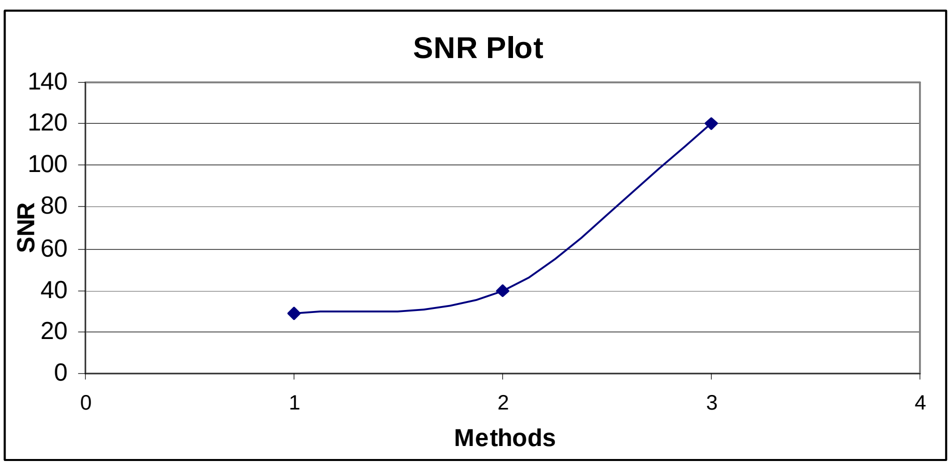

Figure 6.33 Plot of Methods versus SNR – Case II

On comparing performance indices, correlation coefficient and SNR, ANFIS followed by wavelet post processing is found to be the better method for extraction.

6.8.3 EVALUATION AND ANALYSIS OF CASE III

The performance evaluation of case III is shown in table 6.6. Method I and method II have the same performance indices and very close correlation coefficient. All the performance indices have the same and maximum value in ANFIS & wavelet post processing method.

Table 6.6 Performance Evaluation for Case III

METHODS	SEN	SPE	PPV	NPV	ACC	CORR	SNR
Method I- ANFIS	0.83	1	1	0.86	0.92	0.1482	39.1487
Method II- Wavelet preprocessing & ANFIS	0.83	1	1	0.86	0.92	0.1437	68.852
Method III- ANFIS & wavelet post processing	1	1	1	1	1	0.1443	77.7112

Figure 6.34 and Figure 6.35 are plots for correlation coefficient and SNR. The correlation coefficient for all the methods has the similar range of values. Method III has the the highest value of SNR. Thus comparing performance indices, correlation coefficient and SNR it is concluded that the ANFIS & wavelet post processing method is the best method.

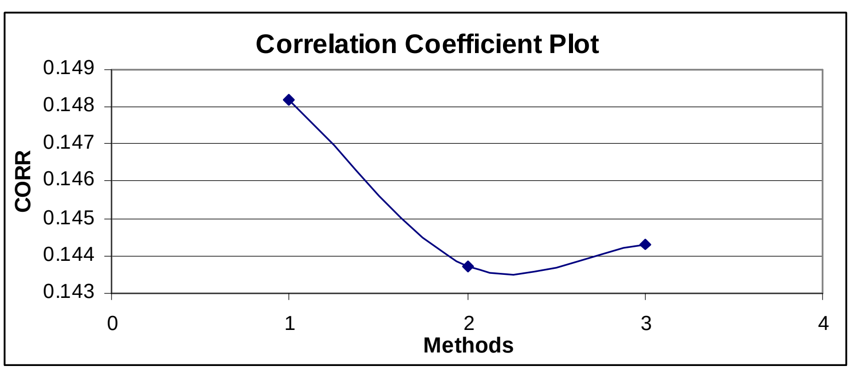

Figure 6.34 Plot of Methods versus Correlation Coefficient – Case III

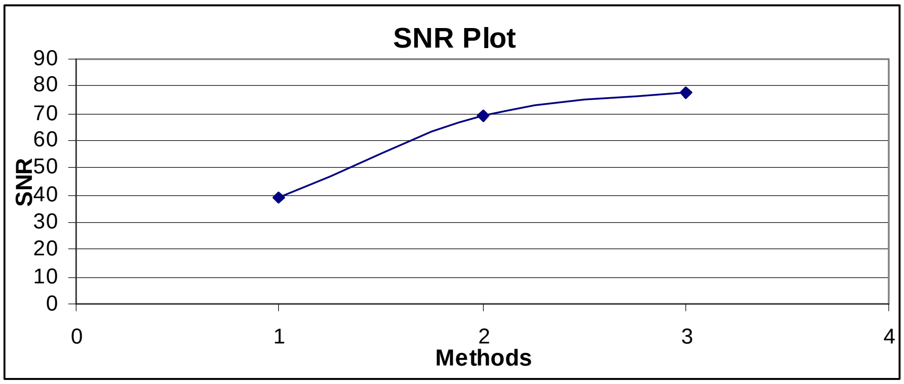

Figure 6.35 Plot of Methods versus SNR – Case III

6.8.4 EVALUATION AND ANALYSIS OF CASE IV

The performance evaluation for case IV is shown in table 6.7. All the performance indices have the same and maximum value in method II and method III which indicates no false detections in the extraction.

Table 6.7 Performance Evaluation for Case IV

METHODS	SEN	SPE	PPV	NPV	ACC	CORR	SNR
Method I- ANFIS	0.83	1	1	0.85	0.91	0.3283	25.0311
Method II- Wavelet preprocessing & ANFIS	1	1	1	1	1	0.2791	40.6417
Method III- ANFIS & wavelet post processing	1	1	1	1	1	0.319	119.1923

Figure 6.36 and Figure 6.37 shows the plot for correlation coefficient and SNR for case IV. The correlation is seen to be very close in method I and method II. By comparing SNR, the ANFIS & wavelet post processed method has the highest value. Hence to conclude ANFIS followed by wavelet post processing is the better method for extraction.

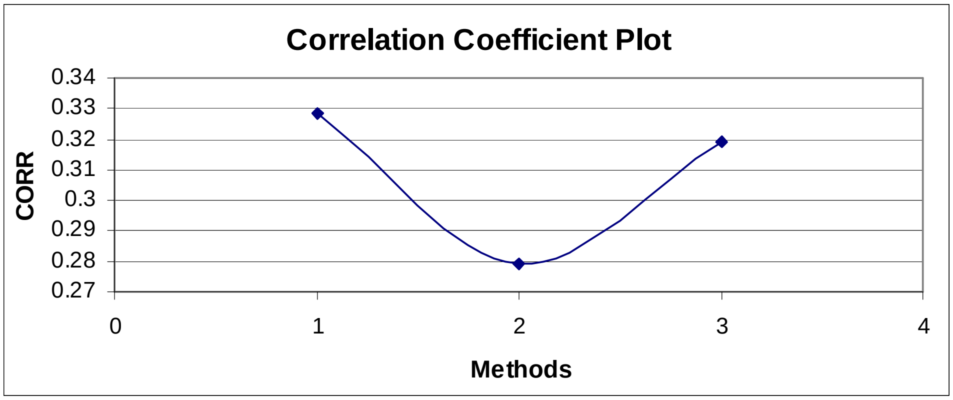

Figure 6.36 Plot of Methods versus Correlation Coefficient – Case IV

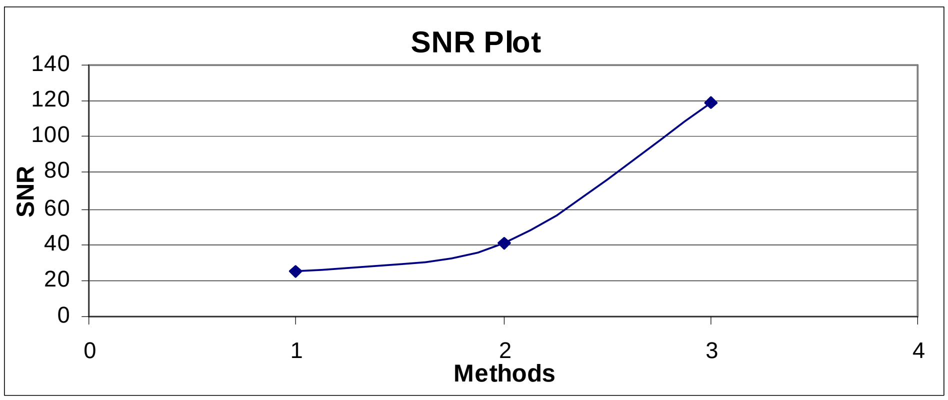

Figure 6.37 Plot of Methods versus SNR – Case IV

6.8.5 EVALUATION AND ANALYSIS OF CASE V

The performance evaluation for case V is shown in table 6.8. This is a case of data set during labor without drug administration.

Table 6.8 Performance Evaluation for Case V

METHODS	SEN	SPE	PPV	NPV	ACC	CORR	SNR
Method I- ANFIS	1	.75	.8	.75	.88	0.4661	43.1815
Method II- Wavelet preprocessing & ANFIS	1	1	1	1	1	0.5494	100.2257
Method III- ANFIS & wavelet post processing	1	1	1	1	1	0.5645	142.5646

All the performance indices have the same and maximum value in method II and method III. Figure 6.38 and Figure 6.39 are the correlation coefficient and SNR plots for case V.

The correlation coefficient is smaller in method I and higher in method III. Also, SNR is higher in method III and lower in method I. By comparing the performance parameters, correlation coefficient and SNR it is concluded that the ANFIS followed by wavelet post processing method is the best method.

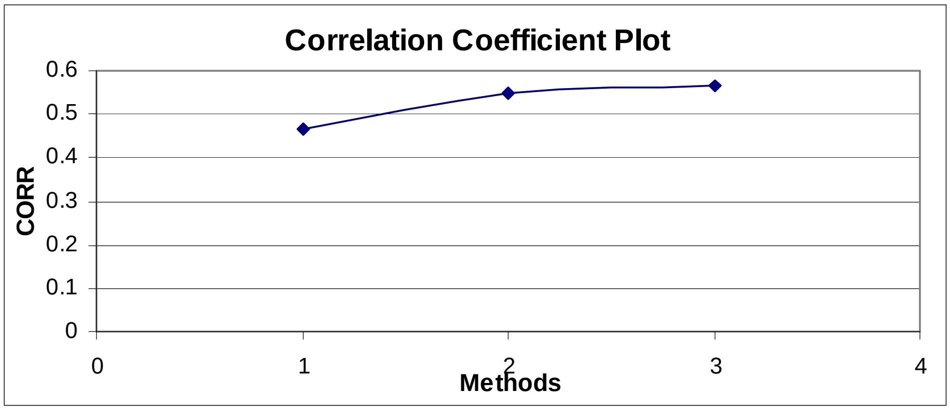

Figure 6.38 Plot of Methods versus Correlation Coefficient – Case V

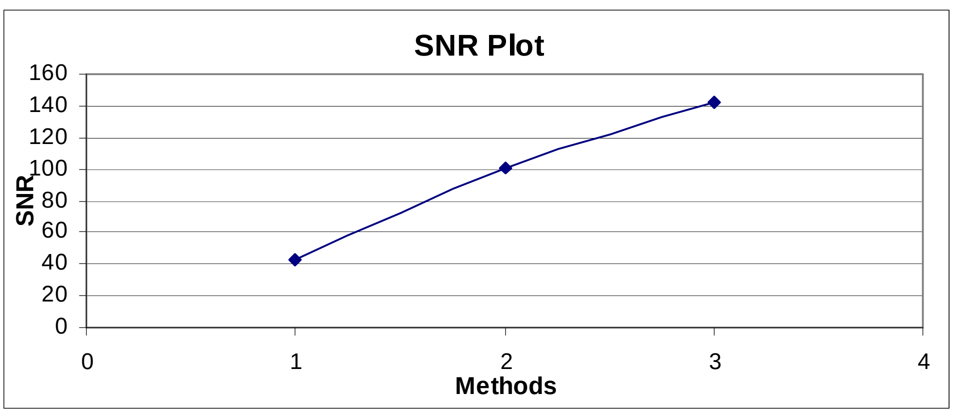

Figure 6.39 Plot of Methods versus SNR – Case V

6.8.6 EVALUATION AND ANALYSIS OF CASE VI

The evaluation for case VI is shown in table 6.9.

Table 6.9 Performance Evaluation for Case VI

METHODS	SEN	SPE	PPV	NPV	ACC	CORR	SNR
Method I- ANFIS	1	.75	.8	1	.88	0.2773	42.1720
Method II- Wavelet preprocessing & ANFIS	1	.85	.88	1	.92	0.2773	97.9669
Method III- ANFIS & wavelet post processing	1	1	1	1	1	0.2927	124.0231

This is a case of data set during labor with drug administration. This increases the contractile activity of the uterus. All the methods were able to extract fetal ECG completely. Method I and method II are performing in a similar way. All the performance indices have the same and maximum value in ANFIS & wavelet post processing method.

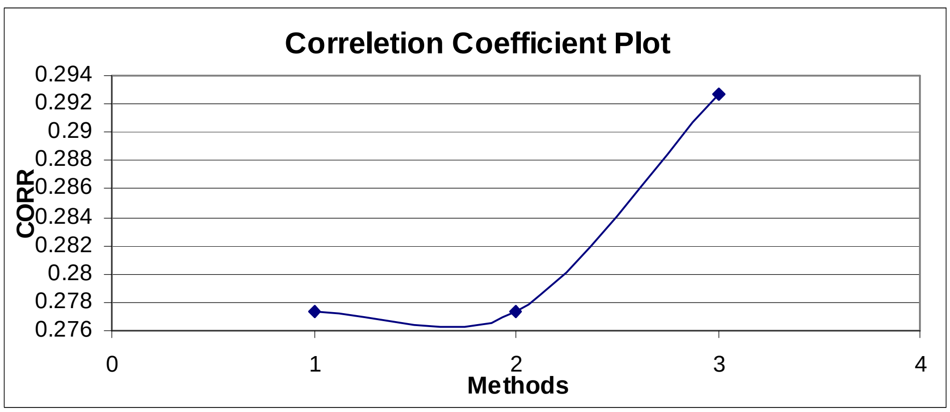

Figure 6.40 Plot of Methods versus Correlation Coefficient – Case VI

Figure 6.40 and 6.41 are the plots for correlation coefficient and SNR for case VI. The value of correlation coefficient in all the methods suggests that the maternal ECG is totally absent. The SNR has the highest value in method III. To conclude ANFIS followed by wavelet post processing method is best for FECG extraction with drug administration.

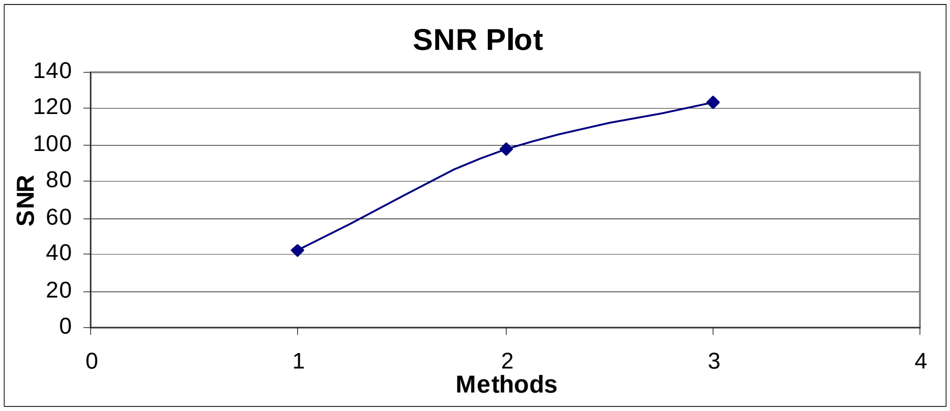

Figure 6.41 Plot of Methods versus SNR – Case VI

6.9 CHAPTER SUMMARY AND CONCLUSION

In this chapter, three methods proposed in chapter 5 namely (1) Method I- FECG extraction using ANFIS (2) Method II- FECG extraction using wavelet preprocessing and ANFIS (3) Method III- FECG extraction using ANFIS followed by wavelet post processing were tested with the data during the pregnancy period from 22nd to 40th week and during labor before and after oxytocin administration. In the cases discussed, the correlation coefficient is similar in method II and method III. The comparison between all the methods, in all the cases shows that the SNR is highest in ANFIS followed by wavelet post processing method. This method shows considerable improvement in performance indices also. To conclude the correlation coefficient, SNR and performance indices indicate that the ANFIS & wavelet post processing method is more preferred method for FECG extraction. The visual quality indicates that the extracted FECG is of superior quality in ANFISfollowed by wavelet post processing method. This method is capable of extracting FECG even when, the FECG is overlapping with MECG. And also the morphology of the extracted FECG remains same and it can be used by the physicians to diagnose.

CHAPTER 7
CONCLUSIONS

In this research, new methods of extracting fetal electrocardiogram signals from the maternal abdominal recordings were proposed and developed. Fetal ECG extraction methods are using multi stage adaptive filtering, wavelets, and soft computing techniques. These methods were evaluated on the real signals in different patients. The algorithms were designed to cancel the maternal ECG from the abdominal signal and enhance the fetal ECG signal. The main contribution of this work was to develop ten processing algorithms that use information of fetal and contaminating signals and improve the quality of the extracted FECG. The extracted FECG from different algorithms were evaluated with performance indices; Sensitivity (SEN), Specificity (SPE),Positive Predictive Value (PPV),Negative Predictive Value (NPV),Accuracy (ACC),Correlation Coefficient (CORR) and Signal to Noise ratio (SNR).

7.1 CONCLUSIONS

In chapter 3, three different methods for fetal ECG extraction using multi stage adaptive filtering were developed. These are named as (1) Method I- FECG Extraction Method (2) Method II-Improved FECG Extraction Method (3) Method - III Novel Method of FECG Extraction. These proposed methods detect the fetal ECG by preprocessing of the abdominal ECG and subsequent cancellation of the maternal ECG by multi stage adaptive filtering. The preprocessing stage is required to remove the DC signal, baseline wander, power line interference and any other noise components. Using the preprocessed signal, a non linear operator has been defined. The inability of the one adaptive filter, to cancel maternal ECG completely has led to the addition of the second stage. The optimum combination of adaptive filters was chosen as RLS and LMS algorithms. The method I and method II uses the same non linear parameter Ψ=DS(0.02*DS-1). Method II is different from method I as it uses a new stage of refinement. The different non linear operators have helped to reduce the maternal ECG. The method III uses the non linear parameter Ψ = DS (K-1) for the extraction of fetal ECG. The K value has been optimized by studying the power spectral density variations of the extracted FECG signal. By comparing the performance indices, it is concluded that all the three methods were performing well. However, by comparing the correlation coefficient and SNR it is concluded that the method III was seen to be better method for FECG extraction.

In chapter 4, four different methods for fetal ECG extracting using combinations of the wavelet and adaptive filters have been suggested. These are named as (1) WAF Method I (2) WAF Method II (3) WAF Method III (4) WAF Method IV. The wavelets are used here as a 5 level decomposition and denoising tool. The approximation coefficient of the abdominal signal is further processed by adaptive filtering stages. The methods are differentiated based on the non linear parameter being used. The method I and method II uses the same non linear parameters Ψ = DS (0.02*DS-1). The method II uses the additional stage for refinement. The method III uses the non linear parameter Ψ=DS(K-1) for the fetal ECG extraction. The method IV uses the same nonlinear parameter as method III but with the modified thoracic signal. The comparison of the methods was made using the parameter indices, correlation coefficient and SNR. It is found that the WAF method II yielded the best quality of fetal ECG signal.

In chapter 5, three different methods were proposed using the combination of soft computing techniques and wavelets. These are named as (1) Method I- FECG extraction using ANFIS (2) Method II- FECG extraction using wavelet preprocessing and ANFIS

(3) Method III- FECG extraction using ANFIS followed by wavelet post processing. These methods use adaptive maternal cancellation techniques. The ANFIS is trained to identify the thoracic signal in the composite abdominal signal. The estimated thoracic signal is used to extract FECG. Out of these, method II and method III make use of wavelets as a preprocessing tool and post processing tool. All the three soft computing methods are capable of extracting fetal ECG. But comparing the performance indices and correlation coefficient, the method II and method III are similar. On comparing SNR, the method III out performs method II.

Table 7.1 Summary of the proposed methods

Methods	**SEN**	**SPE**	**PPV**	**NPV**	**ACC**	**CORR**	**SNR**
Method I- FECG extraction method	0.8	1	1	0.84	0.9	0.2024	11.81
Method II – Improved FECG extraction method	0.8	1	1	0.8	0.89	0.1546	19.42
Method III – Novel method of FECG extraction	**1**	**0.77**	**0.89**	**1**	**0.89**	**0.187**	**19.98**
WAF Method I	0.67	1	1	0.75	0.83	0.1851	24.2001
WAF Method II	**0.8**	**1**	**1**	**0.83**	**0.9**	**0.165**	**26.5029**
WAF Method III	0.79	1	1	0.7	0.79	0.2369	14.1796
WAF Method IV	0.67	1	1	0.72	0.82	0.2711	14.3583
Method I- ANFIS extraction method	1	1	1	1	1	0.3888	28.6781
Method II - Wavelet and ANFIS extraction method	1	1	1	1	1	0.3132	39.3100
Method III -ANFIS and Wavelet extraction method	**1**	**1**	**1**	**1**	**1**	**0.3816**	**120.404**

Comparing all the ten proposed methods for the same data sets from Sista and Pyhsio, it is noted that soft computing techniques are performing better. To confirm the robustness of the algorithms these methods were further tested with data during the early stages of pregnancy period from 22nd to 40th week and during the labor with and without oxytocin administration. Six cases were tested and the evaluation results show that the ANFIS followed by wavelet post processing is more preferred method for FECG extraction. In table 7.1 a general comparison is made between the proposed methods for the data set from Sista. Accordingly each proposed methods has its own benefits and limitations. The highlighted methods are the better methods in adaptive filtering, wavelet adaptive filtering and soft computing techniques.

To conclude, all the ten proposed methods were able to extract the fetal ECG when it is overlapped with the maternal ECG. Also, these methods have an advantage of using only one abdominal signal and one thoracic signal for FECG extraction. Compared to adaptive and wavelet adaptive methods, the soft computing methods were performing better. Mathematical analysis is very less in this method because of the qualitative aspect of the artificial intelligence. Since this technique uses neural network it requires fewer inputs to extract the FECG signal. Convergence time is less compared to methods using neural network alone due to the hybrid rule used in the ANFIS technique. ANFIS methods can separate the FECG without dividing the signals into different frames. After removing the major interference (MECG) from the FECG, it is easier to suppress the noise using the wavelets. In these soft computing methods, ANFIS followed by wavelet post processing is well suited for FECG extraction. This technique is able to extract the fetal ECG in the early stages of pregnancy. Since the morphology of the extracted FECG using this technique remains same, it can be used by the physician to diagnose.

It is believed that the proposed methods are specifically powerful in the following cases.

- To extract the FECG signal from the composite abdominal signals and to improve the quality of fetal ECG extraction even during the early stages of pregnancy and labor.

- Development of different methods for cancellation of maternal cardiac interference using any electrode position from multiple channels with minimum influence on fetal ECG components as long as maternal R peaks are detected from the noisy data.
- Decomposition of the abdominal signals to improve the quality of extraction.
- Fetal cardiac signal detection using fetal cardiac peaks.
- More generally denoising and enhancement of the signals
- Extraction of FECG in overlapping case with MECG.

The decomposition techniques though simple, have issues such as signal mixture, degenerosity and noise which limits their performance of these methods. The methods proposed in this work have the benefits of non linear filtering without losing any significant data. The methods proposed are not a replacement but rather complements for the existing methods. Due to various measurement setups, fetal conditions and gestation ages, SNR etc it is neither reasonable nor possible to present a universal filtering solution. What is feasible is to focus on specific applications such as fetal R peak detection using fixed electrode position and for specific ranges of gestational age. However, for morphological studies a combination of decomposition and filtering methods may be required.

The methods that were developed are based on maternal ECG cancellation and detection of fetal ECG. Although this is an important factor that can improve the signal quality it can be considered as a point of weakness, that the R peaks of the fetus are not well detected in filtering methods. In multi stage adaptive filtering and wavelet - adaptive filtering techniques, the complete cancellation of maternal ECG is not seen in certain electrode positions. This is predominant when the maternal ECG is very large in magnitude compared to fetal ECG. Some components which do not belong to fetal ECG also appear in the extracted signal. This may be mistaken as fetal ECG component by the detection algorithm. Despite these limitations it might be argued that these techniques are able to perform better. It should be noted, that no general filtering procedure has been developed which can be applied to normal and abnormal abdominal signal.

Table 7.2 Summary of the existing methods and the proposed methods

Author	**Method**	**Accuracy**
Pieri *et al*. 2001	Matched filter	65%
Mooney *et al*. 1995	Adaptive algorithm	85 %
Azad, 2000	Fuzzy Approach	89 %
Ibrahimy *et al*.2003	Statistical analysis	89%
Swarnalatha & Prasad. 2010	Multi stage Adaptive filters	89%
Swarnalatha & Prasad.*	Wavelet-Adaptive filtering	90%
Camps *et al*. 2001	FIR Neural Networks	91 %
Karvounis *et al*. 2004	Complex wavelets	98 %
Khamene *et al*. 2000	Quadratic spline wavelet	100%
Swarnalatha & Prasad.*	ANFIS & wavelet postprocessed method	100%

*** Journal in press.**

Comparison of existing methods and the proposed method

The table 7.2 summarizes the results obtained by other methods in the literature for fetal ECG extraction. The different proposed methods are compared to other existing methods in terms of accuracy. It should be noted that there is lack of standard reference data base available in the literature. This means that different methods in the literature cannot be directly compared since they were evaluated using different data sets. The majority of the methods were either tested using small number of simulated signals or with real recordings.

7.2 SPECIFIC CONTRIBUTIONS

Specific contributions of this study are:

(i) The proposed research work extracts the fetal ECG by two lead signals which are the abdominal signal and thoracic signal of the mother's abdomen and thorax region.

(ii) The fetal ECG extraction based on adaptive noise cancellation is more suitable due to computational simplicity and ease of implementation. Hence, the proposed method includes preprocessing, modification of thoracic signal and multi stage adaptive filtering for extraction even if FECG over laps with MECG.

(iii) The multi stage adaptive filtering is combined with wavelet processing for better fetal ECG extraction.

(iv)Soft computing techniques to extract the fetal ECG signal are proposed. This method cancels the MECG present in the abdominal signal using hybrid neuro fuzzy logic technique which combines the advantages of neural network and fuzzy logic technique.

7.3 FUTURE SCOPE OF WORK

There are number of questions to be answered in this kind of work. Some of the questions concerning the extraction and analysis of fetal cardiac signals are suggested.

- Further study of the performance limits of the fetal ECG signal extraction in other environments and for different sets of abdominal signals is necessary. Especially for the quasi periodic signal case (P,Q,R,S and T component waves repeatedly occur in the ECG signal), the extracted fetal ECG signals are clinically acceptable. This calls for further experiments of the fetal ECG extraction approach on actual abdominal ECG signal.
- There are several elements in the ECG signal separation algorithm that can be modified to improve performance of the fetal ECG extraction.

- The disadvantage of the multi stage adaptive filtering and wavelet adaptive filtering techniques is to change the shape of the extracted fetal ECG in some electrode positions depending on the duration of the maternal ECG and fetal ECG.
- Better FECG extraction may be possible if there is a priori knowledge about the morphology of the maternal ECG signal and the fetal ECG.
- Development of FECG extraction technique with single channel abdominal signal using ANFIS methods.
- Clinical validation of the proposed methods should be considered in future works.

The proposed methods were presented as processing tools and were validated on discrete data bases each having different sampling frequencies. Due to lack of unique data base recorded at different gestational ages and from various subjects, the proposed methods have a limited testing. Thus before taking up any of the proposed methods for clinical studies it should be further tested with unique fetal data base.

REFERENCES

Abboud S, Alaluf A, Einav S, Sadeh D. Real time abdominal fetal ECG recording using hardware correlator. Comput. Biol. Med.1992 ; 22(5):325–335.

Abboud S, Sadeh D. Power spectrum analysis of fetal heart rate variability using the abdominal maternal electrocardiogram. J Biomed Engg. 1990; 12:161-4.

Abboud S, Sadeh D. Spectral analysis of the fetal electrocardiogram. Comput Biol Med.1989; 19:409–415.

Amer Wahlin I. Fetal ECG Waveform Analysis for Intrapartum Monitoring. Ph.D. Dissertation, Lund University, Lund, Sweden.2003.

Assaleh K, Al-Nashash H. A Novel Technique for the Extraction of Fetal ECG Using Polynomial Networks. IEEE Trans Biomed Eng. 2005 ; 52: 1148-1152.

Assaleh K. Extraction of fetal electrocardiogram using adaptive neuro-fuzzy inference systems. IEEE Transactions in Biomedical Engineering. 2007 ;54 :59-68.

Azad KAK. Fetal QRS complex detection from abdominal ECG: a fuzzy approach. Proceedings of IEEE Nordic Signal Processing Symposium. Kolmarden, Sweden 2000;275–278.

Barros AK. Extracting the fetal heart rate variability using a frequency tracking algorithm. Neurocomputing. 2002 ;49:279–288.

Barros AK, Cichocki A. Extraction of specific signals with temporal structure. Neural Comput. MIT Press Cambridge.2001;13:1995-2003.

Bassil HE, Dripps JH. Real time processing and analysis of fetal phonocardiographic signals. Clin Phys Physiol Meas.1989; 10:67–74.

Bergveld P, Arjan JK, Peuscher JHJ. Real-time fetal ECG Recording. IEEE Trans Biomed Eng BME.1986 ;33:505– 509.

Burghoff M, Van Leeuwen P. Separation of fetal and maternal magnetocardiographic signals in twin pregnancy using independent component analysis (ICA).Neurol Clin Neurophysiol.2004;1-4.

Callaerts D, Moor B, Vandewalle J, Sansen W. Comparison of SVD methods to extract the fetal electrocardiogram from coetaneous electrode signals. Med. Biol. Eng.Comput.1990; 28:217–224.

Camps G, Martinez M, Sofia E.Fetal ECG Extraction using an FIR Neural Network. IEEE,Computers in Cardiology. Computer Society Press.2001: 249-252.

Camps-Valls G, Martinez-Sober M, Soria-Olivas, Guerrero-Martinez J, Calpe-Maravilla J. Foetal ECG recovery using dynamic neural networks. Artificial Intelligence in Medicine. 2004;31: 197-209.

Chareonsak C, Farook S, Yu, W. et al. Design of FPGA hardware for a real-time blind source separation of fetal ECG signals, Biomedical Circuits and Systems. IEEE International Workshop on Biomedical Circuits and Systems.Singapore.2004; 13–16.

Charoensak C, Sattar F. Design of low-cost FPGA hardware for real-time ICA-based blind source separation algorithm. EURASIP Journal on Applied Signal Processing.2005; 3076–3086.

Chen P. Fetal heart monitoring. Department of Obstetrics & Gynecology, University of Pennsylvania Medical Center.2004. http://pennhealth.com/ency/article/003405.htm.

Crowe JA, Herbert JM, Huang XB, Reed N. Sequential recording of the abdominal fetal electrocardiogram and magnetocardiogram. Physiol Meas.1995;16:43–47.

Datian Y, Xuemei O. Application of wavelet analysis in detection of fetal ECG. Engineering in Medicine and Biology Society. Proceedings of the 18th Annual International Conference of the IEEE. Amsterdam. Netherlands.1996;3:1043–1044.

Daubechies I. Ten Lectures on Wavelets, Society for industrial and applied mathematics. 1992.

De Moor BLR (ed.), Daisy: Database for the Identification of Systems. Department of Electrical Engineering, ESAT/SISTA, K.U. Leuven, Belgium 2005.[Used dataset:Cutaneous potential recordings of a pregnant woman, section Biomedical Systems, code [96-012]] [Online]www.esat.kuleuven.ac.be/sista/daisy

Deam A. The use of foetal electrocardiogram. American Journal of Obstetrics and Gynecology.1994; 101: 9-17.

Devedeux D, Marque C, Mansour S, Germain G, Duchene J. Uterine electromyography: a critical review. Am J Obstet Gynecol. 1993; 169(6): 1636–1653.

Echeverria JC, Ramirez N, Pimentel AB. et al. Fetal QRS extraction based on waveleton analysis and pattern matching. Engineering in medicine and biology society. Proceedings of the 18th Annual International Conference of the IEEE. Amsterdam. Netherlands.1996 ; 4: 1656–1657.

Emmanuel, Ifeachor C, Barrie W Jervis. Digital Signal Processing – A pratical approach. Pearson Education Asia 2nd Edn. 2002.

Ferrara E, Widrow B. Fetal electrocardiogram enhancement by time-sequenced adaptive filter.IEEE Trans. on Biomedical Engineering.1982; 29(6): 458-460.

Ferrara ER, Widrow B. Multichannel adaptive filtering for signal enhancement. IEEE Trans Acoust. Speech, Signal Processing. June 1981;29:766-770.

Friesen GM. *et al*. A Comparison of the Noise Sensitivity of Nine QRS Detection Algorithms IEEE Trans. Biomed. Engineering.1990; 37: 85–98.

Fukushima T, Flores CA, Hon EH, Davidson EC . Limitations of autocorrelation in fetal heart rate monitoring. Am J Obstet Gynecol. 1985; 153(6):685-92.

Georgoulas GG, Stylios CD, Nokas G. et al. Classification of fetal heart rate during labour using hidden Markov models. IEEE International Joint Conference on Neural Networks. Budapest, Hungary.2004; 3:2471–2475.

Glover J. Adaptive noise cancelling applied to sinusoidal interferences, IEEE Trans. Acoust. Speech, Signal Processing. Dec. 1977;25:484-491.

Golbach EGM, Stinstra JG, Grot P, et al. Reference values for fetal MCG/ECG recordings in uncomplicated pregnancies. Proceedings 12th International Conference on Biomagnetism. Espoo. Finland. 2000; 595–598.

Goldberger AL, Goldberger E. Clinical electrocardiography, a simplified approach. Missouri: Mosby, 1994.

Hamilton PS. A comparison of adaptive and nonadaptive filters for reduction of power line interference in the ECG, IEEE Trans. Biomed. Eng.1996; 43 (1) : 105–109.

Haykin S. Adaptive Filter Theory (4th edition). Englewood Cliffs,N.J: Prentice Hall, Inc. 2002.

Hild KE, Erdogmus DE, Principe J. Blind source separation using Renyi's mutual information. IEEE Signal Process Lett.2001; 8:174–176.

Hornberger LK, Sahn DJ. Rhythm abnormalities of the fetus Heart.2007; 93(10):1294–1300.

Horner S, Holls W, Crilly PB. Non-invasive fetal electrocardiograph enhancement. Proceedings of Computers in Cardiology. Durham, NC, USA.1992;163–166.

Ibahimy MI, Ahmed F, Mohd Ali MA, Zahedi E. Real time signal processing for fetal heart rate monitoring. IEEE Med. Biol. Eng. Comput.2003 ; 50(2):258–262.

Ihara Z, Van Oosterom A, Hoekema R. Atrial repolarization as observable during the PQ interval. J Electrocardiol.2006; 39: 290–297.

Jana L. Early Fetal Heart Development: 0-9 Weeks, the Dr. Spock Company, 2004. [Online] http://www.drspock.com/article/0,1510,5287,00.html

Jang JSR, Gulley N.The fuzzy logic toolbox for use with MATLAB, MA: The MathWorks Inc. 1995.

Jang JSR, Sun CT, Mizuatani E.Neuro-fuzzy and soft computing. Prentice Hall International Inc. 1997.

Jang JSR. ANFIS: Adaptive-network-based fuzzy inference systems. IEEE Transactions on Systems.Man and Cybernetic. 1993; 23(3):665-685.

Kam A, Cohen A. Detection of fetal ECG with IIR adaptive filtering and genetic algorithms. IEEE International Conference on Acoustics, Speech, and Signal Processing.1999 ; 4:2335–2338.

Kam A, Cohen A. Maternal ECG elimination and Foetal ECG Detection -Comparison of Several Algorithms, Proceedings of the 20th Annual International Conference IEEE EMBS, Hong Kong. 1998;1:174-177.

Kanjilal PP, Palit S, Saha G. Fetal ECG extraction from single-channel maternal ECG using singular value decomposition. IEEE Trans Biomed Eng.1997; 44:51–59.

Karvounis EC, Papaloukas C, Fotiadis DI. Fetal heart rate extraction from composite maternal ECG using complex continuous wavelet transforms Comput.Cardiol. 2004;31: 737–740.

Karvounis EC, Tsipouras MG, Fotiadis DI. An automated methodology for fetal heart rate extraction from the abdominal electrocardiogram. IEEE Trans Inf Technol Biomed.2007; 11:628–638.

Karvounis EC, Tsipouras MG, Fotiadis DI. et al. A method for fetal heart rate extraction based on time-frequency analysis. 19th IEEE Symposium on Computer-Based Medical Systems. Salt Lake City, UT, USA.2006;347–347.

Khamene A, Negahdaripour S. A New Method for the Extraction of Fetal ECG from the Composite Abdominal Signal. IEEE Med Biol Eng Comput. 2000; 47(4):507-16.

Khandpur RS. Handbook of Biomedical Instrumentation. Tata Mc.Graw-Hill Publishing Company limited.2002.

Kohler BU, Hennig C, Orglmeister R. The Principles of Software QRS Detection. IEEE Engineering in Med. And Biol.2002;21:42-57.

Kotas M. Projective filtering of time aligned beats for foetal ECG extraction. Bulletin of the Polish Academy of Sciences Technical Sciences.2007; 55(4):331–339.

Laguna P, Jane R, Caminal P. Adaptive filtering of ECG baseline wander. proc. Ann.Int.conf IEEE EMBS. 1992; 2:508-9.

Lai KC, Shynk JJ. A signal separation algorithm for fetal heart-rate estimation. Signals, 34th Asilomar Conf. on Signals,Systems and Computers .2000;1:348-351.

Laim KC, Shynk JJ. A successive cancellation algorithm for fetal heart-rate estimation using an intrauterine ECG signal. IEEE Trans Biomed Eng.2002; 49:943–954.

Lathauwer LD,Moor BD,Vandewalle J.Fetal lectrocardiogram Extraction by Blind Source Subspace Separation. IEEE Trans Biomed Eng. 2000 ;. 47: 567-572.

Lawrence CD. Fetal Heart Development, 1995. [Online]. Available: http://user.gru.net/ clawrence/vccl/chpt1/embryo.html.

Lee J, Park KL, Lee KJ. A new over-determined BSS based algorithm for a single channel wearable fetal heart rate monitoring system. Proceedings of the Conference the Japan Society of Medical Electronics&Biomedical Engineering. Japan.2005;44:685–686.

Lewis MJ. Review of Electromagnetic Source Investigations of the Fetal Heart.Med. Engineering & Phys. 2003 ;25: 801–810.

Liszka-Hackzell JJ. Categorization of fetal heart rate patterns using neural networks. Computers in Cardiology.1994; 25:97–100.

Longini R, Reichert T, Cho J, Crowley J. Near orthogonal basis functions: a real time fetal ECG technique. IEEE Trans. Biomed. Eng.1997 ;24:.29–43.

Magalhaes F, Marques de Sa JP, Bernardes J. et al. Characterization of fetal heart rate irregularity using approximate entropy and wavelet filtering. Comput Cardiol Valencia, Spain.2006; 33:933−996.

Magann EF. Bass JD, Chauhan SP, Young RA, Whitworth NS. Morrison JC. Amniotic fluid volume in normal singleton pregnancies.Obstet Gynecol.1997; 90(4): 524–528.

Magenes G, Signorini MG, Arduini D. Detection of normal and pathological fetal states by means of neural and fuzzy classifiers applied to CTG parameters. 21st Annual Conference and the 1999 Annual Fall Meeting of the Biomedical Engineering Soc. Atlanta,GA, USA.1999; 2: 936–946.

Maha Shadaydeh, Yegui Xiao, Rabab Kriedieh Ward. Extraction of fetal ECG using adaptive volterra filters. 16th European Signal Processing Conference. Lausanne, Switzerland, 2008.

Mahmoodabadi1 SZ, Ahmadian1 A, Abolhasani MD. ECG feature extraction using Daubechies wavelets. Proc.of 5th Int.Conf of Visualization, Imaging and Image Processing.Benidom.Spain. 2005: 343-348.

Mallat S, Hwang WL. Singularity detection and processing with wavelets.IEEE Trans Inform Theory.1992. 38:617–643.

Mallat S. A Wavelet tour of signal processing. Academic Press. 1998.

Mallat SG. A theory for multiresolution signal decomposition: the wavelet representation. IEEE Trans Pattern Anal Mach Intell.1989; 1:674–693.

Marcelino Martinez Sober and Jorge Granado Marco.Non-invasive fetal electrocardiogram.database.http://www.physionet.org/physiobank/database/nifecgdb/.1997.

Maria P, John C, Jean-Francois P. et al. Monitoring the fetal heart noninvasively: a review of methods. J Perinat Med.2001; 29:408–416.

Marossero DE, Erdogmus D, Euliano N. et al. Independent components analysis for fetal electrocardiogram extraction: a case for the data efficient mermaid algorithm. Neural Networks for Signal Processing. IEEE 13th Workshop.Toulouse,France.2003; 399–408.

Marques de Sa JP, Reis LP, Lau JN. et al. Estimation and classification of fetal heart rate baselines using artificial neural networks. Comput Cardiol. Bethesda,Maryland, USA. 1994; 541–544.

Martens SMM, Mischi M, Oei SG, Bergmans JWM. An improved adaptive power line interference canceller for electrocardiography.IEEE Trans. Biomed. Eng. 2006 ; 53(11): 2220–2231.

Martinez M, Soria E, Calpe J. et al. Application of the adaptive impulse correlated filter for recovering fetal electrocardiogram. Comput Cardiol.1997; 24:9–12.

Mazzeo JR. Non invasive fetal electrocardiography. Med. Prog. Technol.1994; 20: 75-79.

Minino AM, Heron M P, Murphy SL ,Kochanek KD. Deaths: Final data for National Vital Statistics Reports. 2007; 55(19):235-238.

Mochimaru F, Fujimoto Y. Detecting the fetal electrocardiogram by wavelet theory-based methods. Progress in Biomedical Research.2002 ; 7(3):185–193.

Mooney DM, Grooome LJ, Bentz LS. et al. Computer algorithm for adaptive extraction of fetal cardiac electrical signal. Proceedings of ACM Symposium on Applied Computing. Nashville, Tennessee, USA. 1995; 113–117.

Najafabadi FS, Zahedi E, Ali MAM. A novel model for abdominal electrocardiography of a pregnant woman. Sensors and the international conference on new techniques in pharmaceutical and biomedical research KualaLumpur, Malaysia.2005; 64–68.

Najumnissa D, Shenbaga Devi S. Intelligent identification and classification of epileptic seizures using wavelet transform.Int. J. Biomedical Engineering and Technology. 2008;1(3):293–314.

Noguchi Y, Mamune H, Sugimoto S,Yoshida J. Measurement characteristics of the ultrasound heart rate monitor. Engineering in medicine and biology society. Proceedings of the 16th annual international conference of the IEEE. 1994; 1: 670–671.

Onaral B, Sun HH, Schwan HP. Electrical properties of bioelectrodes. IEEE Trans Biomed Engg. 1984; 31:827-32.

Oostendorp T, van Oosterom A, Jongsma H. Electrical properties of tissues involved in the conduction of fetal ECG. Biomed Eng Comput.1989; 27: 322–324.

Osei EK, Faulkner K. Fetal position and size data for dose estimation.Br J Radiol.1999; 72(856):363–370.

Pajkrt E, Weisz B, Firth HV, Chitty LS.Fetal cardiac anomalies and genetic syndromes. Prenat Diagn. 2004; 24(13):1104–1115.

Pan Jaipu, Tompkins, Wills J. A real time QRS Detection Algorithm. IEEE Transactions on Biomedical engineering.1985;32(3):230-236.

Papadimitriou S, Gatzounas D, Papadopoulos V. et al. Fetal heart rate signal denoising by processing the wavelet transform modulus maxima. Engineering in Medicine and Biology Society, Proceedings of the 18th Annual International Conference of the IEEE. Amsterdam. Netherlands.1996 ;3: 1029–1030.

Paraschiv-Ionescu A, Jutten C, Aminian K, Najafi B, Robert Ph. Source separation in strong noisy mixtures, a study of wavelet de-noising pre-processing, Proceed. Of ICASSP, Orlando. 2002.

Peters C, Vullings R, Bergmans J. et al. Heart rate detection in low amplitude non-invasive fetal ECG recordings. 28th Annual International Conference of the IEEE EMBS. New York. USA. 2006; 6092–6094.

Peters M, Crowe J, Pieri JF, Quartero H, Hayes Gill B, James D, Stinstra J, Shakespeare S. Monitoring the fetal ECG throughout gestation. Clin.phys.physiol.Measu. 2001; 10:11-20.

Peters M, Crowe J, Pieri JF, Quartero H, Hayes-Gill B, James D, Stinstra J, Shakespeare S. Monitoring the fetal heart non-invasively: a review of methods. J. Perinat. Med.2001;29: 408–416.

Pieri JF, Crowe JA. Hayes-Gill BR. et al. Compact long-term recorder for the transabdominal foetal and maternal electrocardiogram. Med Biol Eng Comput.2001; 39:118–125.

Pimentel BS, de Avila Valgas Filho JH, Campos RL. et al. A FPGA implementation of a DCT-based digital electrocardiographic signal compression device. 14th symposium integrated circuits and systems design. Pirenopolis.Brazil.2001;44–49.

Ping G, Ee-Chien C, Wyse L. Blind separation of fetal ECG from single mixture using SVD and ICA. 4th International Conference on Information, Communications & Signal Processing and 4th Pacific-Rim Conference on Multimedia (ICICS-PCM 2003). Singapore.2003; 3:1418–1422.

Reaz MBI, Wei LS. Adaptive linear neural network filter for fetal ECG extraction. Proceedings of international conference on intelligent sensing and information processing. Chennai. India.2004; 321–324.

Richter M, Schreiber T, Kaplan DT. Fetal ECG Extraction with Nonlinear State-Space Projections. IEEE Trans. on Biomed. Engineering.1998 ;45 :133–137.

Selvan S, Srinivasan R. A novel adaptive filtering technique for the processing of abdominal fetal electrocardiogram using neural network. Adaptive systems for signal processing, communications and control symposium 2000. Louise, Alta,Canada.2000; 289–292.

Signorini MG, Magenes G, Cerutti S, Arduini D. Linear and nonlinear parameters for the analysis of fetal heart rate signal from cardiotocographic recordings.IEEE Trans Biomed Eng.2003; 50(3): 365–374.

Snowden S, Simpson NA, Walker JJ. A digital system for recording the electrical activity of the uterus. Physiol Meas.2001; 22(4): 673–679.

Solum T, Ingemarsson I, Nygren A. The accuracy of abdominal ECG for fetal electronic monitoring. J Perinat Med.1980; 8:142–149.

Song Y, Xie W, Chen JF. et al. Passive acoustic maternal abdominal fetal heart rate monitoring using wavelet transform. Comput Cardiol.2006; 581–584.

Stinstra J. Reliability of the fetal magnetocardiogram. Ph.D. dissertation, University of Twente,Enschede, The Netherlands,2001.[Online] http://doc.utwente.nl/35964.

Stoughton JW, Weber GN, Pretlow RA. Fetal heart rate estimation via adaptive least mean square linear prediction methods. Proc IEEE Southeastcon. New Orleans, LA, USA.1990 ;1:260–264.

Sundstrom AK, Rosen D, Rosen KG. Fetal Surveillance. Molndal:Neoventa Medical AB. 2005.

Swarnalatha R, Prasad DV. A New Method of Extraction of FECG from Abdominal Signal. ICBME Proceeding, Springer Berlin Heidelberg.Singapore. 2008;98–100.

Swarnalatha R, Prasad DV. A New Method to Detect Subtle Changes in ECG. Proc. of the 3rd WACBE World Congress on Bioengineering. Bangkok, Thailand. 2007; 1-4.

Swarnalatha R, Prasad DV. A Novel Technique for Extraction of FECG using Multi Stage Adaptive Filtering. Journal of Applied Science.2010; 4:319-324.

Symonds EM, Sahota D , Chang A. Fetal Electrocardiography , London ,UK; Imperial College Press.2001.

Takagi T, Sugeno M. Fuzzy identification of systems and its application to modeling and control. IEEE Trans Syst Man Cybern. 1985;15:116-132.

Tal Y, Akselrod S. Fetal heart rate detection by a special transformation method. Proceddings of Computers in Cardiology.1989; 275–278.

Taylor MJO. *et al.* Non-Invasive Fetal Electrocardiography in Singleton and Multiple Pregnancies. Inter. J. Obstet. and Gynaecol. 2003;110 : 668–678.

Ungureanu M, Bergmans JWM, Mischi M. et al. Improved method for fetal heart rate monitoring. 27th annual international conference of the engineering in medicine and biology society, IEEE-EMBS, Shanghai, China.2005; 5916–5919.

Van Leeuwen P, Lange S, Klein A, Geue D, Gronemeyer DH. Dependency of magnetocardiographically determined fetal cardiac time intervals on gestational age, gender and postnatal biometrics in healthy pregnancies. BMC Pregnancy Childbirth.2004;4(6).

Vasios G, Prentza A, Hintipas E. et al. Investigating the effect of oxygen saturation on very low frequency periodic components of the fetal heart rate during labor using matching pursuits. Proceedings of the 25th Annual International Conference of the IEEE in Engineering in Medicine and Biology Society. Cancun. Mexico.2003;3: 2566– 2569.

Vesal badee, Adrian DC, Chan, Richard M. Dansereau.Fetal ECG extraction using triggered adaptive noise cancellation. 29th Conf.of the Canadian Med Biol Eng Soc.Canada. 2006.

Vigneron V, Paraschiv-Ionescu A, Azancot A. et al. Fetal electrocardiogram extraction based on non-stationary ICA and wavelet denoising, proceedings. 7th International Symposium on Signal Processing and Its Applications.Paris.France.2003;2:69–72.

Vrins F, Jutten C, Verleysen M. Sensor array and electrode selection for non-invasive fetal electrocardiogram extraction by independent component analysis. Proceedings 5th International Conference.Granada, Spain.2004 ;1017–1024.

Vrins F, Vigneron V, Jutten C. et al. Abdominal electrodes analysis by statistical processing for fetal electrocardiogram extraction. Proceedings of the 2nd International Conference Biomedical Engineering. Innsbruck, Austria.2004 ; 244–229.

Warrick P, Hamilton E, Macieszczak M. Neural network based detection of fetal heart rate patterns. Proceedings of International Joint Conference on Neural Networks. Montreal. Canada.2005 ;4: 2400–2405.

Webster JG.Ed. Medical Instrumentation: Application and Design. 3rd ed. John Wiley & Sons,1998.

Widrow Bernard, Samuel D Stearns. Adaptive Signal Processing. Prentice Hall Inc,Upper Saddle River, NJ. 1985.

Widrow BJ, Glover JR, McCool JM, Kaunitz J, Williams CS, Hearn RH, Zeidler JR, Dong E, Goodlin RC. Adaptive noise cancelling: principles and applications. Proceedings of the IEEE.1975 ; 63:1692–1716.

Yanjun Zeng Shijin Liu Jianhua Zhang. Extraction of Fetal ECG Signal via Adaptive Noise cancellation Approach. 2nd International Conference on Bioinformatics and Biomedical Engineering.2008; 2270-2273.

Zaben A Al, Smadi A Al.Extraction of foetal ECG by combination of singular value decomposition and neuro fuzzy inference system. Phys. Med. Biol. 2006;51 :137-143.

Zarzoso V, Nandi AK, Bacharakis E. Maternal and fetal ECG separation using blind source separation methods. Journal of Mathematics Applied in Medicine and Biology.1997; 14(3): 207–225.

Zuckerwar A, Pretlow R, Stoughton J, BakerD. Development of a piezopolymer pressure sensor for a portable fetal heart rate monitor. IEEE Trans. Biomed. Eng. 1993;40 (9):963-969 .

List of Publications

International Journals

[1] Swarnalatha R, Prasad DV. Interference Cancellation in FECG using wavelet-Adaptive Filtering Technique. Journal of Engineering and Applied Sciences. 2009; 4(5-6): 353-357.

[2] Swarnalatha R, Prasad DV. A Novel Technique for Extraction of FECG using Multi Stage Adaptive Filtering. Journal of Applied Science. 2010; 10(4): 319-324.

[3] Swarnalatha R, Prasad DV. Maternal ECG Cancellation in Abdominal Signal using ANFIS and Wavelets. Journal of Applied Sciences. 2010; 10(11): 868-877.

[4] Swarnalatha R, Prasad DV. WAF Extraction Methods of Fetal Electrocardiogram. Int.Journal of Biomedical Engineering and Technology. (Accepted – in Press).

[5] Swarnalatha R, Prasad DV. Fetal ECG Extraction using Combination of Wavelet and Hybrid Algorithm based ANFIS. Int.Journal of Biomedical Engineering and Technology. (Accepted – in Press).

International Conferences

[6] Swarnalatha R, Prasad DV. A New Method to Detect Subtle Changes in ECG. Proc.of the 3rd WACBE World Congress on Bioengineering, Bangkok, Thailand, 2007.

[7] Swarnalatha R, Prasad DV. A New Method of Extraction of FECG from Abdominal Signal. ICBME Proceedings 23, Springer Berlin Heidelberg. Singapore. 2008; 98-100.

[8] Swarnalatha R, Prasad DV. Extraction of Fetal ECG from Abdominal Signal, Biosignals. Proceedings of the International Conference on Bio-inspired Systems and Signal Processing, Portugal. 2009; 245-248.

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