FETAL ECG SIGNAL ENHANCEMENT

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ABSTRACT

Fetal heart monitoring yields vital information about the fetus health and can support medical decision making in critical situations. A compound signal is obtained non-invasively by placing electrodes on the abdomen area of the mother which contains maternal and fetal ECG signals contaminated by various other signals from body and externally induced noises. The Polynomial Networks technique has been exploited to isolate fetal electrocardiogram (FECG) from the undesired mapped maternal electrocardiogram (mapped MECG). Wavelet transform has been used as a post processing tool to de-noise the extracted FECG. This thesis addresses the enhancements achievable by the application of wavelet transform to FECG signals extracted by polynomial networks. Processing of both real and synthetic ECG data have been examined with proposed pre and post wavelet de-noising algorithms. Test results show improved extraction performance and successful removal of baseline wandering. Numerical results on signal-to-noise ratio for synthetic data are presented and results

compared with various configurations of processing blocks. The characteristics of the FECG signal were shown to be preserved and a relatively clean FECG signal is obtained.

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ABBREVIATIONS

AHA- American Heart Association

ANFIS- Adaptive Neuro-Fuzzy Inference System

BSS- Blind Source Separation

CWD- Choi-Williams Distribution

CWT- Continuous Wavelet Transform

DWT- Discrete Wavelet Transform

ECG- Electrocardiography

EMG- Maternal Electromyogram

FECG- Fetal Electrocardiography

FHR- Fetal Heart Rate

fmSNR- Fetal to Maternal Signal to Noise Ratio

ICA- Independent Component Analysis

i.i.d- Independent and Identically Distributed

LP- Linear Prediction

MECG- Maternal Electrocardiography

MHR- Maternal Heart Rate

MRA- Multi-Resolution Analysis

MW- Mother Wavelet

NLMS- Normalized Mean Squares

qSNR- Extracted Fetal to Original Fetal Signal to Noise Ratio

SNR- Signal to Noise Ratio

STFT- Short Time Fourier Transform

SVD- Singular Value Decomposition

WVT- Winger-Ville Transform

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Chapter 1

Introduction

1.1. Background

Just as it is essential to monitor adult heart condition, it is often necessary to monitor the fetal heart activity during pregnancy and at childbirth. This monitoring is called electrocardiography which demonstrates the electrical activity of the heart; and in the case of fetus, it is called fetal electrocardiography (FECG). Fetal electrocardiography provides information in both fetal heart rate and fetal heart condition. A typical ECG signal is shown in figure 1. It consists of three waveforms, P-wave, QRS-complex and T-wave. In chapter 2 the components of this signal are described in details. Most of the clinically useful information in the FECG signal is found in the amplitude and duration of its waveforms [1]. Fetus cardiac waveform helps physicians to diagnose fetal heart arrhythmia such as Bradycardia, Tachycardia, Congenital heart disease, Asphyxia and Hypoxia. Approximately the number of fetal heart rate ranges is from 120bpm to 160bpm. In the case of Bradycardia, the fetus' heart rate reduces and goes below 120bpm; and in Tachycardia, this rate increases and goes from 161bpm to 180bpm [2]. The configuration of ST-segment and T-wave provide information about fetal cardiovascular adaptation to experimental hypoxia and as an adjacent to standard FHR monitoring during labour [2]. Changes in the duration of PR and RR intervals present clinically useful information about deceleration, Bradycardia and experimental Hypoxia [2]. The QT interval on the FECG signal could provide information on physiology of the fetal myocardium and may provide additional information on the fetal myocardial adaptation to the ultimate stress of labour [2].

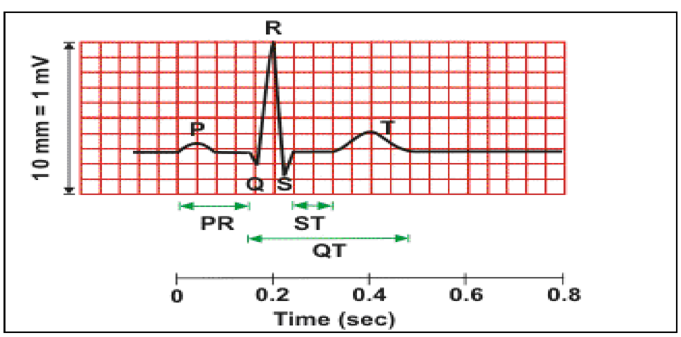

Figure 1. A Typical ECG Signal [3]

In brief changes in PR and PQ intervals, P-wave, T-wave and ST-segment, and also in the width of QRS-complex have been associated with the level of oxygenation. Lack of oxygen for a long period; results in brain injuries for human. In the case of fetus, it may result in permanent damage to the fetus' brain and nervous systems, so early diagnosis helps physicians to have an effective and appropriate intervention.

There are two methods of obtaining fetal ECG. The first one is obtaining FECG non-invasively by placing electrodes on the abdomen surface region of a pregnant woman, and the second one is invasive; that is, by placing electrodes inside the uterus of the mother on the scalp of the fetus during labour. Invasive extraction of fetal ECG is more accurate because of the recording electrode placed on the fetus' scalp but it can be done just during delivery. The non-invasive method is a promising one which can be used in all gestation weeks and also during delivery process, but there are some difficulties in this method. Since in non-invasive method the recording electrodes are placed on the abdomen region of the pregnant woman, they record both maternal electrocardiogram (MECG) and the fetal electrocardiogram (FECG), also in this case it may contain a relatively large amount of noise. The main sources of possible noise in the field of extraction of fetal ECG include the maternal electromyogram (EMG) which has a wide frequency range, 50Hz power line interference, baseline wander and random electronic noise. Recent literatures indicate that several methods have been proposed for extracting fetal ECG from composite abdominal signal. Basically, the fetal ECG extraction from composite abdominal recording which contains both maternal ECG and fetal ECG and also contaminates by noise, is carried out by subtracting the MECG from composite signal and later on obtaining some de-noising techniques to improve the extracted fetal ECG and achieve relatively clean fetal ECG signal. In the following, some of these techniques are reviewed.

V. Zarzoso, J. Millet-Roig and AK. Nandi [4] studied two methods of FECG extraction, blind source separation (BSS), and Widrow's multi-reference adaptive noise cancellation (MRANC). They applied both techniques in real data and observed that the performance of MRANC method depends on the electrodes placement while BSS is robust with respect to the electrode placement and number, also BSS method appears cleaner with respect to noise and residual MECG. Over all, they showed that BSS method has better performance in the problem of FECG extraction from maternal cutaneous recording rather than ANC.

L. De Lathauwer. B. De Moor and J. Vandewalle [5] proposed Blind Source Subspace Separation (BSSS) method. This method is similar to Independent Component Analysis (ICA) which is also known as blind source separation (BSS). The difference is, in BSSS the sources are of a multidimensional nature and it can be said it is a somehow improved version of BSS. They examined their method in real data even in the case of twins successfully. They also compared their results with Singular Value Decomposition (SVD-based methods) and concluded the BSSS method is more powerful for ECG source separation rather than SVD-based method. In some cases the extracted fetal ECG signal using BSSS method has higher signal-to-noise ratio compare to the extracted result using SVD-based method.

A. Khamene and S. Negahdaripour [6] developed a wavelet transform-based method to extract the fetal electrocardiogram (ECG) from the composite abdominal signal. In this method singularities in abdominal signal are detected by modulus maxima in wavelet domain. The location of modulus maxima in wavelet domain are calculated by finding the maxima of wavelet coefficient absolute value and by using modulas maxima of mother ECG which is extracted from thoracic signals those belonging to the fetal signal are identified. At the end fetal ECG is reconstructed from its modulus maxima. The presented method is examined in two different approaches. In the first approach, they were needed to consider a minimum of two signals, one from the abdomen and the other one from the chest; and for the second, just one from abdominal signal. The result in both synthetic and real data presented good detection of singular points locations and good FECG extraction although the amplitude of the extracted FECG is not quite accurate. This method is a good candidate for fetal heart rate (FHR) detection.

K. V. K. Ananthanag and J. S. Sahambi [1] studied the extraction of fetal ECG signal with Blind Source Separation technique. According to this technique, extracting FECG is accomplished by estimation of independent sources of fetal and maternal cardiac activity. In this article, four major algorithms of BSS (Bell and Sejnowski's infomax algorithm, Cardoso's joint approximate diagonalization of eigen matrices (JADE) algorithm, fixed point algorithm and Comon's algorithm), all used for FECG extraction, are studied and compared. Two signals, one of which is made 5 or 10 times less in amplitude and the cycles are doubled to yield FECG and the other one AECG is mixed by a random matrix; and a random white Gaussian noise is added to them to simulate the observed signal in the electrodes. The four algorithms are exerted on the simulated signal to observe the ability of each in extracting FECG. As discussed in the paper, all of them were able to extract FECG if the input SNR was high, even if there is a possibility to add a third or fourth signal, such as adding noise to the simulated signal all four algorithms were able to separate signals and extract FECG although the first three algorithms gave better results. In the BSS technique, the accuracy of the FECG extraction depends on the number of electrodes, the more the number of electrodes, the more the accuracy; also by using high order statistic BSS method, extracting FECG will not be affected by the placement of electrodes.

M. I. Ibrahimy, F. Ahmed, M. A. Mohd Ali and E. Zahedi [7] developed an algorithm to determine fetal heart rate in real-time and for long-term monitoring with single lead configuration. A technique based on digital filtering, adaptive thresholding, statistical properties in the time domain, and differencing of local maxima and minima, is implemented on a low-power 8-bit microcontroller board to do so. The proposed technique was also compared to Doppler ultrasound fetal monitor. In Doppler ultrasound method, FHR is monitored by transmitting ultrasonic waves towards the fetal heart and calculating the delay between the transmitted waves and the reflected waves. Attempts are made to get better results for fetal heart rate with the proposed method rather than Doppler ultrasound method. Results show that although the presented method is less accurate than Doppler ultrasound, it is safer and can determine FHR and MHR in real-time.

K. T. Assaleh and H. A. Al-Nashash [8] presented polynomial networks technique for extraction of fetal electrocardiogram problem. In order to simplify the problem, they assumeed using low noise electronic amplifiers with high common mode rejection ratio and classical low pass filtering techniques to eliminate the 50Hz interference and to reduce EMG noise, respectively; hence, suppressing the maternal ECG to extract fetal ECG. Having access to thoracic and abdominal signals via two leads, polynomial networks provide nonlinear mapping between maternal ECG and the component of maternal ECG in the abdominal signal. In other words polynomial networks technique is used to align the maternal component of abdominal signal recorded at abdomen with the maternal ECG signal recorded at thorax. By aligning these two signals fetal ECG is extracted by subtracting the maternal ECG component from abdominal signal. The extraction technique is based on polynomial networks whereby a nonlinear mapping between maternal ECG signal and its component in abdominal signal is determined by minimizing the mean-squared error criterion. Extraction was accomplished well in both non-overlapping and overlapping of FECG and MECG signals using this proposed technique. The extraction results are visually compared to extraction results using ICA method which is the most common technique for fetal ECG extraction problem. The results are comparable however the polynomial networks technique is superior in that it just requires two leads for FECG extraction while ICA needs usually more leads.

B. Azzerboni, F. La Foresta, N. Mammone and F. C. Morabito [9] proposed Wavelet-ICA (WICA) method. In this technique wavelet transform and ICA method are used for fetal ECG extraction. They used the fact that wavelet decomposition projects each row data into an n-dimensional orthogonal basis. The extraction occurs with discrete six levels biorthogonal wavelet decomposition. Fetal ECG signals collected from abdomen area of mother's skin with multi- channel recordings, enter the discrete wavelet decomposition and from there the raw data are projected into the n-dimensional space. After that, the Fetal ECG related details are selected by visual inspection, and a new data-set X is built with them. This new data set is processed by extended-INFOMAX algorithm. The extended-INFOMAX is a learning rule which compute the demixing matrix. By this algorithm the independent components (ICs) are extracted and the IC accounting for FECG is selected. The proposed method is tested and compared to extraction based on non-stationary ICA and wavelet de-noising. For WICA method FHR was detected and the Q, R, and S waves are visible without any signal amplification. In the other method, the detected FHR is composed by some non-cardiac spikes; furthermore, the Q and S waves are not emphasized although the extracted signal is amplified in this method. The only problem with WICA is that P and T waves are not visible.

S. Almagro, MM. Elena, MJ. Bastiaans and JM. Quero [10] presented an algorithm to design a new mother wavelet (MW) called abdominal ECG mother wavelet (AECG MW) for extraction of fetal ECG. Unlike other MWs which are used in extraction of fetal ECG, this newly proposed MW is designed to have a shape similar to AECG. To design such an MW, at least eight Gaussians should be used to model the 4 peaks in QRST of MECG and 4 peaks in QRST of FECG. In the proposed experiment, It is mentioned that eight Gaussians are needed to synthesize the modeled normal MECG (mnMECG) and eight for the modeled normal FECG (mnFECG), so 16 Gaussians are needed to construct AECG MW, but in this paper, AECG MW is designed by using just eight Gaussians in modeling of mnMECG. This is possible because of similarity between FECG and MECG. Selecting just mnMECG to construct AECG reduces the quality of the model, but on the other hand, it reduces the processing time. The presented technique is tested on different scale levels, and it is shown in the paper that the AECG MW has good visual similarity up to scale level 3, also it is compared to existing MWs (scale level 3), and results show that existing MWs perform better than AECG MW. It is mentioned in the paper this performance could be because of just selecting eight Gaussians in modeling AECG, and performance can be improved by using the model of the mnMECG with more than 8 Gaussians, or model the AECG by using the superposition of the mnFECG and mnMECG.

A. Matonia, J. Jezewski, K. Horoba, A. Gacek and P. Labaj [11] presented a method for detection and suppression of maternal ECG. According to this method, FECG signal is extracted by determination of template maternal PQRST complex, and then subtraction of this complex from abdominal signal. It is assumed that abdominal signal is composed of three signals, maternal electrocardiogram, fetal electrocardiogram and interference noise, so if the PQRST complex is determined, subtraction of this complex results in having FECG signal with noise. This method of suppression is compared to two other suppression methods, weighted assumption of abdominal signals using Hildreth d'Esopo optimization algorithm (M1) and spatial filtration combined with singular value decomposition technique (M2). Four signals recorded from maternal abdomen are given to each method. The first method (M1) is just able to extract one FECG from each four-signal set; this is because of the high dependency of this method on the placement of electrodes in abdomen area. For the second method (M2) extraction is possible in some leads just in the case of having a large number of abdominal leads, but in this particular study with four leads, it is able to detect only one FECG signal. The method which is presented in this paper can extract FECG in every abdominal signal, but in this method the efficiency to remove noise signals is lower than the other two methods. Also the influence of MECG suppression in distortion of fetal QRS complex is higher than the other two methods.

R. Vullings, C. Peters, M. Mischi, G. Oei and J. Bergmans [12] used the extended version of linear prediction method to remove maternal ECG from non-invasive fetal ECG recording. In this paper, they introduced this new technique (SLP) and compared it with the former technique which is Linear Prediction method (LP) by calculating the least mean square error (rms error) between the resulting FECG signals and the actual FECG signal, while the amplitude of the FECG signal is kept constant. Results show that the rms error between the FECG signal obtained from the SLP method and the actual FECG signal is smaller than the one between actual FECG signal and the FECG signal obtained from the LP method. It means that the introduced method (SLP method) is capable of removing the MECG signals more than the former method (LP method), although if noise increases, the LP method has a better result than SLP method.

K. Assaleh [13] presented adaptive neuro-fuzzy inference system (ANFIS) for Fetal Electrocardiogram extraction. Two leads collect ECG signals at the thoracic and abdominal areas of mother's skin whereas the first signal is assumed to be completely maternal and the second one composite of mother's and fetus' ECG signal in the case of proper placement of the thoracic and abdominal electrodes. In this proposed paper, the ANFIS is used to nonlinearly align the maternal ECG signal with the components of maternal ECG in the abdominal ECG signal. Hence cancel the maternal components of abdominal ECG signal and finally extract the Fetal ECG signal. The algorithm is tested using synthetic and real ECG data and in both, good FECG extraction is achieved even in the case of full overlapping of maternal and fetal ECG signals. To assess and validate the proposed method, signal to noise ratio of the extracted FECG is compared with classic adaptive filtering method which is based on normalized mean squares (NLMS) and with polynomial-networks-based method. It is shown that in the range of -5dB to -30dB of fetal to maternal signal-to-noise ratio (fmSNR) the NLMS-based method has the poorest FECG extraction while the polynomial networks and ANFIS methods have the same result up to -10dB. For fmSNR higher than -10dB better extraction result is for ANFIS rather than polynomial networks technique. However the computational time for ANFIS extraction method is much higher than polynomial networks technique.

P. Bhatia, J. Boudy and R. V. Andreao [14] proposed a combination of mother wavelets for detecting different sub-parts of ECG beat signal (P, QRS complex and T waves). To do so, they presented and compared four mother wavelets (Morlet wavelet, Derivative of Gussian wavelets, Paul wavelet and B-Spline wavelet) which can be used in ECG sub-parts detection. They divided ECG signal to two parts: signal peaks (QRS complex) and oscillatory parts (P and T waves) then they selected specific wavelet to detect each part. It is mentioned that complex wavelets are suitable for detecting oscillatory signals while real valued wavelets are suitable in detecting signal peaks or discontinuities. They concluded although Gaussian first derivative is robust to noise, Mhat and Paul (4'th order) are the best wavelets for ECG signal detection and B-Spline or Paul-4 are suitable for P and T waves detection.

E Karvounis, C Papaloukas, DI Fotiadis and LK Michalis [15] presented a method to extract fetal heart rate from composite maternal ECG by using complex continuous wavelet transform. The extraction is done in four steps. In the first step, they averaged three recorded signals to make sure of having FECG in the processing abdominal signal. In second step, they detected maternal QRS complexes by wavelet and thresholding techniques. In the next steps, first they tried to find any fetal QRS complex between any two continuous maternal QRS complexes by thresholding method and then, using heuristic algorithm, they detected fetal QRS complexes which overlapped maternal ones. They tasted their algorithm using real ECG recordings and they got good results of fetal R peak detection.

S. Z. Mahmoodabadi, A. Ahmadian and M. D. Abolhasani [16] studied ECG feature extraction using Daubechies wavelets. They maintained that "the wavelet filter with scaling function more closely similar to the shape of the ECG signal achieved better detection" and " Daubechies wavelet family are similar in shape to QRS complex and their energy spectrum are concentrated around low frequencies." According to their job they compared db4 (Daubechies number four mother wavelet) and db6 wavelets and concluded better similarity of db6 in level five decomposition details, to the ECG signal. Using db6 wavelets and its eight level decomposition details, they followed four steps for ECG feature extraction. Keeping details from level three to level five they removed the rest low frequencies and high frequencies and detected R peaks, then removing all details before level five, and with the known time duration of QS interval which is 0.1, they detected QS. Finally, with zero level detection of signal also keeping details from level four to level eight and finding zero crossing of the signal before and after each R peak, P and T waves were detected. They concluded good feature detection performance by using D6 wavelet.

S. Kadambe, R. Murray and F. Boudreaux-Bartels [17] represented a way for detecting QRS complex based on dyadic wavelet transform (D_yWT). They designed a Spline wavelet for detecting QRS complex which is the transient part in the ECG signal. In their study, the detection process is based on "the property that the absolute value of D_yWT has localized maxima across several consecutive scales at the instant of the occurrence of transient." In this case, for each scale they found the local maxima of the absolute value of dyadic wavelet transform by using threshold method, then if in two consecutive scales the number of the peaks is the same and their location align within ± 25 neighboring samples, the position of each local maxima is considered to be the location of a QRS complex. They compute the heart rate by calculating the inverse of the time interval between two consecutive R waves. The algorithm was examined by using American Heart Association (AHA) data base and then the results were compared with detectors based on Okada, Hamilton-Tompkins and multiplication of the backward difference algorithms. It is concluded that the proposed algorithm is quite comparable with the other standard techniques. In addition, the D_yWT -based QRS detection algorithm has fewer number of missing QRS complexes compared to other algorithms.

D. Graupe, Y. Zong and M. H. Graupe [18] discussed the theoretical problems in non-invasive extraction of fetal ECG especially the problems with detecting P and T waves in FECG waveform by some well-known extraction methods such as averaging/ subtraction approach, ICA, undetermined ICA and Widrow's methods. They maintained that these methods are not precise in extraction problems in which the number of source signals exceeds the number of observations especially when the extraction signal has very low amplitude and it is surrounded by noise. For example, averaging/ subtraction method in which FECG is extracted by large number synchronized maternal heart beats and removing this average value from abdominal observation signal and finally extracting averaged FECG, cannot well present the temporal variations in RR, PR and QT duration. In ICA extraction method some theoretical ICA conditions are required; for instance, in this method, it is considered that the abdominal noise is negligible although this noise can be stronger than the abdominal recorded signal or it is considered that the recorded FECG signal are linearly related and the same consideration for recorded MECG which in reality is not true. These assumptions reduce the precision of extracted P and T waves and also the duration of intervals in the FECG signal. In udICA and Widrow's methods also some assumption affects the extraction result. In this article, the authors proposed Blind Adaptive Filtering (BAF) approach to overcome the problem of the above methods and achieve beat-wise extraction of fetal ECG. BAF approach which is a single channel extraction procedure extract FECG in two BAF stages. In the first stage, a feature is selected which is common in both MECG and FECG. It is considered that " any ECG frequency spectrum is in the form of comb spectrum, which is in terms of an array of narrow band-stop region, the first following a narrow pass band at the heart beat frequency f0, each having another fundamental frequency f0." Because of band-stop parts of the comb filters, any noise in between is removed in the first stage. The output of this stage is an array of signals in which the MECG and FECG can be observed. In the second stage, neural network is hired to distinguish FECG from MECG. They examined their algorithm and they compared the extracted R wave with Sonicaid extraction results. The result is almost the same. They also mentioned that the extracted PR and QT duration is comparable to those of averaged-ICA and averaging using magneto-cardiograph.

V. Vigneron, A. Paraschiv-Ionescu, A. Azancot, O. Siboney and C. Jutten [19] presented an algorithm based on non-stationary ICA and wavelet de-noising for fetal ECG extraction. In their paper they declared that according to low amplitude and poor signal to noise ratio (SNR) of the fetal ECG recorded at the abdominal region of a pregnant woman, the signal processing algorithm needs to remove the maternal ECG, reduce motion artifact and enhance extracted fetal ECG signal. To do so and because of non-stationary nature of the fetal ECG signal, they used non-stationary ICA method to eliminate maternal complex noise from the composite ECG signal recorded at abdomen, and then they used wavelet transform to remove baseline wander and enhance fetal ECG signal. In the first step of wavelet de-noising, biorthogonal wavelet decomposition-reconstruction is used. They presented that the most useful information of the signal is in the approximation components between scales 1 and 7, and they consider the 7-th scale component as fetal ECG baseline. They proposed that by removing the baseline by this method of de-noising only R-wave of fetal ECG will appear. Therefore they added a processing step consist of detecting R-wave and amplifying the PQRST, before wavelet de-noising stage. They examine their method on the real ECG signal and they conclude a clear detection of PQRST of fetal ECG signal.

As it is reviewed the most common technique for fetal ECG extraction is ICA method. In this technique FECG extraction is done by using several leads. FECG extracted by this method should identify visually.However there are two new methods, polynomial networks technique and ANFIS technique, which have similar results to ICA method and they just need two recording leads for fetal ECG extraction. In these two techniques one lead in thoracic region of mother and one in abdominal region are required. These two extraction techniques have similar extraction results however ANFIS method works better when signal-to-noise ratio of the fetal to maternal ECG signal (fmSNR) is low. Although ANFIS is superior in low fmSNR situation but it requires high computational time. Hence polynomial networks technique will be a good candidate for the problem of fetal ECG extraction as it needs just two recording leads and its computational time is much lower than the ANFIS technigue.

In this thesis attempt is made to understand the fetal ECG extraction using Polynomial networks methodology and enhance the extracted fetal ECG signal using wavelet de-noising algorithm.

1.2. Problem Statement

The goals of this thesis are as follows

- Understanding algorithm of fetal ECG signal extraction using Polynomial networks technique
- Modifying the FECG signal extraction algorithm in order to eliminate the baseline wander
- Enhancing the extracted fetal ECG using wavelet transform

The thesis is organized as follows: Chapter one contains the introductory part of this thesis and it is followed by some literature review and the problem statement. The second chapter gives an introduction to the heart, electrophysiology, electrocardiography (ECG) and fetal electrocardiography (FECG). The third chapter provides the methodology and describes the de-noising technique used in this work. In the fourth chapter, the available data sets are introduced and it provides a summary of achievements in enhancement of FECG with our method and data. The thesis concludes in chapter five with a summary of work done and some points for future research in this area.

Chapter 2

On Biology

In this chapter a brief description of different parts of the heart and its components of the conduction system which creates heart beats are introduced. This is followed by Electrocardiography (ECG); and in the case of fetus fetal Electrocardiography (FECG) introductions. The chapter closes with a brief history of fetal electrocardiography.

2.1. The Heart

The human heart is located in a position between the lungs with a little gradient to the left, Figure 2. It is composed of three main muscles; myocardium is the thickest one, endocardium which is lined inside the myocardium and epicarduim that is located on the outside of myocardium the atria and ventricles. The separating walls which divide the chambers are called septum. The upper septum which separates the ventricles is called interventricular septum and the lower one which separates the atria is called interatrial septum. On the other hand, the atrium and the ventricle in each side are divided by a septum. Heart works by pumping blood in two cycles. In the first cycle, the blood is pumped to the lungs for oxygenation by right ventricle through pulmonary circuit. In the second cycle, blood is pumped to the remainder of the body by the left ventricle through systemic circuit [20].

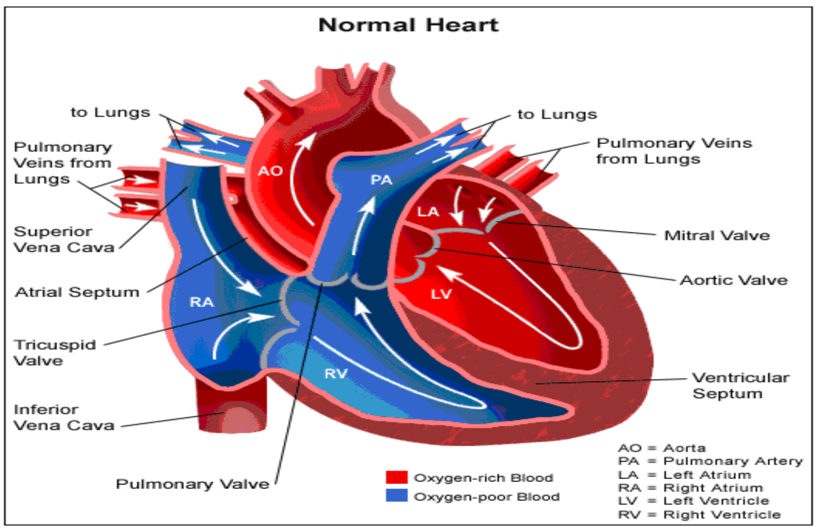

Figure 2. Normal Heart [21]

In Figure 3 the components of the conduction system of the heart are shown. The electrical signal generated by the S-A node (pacemaker which sets the rate of heartbeat) goes to both atria. This electricity causes the atria to contract and, results in pumping blood to the ventricles. When the electrical signal reaches the AV node, there is a pause in the conduction process to give time to ventricles to be filled with blood. When the electricity reaches the bundle of His, both ventricles contract and they push blood to the lungs and to the whole body [3].

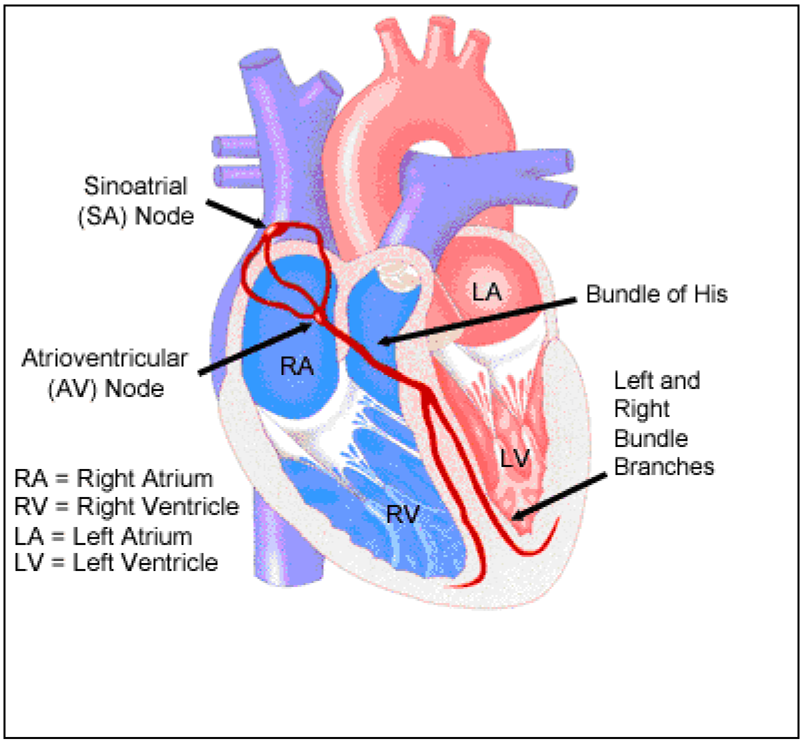

Figure 3. Components of Conduction System in Heart [22]

2.2. Electrocardiogram (ECG)

The generated electrical current through depolarization and repolarization of the heart can be measured by placing an array of electrodes on the body surface. The recorded signal is known as the electrocardiogram (ECG). Figure 4. shows a typical ECG signal. "The ECG is recorded at a speed of $25\,mm/\sec$, and the voltages are calibrated so that 1mV=10mm in the vertical direction [3]." As it is illustrated in Figure 4, ECG signal is composed of different waves each of which represents a particular activity of the heart (depolarization and repolarization of the atria or ventricles).

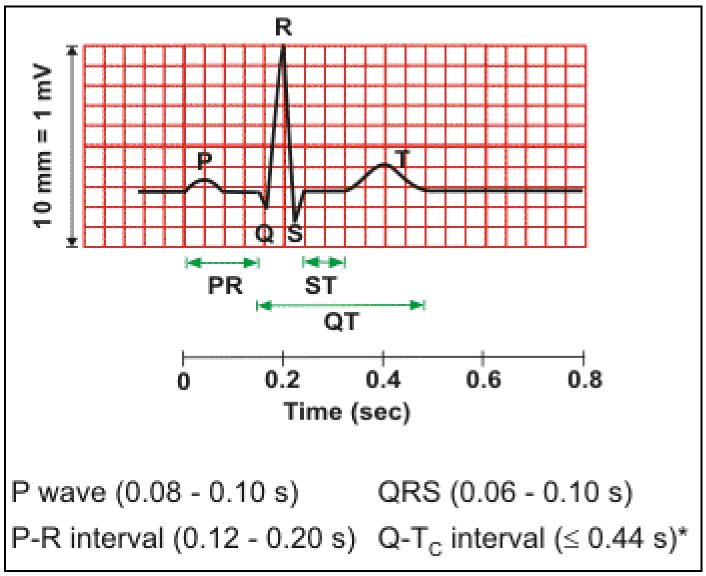

Figure 4. A Typical ECG Signal [3]

The P wave represents the atria depolarization and usually takes place 80-100ms. After the P wave, there is a small isoelectric (zero voltage) period. This brief period represents the traveling time of the impulse within the AV node and the bundle of His. The atrial rate is the time between two P waves. The P-R interval is the period between P wave and the beginning of the QRS complex. It represents the time between atrial depolarization and ventricle depolarization and it usually takes 120-200ms. The QRS complex represents the ventricular depolarization and its duration is from 60 to 100ms. The QRS complex shape is not unique and it changes by changing the place of recording position. Also in some cases, abnormal impulses within ventricles cause changes in the shape of QRS complex. Figure 5 shows some kinds of these QRS complexes.

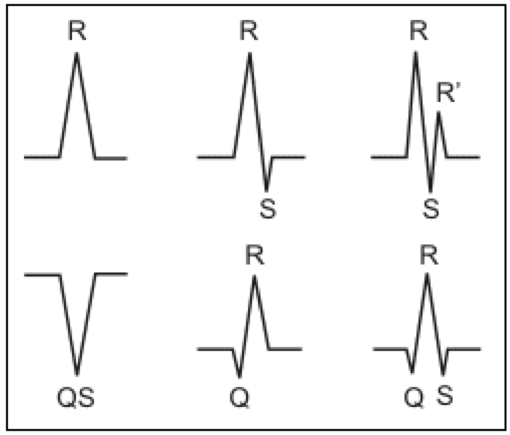

Figure 5. Different Components of the QRS Complex [3]

Following QRS complex is the next isoelectric period (the ST segment). In this period, the ventricle is depolarized entirely. In the case of ventricular ischemia or hypoxia this segment may be depressed or elevated. The T wave represents ventricular repolarization. The duration of the repolarization period is longer than that of depolarization period. In some cases, a small positive wave is followed by T wave which is the U wave (it is not shown in Figure 4) and it presents the last remnants of ventricular repolarization. The atrial repolarization doesn’t have a distinct wave in the ECG signal. It is because it occurs during ventricular depolarization, and as the ventricular depolarization generates a large QRS complex, it masks the atrial repolarization wave (low voltage wave) [3].

2.3. Fetal Electrocardiograms (FECG)

The fetal electrocardiogram (FECG) contains the same basic waveforms, the P wave, the QRS complex and the T wave, just like the adult ECG. Its PR interval indicates conduction time in the AV node and its QRS complex reflects ventricular depolarization. The fetal electrocardiogram represents the fetus heart condition by FECG waveforms. In this case, any specific abnormalities or malfunctions in fetal heart can be observed by FECG signal.   The first documented recording of a fetal heart signal was performed by Cremer in 1906. In the next 50 years, many works were done to improve the resolution of the fetal QRS complex and to calculate the fetal heart rate (FHR) such as improving the amplification methods and electrodes placement in abdomen area although all these efforts caused elimination of the P and T waves in the extracted FECG signal. In 1950 the intrauterine electrodes (electrodes which are connected to the baby's scalp via child birth canal during labour) was introduced. By that time, using intrauterine electrodes and some improvement in filtering techniques, technicians obtained P and T waves which helped physicians to diagnose the oxygen saturation and bradycardia of the fetus. From then on many efforts have been made to improve the fetal ECG signal which is directly recorded from the scalp of the baby during child birth. Recent works mostly focus on extracting fetal electrocardiogram non-invasively rather than via child birth channel. Many methods of non-invasive extraction of FECG and different techniques for improving the extracted QRS complex, P and T waveforms have been presented since then. In this work we use polynomial networks for extracting fetal ECG signal [8] and we try to enhance fetal ECG signal using wavelet de-noising. In Figure 6 a real abdominal ECG signal is illustrated. Using polynomial networks technique the maternal component of the abdominal signal is removed and fetal ECG signal is extracted [8], Figure 7. In this work attempt is made to enhance the extracted fetal ECG signal using wavelet de-noising technique.

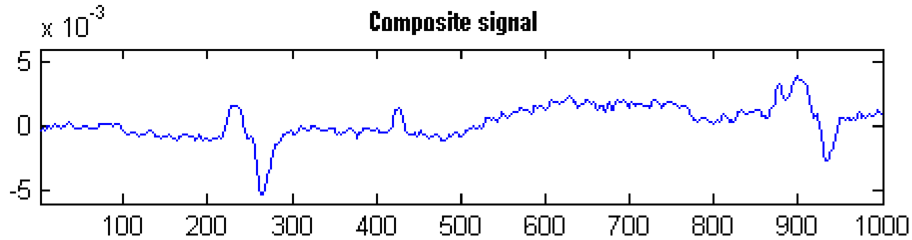

Figure 6. Real Abdominal Signal

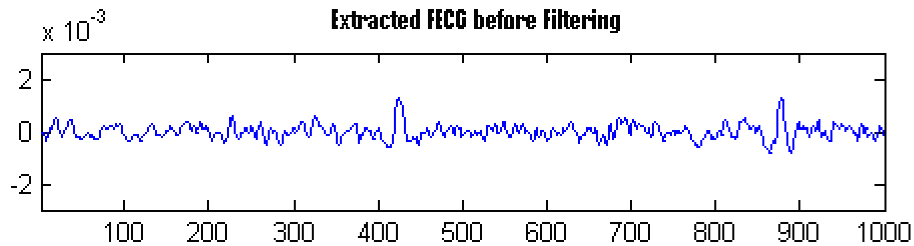

Figure 7. Real Extracted Fetal ECG Signal

Chapter 3

Methodology

In this chapter, the polynomial networks technique in extracting fetal ECG signal from composite abdominal signal is described. Introductions to the wavelet transform and some families of mother wavelets are added and at the end the procedure of enhancing fetal ECG is presented.

3.1. The Polynomial Networks Technique in FECG Extraction

In the field of fetal ECG extraction, polynomial networks technique is one of the recent and promising techniques which gives good extraction results. In this method, using just two leads, one in the thoracic region and one in abdominal region of a pregnant woman, the mapped maternal ECG is subtracted from the abdominal ECG signal (AECG) and the result would be a noisy fetal ECG signal. The technique is described in details in [8].

Having access to two discrete recorded ECG signals one from thoracic region x(n) and one from abdominal region of a pregnant woman w(n), the goal is to extract fetal ECG signal s(n) from composed abdominal signal. This problem is pictorially illustrated in Figure 8. In this figure x(n) is the recorded maternal ECG signal and w(n) is the recorded abdominal ECG signal. Both signals are recorded by attaching two leads to the thoracic area and abdomen region of the mother.

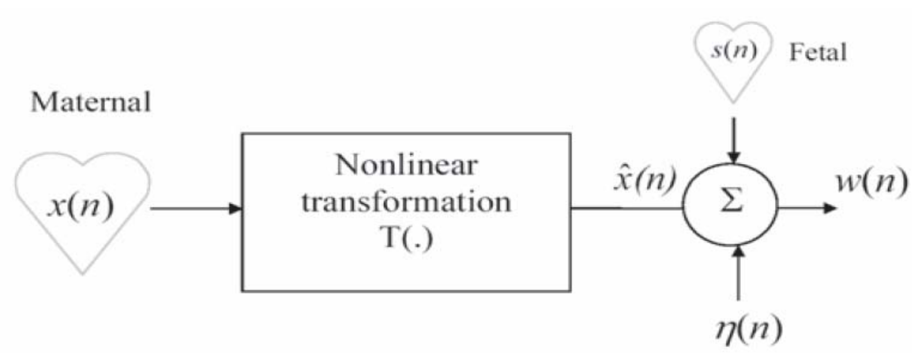

Figure 8. Signal Flow Diagram Showing Two Discrete-Time ECG Signals (w (n) and x (n)) Taken form the Abdominal and Thoracic Areas of the Mother Respectively [8]

As shown in Figure 8, in the abdominal area there are three signals, a distorted version of maternal ECG signal or mapped maternal ECG signal $\hat{x}(n)$, a fetal ECG signal s(n) and some noises. We can express the abdominal ECG signal w(n) as the sum of two signals, a noisy fetal ECG signal $\hat{s}(n)$ and mapped maternal ECG signal $\hat{x}(n)$.

$$w(n) = \hat{x}(n) + \hat{s}(n) \tag{3.1}$$

$$\hat{x}(n) = T(x(n)) \tag{3.2}$$

$$\hat{s}(n) = s(n) + \eta(n) \tag{3.3}$$

It should be mentioned that the transformation T between x(n) and $\hat{x}(n)$ is nonlinear. In order to extract noisy fetal ECG signal $\hat{s}(n)$, the traveled version of thoracic ECG signal $\hat{x}(n)$ should be obtained and then subtracted from composite abdominal signal. To obtain traveled version of thoracic ECG signal in abdominal area of the mother the nonlinear transformation (T) should be modeled. Hence the goal is to estimate transformation T, and from that, estimate $\hat{x}(n)$ and finally approach $\hat{s}(n)$ by subtracting an aligned version of thoracic ECG signal from w(n). To do so, the polynomial technique is used whereby aligning x(n) with w(n) is done by minimizing the mean-squared error criterion. In this technique, both signals (x(n) and w(n)) are divided to N samples and each N samples are located in an individual frame. The i^{th} frames are as follows:

$$x_i\ (m) = x(iN + m) \tag{3.4}$$

$$w_i(m) = w(iN + m) \tag{3.5}$$

Where $0 \le m \le N - 1$

The mapping algorithm has two inputs. For the i^{th} frame the inputs are the sequence $w_i(m)$ and the vector sequence $X_i(m) = [x_i(m) \quad \dot{x}_i(m) \quad \dots \quad x_i^{(j)}(m)]$. The derivative terms in the vector sequence is used to model the dynamics of the x(n) in order to model $\hat{x}(n)$.

The inputs to the polynomial networks are as follows:

$$W_i = [w_i(0) \quad w_i(1) \quad \dots \quad w_i(N-1)]^t \tag{3.6}$$

$$X_i = \begin{bmatrix} x_i(0) & \dot{x}_i(0) & \cdots & x^{(J)}{}_i(0) \\ x_i(1) & \dot{x}_i(1) & \cdots & x^{(J)}{}_i(1) \\ \vdots & \vdots & \ddots & \vdots \\ x_i(N-1) & \dot{x}_i(N-1) & \cdots & x^{(J)}{}_i(N-1) \end{bmatrix} \tag{3.7}$$

In the K^{th} order polynomial expansion, the polynomial basis terms are the monomials of the form

$$\prod_{j=0}^{J}(x_i^{(j)}(m))^{k_j} \text{ , where } \sum_{j=0}^{M} K_j \leq K \tag{3.8}$$

In this case, the vector sequence placed in the polynomial expansion creates the high nonlinear model of transformation T. The vector sequence which composed of polynomial basis term is denoted by matrix P_i . In the following, mapping between $x_i(n)$ and $w_i(n)$ is done by the use of mean-square error criterion.

$$C_i = \underset{C_i}{\arg\min} \left\| P_i C_i - W_i \right\|^2 \tag{3.9}$$

Finding C_i , this vector multiply by the matrix P_i is the model for mapped maternal ECG signal ($\hat{x}(n)$) and from this, the fetal ECG components $\hat{S} = [\hat{s}_i(0) \quad \hat{s}_i(1) \quad \dots \quad \hat{s}_i(N-1)]$ are extracted by the following subtraction

$$\hat{S}_i = W_i - P_i C_i \tag{3.10}$$

Figure 9 shows the block diagram of the proposed polynomial networks technique for fetal ECG extraction.

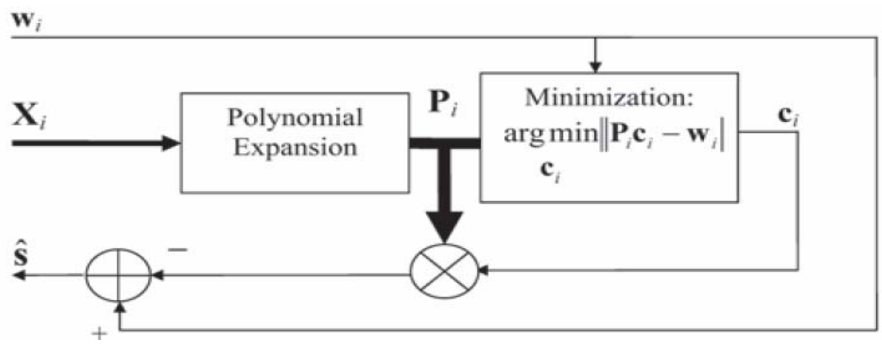

Figure 9. Signal Flow and the Main Block of Polynomial Networks Technique [8]

3.2. Wavelet Transform and FECG De-noising Process

Although the Fourier transform is the most common transform being used in the field of signal and image processing, it provides just frequency information in the transformed signal. This kind of transform can be required when the signal is stationary, but for non-stationary signals we need to know at what times which frequency components exist. For the case of non-stationary signals there are a number of time-frequency transforms such as Short Time Fourier Transform (STFT), Choi-Williams Distribution (CWD), Wigner-Ville Transform (WVT) and Continuous Wavelet Transform (CWT) which present both time and frequency information of the signal[23]. Wavelet transform is the most popular time-frequency transform for signal and image processing and also in applied mathematics. It is because of "its uniqueness in fast and efficient computation with localization and quick decay properties [23]." Although the idea of wavelet transform has been in existence since 1975, it has entered the electrocardiogram (ECG) studies since the 80's due to its efficiency, high speed in data processing and large number of basis functions. Wavelet transform has been previously applied in QRS detection, arrhythmia analysis, parameter extraction and data compression and smoothing [14]. In this thesis, we attempt to apply wavelet transform to electrocardiogram (ECG) signals for noise reduction, in order to enhance the characteristics of the extracted FECG signals.

3.2.1. Brief Description of Wavelet Transform

What is called wavelet is a waveform with limited duration and average value of zero. If we compare wavelets with sinusoids which are the basis functions of Fourier transform, it is clear that unlike wavelets, sinusoids don't have limited duration and also they are smooth and predictable. Wavelets are not predictable and they tend to be asymmetric and irregular [24].

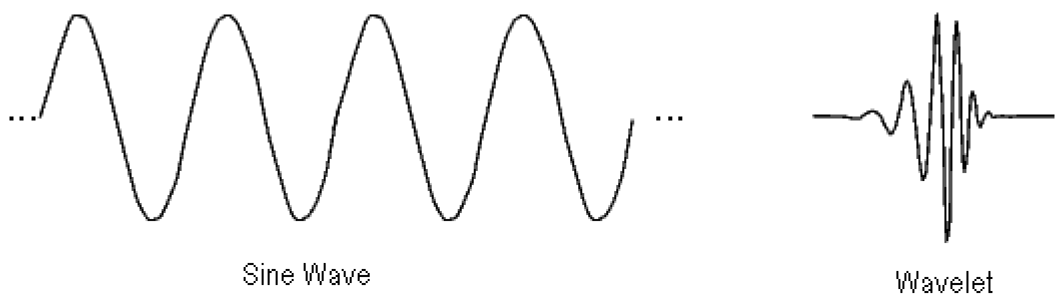

Figure 10. Comparing Sine Wave and Wavelet [24]

Like Fourier analysis which breaks up the signal into sine waves of various frequencies, wavelet analysis breaks up the signal into shifted and scaled versions of the mother wavelet (original wavelet). From Figure 10, it is obvious that signals with sudden and sharp changes are better analyzed with wavelets rather than with sine waves. Since the wavelet transform computes the correlation factor C between the signal and dilated or stretched chosen mother wavelet, hence sudden and sharp changes in the signal will be well detected by mother wavelet.

3.2.2. Continuous Wavelet Transform

Mathematically, the process of continuous wavelet transform (CWT) of f (t) is defined as [25]:

$$CWT_{\Psi} f(a,b) = W_f(a,b) = |a|^{\frac{-1}{2}} \int_{-\infty}^{\infty} f(t)\Psi^*(\frac{t-b}{a})\, dt \qquad (3.14)$$

Where $\Psi(t)$ is the mother wavelet or basis function, b is translation parameter and a is scale parameter. The factor $|a|^{\frac{-1}{2}}$ is considered for energy normalization. In this case the transformed signal has the same energy at every scale. The translation parameter (b) corresponds to the time information in the wavelet transform while scale parameter (a) corresponds to frequency information. Translation parameter changes the location of the wavelet function while scaling parameter either dilates or compresses the signal. We can express the CWT as the sum over all time of the signal multiplied by scaled, shifted version of the wavelet. This CWT analysis results in many wavelet coefficients C that are a function of scale and position. In the process of CWT, a chosen wavelet is compared by a section of the original signal each time and the correlation factor C is calculated (this is when the signal energy and wavelet energy are both equal to one). Then the wavelet will be stretched (scaled) and the above process is repeated. The process of CWT operates at every scale, as it is continuous transform and it just depends on the application and available computation horsepower [24].

3.2.3. Discrete Wavelet Transform and Multi-Resolution Analysis

History of the discrete wavelet transform dates back to 1976. In this year a technique to decompose a discrete time signal is invented by Croiser, Esteban and Galand. Also in the same year similar work on speech signals coding was done by Crochiere, Weber and Flanagan. They named their analysis scheme as subband coding. In 1983, Pyramidal coding which is a very similar technique to subband coding was defined by Burt [23]. This coding technique is also known as multi resolution analysis. In the discrete wavelet transform, using digital filtering techniques a time-scale representation of a digital signal is obtained. Signal at different scales is analyzed by filters with different cut off frequencies [23]. In this procedure, a series of high pass filters are used to analyze high frequency components of the original signal and a series of low pass filters are hired to analyze the low frequencies. “The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by filtering operations, and the scale is changed by up-sampling and down-sampling (sub-sampling) operations [23].” Down-sampling is removing some samples of the signal while up-sampling is adding some new samples to the signal. The discrete wavelet transform (DWT) coefficients are derived from sampling the continuous wavelet transform (CWT) on a dyadic grid (in CWT a and b are continuous over R (Real numbers) but in DWT these two terms are based on power of two ($a = 2^{-m}$ and $b = n2^{-m}$ m, n$\in$Z) called dyadic scales and positions) [25]. The DWT procedure starts by passing the original signal through a low-pass filter with impulse response of h[n]. Mathematically, filtering a signal is convolving the signal with the impulse response of the filter. The low-pass filter, removes all frequencies greater than the cut off frequency of the filter. The signal also passes through a high-pass filter with impulse response of g[n]. The high-pass filter removes all frequencies less than the cut off frequency of the filter. In the wavelet analysis, low frequency components of the signal obtained by low-pass filtering are called approximations and high frequency components obtained by high-pass filtering are called details. Two times filtering the original signal gives twice as much data as the original signal; so, to reduce the number of obtained samples, after filtering the signal down-sampling is a subtle way. The above decomposition procedure can be repeated for further level decomposition. The second level decomposition is obtained by low pass and high pass filtering of the level one approximation of the original signal. Figure 11 illustrates the above procedure, where x[n] is the original signal, h[n] is low-pass filter and g[n] is high-pass filter. It is clear that in high frequencies, multi resolution analysis (MRA) gives good time resolution and poor frequency resolution while in low frequencies it gives good frequency resolution and poor time resolution [25].

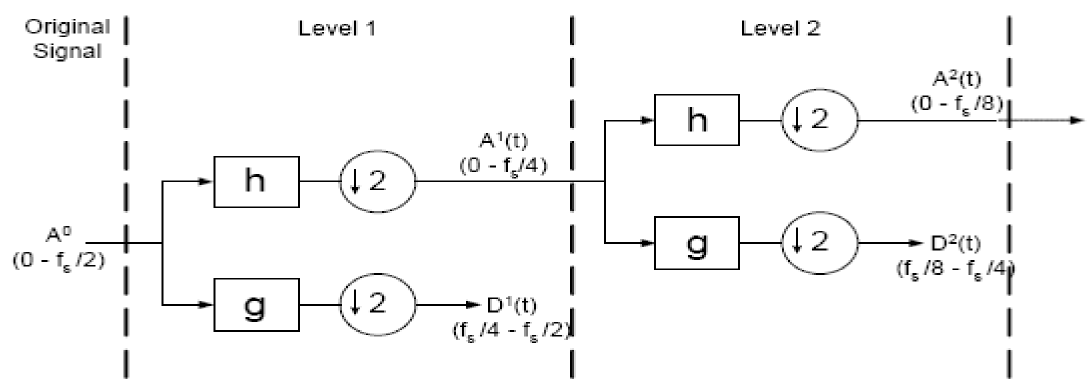

Figure 11. Multi-Resolution Wavelet Decomposition. h = low-pass decomposition filter; g = high-pass decomposition filter; (↓2) = down-sampling operation. $A^1(t)$, $A^2(t)$ are the approximated coefficient of the original signal at levels 1, 2 etc. $D^1(t)$, $D^2(t)$ are the detailed coefficient at levels 1,2[25].

3.2.4. Inverse Discrete Wavelet Transform

In the discrete wavelet transform (DWT) procedure, the signal decomposes to its high frequency components (details) and low frequency components (approximations). The inverse discrete wavelet transform (IDWT) is the reconstruction procedure in which these components are assembled back into the original signal without loss of information. Figure 12 illustrates this reconstruction procedure. The wavelet decomposition consists of filtering and down-sampling while wavelet reconstruction involves up-sampling (adding zeros) and then filtering the details and approximations which come from the decomposition process.

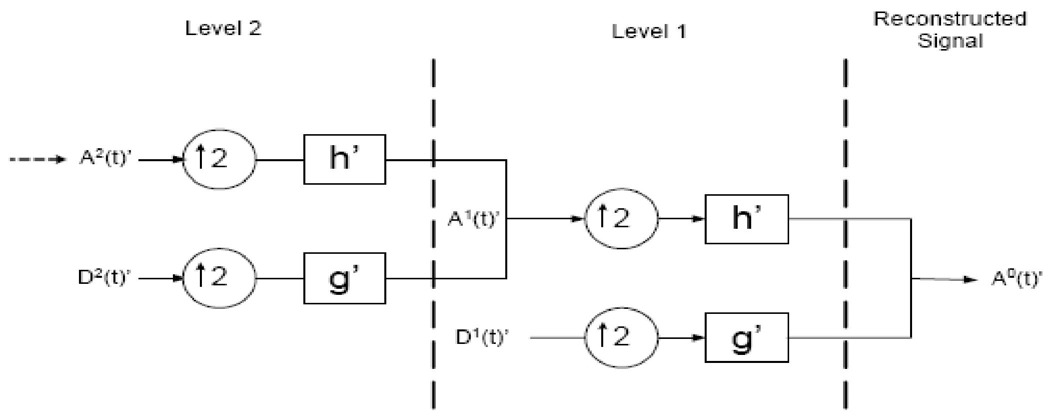

Figure 12. Multi-Resolution Wavelet Reconstruction. h' = low pass reconstruction filter; g' = high-pass Reconstruction filter; ↑2 = up-sampling operation. $A^1(t)', A^2(t)'$ are the processed or non-processed approximated coefficient of the original signal at levels 1, 2 etc. $D^1(t)', D^2(t)'$ are the processed or non-processed detailed coefficient at levels 1,2[25].

3.2.5. An Introduction to the Wavelet Families

The first and simplest wavelet in the world of wavelet transform is Haar wavelet. This wavelet is discontinuous and as it is shown in Figure 13 it is looks like step function.

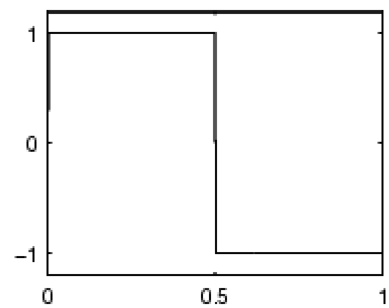

Figure 13. Haar Wavelet [24]

Daubechies wavelets family is the most popular family of wavelets which was invented by Ingrid Daubechies [24]. The name of each member of this family is written as db with a number beside it. For instance, db1 is the first member of this family which looks like Haar wavelet. The fifth and sixth members of this family are illustrated in Figure 14.

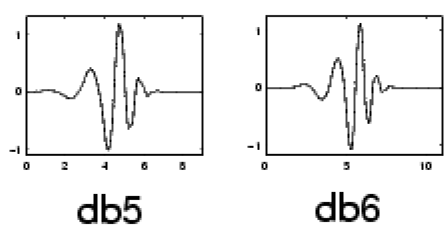

Figure 14. Daubechies Wavelets [24]

Figure 15 shows two members of Symlet wavelet families. This family of mother wavelets is proposed by Ingrid Daubechies. It is the modified version of the db family. [24].

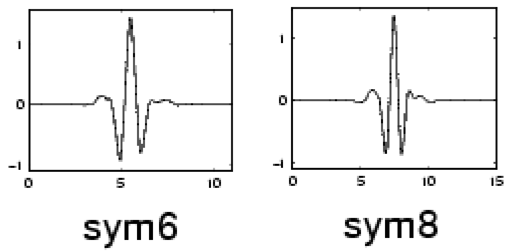

Figure 15. Symlets Wavelets [24]

Some other common real wavelets are biorthogonal, Coiflets, Mexican Hat, Meyer, Morlet, Gaussian derivatives family, reverse biorthogonal and FIR based approximation of the Mayer wavelet. The common complex wavelets are, Morlet, Shannon and Frequency B-Spline.

3.3. Procedure of Enhancing Fetal ECG

In the process of recording abdominal ECG signal, the low power fetal ECG signal is contaminated by a number of noise sources such as uterine contraction EMG, respiratory action noise, thermal noise, 50Hz power line interference, baseline wandering, maternal electromyogram (EMG) and other random electronic noise. In this work the method of fetal ECG extraction using polynomial networks [8] will be hired for FECG extraction. The objective is to enhance the extracted fetal ECG signal and improve its signal to noise ratio. In the first step polynomial networks extraction technique will be modified in order to remove baseline wander of the extracted signal and then wavelet de-noising technique will be used to enhance the extracted FECG signal. Figure 16 shows block diagram of the proposed technique. In this block diagram, MECG is the recorded maternal ECG signal from mother's thoracic region and AECG is the recorded abdominal ECG signal from mother's abdominal area.

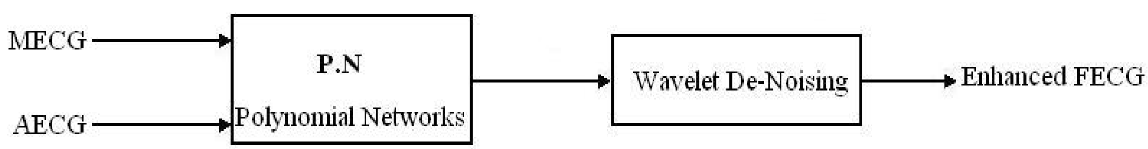

Figure 16. Block Diagram of the Proposed Enhancing Technique

Chapter 4

Data Sources and Results

The available data sources are introduced. The proper wavelet function for ECG signal analysis is selected. Wavelet transform as a de-noising technique is tested using synthetic ECG data and real ECG signals. The effect of de-noising technique is demonstrated by computing and comparing the SNR parameter in synthetic ECG data. Subsequently removing dc-wander by the use of integral terms in the polynomial networks' feature vector is examined.

4.1. Data Sources

The available data sources for this thesis are in the two types.

- Real ECG Data
- Synthetic ECG Data

4.1.1. Real ECG Data Sources

The first source is the real ECG signals recorded by Lieven De Lathavwer [26]. These signals are five-second recordings from eight different points of a pregnant woman's body. The sampling frequency is 500HZ. Five of these signals are obtained from the mother's abdominal area containing maternal ECG signal and fetal ECG signal, while the other three signals are recorded from thoracic region of the pregnant woman and only containing maternal ECG signal. In Figure 17 one of the maternal ECG signal and one of the abdominal ECG signal of this recorded data set are shown. The first signal is the maternal signal and the second one is the abdominal ECG signal.

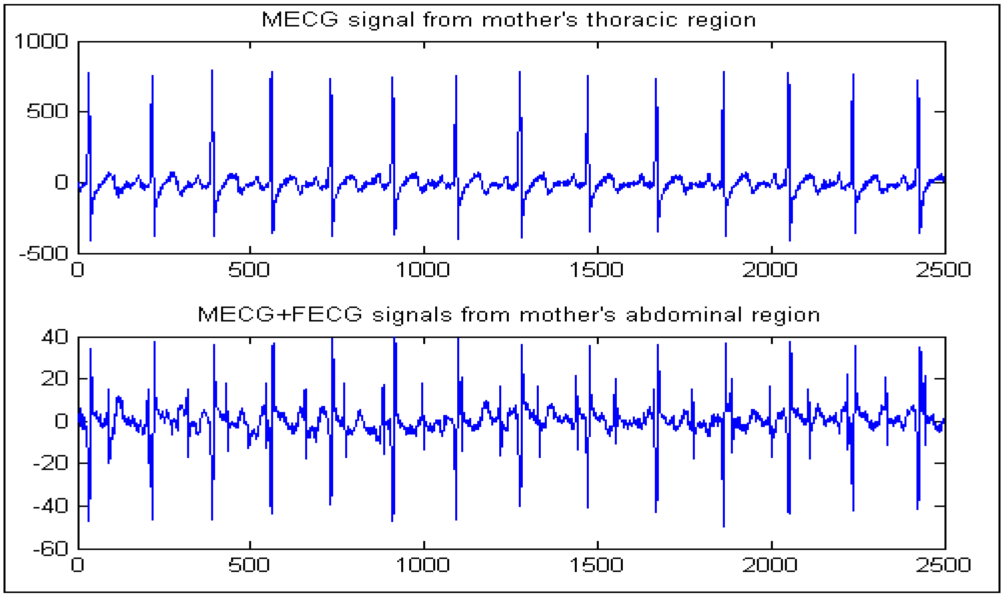

Figure 17. Lieven Real ECG Signals [26]

The second real data source is the real ECG signals recorded in Al-Wasl Hospital in Dubai. Six data sets each contain two signals one from thoracic and one from abdomen region of pregnant women with the sampling frequency of 1000HZ. Figure 18 shows one maternal ECG signal and one abdominal ECG signal from one of the data sets. The first channel is the maternal ECG signal and second channel is the abdominal ECG signal.

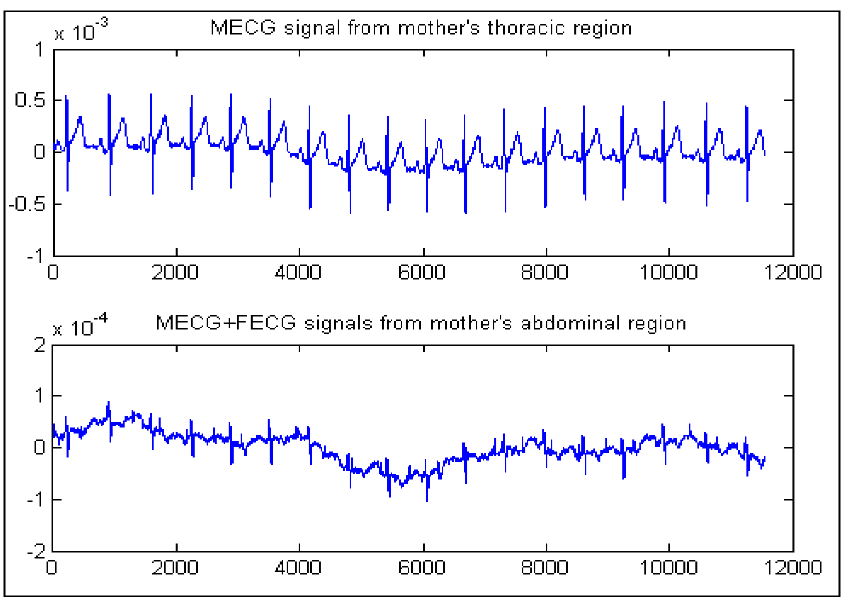

Figure 18. Real ECG Signals Recorded in Al.Wasl Hospital

4.1.2. Synthetic ECG Data Source

ECG signal taken from matlab biomedical signal processing toolbox (BSP) [27]. Figure 19 shows a frame of one thousand samples of a generated maternal ECG signal using this toolbox.

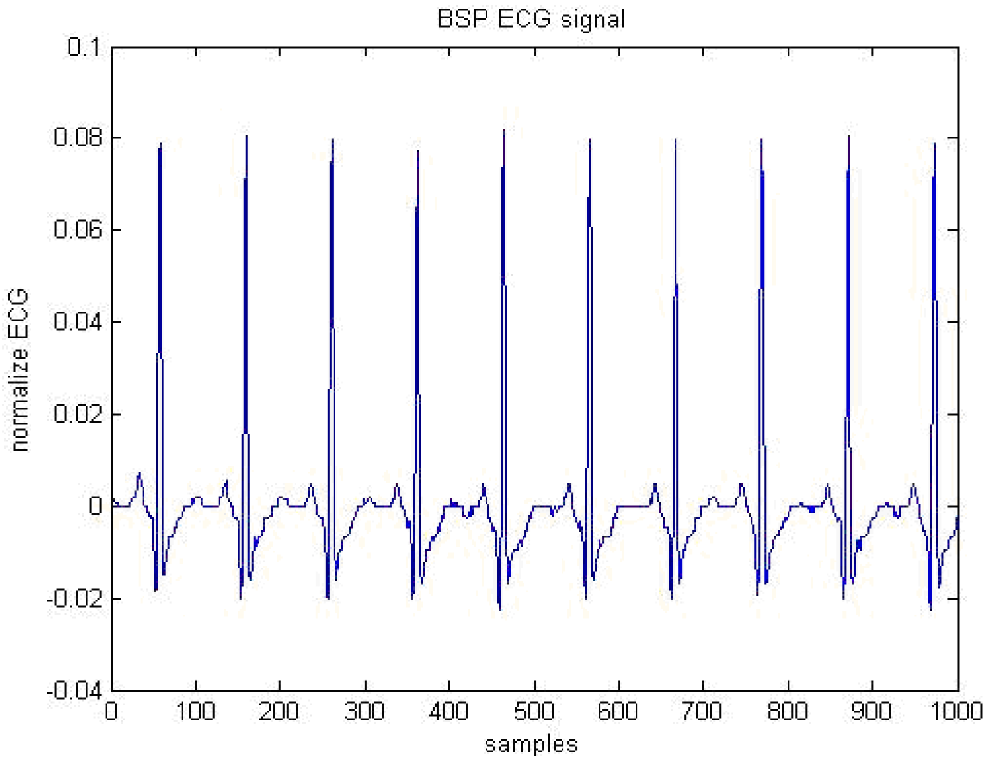

Figure 19. BSP ECG Signal [27]

4.1.2.1. Synthetic ECG Data Generation

To generate synthetic ECG signals the generator of ECG signals in matlab BSP toolbox is used. To obtain abdominal signal the traveled version of maternal ECG signal (the components of maternal ECG signal which are appeared in abdominal signal) and fetal ECG signal are required. Matlab ECG signal generator generates just maternal ECG signals. Hence in order to obtain traveled version of maternal ECG and also the fetal ECG signal, parameters of the generated maternal signals should be changed. A model for generating mapped maternal ECG, fetal ECG and composite abdominal signal is proposed as shown in Figure 20. Having two maternal ECG signals from BSP toolbox, one of them is filtered using linear filter to model the traveled maternal ECG signal (Mapped MECG) and another one is re-sampled in order to model fetal ECG signal. The re-sampling parameter is two as the fetal heart beat is two to three times grater than the maternal heart rate. To generate abdominal ECG signal w(n), the generated fetal ECG signal is added to a the generated mapped maternal ECG signal. Figure 21 shows the synthetic mapped maternal ECG signal. In Figure 22 the synthetic mapped maternal ECG signal and the original ECG from BSP toolbox are compared. We didn't consider the nonlinearity of the transformation of the maternal ECG signal from thorax area to the abdomen region as in [13]. In this case the maternal ECG signal is just filtered with a FIR filter in order to have different shape, to model the mapped maternal ECG signal. Figure 23 illustrates the synthetic fetal ECG signal while Figure 24 shows the synthetic abdominal ECG signal. All the synthetic maternal, fetal and abdominal ECG signals are illustrated in one figure in the Figure 25.

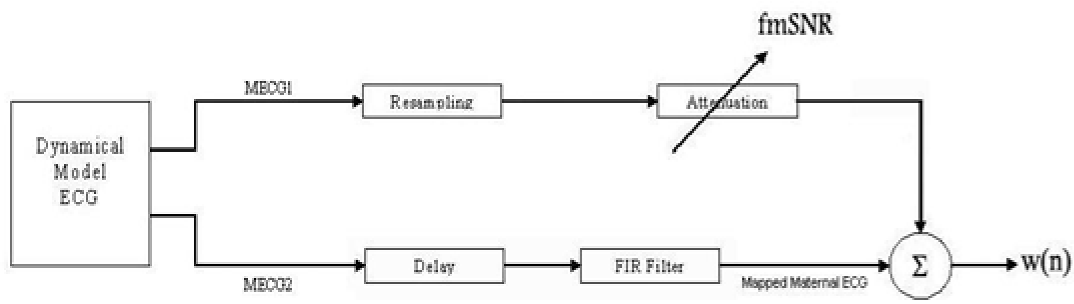

Figure 20. Block Diagram for Simulating the Abdominal ECG Signal

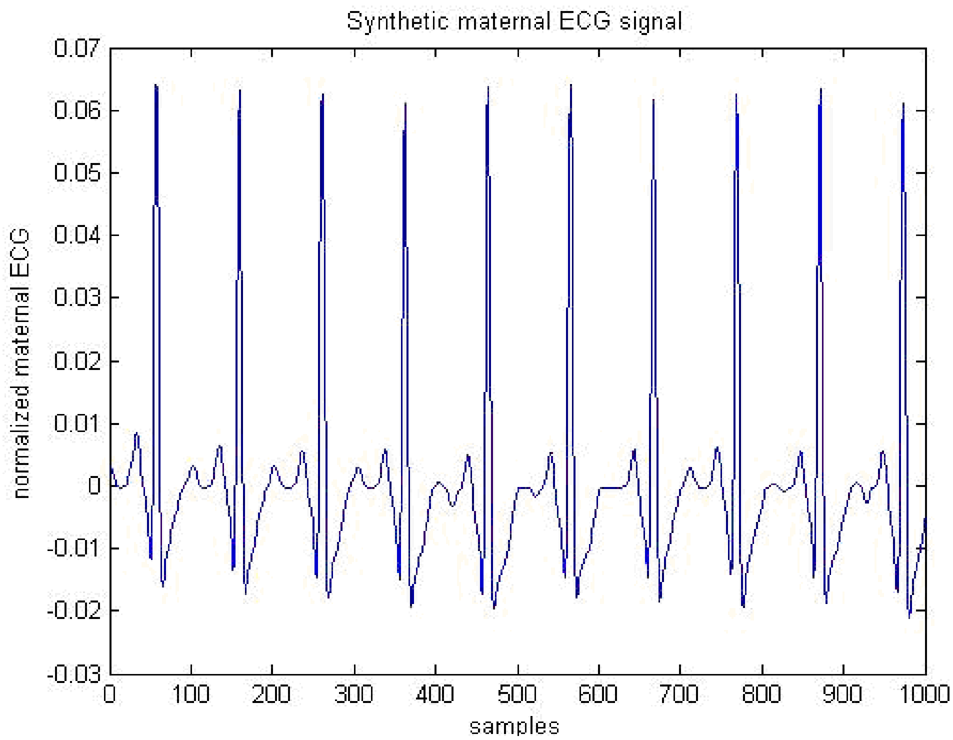

Figure 21. Synthetic Mapped Maternal ECG Signal

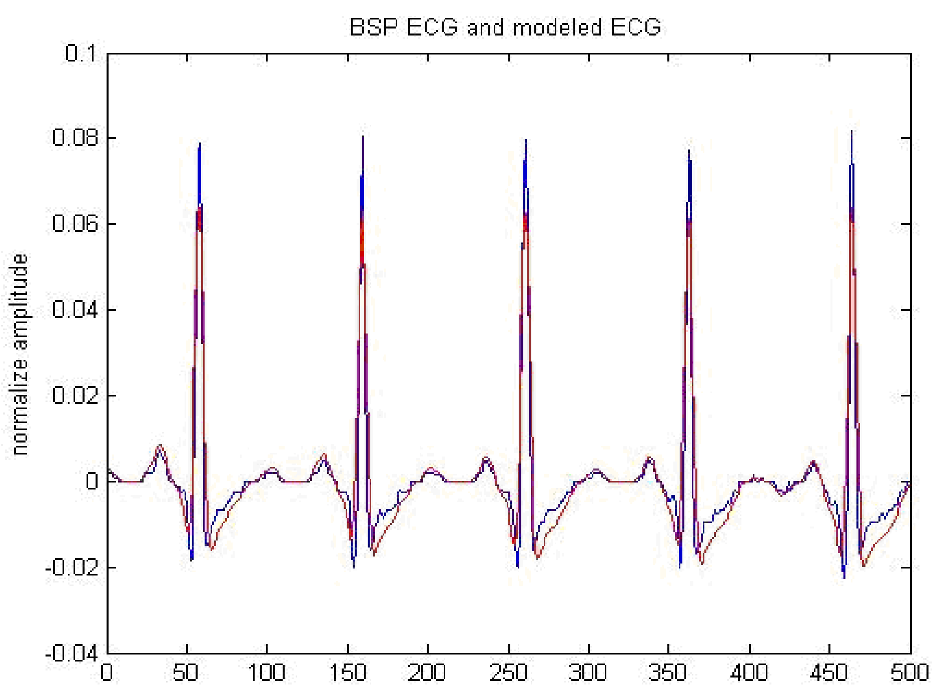

Figure 22. BSP ECG and Synthetic Mapped MECG

In Figure 22 the blue signal is the BSP ECG signal and red signal is the modeled mapped maternal ECG (mapped MECG).

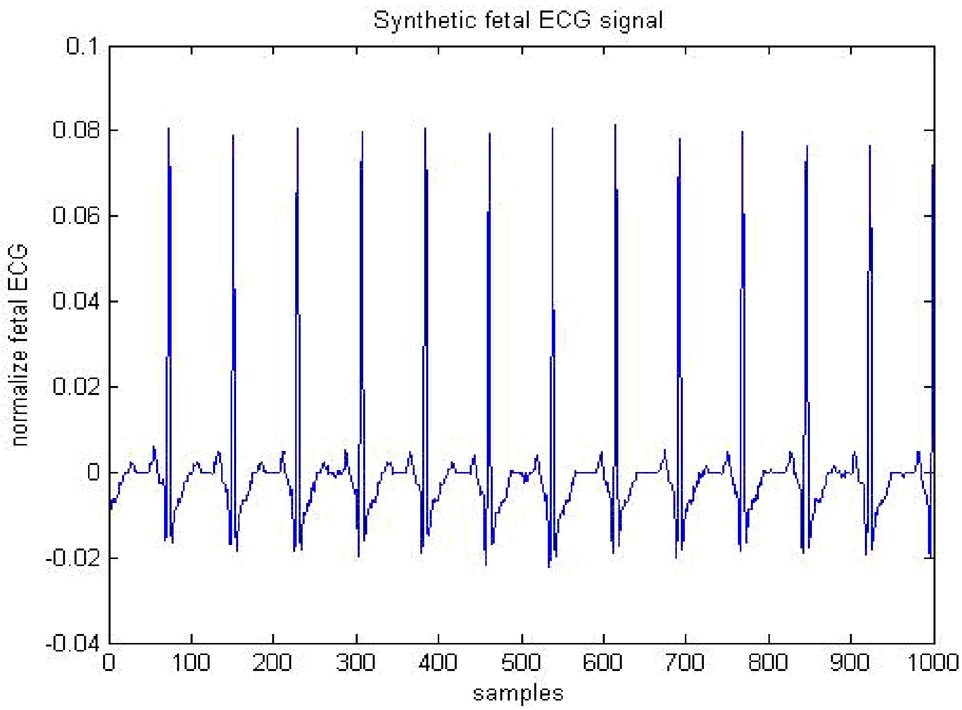

Figure 23. Synthetic Fetal ECG Signal

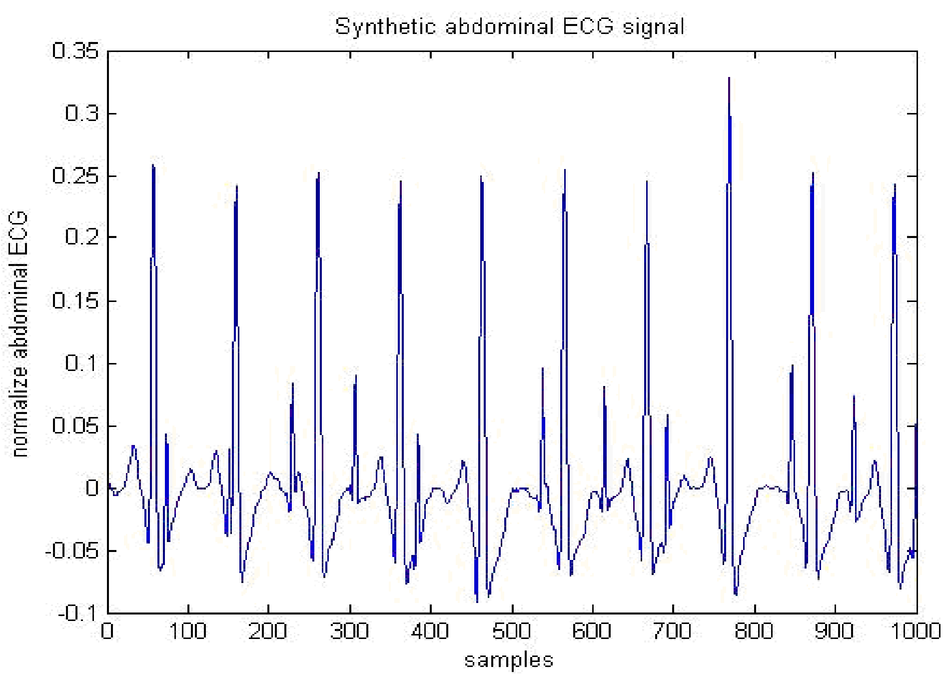

Figure 24. Synthetic Abdominal ECG Signal

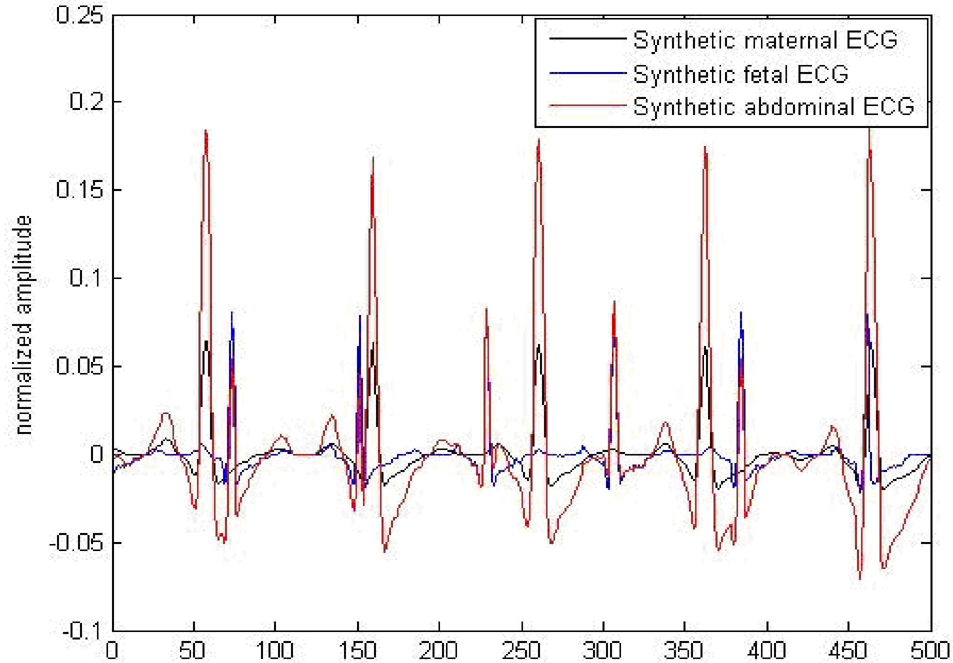

Figure 25. Synthetic ECG Signals

In Figure 25 the black signal is synthetic maternal ECG, the blue signal is synthetic fetal ECG and the red one is synthetic abdominal ECG signal.

4.2. The Proper Selection of Mother Wavelet for ECG Signal Analysis

4.2.1. ECG and Wavelet Analysis

Among various families of wavelets, we should select the one which has good detection of ECG signal details. In the following section, the methodology of selecting mother wavelet for ECG signal analysis is described.

4.2.2. Selection of Mother Wavelet

The first and the most essential stage of working with wavelet transform is a proper selection of mother wavelet. There is no absolute way to select a certain wavelet. The choice of wavelet depends on the application. For instance working with Haar wavelet has the benefits of simplicity in computation and understanding while Daubechies wavelets are more complex, but Daubechies can detect more details of signal compared to the Haar wavelet [16]. In the application of FECG processing, in spite of huge background noise, we need to select a wavelet function which has good detection of signal details and also has shape close to the ECG signal. Also it is mentioned in the literature that "the wavelet filter with scaling function more closely similar to the shape of the ECG signal achieved better detection [16]." In this thesis we selected bior3.9, dmey, rbio3.9, coif5, sym8, db5, db6, db7 and db8 mother wavelets which are similar in shape to the ECG signal and have scaling function similar to ECG signal. Decomposing ECG signal with these mother wavelets, we will show that how similar the considered mother wavelets are to the ECG signal. Also later in this chapter by calculating signal to noise ratio (SNR) of the de-noised FECG signal we will emphasize that these mother wavelets can be used for ECG signal de-noising.

To examine the similarity of ECG signal with the chosen mother wavelets first the referenced ECG signal is decomposed with one of the selected wavelet functions. From the decomposition results we found that the most details of the signal are contained at scale 2^3 or at level three of its wavelet decomposition and level four of its wavelets decomposition. In the next we decomposed our reference ECG signal with the other wavelet functions to examine their scale 2^3 and 2^4 similarity with ECG signal. In the following db6, coif5 and sym8 mother wavelets and the results of decomposition of ECG signal with these mother wavelets are illustrated. The decomposition results of ECG signal with other mother wavelets are shown in Appendix A.

In the following figures

- s: is a reference ECG signal
- a5: is level five approximation
- d1 to d5: are level one details to level five details

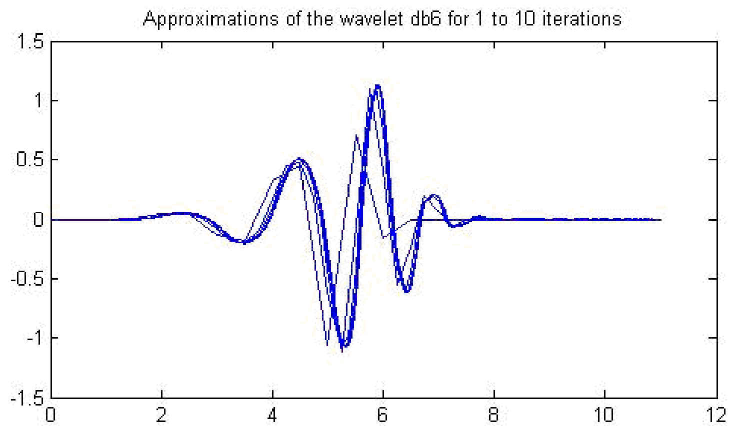

Figure 26. db6 Mother Wavelet Function

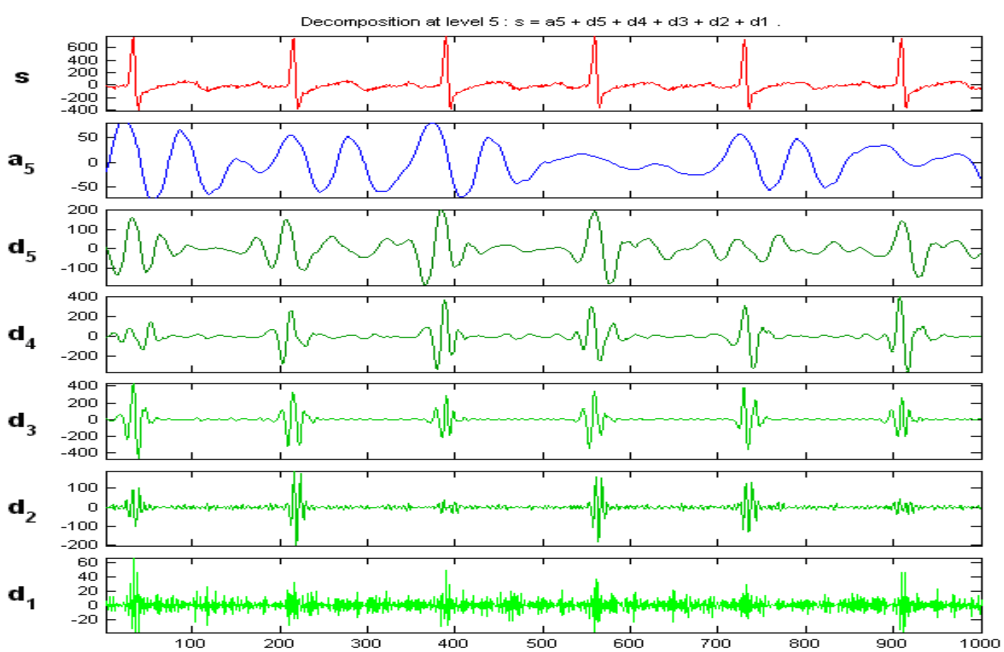

Figure 27. ECG Wavelet Decomposition using db6 Mother Wavelet

Db6 mother wavelet is illustrated in Figure 26. In Figure 27 ECG signal is decomposed using db6 mother wavelet. It is clear from the figure that, level 1 details (d_1) of the ECG signal decomposition is almost noise. Level 2 and level 3 details (d_2 and d_3) contain some essential details of the signal, and level 4 details (d_4) contains the most details of the signal. The similarity of the level 3 and level 4 details to the ECG signal is obvious from the Figure 27 which indicates how db6 mother wavelet is suitable for the ECG signal analysis. In Figure 29 and Figure 31 the results of ECG signal decomposition using coif5 and sym8 mother wavelets are illustrated. The similarities of the level 3 and level 4 details to the ECG signal in both figures are clear.

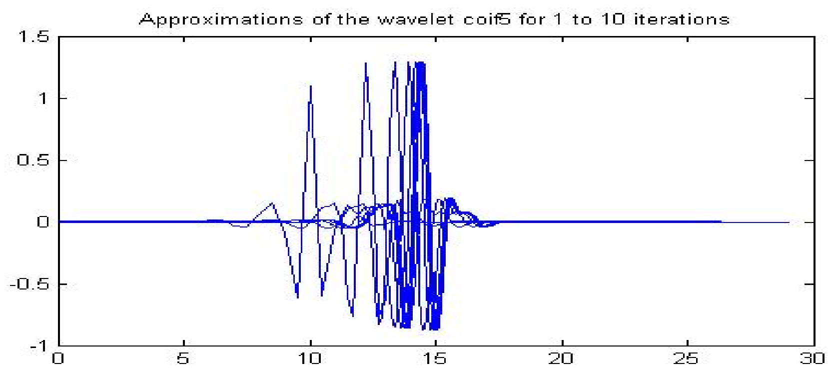

Figure 28. Coif5 Mother Wavelet Function

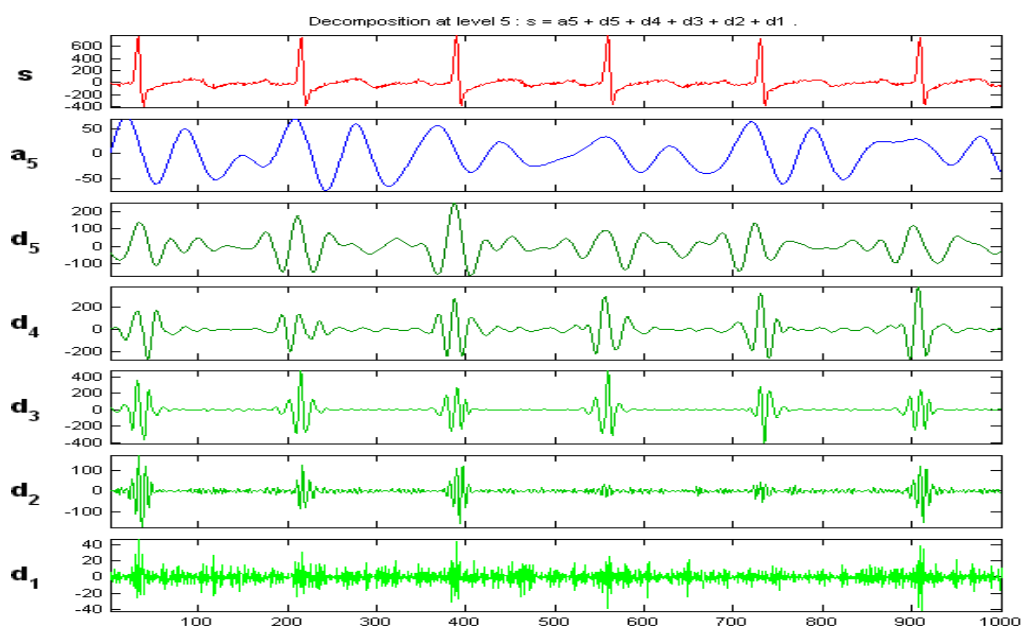

Figure 29. ECG Wavelet Decomposition using coif5 Mother Wavelet

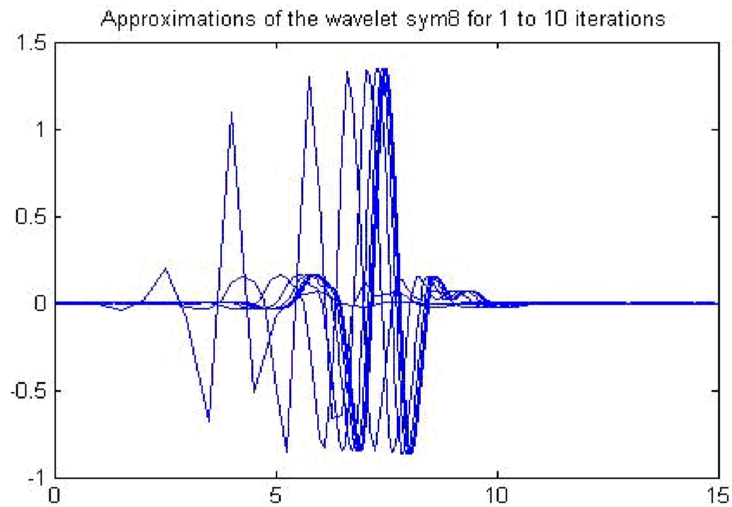

Figure 30. Sym8 Mother Wavelet Function

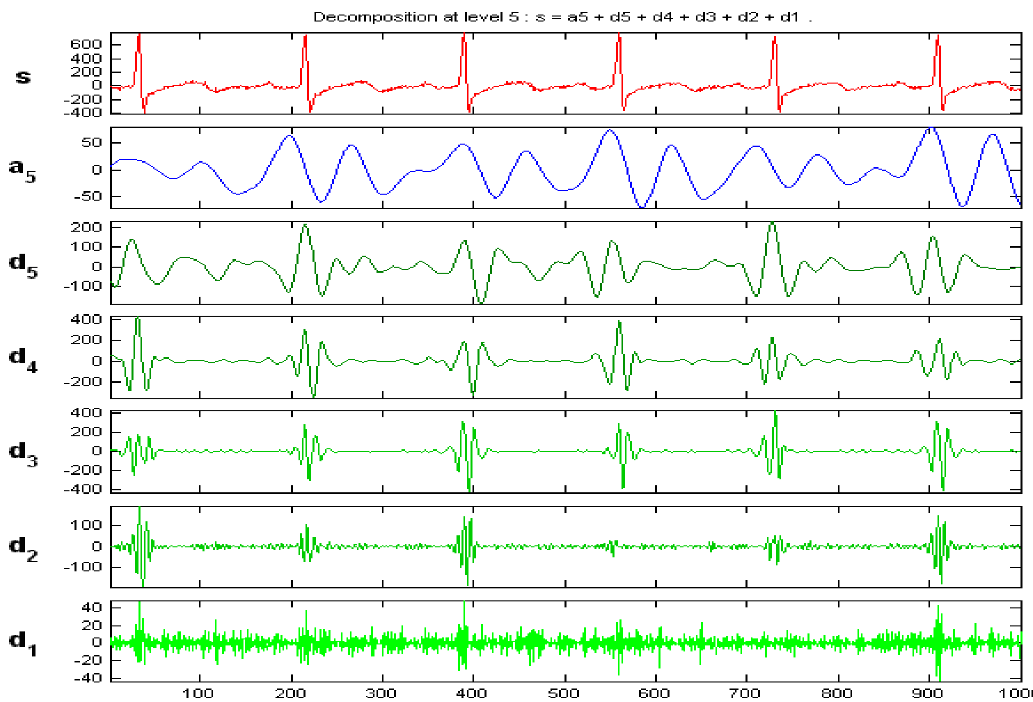

Figure 31. Wavelet Decomposition using sym8 Mother Wavelet

As it is clear from the previous figures and those in Appendix A the selected mother wavelets has similarity with ECG signal, so these wavelets are suitable for the ECG signal processing. Later in this chapter by calculating signal to noise ratio of the de-noised synthetic fetal ECG signal, the efficiency of the work with these mother wavelets in ECG signal analysis is shown.

4.3. Analysis and Results on Synthetic ECG Data

In this work, firstly using synthetic ECG data the efficiency of the considered de-noising algorithm is examined and later this de-noising algorithm will be applied on the real ECG data.

Both maternal and fetal ECG signals (x(n) and s(n)) are generated as described in section 4.1.2.1. These two signals are processed through the model shown in Figure 20 in order to generate abdominal signal w(n). Two factors are exploited to quantify the de-noising algorithm as it is introduced in [13].

$$fmSNR = 10 \times \log_{10} \frac{\sum_n (\hat{s}(n))^2}{\sum_n (\hat{x}(n))^2} \tag{4.1}$$

$$qSNR = 10 \times \log_{10} \frac{\sum_n (\tilde{s}(n))^2}{\sum (s(n)) - \tilde{s}(n))^2} \tag{4.2}$$

Where $\hat{s}(n)$ is the synthetic fetal ECG signal, $\hat{x}(n)$ is the synthetic mapped maternal ECG signal and $\tilde{s}(n)$ is the extracted fetal ECG signal using polynomial network with or without de-noising algorithm. A fixed amount for the fmSNR is considered and by adding noise to the synthetic abdominal signal the qSNR is calculated. The factor qSNR represents how the extracted fetal ECG signal energy is stronger than its noise energy.

4.3.1. Wavelet De-noising

The goal is to examine the considered de-noising algorithm. To do so we will consider a fixed value for the fmSNR and then by adding various amounts of noise to the abdominal signal, the qSNR of the extracted FECG signal will be calculated. Then the de-noising algorithm will be proceed and the qSNR of the extracted de-noised FECG will be calculated. By comparing these two factors the efficiency of the de-noising algorithm will be quantified. In the following wavelet de-noising as pre processing tool, post processing tool and pre& post processing tool is examined and each time the qSNR is calculated. In the pre de-noising, the abdominal signal will be de-noised using wavelet transform and then fetal ECG will be extracted by polynomial networks. In the post de-noising, the fetal ECG will be extracted using polynomial networks and then the extracted FECG will be de-noised using wavelet de-noising algorithm. In the case of pre& post de-noising, the abdominal signal will be de-noised by wavelet de-noising algorithm then polynomial networks will be used for fetal ECG extraction and again the extracted fetal ECG will be de-noised using wavelet de-noising algorithm. In each case of study the qSNR will be calculated. The wavelet de-noising with higher improvement in qSNR will be the best one for our purpose. In the following, the results of wavelet de-noising algorithm as pre, post and pre& post de-noising algorithm are examined. In each figure fmSNR is fixed and we vary the abdominalSNR noise between -20 to 50 and we obtain qSNR. The abdominalSNR is defined as

$$abdo\min alSNR = 10 \times \log_{10} \frac{\sum_n (nw(n))^2}{\sum (w(n)) - nw(n))^2} \tag{4.3}$$

Where $nw(n)$ is the abdominal signal contains the added noise, and $w(n)$ is the abdominal signal.

In the following figures, the blue graph is the qSNR of the extracted FECG signal without any de-noising process. The red graph illustrates the qSNR of the fetal ECG signal with post de-noising. The green graph is the qSNR with pre de-noising process and the black one is qSNR of the pre& post de-noised FECG signal. Also SNR-in is the abdominalSNR and SNR-out is the qSNR.

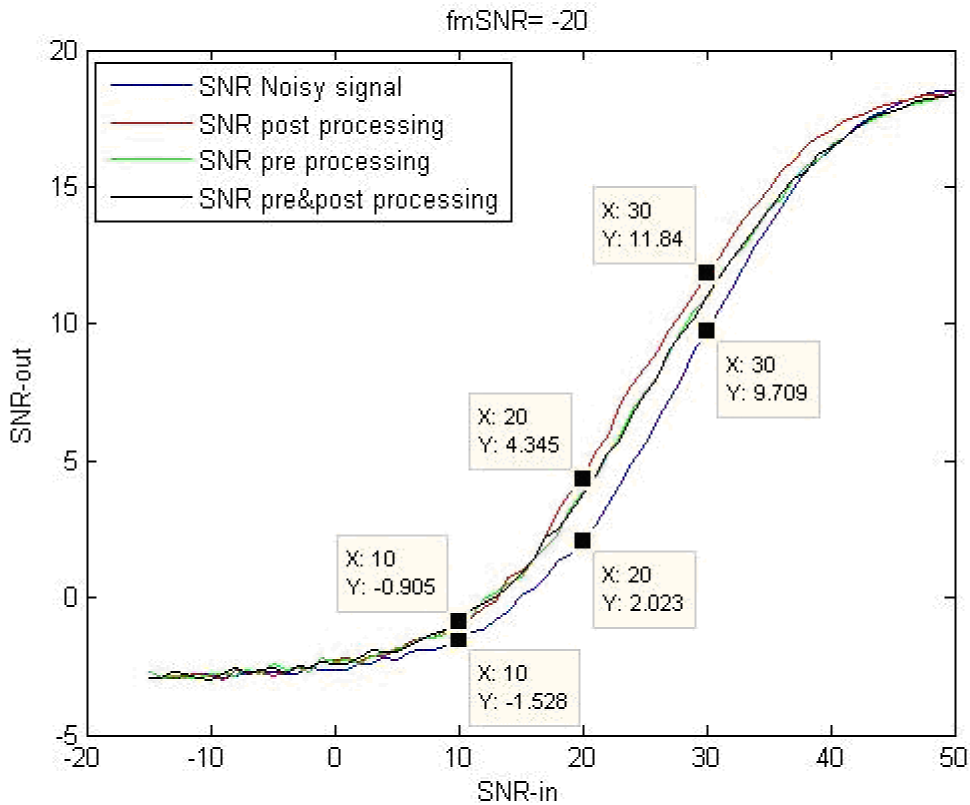

Figure 32. Wavelet De-noising Comparison with fmSNR=-20

In Figure 32 the fmSNR is assumed to be -20 which means the energy of the maternal signal is ten times bigger than the fetal one. The blue graph shows the qSNR of the extracted fetal ECG without any de-noising process. The green graph shows the qSNR of the extracted FECG with pre de-noising. The red graph shows the qSNR of the de-noised extracted fetal ECG and finally the black one is the qSNR of the extracted FECG with pre & post de-noising. Assuming fmSNR=-20 makes poor fetal ECG in abdominal signal, so as it is clear from the figure, even in the presence of very low noise the qSNR is still small. From the Figure 32 it is clear that wavelet de-noising improves qSNR of the extracted fetal ECG in all three cases of pre, post and pre& post processing. The post de-noising offers better improvement compare to the other de-noising schemes.

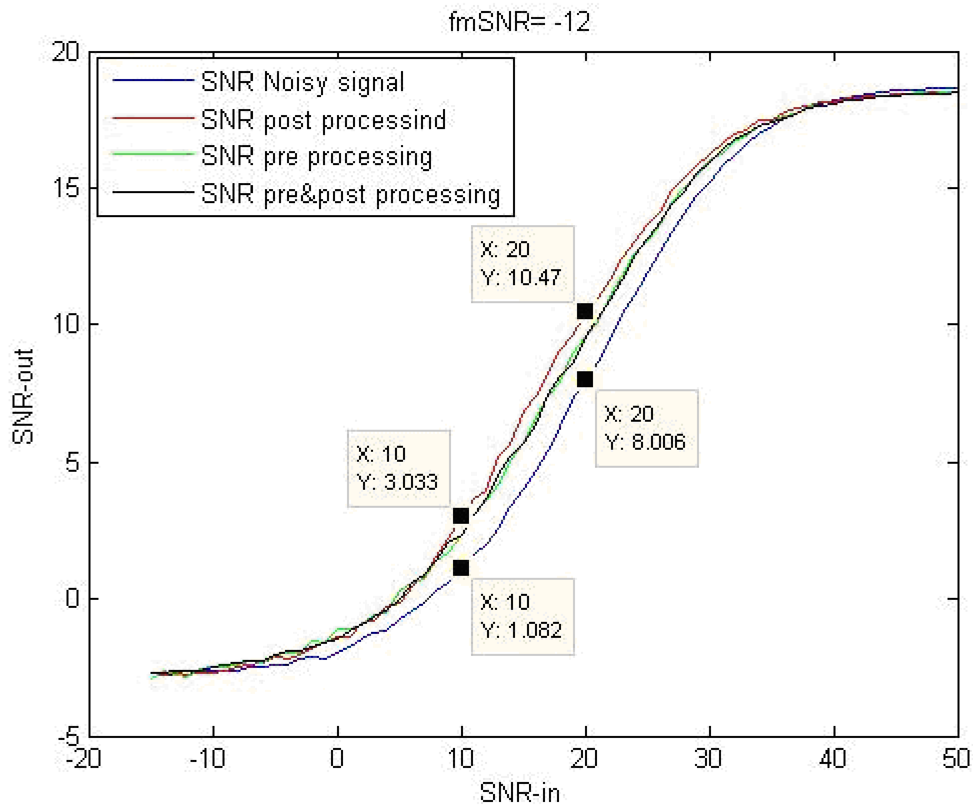

Figure 33. Wavelet De-noising Comparison with fmSNR=-12

Figure 33 attests the post de-noising algorithm gives better improvement in qSNR. In this figure fmSNR is equal to -12 which means the energy of the maternal signal is about four times bigger than the fetal ones. This assumption is near to the case in reality. As it is shown in the figure, the SNR-out when SNR-in is equal to 20db is equal to 10.47db while in the previous figure it was 4.34db. Also in this figure with SNR-in around 30db the SNR-out reaches its final value while in the previous figure it reaches its final value at about 45db. In Figure 34 the most improved region of qSNR is enlarged.

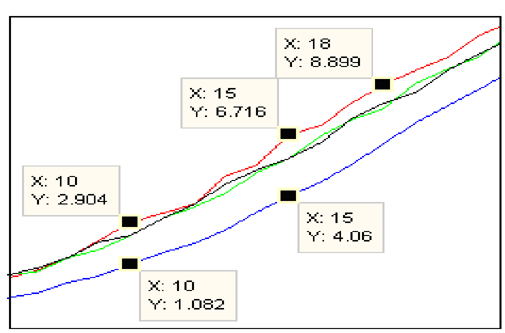

Figure 34. Wavelet De-noising

To observe the efficiency of the wavelet de-noising Figure 35 shows a fetal ECG signal and its de-noised version. In this figure fmSNR is equal to -12, the blue signal is the noisy signal and the red one is the de-noised signal using wavelet de-noising algorithm.

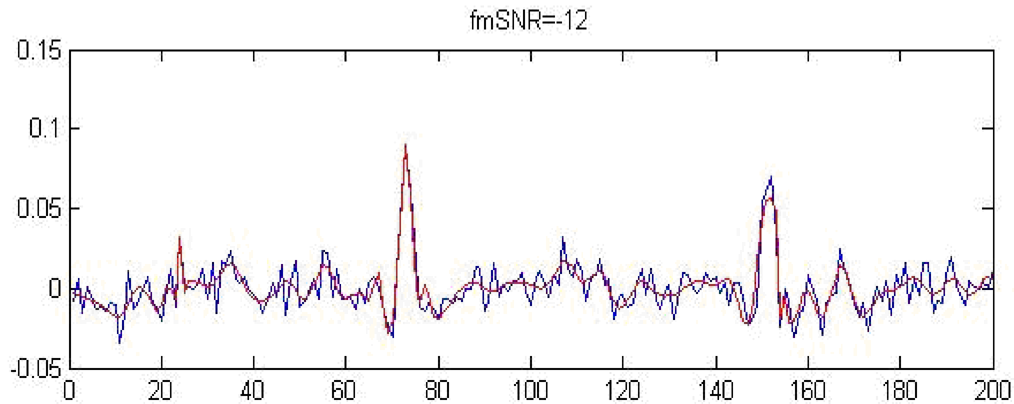

Figure 35. Signal De-noising with Wavelet

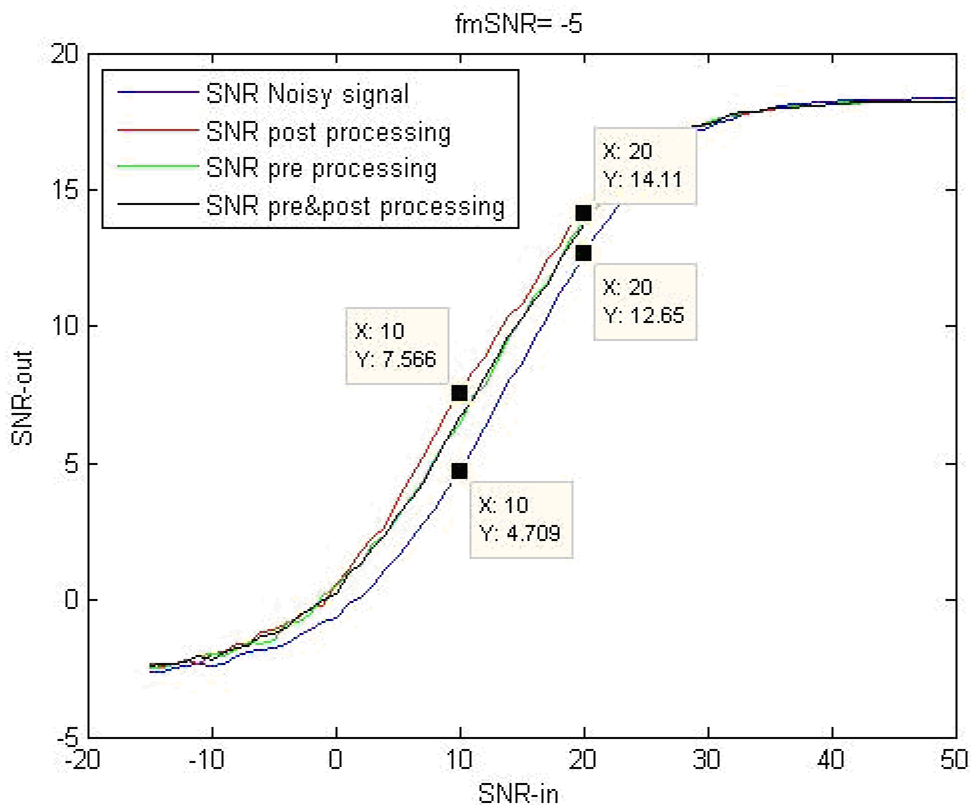

Figure 36. Wavelet De-noising Comprising with fmSNR=-5

In Figure 36 fmSNR is equal to -5 which means the energy of the maternal ECG signal is about two times grater than the energy of the fetal ECG signal. By comparing the last three figures we found that as the fetal ECG component is stronger in the abdominal signal the extracted fetal ECG will be more robust in presence of noise. Figure 37 illustrates a noisy fetal ECG and its de-noised version using wavelet de-noising algorithm.

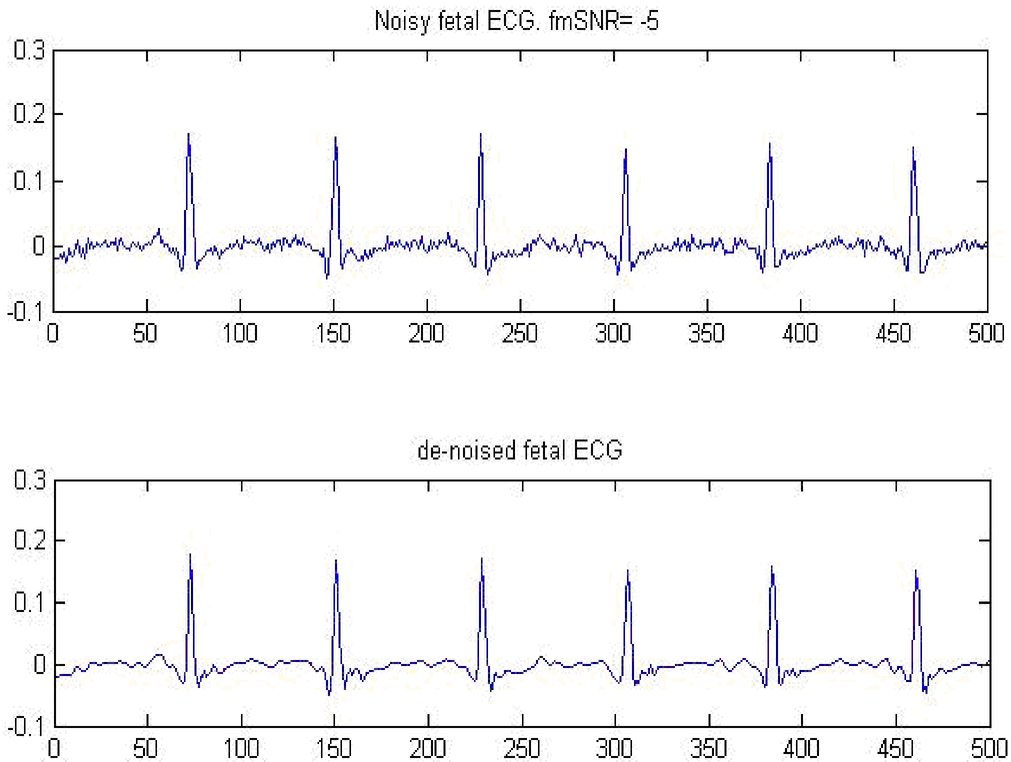

Figure 37. FECG Signal Wavelet De-noising

4.3.2. Examine the Selection of Mother Wavelet

In the section 4.2 the best mother wavelets for ECG signal analysis are selected by examining the similarity of the ECG signal with the mother wavelets and scaling functions of the corresponding wavelets. In this section using synthetic ECG signals and calculating the qSNR of the extracted de-noised fetal ECG signal, the previous result of selecting mother wavelets will be examined. At the end one of this section the proper mother wavelet for this work will be selected. To do so, and from the results of the previous section, we will use the selected mother wavelets for the post de-noising. Table 1 shows the qSNR of the extracted fetal ECG signal without and with de-noising. The results of qSNR of the de-noised fetal ECG signal attest the proper selection of these mother wavelets. Here noise is added to the synthetic abdominal signal and then the qSNR of the extracted fetal ECG signal is calculated. Later the extracted fetal ECG signal will be de-noised, with one of the selected mother wavelets each time and the qSNR of de-noised fetal ECG signal will be calculated. From the Table it is clear that all the selected mother wavelets are suitable for ECG signal de-noising. They improve the qSNR of the extracted FECG signal. For the rest of this work, we will use db6 as the mother wavelet for wavelet de-noising although coif5 mother wavelet gets similar results as db6.

Table 1. Wavelet De-noising qSNR Results

fmSNR=-12, qSNR=18.7		qSNR								
Noise(db)	qSNR without de-noising	db5	db6	db7	db8	bior3.9	dmey	rbio3.9	coif5	sym8
-5	-2.38	-2.11	-2.21	-2.27	-2.13	-2.21	-2.03	-2.25	-1.99	-2.36
5	-0.65	0.04	0.15	-0.04	0.07	-0.19	0.04	-0.11	0.35	0.007
15	4.12	6.05	6.37	6.03	5.79	6.04	5.94	5.9	5.9	6.07
25	11.91	13.28	13.39	13.29	13.15	13.22	12.62	12.37	13.44	13.26

4.4. Analysis and Results in Real ECG Signals

4.4.1. Results of Removing Dc-wander

Baseline wander which is one of the main sources of noise in the field of ECG signal analysis comes from respiration and electrode movements. Usually removing this kind of noise is accomplished by a high pass filter with a cut of frequency equal to 0.3HZ as pre processing to the FECG signal extraction algorithm. In this work, removing dc wander is done simultaneously with the fetal ECG signal extraction algorithm which reduces the computational time. In the process of extraction, in order to model the mapped maternal ECG recorded at the abdomen area of a pregnant woman, a vector sequence composed of the sequence of the maternal signal and its J time-derivatives is fed to the mapping algorithm as one of its inputs. Previously, it was proven that the feature vector components can be the maternal signal and its integration or its shifted version of this signal. FECG extraction is possible with all these three kinds of feature vectors. In this section it is shown that, the baseline removing can be accomplished by considering the vector sequence consist of maternal signal and its integration components. The integration in this procedure acts as low pass filter, so by passing baseline frequencies through the polynomial networks we will have this frequency band at the mapped maternal ECG signal. By subtracting mapped maternal ECG signal from abdominal signal, the baseline wander will be removed from the extracted fetal ECG. Figure 38 shows a real abdominal signal which is recorded at Al-Wasl Hospital in Dubai. The signal contains dc-wander. Using integral terms in feature vector of polynomial expansion this undesired effect is removed from the extracted FECG signal. In Figure 39 the result of removing dc-wander from the extracted FECG signal is illustrated. Here we are not concerned with the efficiency of the extracted fetal ECG signal. This figure just illustrates the art of polynomial networks in removing dc-wander without any pre processing. Another example of removing baseline wander from FECG signal is available in Appendix B.

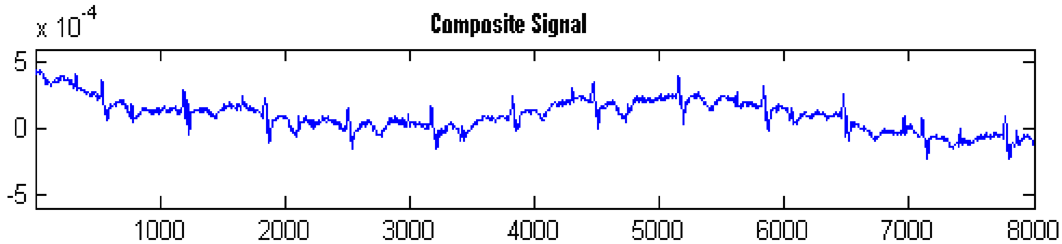

Figure 38. Real Abdominal Signal Recorded in Al-Wasl Hospital

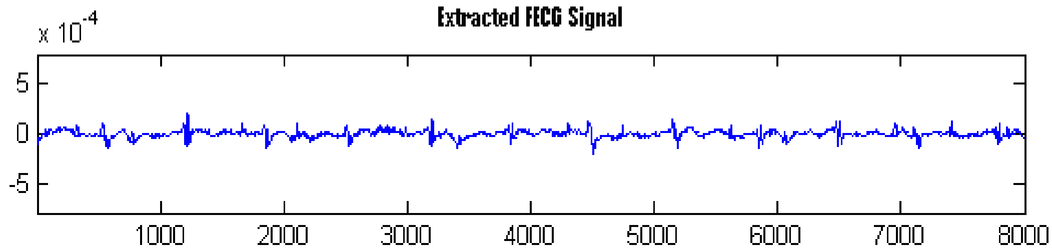

Figure 39. Removing Dc-wander from the Extracted FECG Signal

4.4.2. Results of De-noising the Extracted Real Fetal ECG Signals

Real fetal ECG signals are extracted using polynomial networks. Baseline wander is simultaneously removed from the extracted FECG signal. In this work we enhanced these extracted FECG signal using wavelet de-noising algorithm. According to our findings in section 4.3.1 and 4.3.2, we will use wavelet de-noising algorithm as post processing tool for de-noising extracted fetal ECG signal and we may use db6 mother wavelet as our wavelet function although using other selected mother wavelets give similar de-noising results.

To investigate the usefulness of our de-noising algorithm, in this section the results of fetal ECG signal de-noising are demonstrated. Experiments are done on the real fetal ECG signals. The real maternal and abdominal ECG signals recorded in Al-Wasl Hospital in Dubai are taken to the polynomial networks for extraction of the fetal ECG signals. Then wavelet de-noising is used to reduce the noise from extracted fetal ECG signals. The de-noising algorithm is done on both cases of non-overlapping of fetal with maternal ECG signal and when fetal ECG signal overlaps the maternal one. In both cases of study wavelet de-noising reduces the noise and enhances fetal ECG signal. Figure 40 and Figure 41 depict the result of the fetal ECG signal de-noising in the overlapping case. Figure 42 shows the result of the fetal ECG signal de-noising in the non-overlapping case. More examples are available in Appendix C.

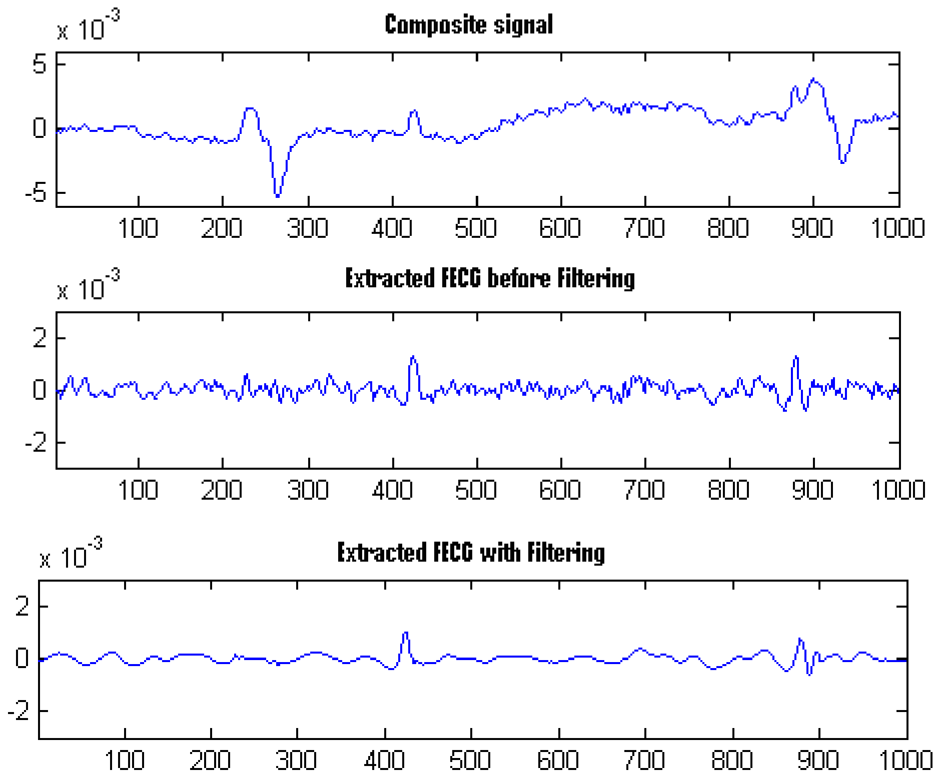

Figure 40. FECG De-noising Overlap Example

In Figure 40 fetal ECG overlaps maternal ECG. The first figure is composite abdominal signal; the second one is the extracted fetal ECG without de-noising process and the last one is the de-noised extracted fetal ECG signal.

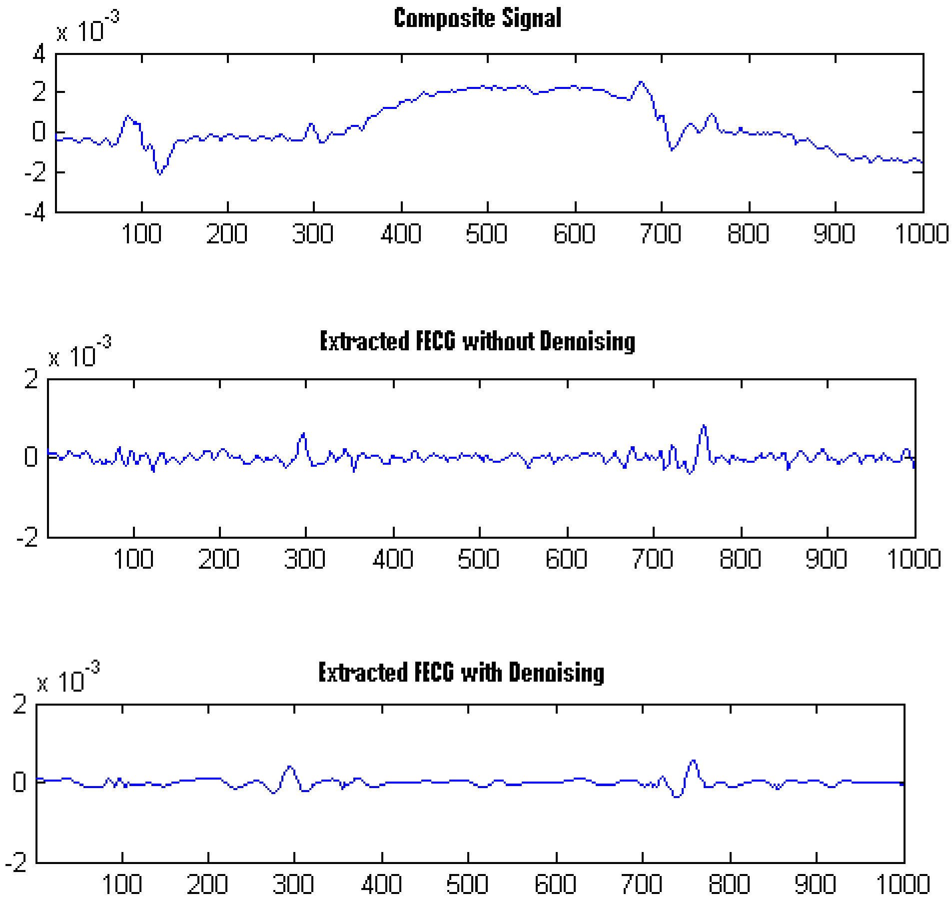

Figure 41. FECG De-noising Overlap Example

In Figure 41 fetal ECG overlaps maternal ECG. The first figure is composite abdominal signal; the second is the extracted fetal ECG without de-noising process and the last one is the de-noised extracted fetal ECG signal.

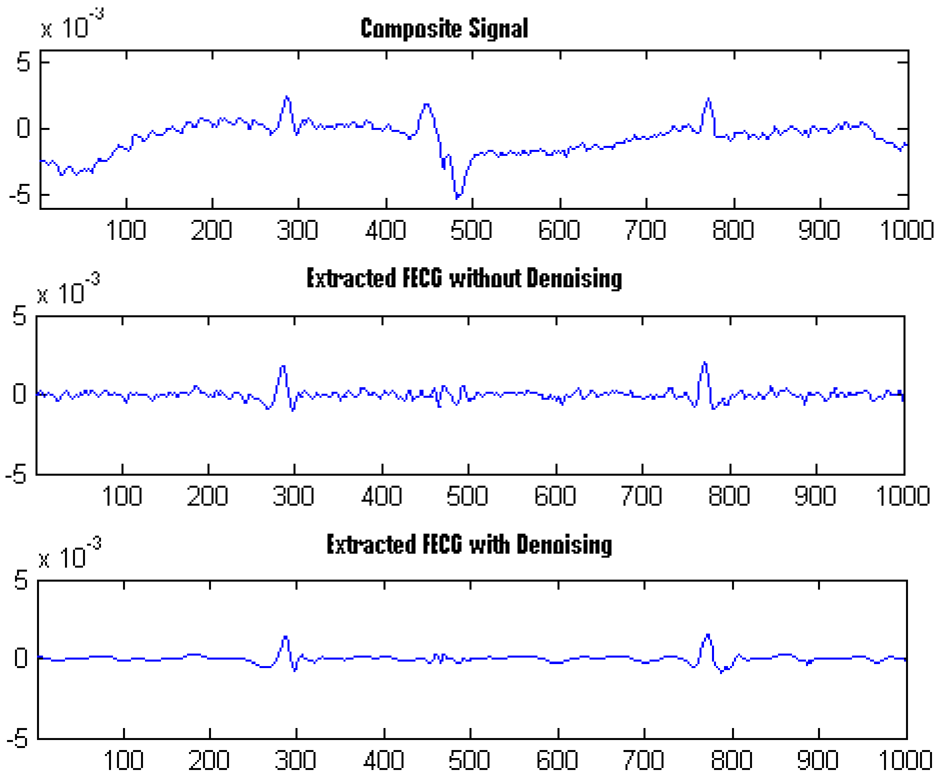

Figure 42. FECG De-noising Non-Overlap Example

In Figure 42 there is no overlap between fetal and maternal ECG signals. The first figure is composite abdominal signal; the second one is the extracted fetal ECG without de-noising process and the last one is the de-noised extracted fetal ECG signal.

Chapter 5

Conclusion and Future Work

5.1. Conclusion

The polynomial networks algorithm is exploited to extract fetal ECG from three datasets: synthetic ECG data, Lieven's real ECG data and ECG data recorded in Al-Wasl Hospital in Dubai. Baseline wander due to the mother breathing and electrode movements is removed from the extracted FECG signal and finally wavelet de-noising is used as a post processing tool in order to de-noise the extracted FECG. From the results presented in chapter 5 the following conclusion can be drawn.

1. With no need of any pre processing, baseline wander can be removed simultaneously with fetal ECG signal extraction which reduces the computational time.

2. Results in synthetic ECG signal show that although wavelet de-noising improves signal to noise ratio of the extracted fetal ECG in all three cases of possible wavelet de-noising algorithm, but it has better improvement result when it is used as post de-noising. Also it can be concluded, as the fetal ECG component is stronger in the abdominal signal, the extracted fetal ECG will be more robust in presence of noise and the de-noising algorithm has better improvement in signal to noise ratio of the extracted FECG signal.

3. Processing of real ECG data with wavelet shows clear improvement in visual representation of the extracted fetal ECG signal. Although the available real ECG data set from Al-Wasl Hospital is not quit accurate, but the extracted results are very close to what is consider as fetal ECG and the de-noise results show clear enhancement.

5.2. Future work

Future work may focus on implementing the extraction of fetal ECG signal from abdominal signal using polynomial networks and implementing enhancing algorithm.

The work presented here, fits into a much wider framework. A complete FECG solution incorporates data acquisition, analog signal processing, digital signal processing, human interface, information storage and retrieval and possibly computer aided medical inference. The achieving enhancement result in this work can be used as part of the digital signal processing unit in FECG monitoring.

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APPENDIX A

ECG signal Decomposition

The results of decomposition of ECG signal with bior3.9, dmey, rbio3.9, db5, db7 and db8 mother wavelets are illustrated in the following figures.

In the following figures

- s: is a reference ECG signal
- a5: is level five approximation
- d1 to d5: are level one details to level three details

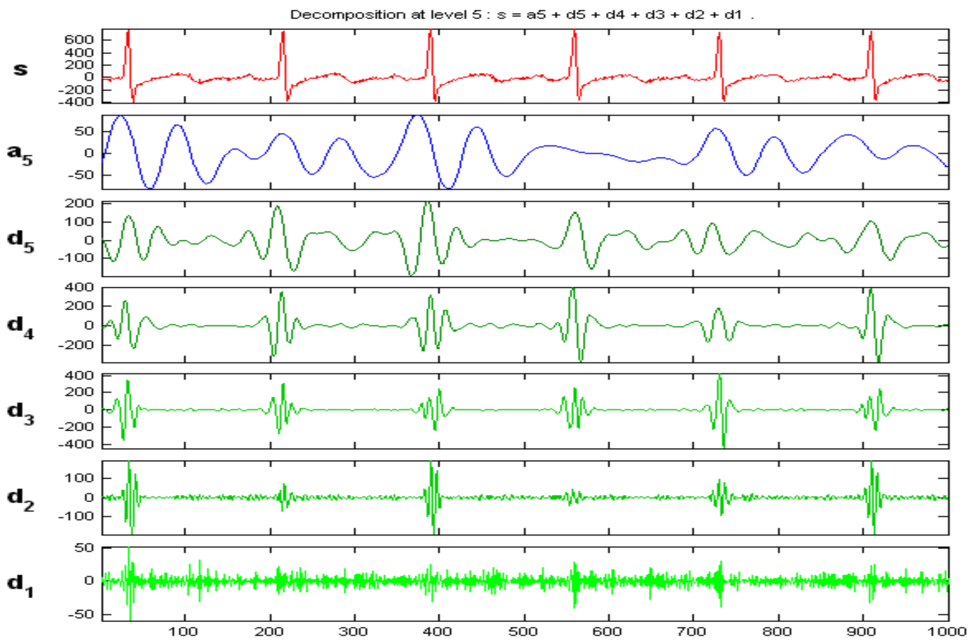

Figure 43. ECG Wavelet Decomposition using bior3.9

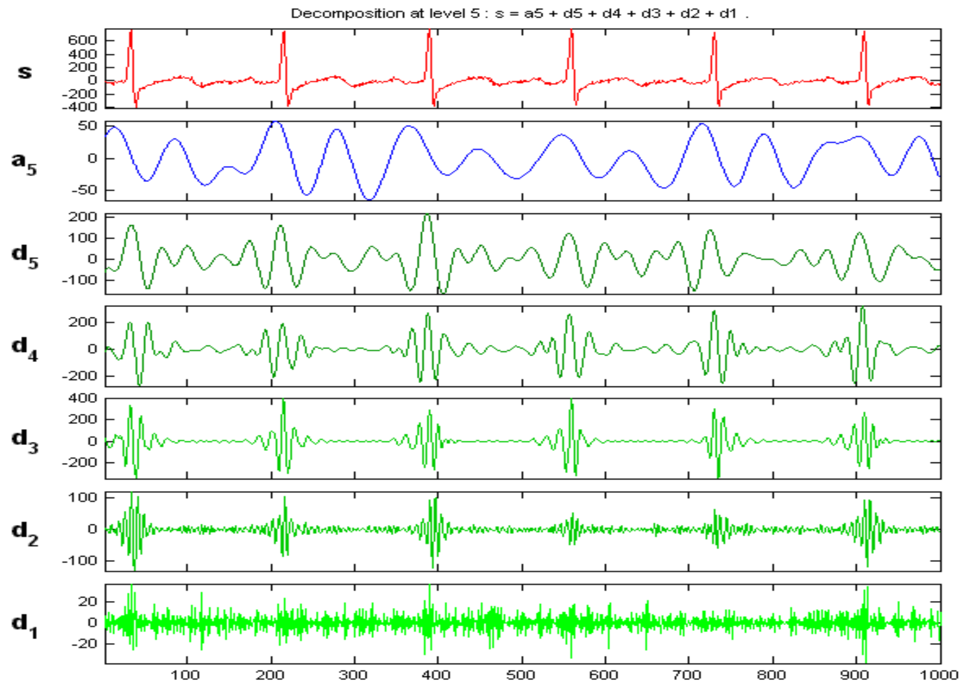

Figure 44. ECG Wavelet Decomposition using dmey

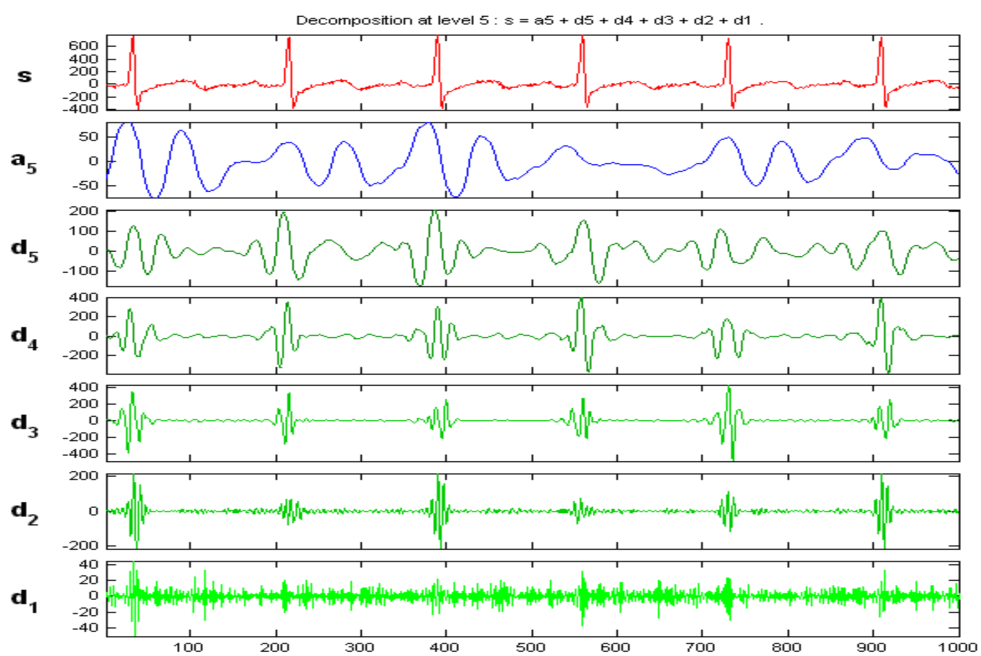

Figure 45. ECG Wavelet Decomposition using rbio3.9

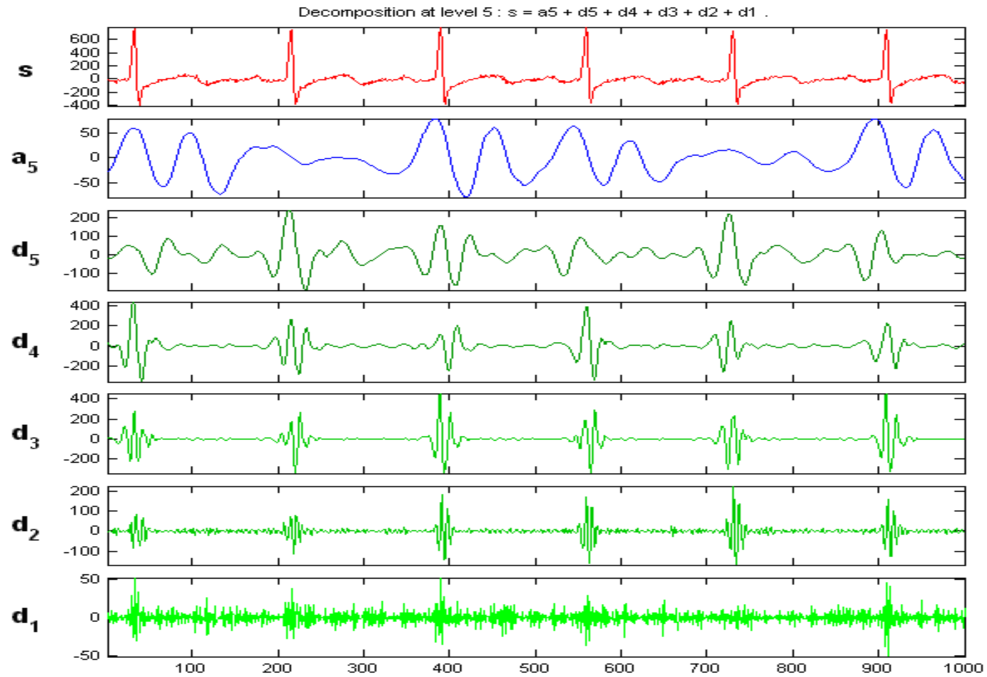

Figure 46. Wavelet Decomposition using db5

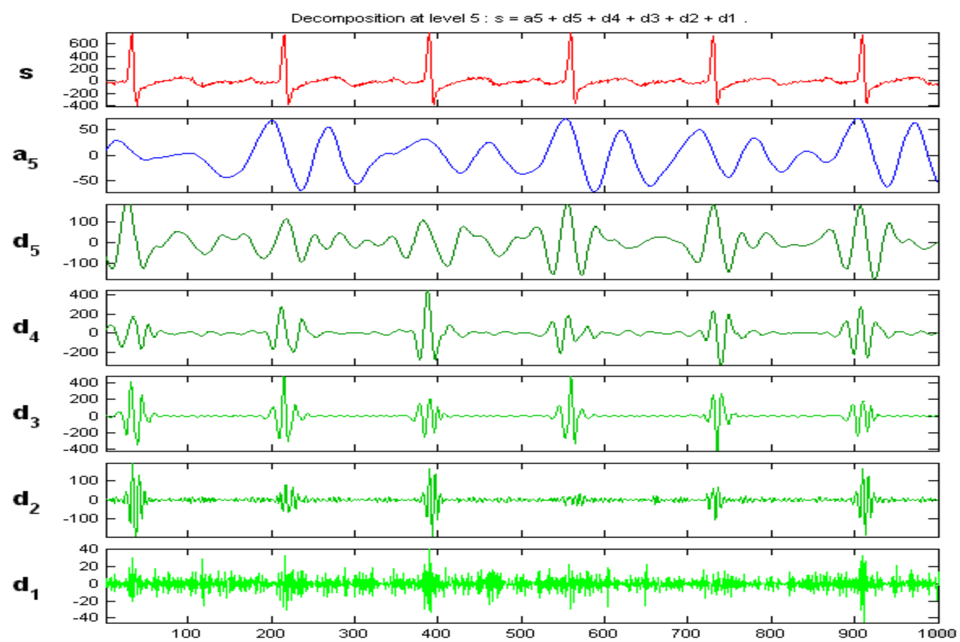

Figure 47. Wavelet Decomposition using db7

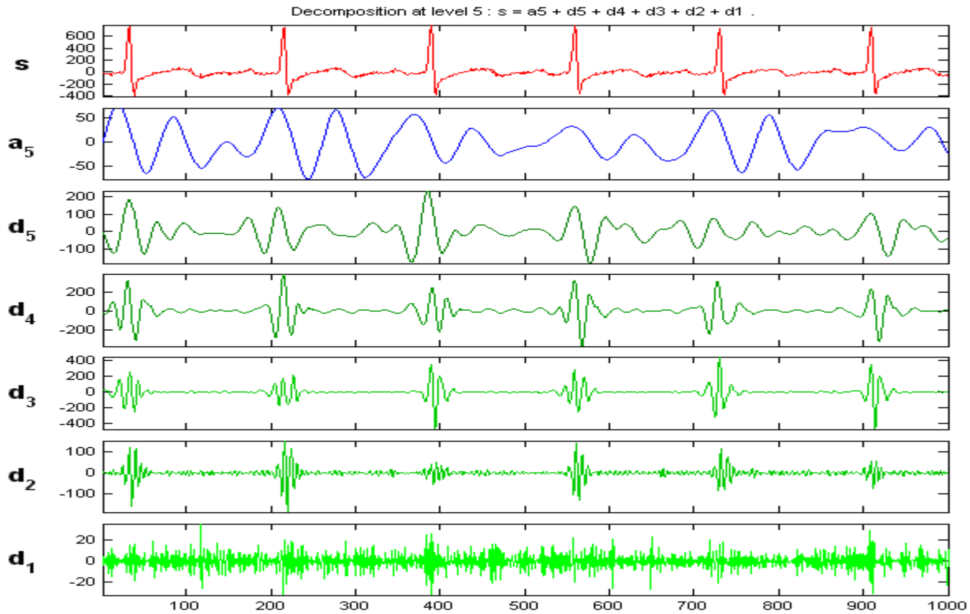

Figure 48. ECG Wavelet Decomposition using db8

APPENDIX B

Removing Baseline Wander

In Figure 49 and Figure 50 another example of removing baseline wander is shown. The first figure demonstrates the abdominal signal which contains baseline wander. The second figure is the extracted fetal ECG signal without baseline wander. Experiment is done on the real abdominal ECG signal recorded at Al-Wasl hospital in Dubai

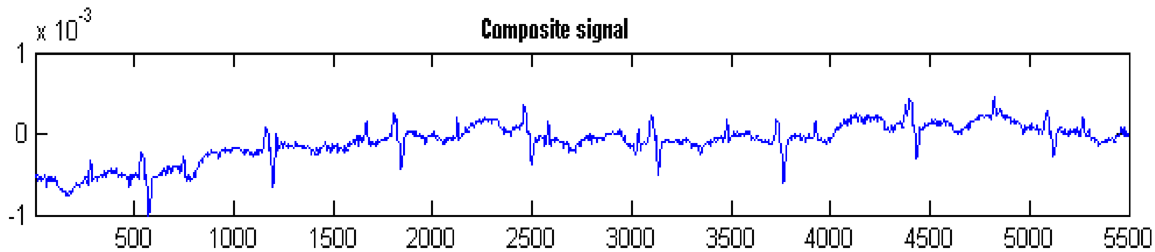

Figure 49. Real Abdominal Signal Contains Baseline Wander

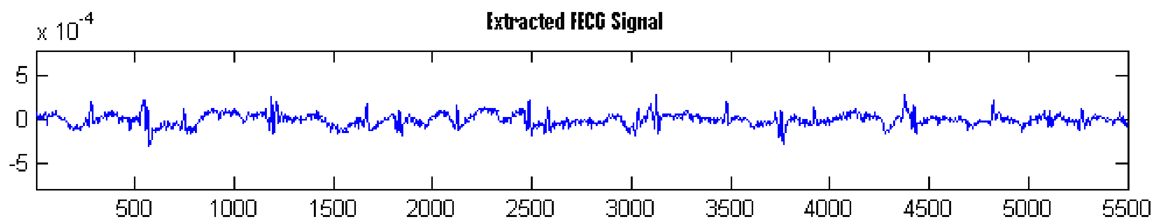

Figure 50. Extracted Fetal ECG Signal without Baseline Wander

APPENDIX C

Real Fetal ECG Extraction and De-noising

In the following five figures, results of fetal ECG signal extraction and de-noising are demonstrated. Experiments are done on the real ECG signals recorded at Al-Wasl hospital in Dubai.

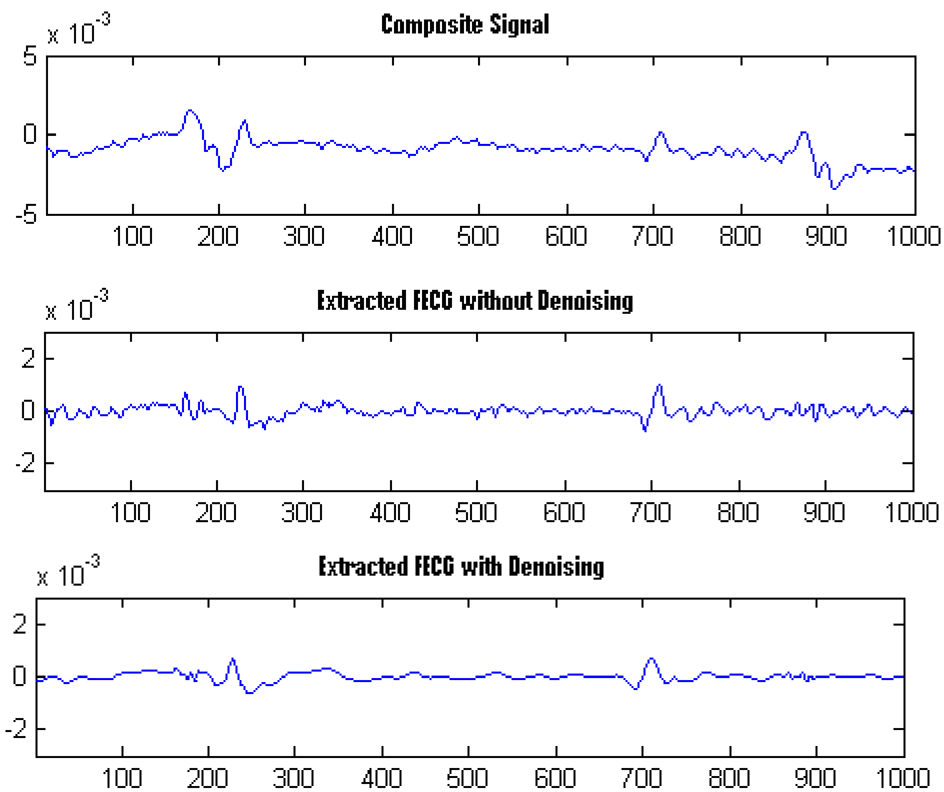

Figure 51. FECG Signal De-noising Overlap Example

In Figure 51 fetal ECG overlaps maternal ECG. The first figure is composite abdominal signal; the second is the extracted fetal ECG without de-noising process and the last one is the de-noised extracted fetal ECG signal.

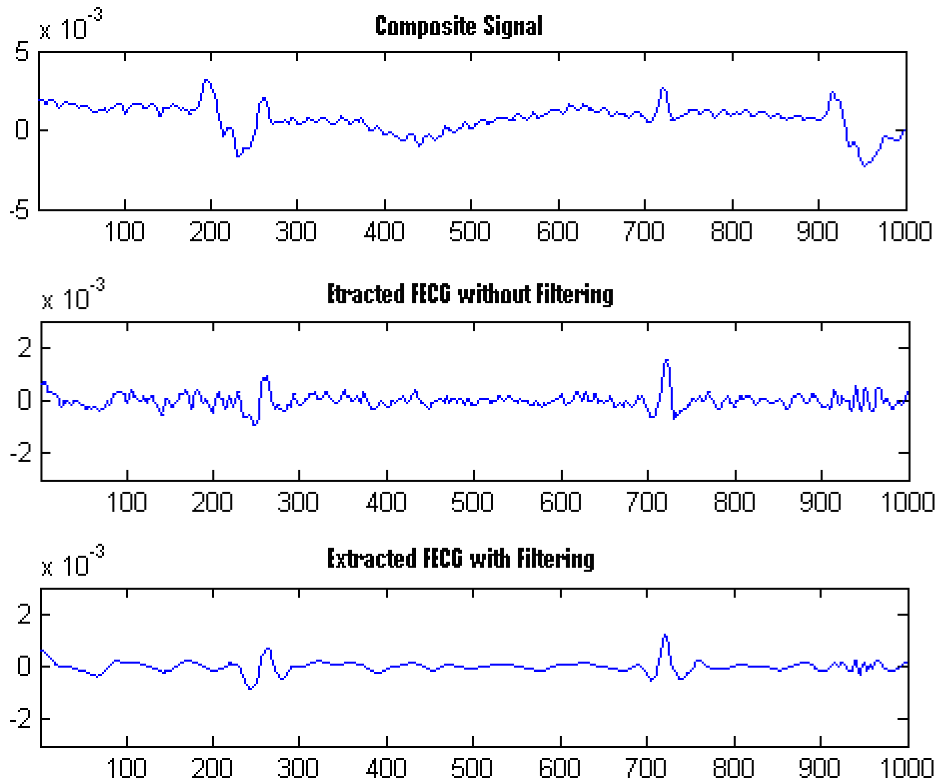

Figure 52. FECG Signal De-noising Overlap Example

In Figure 52 fetal ECG overlaps maternal ECG. The first figure is composite abdominal signal; the second is the extracted fetal ECG without de-noising process and the last one is the de-noised extracted fetal ECG signal.

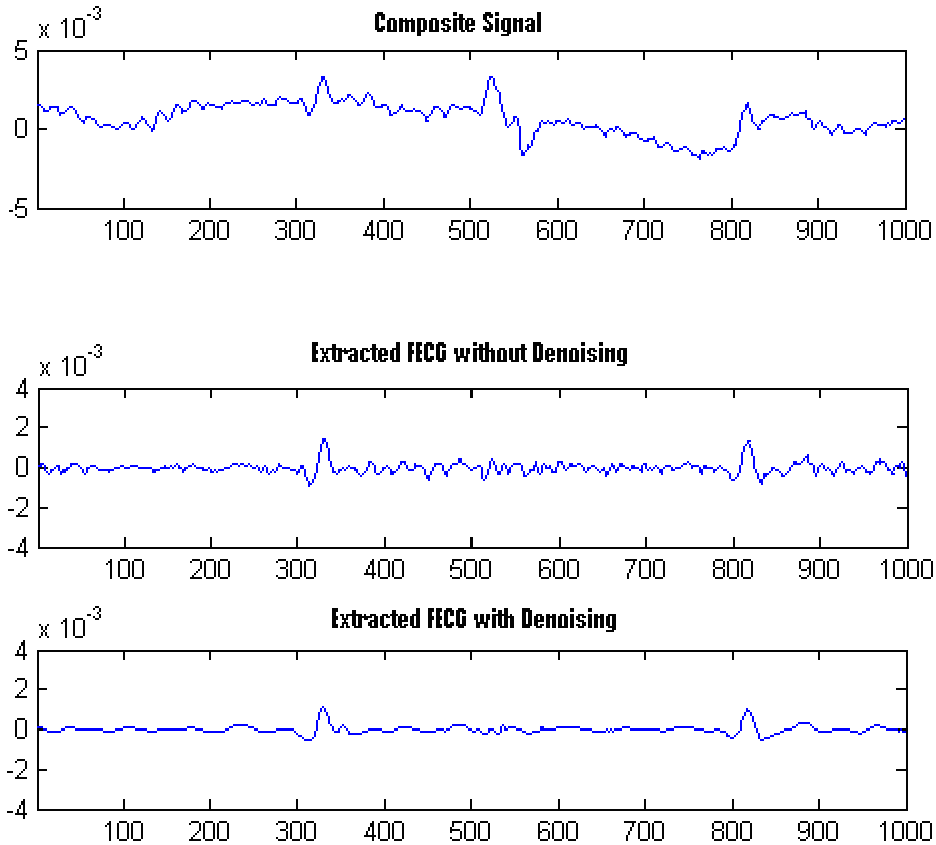

Figure 53. FECG Signal De-noising Non-Overlap Example

In Figure 53 there is no overlap between fetal and maternal ECG signals. The first figure is composite abdominal signal; the second one is the extracted fetal ECG without de-noising process and the last one is the de-noised extracted fetal ECG signal.

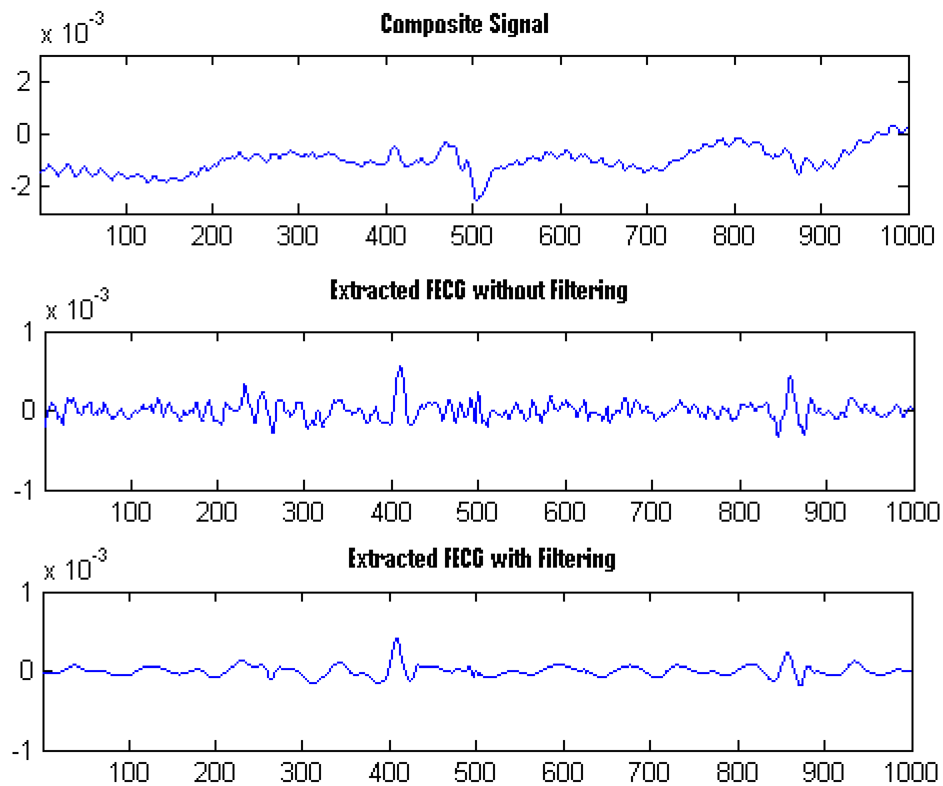

Figure 54. FECG Signal De-noising Non-Overlap Example

In Figure 54 there is no overlap between fetal and maternal ECG signals. The first figure is composite abdominal signal; the second one is the extracted fetal ECG without de-noising process and the last one is the de-noised extracted fetal ECG signal.

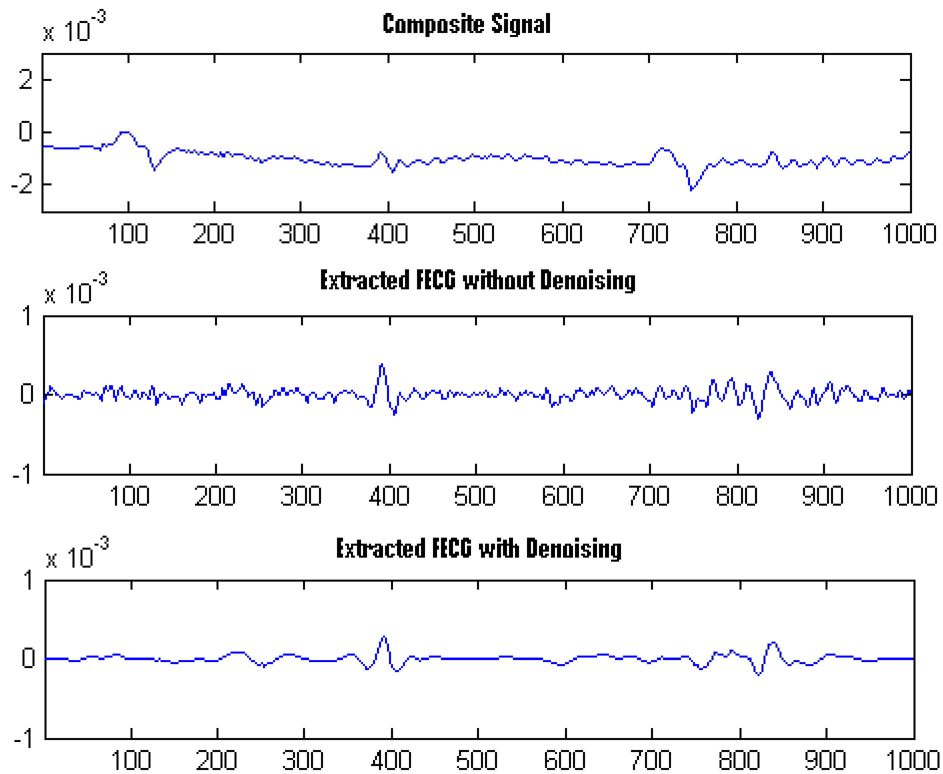

Figure 55. FECG Signal De-noising Non-Overlap Example

In Figure 55 there is no overlap between fetal and maternal ECG signals. The first figure is composite abdominal signal; the second one is the extracted fetal ECG without de-noising process and the last one is the de-noised extracted fetal ECG sig

APPENDIX D

MATLAB Codes

```
close all
load ecg
m_ecg=normalize(ecg(1:2:10000));
f_ecg=normalize(ecg(20001:4:20000+ 20000));
f = [0 0.2 0.2 1]; m = [1 1 0 0];
b = fir2(10,f,m);
m_ecg=normalize(filtfilt(b,1,m_ecg));
f_ecg=resample(f_ecg,3,2);
f_ecg=normalize(f_ecg(1:5000));
 SNRF_a=-12;
kcoeff=addnoiseM(f_ecg,m_ecg,SNRF_a);

a_ecg=f_ecg+kcoeff*m_ecg; %generating abdominal ECG



plot(f_ecg,'-.')
hold on
plot(m_ecg,'-.r');
plot(a_ecg,'K');

fetextract=polyfecg(m_ecg, a_ecg,1,0); %FECG extraction without denoising
SNR=snr(normalize(fetextract),normalize(f_ecg(1:length(fetextract))))%qSNR without
denoising

indexsnr=1;
for cnt=-15:50
   a_ecgnoisy=addnoise(a_ecg,cnt); %adding noise to abdominal signal
   fetextract=polyfecg(m_ecg, a_ecgnoisy,1,0); %extracting noisy FECG
   cnt
```

```
  SNRout(indexsnr)=snr(normalize(fetextract),normalize(f_ecg(1:length(fetextract))));
%qSNR noisy FECG
  indexsnr=indexsnr+1;
end
figure
plot(-15:50,SNRout)


indexsnr=1;
for cnt=-15:50
  a_ecgnoisy=addnoise(a_ecg,cnt); %adding noise to abdominal signal
  fetextract=polyfecg(m_ecg, a_ecgnoisy,1,0); %extracting noisy FECG
  fetextractdenoise=wden(fetextract,'minimaxi','h','sln',2,'db6'); %post denoising
  cnt

SNRout(indexsnr)=snr(normalize(fetextractdenoise),normalize(f_ecg(1:length(fetextractd
enoise)))); %qSNR of the denoised FECG
  indexsnr=indexsnr+1;
end
hold on
plot(-15:50,SNRout,'r')



indexsnr=1;
for cnt=-15:50
  a_ecgnoisy=addnoise(a_ecg,cnt); %adding noise to abdominal signal
  a_ecgdenoisy=wden(a_ecgnoisy,'minimaxi','h','mln',1,'db6'); %pre denoising

  fetextract=polyfecg(m_ecg, a_ecgdenoisy,1,0);%extracting FECG
```

```
  cnt

SNRout(indexsnr)=snr(normalize(fetextract),normalize(f_ecg(1:length(fetextract))));%qSNR of the denoised FECG
  indexsnr=indexsnr+1;
end

plot(-15:50,SNRout,'g')


indexsnr=1;
for cnt=-15:50
  a_ecgnoisy=addnoise(a_ecg,cnt); %adding noise to abdominal signal
  a_ecgdenoisy=wden(a_ecgnoisy,'minimaxi','h','mln',1,'db6'); %pre denoising

  fetextract=polyfecg(m_ecg, a_ecgdenoisy,1,0);%extracting FECG

  fetextractdenoise=wden(fetextract,'minimaxi','h','mln',1,'db6');%post denoisnig
  cnt

SNRout(indexsnr)=snr(normalize(fetextractdenoise),normalize(f_ecg(1:length(fetextractdenoise))));%qSNR of the denoised FECG
  indexsnr=indexsnr+1;
end

plot(-15:50,SNRout,'k')
```

```
function noisysig=addnoise(sig,Ndb)

sig=sig(:);
N=length(sig);
sig_pow=sum(sig.*sig);

var_N=sig_pow*10^(-Ndb/10)/N;
sigma_N=sqrt(var_N);
noisysig=sigma_N*randn(N,1)+sig;



function kcoeff=addnoiseM(fecg,mecg,SNR)
%% this fucnction calculate kcoeff for aecg= kcoeff*mecg+fecg =>
%% snr(fecg,mecg)=SNR
kcoeff=1/10^(SNR/20);


function n=normalize(signal)
n=signal-mean(signal);
n=n/sqrt(sum(n.*n));


function SNR=snr(x,y);
% x : orginal input signal
% y : output signal maybe with noise
% SNR : of signa
x=x(:);
y=y(:);
N=length(x);
x_sq = x.*x;
P_x = sum(x_sq)/N;
e = y-x;
e_sq = e.*e;
P_e = sum(e_sq)/N;
SNR = 10*log10(P_x/P_e);
```

```
function [extractecg]=polyfecg(m_ecg,a_ecg,ord,difnum);
 if nargin < 3
   ord=2;
   difnum=2;
end
 if nargin < 4
   difnum=2;
end
 win_size=300;
 win=ones(win_size,1);

sig=a_ecg;
ref=m_ecg;
MAT=[];
FET=[];
SIG=enframe(sig,win,win_size/2);
REF=enframe(ref,win,win_size/2);
[M N] = size(SIG);
loop=1;
MAT=[];
 FET=[];
diffmat=zeros(win_size,difnum);
for i=1:M
   s1=SIG(i,:)/sqrt(sum(abs(SIG(i,:).^2)));     s1=s1(:);%%%%%%sum(abs(SIG(i,:)))     by
sqrt(sum(abs(SIG(i,:).^2))) ayat
   %sd  = wden(s1,'heursure','s','one',1,'sym8');s1=sd;
   r=REF(i,:)/sqrt(sum(abs(REF(i,:).^2)));r=r(:);
   %rd  = wden(r,'heursure','s','one',2,'sym8');r=rd;
   diffmat(:,1)=r;
% %r_int1=cumsum(r);
% r_int2=cumsum(r_int1);
```

```
% r_int3=cumsum(r_int2);
for cntdif=1:difnum
   diffmat(:,cntdif+1)=[0;diff( diffmat(:,cntdif))];
end
%r_diff1=[0;diff(r)];
%r_diff2=[0;diff(r_diff1)];
%r_diff3=[0;diff(r_diff2)];

% r_shift1=[0; r(2:end)];
% r_shift2=[0;r_shift1(2:end)];
% r_shift3=[0;r_shift2(2:end)];

%trn=[r r_shift1 r_shift2 r_shift3];
%trn=[r r_diff1 r_diff2 r_diff3];
trn=diffmat;
strn=repmat(std(trn),length(trn),1);
trn=trn./strn;
trgt=s1;
ptrn=feat_mat2poly_mat(trn,ord);
%w=ptrn\trgt;
w=pinv(ptrn)*trgt;
%w=linprog_L1(ptrn,trgt);
mat=ptrn*w;
fet=s1-mat;

MAT=[MAT; mat(1:win_size/2)];
FET=[FET;fet(1:win_size/2)];
end
```

VITA

Maryam Ahmadi was born on May 29, 1980, in Iran, Isfahan. She was educated in local public schools and graduated from Azmoon High School in 1997. She received her bachelor degree from Azad University of Naien, Isfahan. Her degree was a Bachelor of Science in Electronics Engineering.

In 2004, Ms. Ahmadi began a master's program in Mechatronics Engineering at the American University of Sharjah.