SMALS: A SVD Multi-Stage Adaptive Least Square Approach for FECG Signal Extraction in Multichannel System

S. Ravindrakumar

Abstract--- *In this paper the abdominal signal is de-noised and the Fetal ECG is extracted for obtaining the important information about the fetus during pregnancy. Noise analysis and removal is done using different signal processing techniques. The results are been compared. To cancel out a Maternal ECG and noise from the Abdominal ECG, different types of filtering techniques are used. A Multistage adaptive filtering along with the SVD denoising techniques to extract the FECG from the abdominal signal is proposed. The proposed architecture is a combination of Singular Value Decomposition (SVD) filtering method and Multistage Adaptive filter model. This method leads to enhancement of fetal ECG by canceling maternal ECG and noises in the first stage using SVD. The FECG extraction is done using multistage multichannel adaptive filter from 4 channels simulated and 5 real time channel signals recorded at the thoracic and abdominal areas of the mother's skin. The thoracic ECG simulated is assumed to be almost completely maternal while the abdominal ECG (AECG) is considered to be composite as it contains both the mother's, fetus ECG signals and the noise. The proposed method is applied to simulated and real time ECG signals to demonstrate its superior effectiveness.*

Keywords--- *SVD, LMS, RLS, NLMS Denoising, FECG, MECG, Multistage Filtering*

I. Introduction

HEART defects are among the most common birth defects and leading cause of birth defects related deaths. Most cardiac defects have some manifestation in the morphology of electrocardiography and are believed to contain much more information as compared with convention sonographic methods. However due to low SNR of fetal electrocardiogram (FECG), recorded from the maternal body surface, the application of fetal electrocardiography has been limited to heart beat analysis and invasive ECG recordings during labor.

The amplitude and frequency range of fetal ECG has been compared with other noises and artifacts in fig1.1. Accordingly the fetal ECG is much weaker than other interfering bio signals .Moreover from the domain (time,space.frequency and feature)[57][58][59][37][31] in which the fetal ECG can be totally separated from the interfacing signals. Although in previous works, a large body of research has been devoted to filtering of fetal complexity signals [14-63], due to complexity of problem there are still many problem or open issues that require improved signal processing techniques. In this paper the improvement in signal processing aspects of fetal cardiograph and an improved modeling and filtering of fetal ECG signal from various noise sources is done. The datas used are recorded FECG signal from array of electrodes placed on maternal abdominals [13].

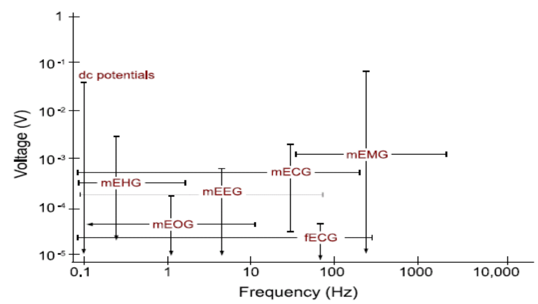

Figure 1.1: The Amplitude and Frequency Range of Bio Signals that can Interfere with Fetal Cardiac

The various components involved in the Fetal monitoring system is shown in figure.1.2.It consists of the Maternal ECG, Fetal ECG and the noise. The CECG is the composite signal which is the abdominal signal which is the combination of MECG, FECG and the noise signal. The different stages of the Fetal monitoring system is shown in the figure.1.3.The major challenge in the design is the removal of the MECG signal from the abdominal signal .Throughout the years different methods has been adopted to remove the MECG signal and the detection of the FECG signal. Different works has been carried out in enhancing the FECG signal. The Fetal QRS provides the information about the fetal well being and the heart rate of the fetus. The diagnosis can be done only if a proper Fetal QRS is obtained.Finally the overlapping of MECG and FECG signal is troublesome. In case of twins or multiple fetus the complexity increases. Both the invasive and non invasive methods fails to detect the fetal ECG signal. The methods to be adapted should overcome all the status of the errors and should promise better results.

S. Ravindrakumar, Senior Assistant Professor, Department of Electronics and Communication Engineering, Chettinad College of Engineering and Technology, Karur, Tamilnadu-639114, India. E-mail:ravindrakumar_mtech@rediffmail.com

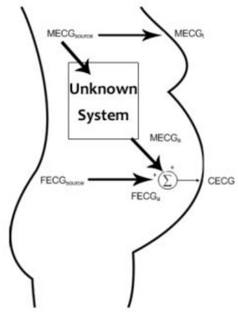

Figure 1.2: Components of Fetal ECG System

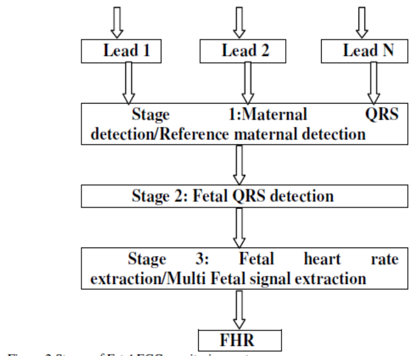

Figure 1.3: Stages of Fetal ECG Monitoring System

A. Mathmatical Model

The major components of the Fetal monitoring system includes the maternal ECG, fetal ECG and the Noise(Figure .1.2).They are represented by $MECG_i(t)$, $FECG_i(t)$ and ($N_{ilf}(t)$ + $N_{ihf}(t)$).Depending on the number of electrodes and their placement in the abdomen and thorax determines the model for which the analysis has to be done. In general the abdominal and the thoracic signal can be represented as

i) Abdominal Signal(CECG)

$$Ab_i(t)=N_{ilf}(t)[F_{ECGi}(t)+M_{ECGi}(t) + Nihf(t)] \quad (1)$$

where

$N_{ilf}(t)$ is the DC noise due to muscle and breathing movements.

$F_{ECGi}(t)$ is the Fetal ECG signal. The amplitude of the Fetal ECG signal will be in Micro Volts

$M_{ECGi}(t)$ is the maternal ECG signal .The amplitude of the maternal ECG signal will be in few milli volts.

N_{ihf} (t) is the noise signal due to EMG,50 Hz hum noises.

Different filtering methods is been used to remove the noise. The noise level depends on the proper placement of the electrodes.

ii) Thoracic Signal

$$T_{hi}(t) = N_{ilf}(t) [M_{ECGi}(t) + Nihf(t)] \quad (2)$$

II. Synthetic ECG Generation

In recent years research has been conducted towards the generations of synthetic ECG signals. Dynamic models has been developed which reproduces the morphology of pqrst complex and their relationship to beat to beat timing in a single nonlinear dynamic model. The simple and flexibility of the model makes it easy to adapt to broad class of normal and abnormal ECGs.Real ECG recordings are always contaminated with noise and arifacts. Hense besides the modeling of cardiac sources and propagation media, it is very important to have realistic models for noise sources. Since common ECG contaminants are non stationary and temporally correlated, time varying dynamic models are required for generation of realistic noises. Here a three dimensional canonical model of the single dipole vector of heart is applied. This model which is inspired by the single – channel ECG dynamic model presented in [1]. A realistic synthetic ECG generator was first proposed by MCSharry et al, using a set of 3D state equations to generate a trajectory in the Cartesian co-ordinates. The dynamic equations were then transformed into polar form for a simpler compact set by Sameni et al [2]. In this model several Gaussians are utilized to approximate the feature waves (P, Q, R, S & T waves) in one heart beat of ECG.

The other works which include the generation of synthetic ECG are by using Asymmetric Gaussians[3], knowledge based system using qualitative ECG simulation [4], Augmented mono domain model [5] a heart model with reaction - diffusion action potentials[6], ECG SIM [8] & synthesizing the standard 12-lead ECG from three differential leads formed by pairs of proximal electrode on the body surface[12]. Boundary element approach[12],labview simulink[7],Tehron – Cairo formula, volume conductor model

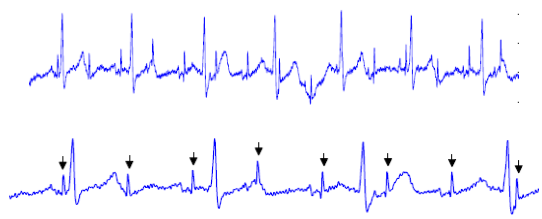

Figure 2.1: Original Abdominal Signal Arrows Indicate the Occurrences of Fetal Heart Beats, which are detected by Visual Inspection

& time series for HRV by modified Zeeman model However the previous works are concerntrated only on single channel ECG modeling, meaning that the parameter of the model should be re-calculated for each of recording channels. For maternal & fetal mixtures analysis only few works are done which considers the cardiac source & propagation media. The works also fasts to include the noise model & filtering.

III. Dynamic Model of ECG

In order to evaluate the effect of noise in ECG suitable models are required to generate the mixture of fetal cardiac signals & noises. In this work we have adapted the dipole theory of heart & been applied for generating an arbitrary number of synthetic ECG channel in single & multiple pregnancies. According to the single dipole model of the heart the myocardium's electrical activity may be represented by a time varying rotatory vector, the origin of which is assumed to be at the centre of the heart as its end sweeps out a quasi periodic path through the torso. This vector may be mathematically represented in the Cartesian co-ordinates as follows.

$$d(t) = x(t)\hat{a}_x + y(t)\hat{a}_y + z(t)\hat{a}_z \tag{3}$$

ax,ay,az - unit vectors of three body axes.

The body volume conductor is assumed to be a passive resistive medium. The ECG signal recorded from the body surface would be a linear projection of the dipole vector d(t) onto the direction of recording electrode axes.

$$V = a\bar{a}_x + b\bar{a}_y + c\bar{a}_z \tag{4}$$

ECG(T)=<d(t)
V>=a.x(t)+b.y(t) +c.x(t)

The potential generated by dipole at a distance IrI (where $r = r_x\bar{a}_x + r_y\bar{a}_y + r_z\bar{a}_z$ is the vector which connects the centre of dipole to observation point) & conductivity of volume conductor [] is

$$\phi(t) - \phi_O = \frac{d(t).r}{4\pi\sigma|r|^3} \tag{5}$$

$$\phi(t) - \phi_O = \frac{}{4\pi\sigma}\left[x(t)\frac{r_x}{|r|^3} + y(t)\frac{r_y}{|r|^3} + z(t)\frac{r_z}{|r|^3}\right] \tag{6}$$

From the single dipole model of heart adapted from MCSharry et al model, it is well known that the different ECG leads can be assumed as projections of heart's dipole vecor onto the recording electrode axes. All leads are time synchronized with each other & have quasi-periodic shape. The three dimensional extension is given by

$$\begin{aligned} \dot{\theta} &= \omega \\ \dot{x} &= -\sum_i \frac{\alpha_i^x \omega}{(b_i^x)^2} \Delta\theta_i^x exp\left[-\frac{(\Delta\theta_i^x)^2}{2(b_i^x)^2}\right] \\ \dot{y} &= -\sum_i \frac{\alpha_i^y \omega}{(b_i^y)^2} \Delta\theta_i^y exp\left[-\frac{(\Delta\theta_i^y)^2}{2(b_i^y)^2}\right] \\ \dot{z} &= -\sum_i \frac{\alpha_i^z \omega}{(b_i^z)^2} \Delta\theta_i^z exp\left[-\frac{(\Delta\theta_i^z)^2}{2(b_i^z)^2}\right] \end{aligned} \tag{7}$$

where

$$\Delta\theta_i^x = (\theta - \theta_i^x) mod(2\pi)$$
$$\Delta\theta_i^y = (\theta - \theta_i^y)\ mod(2\pi)$$
$$\Delta\theta_i^z = (\theta - \theta_i^z)\ mod(2\pi)$$
$$\omega = 2\pi$$

Each of the three co-ordinates of the dipole vector d(t) is modeled by a summation of Gaussian functions with amplitudes α_i^x, α_i^y and α_i^z widths b_i^x, b_i^y and b_i^z, located at rotational angle θ_i^x, θ_i^y and θ_i^z. In our work the model for orthogonal lead VCG co-ordinates are altered using different scaling factors for attenuation of volume conductor.

IV. Noise Modeling and Filtering Methods

Various research areas have been carried out for removal of noise & interference from FECG,including auto and cross correlation[31] subtraction of an averaged pattern[26],matched filtering[31],linear regression, adaptive filtering[39], neural networks[32],[44]IIR adaptive filtering combined with genetic algorithm[30],wavelet transform[26],[25],[36]fuggy[35],[37], SVD method[40],moving average , Hilbert transform [27] and ICA [16], [19] ,28], [35],[40], [42], [46].

Due to the overall of fetal signals and interference in different domain.the methods that use the information in only one of these domain do not usually succeed in extraction of fetal ECG.Therfore which uses the information from various domain(including time,frequency and feature),Inorder to improve the quality of extracted signals. It is shown that due to the generality of the methods for both adult and fetal are applicable to multichannel ECG.Other method used for the extraction of FECG from mixed signal are principal component analysis(PCA) or singular value decomposition and independent component analysis.These methods called blind source separation(BSS) consist of contracting unknown signals(called sources) which are statistically independent from known mixtures of signals.The principal component analysis [14] uses second order statistics which higher order statistics is performed by independent component analysis[43].

Some already proposed ICA-based techniques are INFOMAX[R3],JADE[R4],fastica[41] and MERMAD[R6].BSS in wavelet domain [35] and adaptation of wavelet – ICA(WICA) method[35], The BSS[14],[19],[20],[40] methods produce better results only when the system uses large number of recorded ECG leads so large number of sources are available. Furthermore, the electrodes used for measurement should be adupted This ensures that the recorded mixtures of sources. But BSS method suffer from the problem that manual intervention is required for diagnosis.

V. Methodology and Results

A. *Filtering using SVD*

Singular value decomposition (SVD) is quite possibly the most widely-used multivariate statistical technique used in the atmospheric sciences. The purpose of singular value decomposition is to reduce a dataset containing a large number of values to a dataset containing significantly fewer values, but which still contains a large fraction of the variability present in the original data. Often in the atmospheric and geophysical sciences, data will exhibit large spatial correlations. SVD analysis results in a more compact representation of these correlations, especially with multivariate datasets and can provide insight into spatial and temporal variations exhibited in the fields of data being analyzed. There are a few caveats one should be aware of before computing the SVD of a set of data. First, the data must consist of anomalies. Secondly, the data should be de-trended. When trends in the data exist over time, the first structure often captures them. If the purpose of the analysis is to find spatial correlations independent of trends, the data should be de-trended before applying SVD analysis. In linear algebra the (SVD) is a factorization of a real or complex matrix, with many useful applications in signal processing and statistics. It is very important decomposition of a matrix and tells us a lot about its structure.. After applying SVD on noisy signal, the singular values matrix achieved is described as follows

$$S = \begin{pmatrix} S_a & 0 & 0 \\ 0 & S_{a+n} & 0 \\ 0 & 0 & S_n \end{pmatrix} \quad (8)$$

S_{a+n} is a diagonal matrix contains the combination of singular values of the clean signal and noise signal ,whose values are added together.

The equation for SVD is

$$\alpha_i = \begin{cases} 1 & 1 \le i \le 3 \\ e^{-(i-4)/4.5} & 4 \le i \le 15 \\ 0 & 16 \le i \le 40 \end{cases} \quad (9)$$

The first measuring method to investigate the efficiency of the proposed method is SNR, so we have:

$$SNR = 10 \log_{10} \left(\frac{\sum x^2_{org}}{\sum (x_{org} - x_{est})} \right) \quad (10)$$

In which x_{org} is indicating clean signal and x is indicating the enhanced one. The source of the ECG is obtained from MIT-BIH Arrhythmia Database (MITDB) ,Daisy Chain Database and EDF database which is a set of Holter recordings and multichannel signals.The simulated datas are been generated in MATLAB using the Gaussian Models

- *Preprocessing*

The obtained ECG signal is preprocessed by SVD for the removal of noise components to enhance the quality of abdominal signal.A 42% merge is used in matrix input for SVD which is a random selection.

B. Extraction using Multiinput/Multichannel Multistage Adaptive Filters

An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. Because of the complexity of the optimization algorithms, most adaptive filters are digital filters [14][16][19][22][30]. By way of contrast, a non-adaptive filter has a static transfer function. Adaptive filters are required for some applications because some parameters of the desired processing operation (for instance, the locations of reflective surfaces in a reverberant space) are not known in advance. The adaptive filter uses feedback in the form of an error signal to refine its transfer function to match the changing parameters. Generally speaking, the adaptive process involves the use of a cost function, which is a criterion for optimum performance of the filter, to feed an algorithm, which determines how to modify filter transfer function to minimize the cost on the next iteration.

a. LMS Algorithm

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal) [62]. It was invented in 1960 by Stanford University professor Bernard Widrow .

$$\begin{aligned} \mathbf{x}(n) &= [x(n), x(n-1), \dots, x(n-p+1)]^T \\ e(n) &= d(n) - \hat{\mathbf{h}}^H(n)\mathbf{x}(n) \\ \hat{\mathbf{h}}(n+1) &= \hat{\mathbf{h}}(n) + \mu\, e^*(n)\mathbf{x}(n) \end{aligned} \quad (11)$$

b. RLS Algorithm

The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals . This in contrast to other algorithms such as the least mean Square performance when the filter to be estimated, at the cost of high computational complexity, and potentially poor tracking .

$$\begin{aligned} y(n) &= \mathbf{w}(n-1)\mathbf{u}(n) \\ e(n) &= d(n) - y(n) \\ \mathbf{w}(n) &= \mathbf{w}(n-1) + \mathbf{k}^H(n)e(n) \end{aligned} \quad (12)$$

C. NLMS Algorithm

One of the primary disadvantages of the LMS algorithm is having a fixed step size parameter for every iteration. This requires an understanding of the statistics of the input signal prior to commencing the adaptive filtering operation. In practice this is rarely achievable. Even if we assume the only signal to be input to the adaptive echo cancellation system is speech, there are still many factors such as signal input power and amplitude which will affect its performance. The normalized least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by calculating maximum step size value.

$$\begin{aligned} \mathbf{x}(n) &= [x(n), x(n-1), \dots, x(n-p+1)]^T \\ e(n) &= d(n) - \hat{\mathbf{h}}^H(n)\mathbf{x}(n) \\ \hat{\mathbf{h}}(n+1) &= \hat{\mathbf{h}}(n) + \frac{\mu\, e^*(n)\mathbf{x}(n)}{\mathbf{x}^H(n)\mathbf{x}(n)} \end{aligned} \quad (13)$$

Multistage Adaptive filter is essentially a digital filter with self-adjusting characteristics. The properties of noise changes in time and if the frequencies of the signal and the noise overlap then the adaptive filtering is selected. More over the ECG signals are non stationary in nature. Hence, the best option is to use multistage adaptive filtering. The algorithm(Figure 5.1) uses LMS,NLMS,RLS and in combination also. The proposed method detects Fetal ECG by preprocessing and de-noising of abdominal ECG (AECG) and subsequent cancellation of maternal ECG (MECG) by multichannel multi stage adaptive filtering.

The use of Multistage Adaptive filtering technique in removal of fetal ECG system is due to its advantageous features like more accuracy, It can be of any order, High efficiency and more robust. The algorithm is been tested with simulated and real time readings from DaiSy EDF database and Physionet MIT-BIH database. The algorithm is tested for variable attenuation factor and SNR values. The synthetic ECG signals for maternal and fetal is generated for various noise levels. The filtered outputs are shown in figure 5.2. Various noise signal like muscle artifact, electrode movements, baseline wander, white noise and colored noise are analyzed and filtered. From the observation the adaptive filtering techniques serves the best in preprocessing of the data or contaminated abdominal ECG. To improve the SNR value the adaptive filter stage is extended with multichannel input. The SNR values are calculated for data's (Table 1,2,3) .The input to the filter is from both synthetic and real time data's.

But if the noise level gets increased the fetal ECG will be hard to the extract. So additional improvements required in the data acquisition units which would provide high CMRR and rejection ratio's

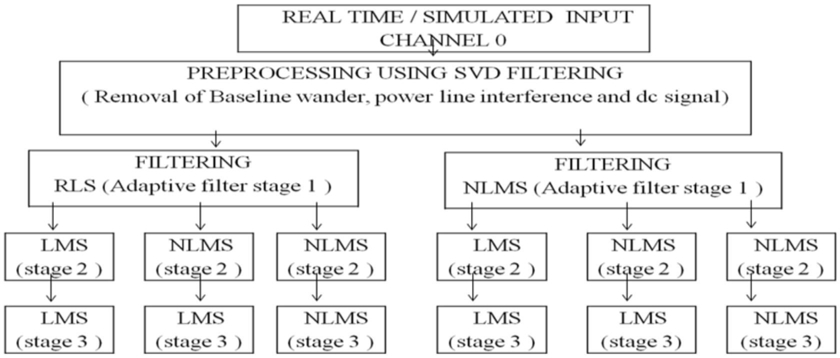

Figure.5.1: Block Diagram of Proposed Method for Single Channel after Applying SVD

Table 1: Comparison of SNR Values in the Algorithm

u	Noise (dB)	Single stage	Multi stage
1	30	-7.0800	3.5011
	40	-0.3135	3.5276
	50	-0.2546	3.5546
	60	-0.1022	4.8040

Table 2 : Comparison of MSE Values in the Algorithm

u	Noise (dB)	Single stage	Multi stage
1	30	0.0029	0.0025
	40	0.0022	0.0020
	50	0.0021	0.0019
	60	0.0021	0.0021

The extraction of Fetal ECG using multistage adaptive filter is done and the results with various algorithms is been compared. The method significantly improves the performance than other methods

The long term aim of this project is to develop a user friendly, intelligent decision support tool that combines the expertise for CTG based assessment and ECG waveform analysis to assist busy clinicians in making more accurate and timely decisions, thus reduce unnecessary clinical intervention and any permanent damage to a fetus..

VI. CONCLUSION AND FUTURE WORK

Depending upon the environment, gestational age, physiological needs different methods are reviewed. The correlation and subtraction method are ineffective in extraction of fetal ECG due to mismatching and poor template design. In noisy environment adaptive filtering technique is used. The scheme is suitable for multi-channel adaptive filtering also.

In this work the abdominal signal and thoracic signal is obtained .Noise analysis and removal is done using different signal processing techniques. Multistage adaptive filtering along with the SVD de-noising techniques to extract the FECG from the abdominal signal is effective and have better signal to noise ratio . This method leads to enhancement of fetal ECG by canceling maternal ECG and noises in multichannel environment. A method is to be proposed for enhancement of Fetal ECG using signal processing technique. Different noise sources occurring will be analyzed and proper corrective approach will be done.

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Table 3: Comparison of SNR of Various Preprocessing Filters

FILTER METHOD	NOISE	5dB	10dB
Butterworth	white	1.6335	2.1152
	pink	2.2289	2.2917
	brown	2.480	2.4556
	Muscle artifact	2.3309	2.3899
	electrode	2.4747	2.4398
	Baseline wander	2.4984	2.4561
Median	white	16.0899	24.6955
	pink	27.5155	40.8177
	brown	53.3405	50.6073
	Muscle artifact	44.3503	47.5741
	electrode	52.384	50.8049
	Baseline wander	53.6322	51.5194
Adaptive LMS algorithm	white	0.0013	0.0016
	pink	0.0023	0.0020
	brown	0.0024	0.0021
	Muscle artifact	0.0024	0.0020
	electrode	0.0024	0.0019
	Baseline wander	0.0027	0.0021
Savitzky Golay	white	14.6888	24.3182
	pink	30.3015	38.6357
	brown	91.1922	92.6525
	Muscle artifact	72.4127	81.4280
	electrode	84.6718	93.2652
	Baseline wander	97.6275	104.0710
Zero phase	white	13.6457	22.7116
	pink	23.9571	36.5736
	brown	46.9149	48.0604
	Muscle artifact	42.1658	45.6598
	electrode	46.95	48.1145
	Baseline wander	47.1783	48.1517

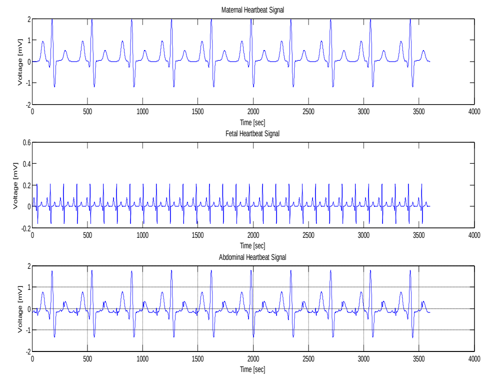

Figure 5.2: Source Signals Maternal (Thoracic), Fetal (single channel) and Abdominal Waveform

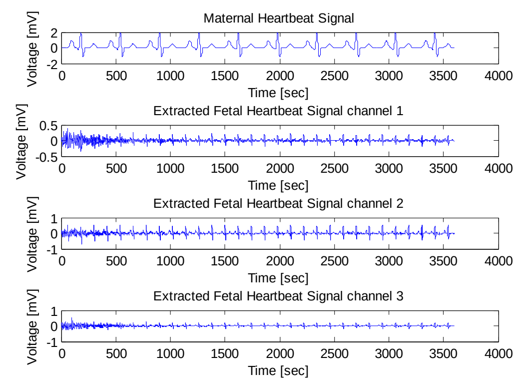

Figure 5.3: Output Waveform of Denoised FECG using Adaptive Filter (Multi stage) for Channel 1,2 and 3

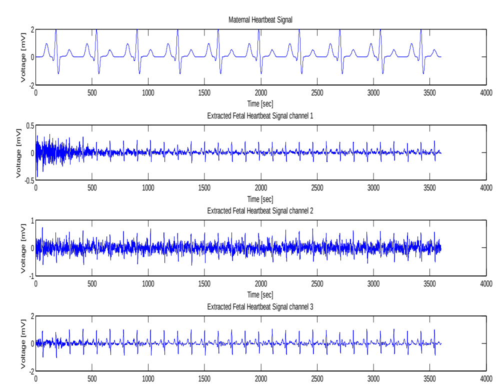

Figure 5.4: Output Waveform of Denoised FECG Using Adaptive Filter (Multi stage) for Channel 1,2 and 3