Australian Journal of Basic and Applied Sciences, 9(5) March 2015, Pages: 372-380

ISSN:1991-8178

Australian Journal of Basic and Applied Sciences

Journal home page: www.ajbasweb.com

Certain Investigation On De-Noising The Multichannel Abdominal ECG Signal Using Various Adaptive Noise Suppression Techniques

[1]S.Ravindrakumar and [2]K. Bommannaraja

[1]*Research Scholar, Department of Electronics and Communication Engineering, Anna University, Chennai, Tamil Nadu, India*
[2]*K.Bommannaraja ,Head of the Department, Biomedical Engineering Department, PSNA college of engineering and technology, Kothandaraman Nagar, Dindigul-624622.Tamil Nadu, India.*

ARTICLE INFO

Article history:
eceived 12 October 2014
Received in revised form 26 December 2014
Accepted 1 January 2015
Available online 27 February 2015

Keywords:

ABSTRACT

Background: The problem of denoising the abdominal ECG is addressed and a multi-channel adaptive approach using affine projection algorithms is proposed. Various adaptive denoising methods for multichannel Abdominal ECG in Fetal monitoring system is presented in this paper. A new method for implementing de-noising process for multi-input multi-output system is proposed using affine projection algorithm. The multichannel denoising system is been implemented using various adaptive filters. The proposed methods are tested with various input signals with noises. Noises like Power line interference, Electrode contact noise, Motion artifacts, Muscle contraction, Base line drift and Instrumentation noise generated by electronic devices are analyzed and removed using proper design. The methods to choose are dependent on the type of electrodes used and their numbers. Since Statistical methods require more number of electrodes for better removal of noise the adaptive filter is preferred. Filtering can alter the signal and may require substantial computational overhead. Real time and simulated ECG signals using dynamic model are used in this work. The results showed that some filtering techniques employed is faster among other filtering methods the affine projection adaptive filtering after tuning the taps to some optimum value gives the best results when compared to other adaptive filters. The Adaptive methods like LMS, DLMS, BLMS, NLMS, SS, SE, SD, RLS, SWRLS, QRDRLS, FTF, AFFINE PROJECTION and Lattice filters are used and the performance are compared. The results are compared with other methods like wavelet transform and ICA and the superiority of adaptive filter is shown.

To Cite This Article: S.Ravindrakumar and K. Bommannaraja., Certain Investigation On De-Noising The Multichannel Abdominal ECG Signal Using Various Adaptive Noise Suppression Techniques. ***Aust. J. Basic & Appl. Sci.,*** *9(5): 372-380, 2015*

INTRODUCTION

A fetal electrocardiogram (FECG) is the basic signal used to analyse the fetal health and physiological condition. As the invasive method is complex the non invasive method is well suited for the acquisition of the FECG from MECG signal .The abdominal Electrocardiographic signals (ECG) will be corrupted by various noises like Power line interference, Electrode contact noise, Motion artifacts, Muscle contraction, Base line drift, Instrumentation noise generated by electronic devices and Electrosurgical noise. The main problem and the major challenge is the denoising technique adapted for MECG removal and extraction of FECG. For denoising various methods are adopted in the past to remove the noise and the detection of the FECG signal. For enhancing the Fetal ECG various works has been carried out throughout the years. The Fetal QRS is used for diagnoses.

Various methods have been reviewed from the literature .One of the method which used average pattern subtraction (Juan, C. Echeverria *et al*, 1996) is the oldest method and is obsolete due to deficiency of proper patterns. As the pattern vary from gestational age to age of the prenatal , weight of the maternal and the number of fetus the method finds difficult to do the denoising . Due to this reasons a FECG signal without noise is rarely obtained when the above method is used. The other oldest methods which is used in many application is the Correlation Technique.The method focuses for delineation of the parameters like P,Q,R,S,T in the ECG signal. Due to the weaker amplitude of P wave and T wave only QRS signal is detected. Using the QRS parameter information only heart rate can be found. The information about P and T wave is lost. The most widely used algorithm in communication field is the adaptive noise cancellation using matched filtering (Ronald, T., *et al*., 2002). The adaptive filters are

Corresponding Author: S.Ravindrakumar, Research Scholar, Department of Electronics and Communication Engineering, Anna University, Chennai, Tamil Nadu, India

based on two algorithms, recursive least square (RLS) and least mean square (LMS). The method is well suited for multiple channel recordings from the thorax and mothers abdomen. The method requires a reference signal which need not be an exact Fetal ECG and MECG but can be a correlated signal. But in several fetal signal enhancement adaptive filtering technique (Kam, A. Cohen, 1999) is used. The signal to noise ratio can be improved using weighted averaging along with adaptive filtering. The adaptive filters are also combined with various statistical methods like BSS and ICA (Jafari, M.G. and J.A. Chambers, 2000). Even though wavelet method (Ming, M.A., WANG Ning, LEI San-Ya, 2009) plays a vital role in the extraction and classification operation proper wavelets have to be chosen and new mother wavelet has to be found. Other techniques which are used for reconstruction can be found for FECG detection (Fazlul Haque A.K.M. *et al*, 2009), Some other techniques are based on wavelet delineation (de Lannoy, G., *et al*.,), denoising the Doppler fetal ECG (James, D. Wilson *et al*, 2008; Yang Xiaofeng, *et al*., 2007; Xiaoli Huang1, Huanglin Zeng, 2010) based on the peaks of the source signal.

The techniques based on modulus maxima with ANFIS (Ping Gao, Ee-Chien Chang, L. Wyse, 2003) performs the classification of abdominal ECG with respect to different patterns.The denoising and extraction process is also carried out using methods like singular value decomposition(SVD) (Ping Gao, Ee-Chien Chang, L. Wyse, 2003) and digital filters (Abbas, H.H., 2011; Xueqiamg Zhon *et al*., 1992; Wenxi Chen, *et al*., 2000), Notch IIR (Manpreet Kaur, Birmohan Singh, 2009; Suzanna, M.M., *et al*., 2006; Rik Vullings, *et al*., 2007). The blind source separation (BSS) is the another technique which extracts the unknown fetal ECG and Maternal ECG signals assuming them as statistically independent from the data recorded from several electrodes.The BSS and Adaptive filter (Zarzoso, V., *et al*., 2000) are combined in a work which is efficient . The other method (Ming, M.A., *et al*., 2009) which combines BSS with wavelet gives accuracy of about 97.47% in extracting the Fetal ECG but the shape is been altered. The methods accuracy discussed so far decreases for less gestational age recordings, less number of electrodes present.

In this work two multi-channel adaptive approaches using QR-Decomposition and affine projection algorithms are proposed. The multichannel denoising system is been implemented using adaptive filters like LMS, DLMS, BLMS, NLMS, SS, SE, SD, RLS, SWRLS, QRDRLS, FTF, AFFINE PROJECTION and Lattice filters , non-adaptive filters like Butterworth, Median, zerophase, savitzky golay, wavelet transform and statistical methods like PCA,FASTICA and SVD. The methods like Butterworth, Median, zerophase, savitzky golay, wavelet transform removes the noise well for less SNR values. But the performance of Adaptive filtering and independent component analysis methods are better towards de noising. The paper is organized in the way that the model of the fetal monitoring system is presented first which describes the various signals involved in the system then followed by the adopted dipole theory of heart which is been applied for generating an arbitrary number of synthetic ECG channel. Then the various denoising methods are presented and next the proposed methods. Finally the results obtained by these methods are described.

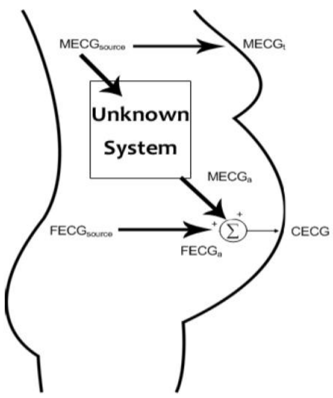

Fig. 1: Components of Fetal ECG system

II. Modelling Abdominal Ecg:

The basic components of the Fetal monitoring system is presented in figure.1.The composite signal (CECG) consists of the maternal ECG, Fetal ECG and noise represented by $m_i(t)$, $f_i(t)$ and $(N_l(t) + n_h(t))$.Normally all analysis in the work is based on the number of channels used represented by 'I'.The composite and the thoracic signal are represented by

i) composite signal(CECG)

$$Ab_i(t) = N_l(t)\left[f(t) + m(t) + n_h(t)\right] \quad (1)$$

where

$N_l(t)$ is the low frequency signal due to baseline wander, electrode contact noise.

ii) Thoracic signal

$$Ab_i(t) = N_l(t)\left[m(t) + n_h(t)\right] \tag{2}$$

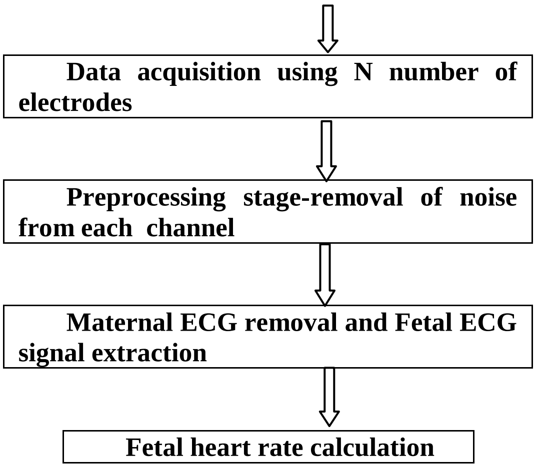

Fig. 2: Stages of Fetal ECG monitoring system

In order to evaluate the effect of noise in ECG we have adopted the dipole theory of heart and been applied for generating the synthetic Abdominal and thoracic ECG signal. In the model a single dipole is used to represent myocardium's electrical activity by a time varying rotatory vector, the origin of which is assumed to be at the centre of the fetal or maternal heart as its end sweeps out a quasi periodic path through the torso. The vector is 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 modeled as 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.

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

$$ECG(T) = < d(t)$$

$$V > a.x(t) + b.y(t) + c.z(t)$$

The potential generated by dipole at a distance r (where r= $\mathbf{r_x\bar{a}_x} + \mathbf{r_y\bar{a}_y} + \mathbf{r_z\bar{a}_z}$ is the vector which connects the centre of dipole to observation point) & conductivity of volume conductor (Ee.fju.edu.tw) 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 adopted from MCSharry *et al* model (Ee.fju.edu.tw), 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

$$\dot{\theta} = \omega$$

$$\dot{x} = -\sum_t \frac{a_i^x\omega}{(b_i^x)^2}\Delta\theta_i^x \exp\left[-\frac{(\Delta\theta_i^x)^2}{2(b_i^x)^2}\right]$$

$$\dot{y} = -\sum_t \frac{a_i^y\omega}{(b_i^y)^2}\Delta\theta_i^y \exp\left[-\frac{(\Delta\theta_i^y)^2}{2(b_i^y)^2}\right]$$

$$\dot{z} = -\sum_t \frac{a_i^z\omega}{(b_i^z)^2}\Delta\theta_i^z \exp\left[-\frac{(\Delta\theta_i^z)^2}{2(b_i^z)^2}\right]$$

$$\Delta\theta_i^x = (\theta - \theta_i^x)\bmod(2\pi)$$

$$\Delta\theta_i^y = (\theta - \theta_i^y)\bmod(2\pi)$$

$$\Delta\theta_i^z = (\theta - \theta_i^z)\bmod(2\pi) \tag{7}$$

where

$$\omega = 2\pi$$

Each of the three co-ordinates of the dipole vector d(t) is modeled by a summation of Gaussian functions (Web.mst.edu) 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.

III. Types of Denoising Methods:

A. Non-adaptive filter:

The noise filtering is done using non-adaptive filters like Butterworth, zerophase filter, savitzky golay (SG) ,median filter and wavelet transform. The Butterworth filter does not attenuate all frequencies outside the desired frequency range completely. The savitzky technique remove the noise in an efficient manner equal to that of the adaptive technique but when comparing the SNR value the adaptive filter gives better performance. Even though non-adaptive filters mentioned above have advantages of using common theoretical background for developing smoothing and differentiation filters, ease of deriving filter coefficients from tables or from explicit equations their performance is less when compared to wavelet transform .

3.1.1. Wavelet transforms:

The main task in wavelet analysis is to find a good wavelet function to perform an optimal decomposition. The performance will be better if the wavelet function is adapted to the maternal or fetal signal, because the computational complexity can be reduced and more accurate analysis can be obtained.As an alternative to the normal filtering techniques, which use different narrow-band filters to extract the frequency contents of the signal, the wavelet transform technique can be used. In wavelet transform technique, the abdominal signal is analyzed at different frequencies with different resolutions to extract the features of the fetal ECG.In our work the method is used for multidimensional signal.

III. Statistical Method

A. Blind source separation (ICA):

The most efficient tool in removal of signals from their sources which are acquired using several channels is the blind source separation method. The BSS method is divided into several categories like Principal Component Analysis (PCA), Singular Value Decomposition and Independent Component Analysis (ICA). Here the noise is not removed; instead it's been considered as a separate source and is extracted as a independent component. So after applying the BSS methods the sources which are assumed to be statistically independent is extracted separately this contains the maternal, fetal and noise signal. But the disadvantage of the method is more channels are required for precise extraction.

B. Singular value decomposition (SVD):

Singular value decomposition (SVD) is a multivariate statistical technique used to reduce a dataset containing a large number of values to a dataset containing fewer values. In linear algebra the (SVD) is a factorization of a real or complex matrix, with many useful applications in signal processing and statistics. The SVD decomposes the matrix and shows the structure of the component present. After applying SVD on noisy signal, the singular values matrix achieved is described as follows.

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

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

The equation for SVD is

$$a_i = \begin{cases} 1 & 1 \le i \le 6 \\ e^{-(i-4)/5)} & 7 \le i \le 30 \\ 0 & 30 \le i \le 40 \end{cases}$$

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

$$SNR = 10\log_{10}\left(\frac{\sum x_{org}^2}{\sum\left(x_{org} - x_{est}\right)^2}\right) \qquad (8)$$

In which x_{org} is indicating clean signal and x_{est} is indicating the enhanced/estimated one.

C. Adaptive filters:

An adaptive filter self-adjusts its transfer function using optimization algorithms and is digital filters. The adaptive filter uses the error signal and the optimization algorithm to change the co-efficient of the transfer function. Various optimization algorithms are available which are based on least mean square minimization or steepest descent algorithm.

***1) LMS Algorithm*:**

Least mean square (LMS) algorithm is a broadly used adaptive algorithm for its robustness and low hardware complexity when compared to wavelet transform and Blind source separation methods. Least mean squares (LMS) algorithms are the class of adaptive filter algorithm which finds or updates the filter coefficients by getting the error signal which is the difference between the desired and the actual signal as feedback.

$$y(n) = [y(n), y(n-1)\ldots\ldots\ldots\ y(n-p+1)]^T$$
$$err(n) = d(n) - \hat{h}^H(n)y(n)$$
$$\hat{h}(n+1) = \hat{h}(n) + \mu err^*(n)y(n) \qquad (9)$$

Where y(n) is the input samples.err(n)is the error signal and h(n) is the impulse response of the filter

2) RLS Algorithm:

The Recursive least squares (RLS) adaptive filter is the algorithm which recursively calculates the filter coefficients which minimizes the weighted linear least squares cost function relating to the input signals (de Lannoy, G., *et al*.,). When compared to other algorithm the recursive least squares algorithm is computationally complex and potentially has poor tracking features (Yang Xiaofeng, *et al*., 2007).

$$x(n) = w(n-1)u(n)$$
$$err(n) = d(n) - x(n)$$
$$w(n) = w(n-1) - k^H(n)err(n) \qquad (10)$$

3) NLMS Algorithm:

The normalized least mean square algorithm (NLMS) is a modified version of the least mean square algorithm which bypasses the issue of

Australian Journal of Basic and Applied Sciences, 9(5) March 2015, Pages: 372-380

calculating the maximum step size value. In LMS algorithm the step size parameter remains fixed for every iteration. The knowledge of the input signal statistics is required which is practically unachievable. Even though the only signal to be input to the adaptive noise cancellation system is abdominal signal,the performance degrades due to signal input power and amplitude .

$$y(n) = [y(n), y(n-1)......... y(n-p+1)]^T$$

$$err(n) = d(n) - \hat{h}^H(n)y(n)$$

$$\hat{h}(n+1) = \hat{h}(n) + \frac{\mu err^*(n)y(n)}{y^H(n)y(n)} \quad (11)$$

4) DLMS:

One of the modified LMS algorithms, the Delayed LMS algorithm performs well in systems where hardware implementation is more dominant but with a little performance degradation. As the conventional LMS adaptive filter is difficult to implement in hardware since error is to be computed and then used to update the tap coefficients before the next sample arrives it's difficult to implement in hardware.The delayed LMS (DLMS) algorithm is described by the following equations:

$$y(n-D) = \hat{w}^H(n-D)u(n-D) \quad (12)$$

From the above equation it can be founded that DLMS algorithm updates the coefficient based on the error samples delayed by D. Mathematical descriptions of DLMS show that it will converge in the mean square error (Ronald, T., *et al*., 2002). Some of the disadvantages of the DLMS is the stability constraint on step- size parameter and the learning curve will take more time to converge.

The coefficients of the filter at the i th stage is updated as

$$w_{L-i}(n-i+1) = w_{L-i}(n-i) + \mu e(n-i)u(n-i-(L-i))$$
$$\Rightarrow w_{L-i}(n-i+1) = w_{L-i}(n-i) + \mu e(n-i)u(n-L)$$
(13)

5) .SS,SE AND SD LMS algorithm:

The SS,SE and SD LMS algorithm reduces the computational complexity of the standard LMS algorithm by replacing the error and input signal by their signs or any one of the signs of either error or the input.The convergence rate is very less when compared to the LMS algorithm. If the same principle is applied for data (sign-data LMS) and error (sign-error LMS) signal the computational complexity can be reduced while not changing the convergence rate .So the LMS algorithm is modified as

Sign - error LMS:

$$w(n+1) = w(n) + i\,sign(err(n))u(n) \quad (14)$$

Sign - data LMS:

$$w(n+1) = w(n) + i\,err(n)sign(u(n)) \quad (15)$$

Sign - sign LMS:

$$w(n+1) = w(n) + i\,sign(err(n))sign(u(n)) \quad (16)$$

The performance of sign - error LMS algorithm is better when compared all other LMS algorithm but the sign - sign LMS algorithm is advantageous when hardware implementation is considered in the first degree.

6) BLMS:

In the Block LMS algorithm the filter co-efficient vector is updated every ith sample instead of updating for every sample like in standard LMS,

$$\hat{w}(n+1) = \hat{w}(n) + \mu u(n)err^*(n) \quad (17)$$

The filter vector after ith sample

$$\hat{w}(k+1) = \hat{w}(k) + \mu\sum_{i=0}^{L-1} u(kL+i)err^*(kL+i) \quad (18)$$

where the block index k and sample index n are related as

$n = kL + i$

The gradient estimation denoted as averaged gradient vector is given by

$$\Phi(k) = \sum_{i=0}^{L-1} u(kL+i)err^*(kL+i) \quad (19)$$

Here the filter vector is updated for every L th sample with the weighted average for the last L Samples. The BLMS Algorithm and LMS algorithm minimizes J (n) = E{|e(n)| and converges towards the Wiener solution. The Block-LMS uses a better estimate of the gradient but the convergence is slower when compared to LMS due to upper limit for μ.

The convergence criteria for the Block-LMS is

$$0\langle \mu < \frac{2}{L\lambda_{max}}$$

At the same time if the block length L is chosen to increase the calculations speed, the convergence speed reduces because of the stricter limit of μ.The Fast LMS is based on the Block-LMS and converges similarly. The filter weight is directly connected to certain eigenmode and updated independently of each other

IV.Proposed Denoising Methods:

In this work the preprocessing stage is been proposed using a new method which is based on the smoothing process. The smoothing process is more complete when compared to the filtering method. The pre processing uses the order-recursive QRD-based least-squares lattice (QRDLSL) smoothing algorithm which is a fast algorithm in order recursive adaptive filtering. Most of the adaptive fast algorithms are numerically instable due to finite-precision effects. But the QR-decomposition (QRD) technique is numerically stable. This algorithm is very fast and stable since the solutions to all lower order problems are obtained as a byproduct upon solving an Nth-order filtering problem. The another method which is been proposed for the denoising of the abdominal ECG is the affine projection algorithm which has low memory requirement for implementation and is efficient. In addition to that affine projection causes no delay in the input or output signals. The performance is robust when colored noise are present in the system. These features make AP an excellent candidate for the denoising using adaptive filter in the noise cancellation problem. It is the generalization of the normalized least mean square (NLMS) adaptive filtering algorithm (Web.mst.edu). One of the disadvantages is that tap weight vector update of NLMS is represented as a one dimensional affine projection. The convergence speed increases as the projection dimension increases but the computational complexity increases.

RESULTS AND DISCUSSION

The database used throughout the work was from MIT-BIH Physionet database, EDF database and DaISy (Database for the Identification of Systems).The database contains cutaneous potential recordings of pregnant woman (8 channels),Sampling of 10 s, The channels 1-5 is abdominal and 6,7,8 thoracic. The simulated ECG signals using dynamic model are used in this work. In order to find a reference, we apply ICA to the total N-channel database and to the channels selected by the maternal rules depending on the placement of electrodes. The value 'N' varies depending upon the gestational age and the number of fetus present. This is the more general problem which happens doing extraction of designed signal from degenerate mixtures of signal plus interface and noise. Next, the external noise has been added using Gaussian function to the abdominal ECG signal. Noise signal like muscle artifact, electrode movements, baseline wander, white noise and colored noise are analyzed and filtered (Table 3). Further, individual noise such as white noise, pink noise, brown noise, muscle artifacts, real electrode movement, baseline wander has been added for different SNR values such as 5db, 10db, 20db, 40db. Those noises are again removed by using the proposed techniques and the best one is determined by means of the lowest SNR value. Table 3 shows the SNR values for various de-noising methods for different noise signals added and then removed .Here the SNR values are calculated based on database so the lower the SNR value better the method is. The Values in the table 3 shows that the adaptive method is dominant in removing the noise from the signal for all noises. For the comparative analysis the de-noising of signals through non-adaptive filters like zerophase, median filter, wavelet transform using different wavelets and statistical methods like Independent component analysis and singular value decomposition are used.

The algorithms are tested for variable attenuation factor and SNR values. The synthetic ECG signals for maternal and fetal is generated for various noise levels. `The wavelet transform methods were implemented using different wavelets like biorthogonal wavelets, daubechies, coiflets and symlets and tested with simulated and real time signals. For Example Considering bi-orthogonal and compactly supported wavelet families (bior1.3, bior2.6, bior3.5, bior5.5, bior3.7) for the 3-level and 5-level decompositions with discrete wavelet transform, the performances are very close to each other and they generally give better results for soft thresholding than hard thres holding denoising rule. Other orthogonal wavelets like Daubachies Db1, Db2, Db3, Db8 are applied. Uniformly distributed white noise is added to the ECG signal. From the table 1 it is seen that 5-level decomposition gives better denoising .The visual inspection of the denoised signal for the bior2.6 and bior5.5 is better than the rest of the biorthogonal set of wavelets and wavelet packet analysis .The computed signal-to-noise ratios are approximately 10.5 dB for the used biorthogonal wavelets family. 1 thoracic and 3 abdominal signal are used with different noise levels imitating the placement of electrodes at different location of the maternal's abdomen. From the application of wavelet denoising techniques all wavelets removes the noise at lower energy levels while failing to remove at higher amplitudes. The shape of the signal/frequency components are altered when high noise components present. As here the interest is towards preprocessing not extraction, the biorthogonal wavelet suits well for the removal of noise in the signal.

The noise removal process using statistical methods are different and mainly based on the number of electrodes used. The noises are removed from the abdominal ECG using statistical methods like fast ICA, EGLD, Pearson ICA and Principle Component Analysis. ICA serves for both noise removal and extraction. The database used for testing the algorithm contains 4-7 channels. 4 channels are used the algorithm identifies the four independent components present in the multidimensional signal (4x2000).The four components constitutes the maternal ECG, fetal ECG, Noise 1 and noise 2.Due to high amplitude noise components the fetal ECG is not identified and the maternal ECG is not clearly removed Since the data itself contains less energy for maternal ECG and the number of electrodes are less the algorithm does not remove the MECG signal noise effectively. All ICA algorithms extracts the fetal ECG when the noise components /energy is very less. The extraction performance is good only when there are more number of electrodes involved (5 at least),which is practically difficult during labor and its impossible. With high noise/maternal present in abdominal signal the fetal ECG is hard to extract and the convergence steps increases when the

Australian Journal of Basic and Applied Sciences, 9(5) March 2015, Pages: 372-380

independent component identification is difficult which also depends on the strength of the source present (maternal, fetal and noise). But when the energy of noise is increased further the algorithm takes longer time to converge. Even though the fetal ECG is identified the convergence takes place after 1000 iteration where the memory requirement is too large which is practically not viable. But more number of convergence steps leads to high memory requirements where cost involved will be high. The algorithm is tested with simulated database and identifies the four independent components present in the multidimensional signal (4x3600). Due to less amplitude noise components the fetal ECG is identified and the maternal ECG is clearly removed since the data itself contains less energy for noise.

Using various parameters like SNR, PSNR the best filter is identified. Thus Adaptive filtering technique is considered as the best filtering technique through the comparison of parameters values and observation as shown in Table 1,2 and 3.From the observation the adaptive filtering techniques serves the best in preprocessing of the data or contaminated abdominal ECG . Here various adaptive algorithms are implemented and table 2 shows the performance of various adaptive filtering methods. From the values it is proved that the proposed algorithm QRD and Affine projection gives equal performance when compared to LMS algorithm. Even though LMS algorithm gives 1% more PSNR measurement it lags in convergence behavior. The proposed methods have key features which include LMS like complexity, memory requirements (low), and RLS like convergence (fast).So the proposed method is better when compared to various other adaptive methods. To improve the SNR value the adaptive filter stage is extended with multi stage. The PSNR values and MSE are calculated (Table.2) . 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. The results Table 1 showed that some filtering techniques we employed is faster when compared with adaptive filtering methods but the adaptive filtering after tuning the taps to some optimum value gives the best results. The Tables shows the performance of non-adaptive, adaptive and statistical methods for various parameters measured. The figure 3 shows the comparison of the PSNR values of various methods for two different SNR values of additive noise about 20dB and 60dB. Adaptive filter give better performance as a whole in single stage and multistage with better stability and noise rejection. The Adaptive methods like LMS, DLMS, BLMS, NLMS, SS, SE, SD, RLS, SWRLS, QRDRLS, FTF, AFFINE PROJECTION and Lattice filters are used and the performance are compared. From the results (Table 1 and table 2) compared, the proposed method QRDISL and Affine projection has higher efficiency than other methods in all aspects. When compared to non adaptive methods where the scope for multichannel is less adaptive filter becomes dominant. Even though the statistical methods like ICA and SVD are efficient they require more number of input channels which the complexity of design and implementation is high. So for the pre-processing of abdominal ECG the proposed adaptive filter is better when compared to non-adaptive and statistical methods. The work will be further extended towards the extraction of fetal ECG from the abdominal ECG signals.

Table 1: Performance of Various Denoising Techniques

YPE	NON ADAPTIVE											
NAME	savitzygolay		butterworth		median		zerophase		wavelet db54		wavelet rbio354	
NOISE)DB)	20	60	20	60	20	60	20	60	20	60		60
PSNR	73.003	91.6767	62.069	62.069	71.3986	76.5689	61.671	61.6685	69.247	69.47	69.268	69.4773
MSE	0.0033	4.42E-05	0.0404	0.0404	0.0047	0.0014	0.0443	0.0443	0.0077	0.0073	0.0077	0.0073
MAXERR	0.1971	0.0663	0.9805	0.9751	0.2366	0.1374	1.0204	1.0192	0.4518	0.417	0.458	0.4237
L2RAT	1.0619	0.9795	0.0146	0.014	1.0617	0.9795	0.0016	0.0016	0.6996	0.6839	0.6827	0.6677

Table 1: Continue

YPE	ADAPTIVE			
NAME	nlms	QRD	ap	SVD
NOISE)DB)	60	60	60	60
PSNR	70.94	72.524	70.106	72.36
MSE	0.005	0.0036	0.0063	0.003
AXERR	0.337	0.3713	0.3628	0.361
L2RAT	0.896	0.923	0.9844	0.982

Table 2: Performance of Various Adaptive Filters For A Multistage Design

	LMS					RLS				AFFINE PROJECTION		
STAGE 1	LMS	NLMS	DLMS	BLMS	SS	RLS	SWRLS	QRDRLS	FTF	AP	QRDLSL	GAL
PSNR	78.8989	78.8278	78.7898	78.8571	78.8961	77.1922	75.5589	77.1897	77.194	76.5263	77.4792	77.484
MSE	8.38E-04	8.52E-04	8.59E-04	8.46E-04	8.38E-04	1.20E-03	1.80E-03	0.0012	0.0012	1.40E-03	1.20E-03	0.0012
MAXERR	0.2321	0.2974	0.3276	0.2795	0.2317	0.3952	0.2624	0.2493	0.2728	0.3014	0.3097	0.2474
L2RAT	1.3636	1.3558	1.3538	1.358	1.3611	1.2027	1.3107	1.2021	1.1995	1.4074	1.2803	1.2845
STAGE 2	LMS	NLMS	DLMS	BLMS	SS	RLS	SWRLS	QRDRLS	FTF	AP	QRDLSL	GAL
PSNR	75.8155	75.5581	75.8818	75.622	75.731	74.7244	74.0163	75.0008	75.0163	74.518	74.9958	75.1721
MSE	0.0017	0.0018	0.0017	0.0018	0.0017	0.0022	0.0026	0.0021	0.002	0.0023	0.0021	0.002
MAXERR	0.4649	0.448	0.4088	0.3713	0.5598	0.4112	0.4086	0.3836	0.3834	0.3858	0.4761	0.3762
L2RAT	1.7299	1.7498	1.7024	1.7592	1.755	1.6007	1.6439	1.5522	1.5484	1.7738	1.6535	1.6367

Australian Journal of Basic and Applied Sciences, 9(5) March 2015, Pages: 372-380

Table 3: Performance of Various Denoising Techniques For Various Noises

Filter Method	Butterworth		Moving average		Adaptive		Savitzky Golay		Zero phase	
Noise	5 db	10db	5 db	10db	5 db	10db	5 db	10db	5 db	10db
White	1.6335	2.1152	16.0899	24.6955	0.0013	0.0016	14.6888	24.3182	13.6457	22.7116
Pink	2.2289	2.2917	27.5155	40.8177	0.0023	0.0020	30.3015	38.6357	23.9571	36.5736
Brown	2.480	2.4556	53.3405	50.6073	0.0024	0.0021	91.1922	92.6525	46.9149	48.0604
Muscle artifact	2.3309	2.3899	44.3503	47.5741	0.0024	0.0020	72.4127	81.4280	42.1658	45.6598
Electrode	2.4747	2.4398	52.384	50.8049	0.0024	0.0019	84.6718	93.2652	46.95	48.1145
Baseline wander	2.4984	2.4561	53.6322	51.5194	0.0027	0.0021	97.6275	104.0710	47.1783	48.1517

REFERENCES

Juan, C. Echeverria *et al*, 1996. “Fetal QRS extraction based on wavelet analysis and pattern matching", Proceedings of the 18th Annual International Conference on Engineering in Medicine and Biology Society, 4: 1656-1657.

Ronald, T., Wakai and William J. Lutter, 2002. “Matched-Filter Template Generation via Spatial Filtering: Application to Fetal Bio magnetic Recordings”, IEEE transactions on biomedical engineering, 49.

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

Jafari, M.G. and J.A. Chambers, 2000. “Adaptive noise cancellation and blind source separation.

Ming, M.A., WANG Ning, LEI San-Ya, 2009. “Extraction of FECG Based on Time Frequency Blind Source Separation and Wavelet De-noising”, 3rd International Conference on Bioinformatics and Biomedical Engineering, ICBBE 2009. IEEE.

Fazlul Haque A.K.M. *et al*, 2009. “Detection of small variations of ECG features using wavelet “, ARPN Journal of Engineering and Applied Sciences, 4: 6.

de Lannoy, G., B. Frenay, M. Verleysen and J. Delbeke, “Supervised ECG Delineation using the Wavelet Transform and Hidden Markov models”.

James, D. Wilson *et al*, 2008. “Integrated Approach for Fetal QRS Detection”, IEEE Transactions on biomedical engineering, 55(9).

Yang Xiaofeng, Li Peng, Zhang Xin, Bian Zhengzhong, Wang Bo, 2007.“ De-noising of the Doppler Fetal Heart Rate Signal with Wavelet Threshold Filtering Based on Spatial Correlation”, The 1st International Conference on Bioinformatics and Biomedical Engineering, ICBBE. (s): 928-931.

Xiaoli Huang1, Huanglin Zeng, 2010. “Face Blind Separation Using Wavelet Packet Independent Component Analysis”, International Conference on Image Analysis and Signal Processing (IASP) (s): 680- 685.

Swarnalatha, R. and D.V. Prasad, 2010. “Maternal ECG Cancellation in Abdominal Signal Using ANFIS and Wavelets”, Journal of Applied Sciences, 10: 868-877.

Ping Gao, Ee-Chien Chang, L. Wyse, 2003. “ Blind separation of fetal ECG from single mixture using SVD and ICA”, Information, Communications and Signal Processing, 2003 and Fourth Pacific Rim Conference on Multimedia. Proceedings of the 2003 Joint Conference of the Fourth International Conference, 3(s): 1418-1422.

Abbas, H.H., 2011. “Removing 0.5 Hz Baseline Wander From ECG Signal Using Multistage Adaptive Filter” Engineering. & Techology Journal, 29: 11.

Manpreet Kaur, Birmohan Singh, 2009. “Power line Interference Reduction in ECG Using Combination of MA Method and IIR Notch” International Journal of Recent Trends in Engineering, 2: 6.

Suzanna, M.M., Martens, Massimo Mischi, 2006. “An Improved Adaptive Power Line Interference Canceller for Electrocardiography” IEEE transactions on biomedical engineering, 53: 11.

Rik Vullings, Chris Peters, Massimo Mischi, Rob Sluijter, Guid Oei and Jan Bergmans, 2007. “Artifact reduction in maternal abdominal ECG recordings for fetal ECG estimation ”, Proceedings of the 29th Annual International Conference of the IEEE EMBS, France, 23-26.

Xueqiamg Zhon,Peter Engler and Malcolm G. Coblentz, 1992. “Adaptive Filter Application in Fetal electrocardiography”,Fifth annual symposium on Computer-Based Medical Systems, Proceedings., Page(s): 656-662.

Zarzoso, V., J. Millet-Roig, A.K. Nandi, 200. “Fetal ECG Extraction from Maternal Skin Electrodes Using Blind Source Separation and Adaptive Noise Cancellation Techniques ”, Proceedings of the Computers in Cardiology.

Ming, M.A., WANG Ning; LEI San-Ya, 2009. “Extraction of FECG Based on Time Frequency Blind Source Separation and Wavelet De-noising”, IEEE.

Wenxi Chen, Tetsu Nemoto, Toshio o Saito, Etsuko Kasuya, and Yoshifumi Honda 2000. “ECG and Heart Rate detection of prenatal Cattle Foetus- Usiing adaptive digital filtering Filtering ”, Proceedings of the 22”d Annual EMBS international conference, Chicago IL, 23-28.

Martinez, M. *et al*, E. Soria, J. Calpe, J.F. Guerrero, J.R. Magdalena, 1997. “Application of the Adaptive Impulse Correlated Filter for Recovering Fetal Electrocardiogram”, IEEE proceeding on Computers in Cardiology Page(s): 9-12.

McSharry, P.E., G.D. Clifford, L. Tarassenko and L.A. Smith, 2003. “A Dynamic Model for Generating Synthetic Electrocardiogram Signals,” IEEE transactions on biomedical engineering, 50: 289–294.

Reza Sameni, Shamsollahi, M.B., C. Jutten, G.D. Clifford, 2007. “A Nonlinear Bayesian Filtering Framework for ECG Denoising”, IEEE transactions on biomedical engineering, 54(12): 2172-2185.

Ee.fju.edu.tw

Web.mst.edu