Detection Of Fetal ECG From Abdominal ECG Recordings Using ANFIS And Equalizer

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Abstract

In this paper, FECG extracted from the maternal electrocardiogram (MECG) using hybrid soft computing technique called Adaptive Neuro Fuzzy Inference Systems (ANFIS) and Equalizers is proposed. Here, we investigate the use of (ANFIS) for fetal electrocardiogram (FECG) extraction from two ECG signals recorded at the thoracic and abdominal areas of the mother's skin. The thoracic ECG is assumed to be almost completely maternal (MECG) while the abdominal ECG is considered to be composite as it contains both the mother's and the fetus' ECG signals. Three methods have been proposed namely (1) ANFIS (2) Equalizer preprocessing followed by ANFIS (3) ANFIS followed by Equalizer post processing. Performances of all the above methods are compared. For numerical evaluation, the mean square error (MSE) between de-noised and FECG signal and original FECG signal and Peak signal to Noise Ratio (PSNR) is used.

Keywords: Adaptive neuro-fuzzy inference systems (ANFIS), Fetal electro cardiogram (FECG), Maternal electro cardiogram (MECG), Mean square error (MSE), Peak signal to noise ratio (PSNR), Equalizer.

1. Introduction

The analysis of the fetal heart rate (FHR) has become a routine procedure for the evaluation of the well-being of the fetus. Factors affecting FHR are uterine contraction, baseline variability, hypoxia and oxygenation. It has many drawbacks such as position-sensitivity, signal drop out, frequent confusion between maternal heart rate and fetal heart rate, failure in obese patients which in turn increases the rate of cesarean sections due to over diagnosis of fetal distress, misinterpretation of cardiogram traces and failure to act in time. FECG measurement is used to overcome all these limitations. FECG is useful to get reliable information on fetal status, the detection of abnormalities and monitorization task during labor, to enable the adoption of measures for assuring fetal wellbeing, to detect whether the fetus is alive or dead, and to determine twin pregnancies. The diagnostic tests of fetal well-being can be categorized as invasive and noninvasive. During delivery, accurate recordings can be made by placing an electrode on the fetal scalp. However, as long as the membranes protecting the child are not broken, one should look for noninvasive techniques.

There are several technical problems associated with the noninvasive extraction of FECG from ECG signals recorded at the abdominal surface. These problems are mainly due to the low power of the FECG signal which is contaminated by various sources of interference. These sources include the maternal ECG, the maternal electromyogram EMG, 50 Hz power line interference, baseline wander and random electronic noise [1]. Assuming that we are using state of the art low noise electronic amplifiers with high common mode rejection ratio, the effect of the 50 Hz interference and electronic random noise can be eliminated. The EMG noise can also be reduced but not necessarily eliminated with the use of classical low pass filtering techniques. Therefore, it is safe to say that if one is able to eliminate the maternal ECG component in the composite signal, a reasonable estimate of the FECG signal can be obtained. To further enhance this FECG estimate one needs to apply adaptive equalizer techniques.

A detail review and implementation issue of fetal ECG extraction and enhancement is presented in [2]. The methods like correlation, subtraction were used. Also, adaptive filtering and independent component analysis methods are mainly used for extraction and enhancement of FECG [3].

A method of extracting fetal ECG based on FIR neural network is proposed in [4]. It can be realized by training a small quantity of data in order to provide with highly non linear dynamic capabilities to the recovery model. Results from the application are benchmarked with the classical LMS and NLMS algorithms.

An attempt is made on extraction of FECG from MECG based on fundamental frequency (Fourier) theorem using notch filter and band-pass filter [5]. A blind separation of fetal ECG from single mixture using Singular value Decomposition (SVD) and Independent Component Analysis (ICA) is presented in [6].

A robust FECG detection method for abdominal recordings is presented in [7]. They used sequential analysis and compared results with that of ICA results. In one of the paper they proposed the method of extracting FECG using Adaptive Volterra Filter (AVF) that is capable of synthesizing the nonlinear relation between the mother thoracic signal, FECG and noise signal [8].

A system for fetal heart rate monitoring based on Adaptive Noise Cancellation and Maternal QRS removal window is presented in [9]. According to them, this method is 85% accurate. An efficient technique of FECG extraction from maternal abdominal ECG using neural network was proposed in [10]. According to output this algorithm is working satisfactory on high learning rate.

A wavelet transform is also used in some papers. A FECG extraction from composite maternal ECG using complex Continuous wavelet Transform is proposed in [11]. A technique for maternal ECG cancellation in abdominal signal using ANFIS and wavelet is presented in [12].

In this paper, FECG extraction based on adaptive neuro fuzzy inference systems, ANFIS followed by Equalizer is presented. The remainder of this paper is organized as follows. Section 2 describes the concept of canceling the MECG. The proposed technique is explained in section 3 and 4. The performance of the proposed technique is shown in section 5. Results are discussed in 6 and 7. Conclusions are drawn in section 8.

2. METHOD OF MECG CANCELLATION

The method used in this paper is adaptive noise cancellation (ANC) based on neuro fuzzy logic technique. ANC is a process by which the interference signal can be filtered out by identifying a non linear model between a measurable noise source (MECG) and the corresponding immeasurable interference. This is an extremely useful technique when a signal is submerged in a very noisy environment. Usually, the MECG noise is not steady; it changes from time to time. So the noise cancellation must be an adaptive process: it should be able to work under changing conditions, and be able to adjust itself according to the changing environment. The basic idea of an adaptive noise cancellation algorithm is to pass the corrupted signal (abdominal) through a filter that tends to suppress the MECG while leaving the signal unchanged. As mentioned above, this is an adaptive process, which means it does not require prior knowledge of signal or noise characteristics. Figure 1 shows noise cancellation with ANFIS filtering.

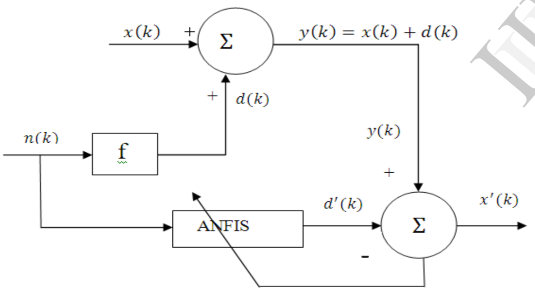

Figure 1: Schematic diagram of Adaptive Noise Cancellation using neuro fuzzy logic technique

Here, $x(k)$ represents the FECG signal which is to be extracted from the noisy signal. $n(k)$ is the MECG which is the noise source signal. The noise signal goes through unknown nonlinear dynamics (f) and generates a distorted noise $d(k)$, which is then added to $x(k)$ to form the measurable output signal (abdominal) $y(k)$. The aim is to retrieve $x(k)$ from the measured signal $y(k)$which consists of the required signal $x(k)$ plus $d(k)$, a distorted and delayed version of $n(k)$ i.e. the interference signal. In symbols, the measured signal is expressed as

$$y(k) = x(k) + d(k) = x(k) + f(n(k), n(k-1), n(k-2), \ldots \ldots \qquad (1)$$

In Figure 1, ANFIS is used to estimate the unknown interference $d'(k)$. When $d'(k)$ and $d(k)$ are close to each other, these two get cancelled and we get the estimated output signal $x(k)$ which is close to the required signal (FECG).

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

ANC using linear filters have been used successfully in real world applications such as interference canceling in Electrocardiograms, echo elimination on long distance telephone transmission lines, and antenna side lobe interference canceling. This concept of linear adaptive noise cancellation can be extended to non-linear realms by using nonlinear adaptive systems. Thus, ANFIS, which is one such nonlinear adaptive system, is proposed in this paper, to estimate an unknown interference present in the FECG signal.

Over the last few decades, neural networks and fuzzy systems have established their reputation as alternative approaches to signal processing. Both have certain advantages over conventional methods, especially when vague data or prior knowledge is involved. However, their applicability suffered from several weaknesses of the individual models. Neural networks recognize patterns and adapt themselves to cope with changing environments. Fuzzy inference systems (FIS) incorporate human knowledge and perform inferencing and decision-making. ANFIS takes the advantages of the combination of neural network and fuzzy logic [13]. The basic idea of combining fuzzy systems and neural networks is to design an architecture that uses a fuzzy system to represent knowledge in an interpretable manner, in addition to possessing the learning ability of a neural network to optimize its parameters. The drawbacks of both of the individual approaches - the black box behavior of neural networks, and the problems of finding suitable membership values for fuzzy systems - could thus be avoided.

3.1 ANFIS Architecture

The general architecture of ANFIS is shown in Figure 2 It has two inputs x and y and one output z. Assume the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type.

Rule 1: If x is A_1 and y is B_1,
then $f1 = p1x + q1y + r1$.

Rule 2: If x is A_2 and y is B_2,
then $f2 = p2x + q2y + r2$.

Here, x is A_1 and y is B_1 and x is A_2 and y is B_2 are called the premise section (non linear section), while, $f_1 = p_1x + q_1y + r_1$ and $f_2 = p_2x + q_2y + r_2$ are called as the consequent section (linear section). i.e. p_1, p_2, q_1, q_2, r_1, r_2 are linear parameters and A_1, A_2, B_1, B_2 are non linear parameters. The corresponding equivalent ANFIS architecture is shown in Figure 3.

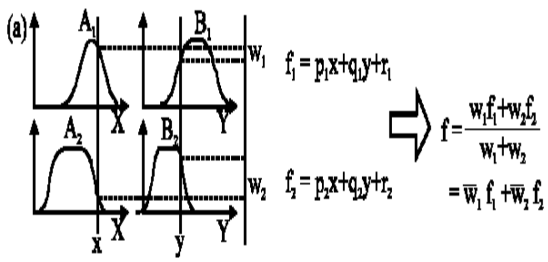

Figure 2: First – order Sugeno fuzzy model [13].

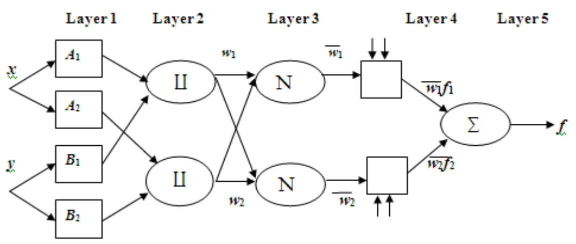

Figure 3: ANFIS Architecture [13]

Architecture consists of 5 layers excluding inputs and output. The node functions in the same layer are of the same function family as described below.
Layer 1: Every node *i* in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{Ai}(x) \text{ for } i = 1, 2 \text{ or}$$
$$O_{1,i} = \mu_{Bi}(y) \text{ for } i = 3, 4 \quad (2)$$

Where x is the input to node i , and i A is the linguistic label associated with this node function. Parameters in this layer are called premise parameters.
Layer 2: Every node in this layer is a fixed node labeled Π, whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = (\mu_{Ai}(x)) \text{ X } (\mu_{Bi}(y)),\ i = 1,2 \quad (3)$$

Each node output represents the firing strength of a rule.
Layer 3: Each node in this layer is a fixed node labeled N. The i -th node calculates the ratio of the i -th rule's firing strength to the sum of all rules' firing strength:

$$O3,i = \bar{w}_i = (w_i) / (w_1 + w_2),\ i = 1,2 \quad (4)$$

Outputs of this layer are called normalized firing strengths.
Layer 4: Every node *i* in this layer is an adaptive node with a node function

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i),\quad i = 1,2 \quad (5)$$

where $\bar{w}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i\ r_i\}$ is the parameter set of this node. Parameters in this layer are called consequent parameters.
Layer 5: The single node node in this layer is a fixed node labeled, which computes the overall output as the summation of all incoming signals:

$$\text{Overall output} = O_{5,i} = \sum \bar{w}_i f_i = \left(\sum_i w_i f_i\right) / \left(\sum_i w_i\right),$$
$$i = 1, 2 \quad (6)$$

The structure of this adaptive network is not unique. We can combine layers 3 and 4 to obtain an equivalent network with only four layers.

3.2 Computation in ANFIS

The basic steps used in the computation of ANFIS are given below.

- Generate an initial Sugeno-type FIS system using the matlab command *genfis 1*. It will go over the data in a crude way and find a good starting system.
- Give the parameters like number of epochs, tolerance error, number of MF, type of MF for learning.
- Start leaning process using the command *anfis* and stop when goal is achieved or the epoch is completed. Anfis applies the least squares method and the back propagation gradient descent for identifying linear and nonlinear parameters respectively.
- The *evalfis* command is used to determine the output of the FIS system for given input.

In this paper, we have taken the MECG as the reference signal and the abdominal signal as the desired signal. These two signals act as training pair for ANFIS training.

3.3 FECG Extraction Using ANFIS

The inputs to the ANFIS are (i) abdominal signal (MECG + FECG) acting as the reference signal (ii) thoracic signal (TECG) acting as the desired signal as shown in Fig. 4.

The ANFIS uses hybrid learning technique to calculate the linear, non-linear parameters. The output of the ANFIS is the estimated thoracic signal present in the abdominal signal. The error between the estimated thoracic signal and the abdominal signal gives the FECG. The training and learning procedure is needed only one time and can be done offline. Thus the computational complexity can be reduced. The ANFIS converts the fuzzy inference engine in to an adaptive network that learns the relationship between the inputs and outputs. Extraction of FECG using ANFIS yields satisfactorily results. In this work, generalized bell shape MF is used for ANFIS training.

Selecting an appropriate number of membership functions is essential for improving the convergence speed of the ANFIS algorithm.

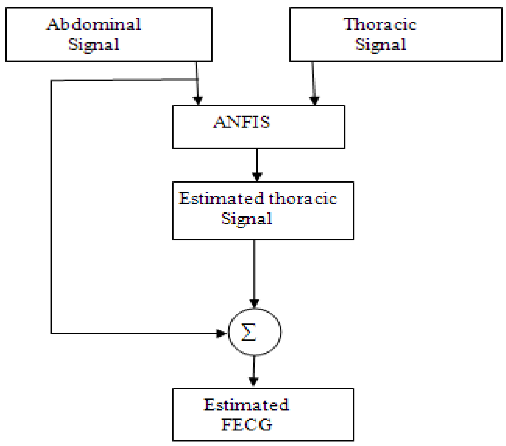

Figure 4: FECG extraction using ANFIS

4. EQUALIZER

Equalization is the process of adjusting the balance between frequency components within an electronic signal. The most well known use of equalization is in sound recording and reproduction but there are many other applications in electronics and telecommunications. The circuit or equipment used to achieve equalization is called an equalizer. These devices strengthen or weaken the energy of specific frequency bands.

In telecommunications, equalizers are used to render the frequency response for instance of a telephone line flat from end-to-end. When a channel has been "equalized" the frequency domain attributes of the signal at the input are faithfully reproduced at the output. Telephones, DSL lines and television cables use equalizers to prepare data signals for transmission. The working principle of adaptive equalizer is shown in Fig. 5.

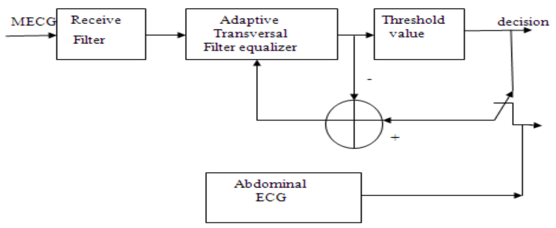

Figure 5: Block diagram for Equalizer

In this method, the MECG signal is applied to receive filter. The receive filter is a low pass filter that rejects all out of band noise. The output of the receive filter is sampled at the symbol rate or twice the symbol rate. Sampled signal is applied to transversal filter equalizer. The aim is to adapt the coefficients to minimize the noise and interferences at the output. The adaptation of the equalizer is driven by an abdominal ECG.

Adaptive equalizers are working under Decision directed mode and training mode. In decision directed mode, the receiver decisions are used to generate the error signal. Decision directed equalizer adjustment is effective in tracking slow variations in the channel response. However, this approach is not effective during initial acquisition.

Training mode is used to make equalizer suitable in the initial acquisition duration. In this mode of operation, the transmitter generates a data symbol sequence known to the receiver. The receiver therefore, substitutes this known training signal in place of the slicer output. Once an agreed time has elapsed, the slicer output is substituted and the actual data transmission begins.

In the field of audio electronics, the term "equalization" is to include the adjustment of frequency responses for practical or aesthetic reasons, often resulting in a net response that is not truly equalized. Stereos typically have adjustable equalizers which boost or cut bass or treble frequencies.

Broadcast and recording studios use sophisticated equalizers capable of much more detailed adjustments, such as eliminating unwanted sounds or making certain instruments or voices more prominent.

ANFIS Followed By Equalizer Post-Processing

In this method, non-linearity between the thoracic ECG and abdominal ECG is removed at first by passing signals through ANFIS and the estimated output from ANFIS is passed through equalizer to extract fetal ECG as shown in Figure 6.

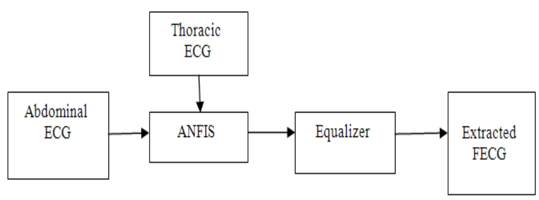

Figure 6: Block diagram of ANFIS with Equalizer.

5. PERFORMANCE ANALYSIS

The MSE can be defined as the mean square of the difference between output signals minus the input signal. The Peak signal to noise ratio (PSNR) is the ratio between a signal's maximum power and the power of the signal's noise. The estimated FECG can be calculated using Mean square error (MSE) and PSNR values which is expressed mathematically as,

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1} \sum_{j=0}^{n-i} [\mathrm{I}(i,j) - \mathrm{K}(i,j)]^2$$

The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression. Signals can have a wide dynamic range, so PSNR is usually expressed in decibels, which is a logarithmic scale.

$$20 \log_{10}\left(\frac{MAX\mathrm{I}}{MSE}\right)$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is $2^B - 1$.

6. SIMULATION RESULTS

6.1 Results on synthetic ECG data

Here, we simulate the shapes of the electrocardiogram for both the mother and fetus. We create an electrocardiogram signal that a mother's heart might produce assuming a 4000 Hz sampling rate. The heart rate for this signal is approximately 89 beats per minute, and the peak voltage of the signal is 3.5 millivolts. The heart of a fetus beats noticeably faster than that of its mother, with rates ranging from 120 to 160 beats per minute. The amplitude of the fetal electrocardiogram is also much weaker than that of the maternal electrocardiogram. So, we create an electrocardiogram signal corresponding to a heart rate of 139 beats per minute and a peak voltage of 0.25 millivolts.

6.1.1 ANFIS: In this method, the simulated thoracic ECG and maternal ECG is directly fed to ANFIS for the estimation of maternal ECG and this estimated MECG is subtracted from the abdominal ECG to extract FECG . The extracted FECG using ANFIS is shown in Figure 7.

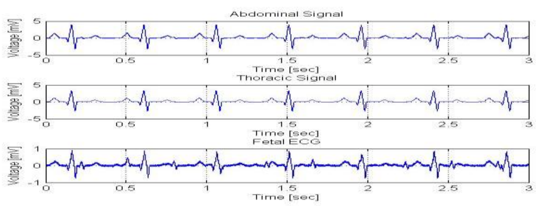

Figure 7: Output of ANFIS

6.1.2. Equalizer: In this method, the simulated thoracic ECG and maternal ECG are directly fed to equalizer for the estimation of FECG. The output of equalizer is shown in Figure 8.

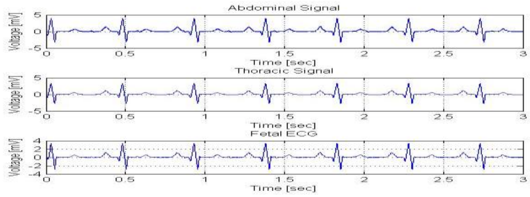

Figure 8: Output of equalizer

6.1.3 **ANFIS with equalizer:** In this method, the simulated thoracic and maternal ECG's are first fed to the ANFIS and then the estimated FECG obtained by ANFIS is post-processed by using equalizer. The extracted fetal ECG output is shown in Figure 9.

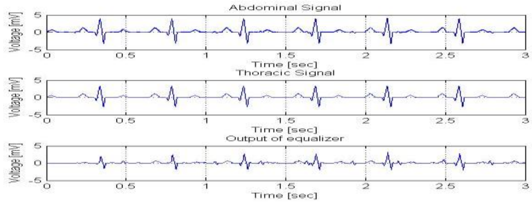

Figure 9: Output of ANFIS with equalizer

6.2. Results on Real ECG data

The real ECG database used in this paper was a subset of a dataset contributed by PhysioNet [16]. This database contains a series of 55 multichannel abdominal non-invasive fetal electrocardiogram (FECG) recordings, taken from a single subject between 21 to 40 weeks of pregnancy.

The ECG signals in this database were recorded from electrodes located on different points of a pregnant women body with 1 KHz sampling rate and bandwidth of 0.01 Hz–100 Hz. Four of these simultaneous signals were obtained from the mother's abdominal region while the other two were obtained from the mother's thoracic region. We have only used one thoracic recording and one abdominal recording which appeared to have the highest SNR and we arbitrarily chose one thoracic recording. The two (thoracic and abdominal) ECG signals that we selected from dataset are shown in Figure 10.

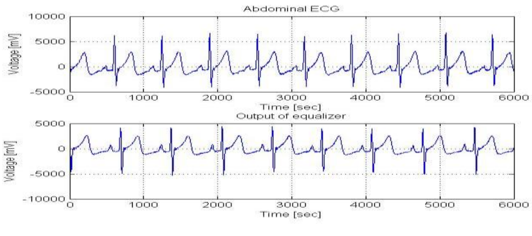

Figure 10: Abdominal ECG and Thoracic ECG signals

The techniques for real ECG data is same as that for synthetic data. So, only simulation results are given below.

6.2.1. ANFIS:

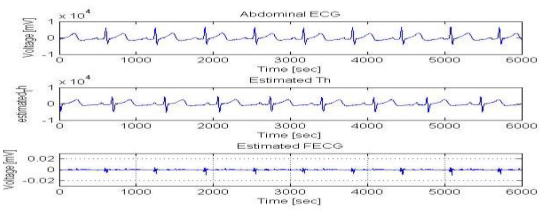

Figure 11: Output of ANFIS

6.2.2. Equalizer:

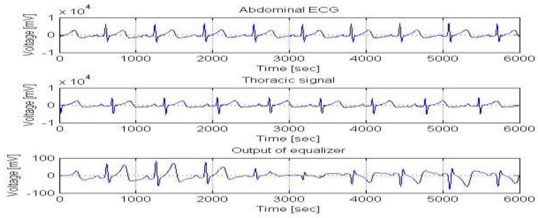

Figure 12: Output of Equalizer

6.2.3. ANFIS with equalizer:

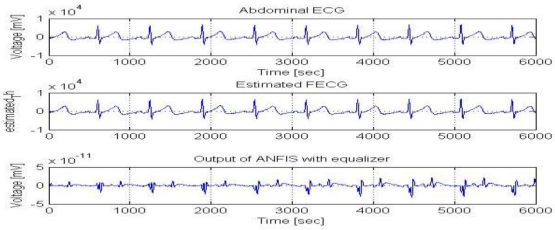

Figure 13: Output of ANFIS with equalizer

7. RESULTS AND DISCUSSIONS

From the results obtained through the proposed methods, we infer that the ANFIS with Equalizer gives better performance even if the complexity of the signal is very high. Hence, the results obtained with this method are compared with the other methods and we have found that we could extract the FECG signal with less MSE and higher signal to noise ratio as in table 1.

Table 1: PSNR comparisons

METHOD	PSNR of Synthetic Data	PSNR of Real Data
ANFIS	12.43	118.35
Equalizer	0.3968	35.44
ANFIS with equalizer	13.156	287.26

8. SUMMARY AND CONCLUDING REMARKS

In this paper, we have proposed a new method of combining ANFIS and Equalizer. The proposed method has been evaluated using mean square error and peak signal to noise ratio. The advantages of this type of methods are it requires only one abdominal signal and one thoracic signal for ECG extraction. This is done by applying the non linear relationship between the maternal component in the abdominal ECG and thoracic ECG which is assumed to have no fetal component in it. The fetal ECG can be extracted by subtracting the MECG from the abdominal signal. The mathematical analysis is very less because of qualitative aspects of Artificial Intelligence (AI). The MSE & PSNR value comparison shows that ANFIS with equalizer is the best method for ECG extraction. The extracted FECG is seen to be of high quality in the proposed method. The proposed method is capable of extracting FECG even when the FECG is overlapping with MECG. The morphology of the extracted FECG remains the same.

REFERENCES

[1] E. R. Ferrara and B. Widrow, "Fetal electrocardiogram enhancement by time-sequenced adaptive filtering", *IEEE Trans. Biomed. Eng.*,vol. BME-29, pp. 458–460, 1982.
[2] S.Ravindrakumar and K. Bommanna Raja, "Fetal ECG Extraction and Enhancement in Prenatal Monitoring - Review and Implementation Issues", *IEEE Trendz in Information Sciences & Computing*, pp. 16-20, December 2010.
[3] W. Chen, T. Nemoto, T. Kobayashi, Y. Honda, T. Saito, E. Kasuya, "Fetal ECG extraction from maternal body surface measurement using independent component analysis".
[4] G. Camps, M. Martinez, E. Soria, "Fetal ECG extraction using FIR neural network", Computer Society Press, Rotterdam, The Netherlands, pp: 249-252.
[5] K. Lweesy, L. Fraiwan, C. Maier, H. Dickhaus, "Extraction of fetal heart rate and heart rate variability from mother's ECG signal", world Academy of Science, Engineering and Technology, 54, 2009.
[6] P. Gao, Ee-Chin Chang, L. Wyse, "Blind separation of fetal ECG from single mixture using SVD and ICA".
[7] S. M. M. Martens, C. Rabotti, M. Mischi and R. J. Sluijter, "A robust fetal ECG detection method for abdominal recordings", Physiological measurement 28 (2007) 373-388.
[8] M. Shadaydeh, Y. Xiao and R. K. Ward, "Extraction of fetal ECG using Adaptive volterra filters", 16th European Signal Processing Conference, Lausanne, Switzerland, August 25-29, 2008.
[9] M. S. M. Algunaidi, M. A. Mohd Ali, K. B. Gan, E. Zahedi, "Fetal heart rate monitoring based on adaptive noise cancellation and maternal QRS removal window", European Journal of Scientific Research, ISSN 1450-216X, Vol. 27, No. 4 (2009), pp. 565-575.
[10] M. A. Hasan, M. I. Ibrahimy, M. B. I. Reaz, "Fetal ECG extraction from maternal abdominal ECG using neural network", J. Software Engineering & Application, 2009, 2: 330-334.
[11] EC Karvounis, C. Papaloukas, DI Fotiadis, LK Michalis, "Fetal heart rate extraction from composite maternal ECG using complex continuous wavelet transform", IEEE Computer Society Press, Chicago, USA, pp : 19-22.
[12] R. Swarnalatha and D. V. Prasad, "Maternal ECG cancellation in abdominal signal using ANFIS and wavelets", J. of Applied Sciences 10 (11) : 868-877, 2010, ISSN 1812-5654.
[13] Jang, S. R., C. T. Sun and E. Mizutani, 1997, Neuro-fuzzy and Soft Computing, Prentice-Hall, USA.
[14] S. Hemajothi and K. HelenPrabha, "ANFIS and Adaptive Equalizer for noise cancellation in Abdominal Signal", European J. of Scie, Research, ISSN 1450-216X, Vol. 79 No. 1 (2012), pp. 59-67.
[15] Khaled Assaleh, "Extraction of Fuzzy Electrocardiogram Using Adaptive Neuro-Fuzzy Inference Systems", IEEE Trans. on Biomedical Engg., vol. 54, No. 1, Jan. 2007.
[16] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K,Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation* 101(23):e215-e220 [Circulation Electronic Pages; http://circ.ahajournals.org/cgi/content/full/101/23/e215 [http://circ.ahajournals.org/cgi/content/full/101/23/e215]; 2000 (June 13).