Detection of fetal heart rate using ANFIS displayed on a smartphone

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***Abstract*— Pregnant mothers can be monitored for accurate fetal ECG (FECG) from the abdominal ECG (aECG). This can help detect fetal asphyxia based on the decreasing fetal heart rate (FHR) before the fetus enters into the acidosis phase. In this paper, a technique is proposed based on the adaptive neuro fuzzy inference system (ANFIS) along with a fetal QRS detector. The proposed QRS detector is based on the Pan and Tompkins algorithm which is optimized to give the least number of incorrect maternal and fetal R peaks. The modified QRS detector adjusts the threshold for each record to obtain FHR. The proposed ANFIS system which was evaluated with the abdominal and direct fetal ECG (adfecgdb) physionet recordings, correctly estimated the FECG signal for most records. Using Matlab Mobile we could wirelessly connect to the laptop running Matlab files with our smartphone, accurately displaying simulations files and average FHR for each record.**

Keywords*— *fetal electrocardiogram; ANFIS; QRS detector; fetal heart rate; adfecgdb , Matlab Mobile ; Android phone

I INTRODUCTION

The condition and health status of the fetal can be easily detected by computing the fetal heart rate. Due to the inaccurate analysis of FHR and fetal hypoxia using the cardiotocogram, the rate of caesarean sections have increased during labor. It is important to detect fetal asphyxia before the fetus goes into the acidosis phase. Electronic fetal heart rate (EFHR) monitoring can reduce and even eliminate fetal asphyxia especially during the 3rd trimester or during labor. In the following research papers [1,2], it is observed from the cardiotocography (CTG) the decreasing fetal heart rates correlate to the fetal hypoxia and fetal acidosis. This continuous decreasing FHR can point to the risk of fetus deaths. As of today, the conventional methods such as ultra sound transducer and CTG are the two main techniques used by doctors to monitor the status of the fetus. As per Maulik et al [3], it is observed that the fetal beats per minute (BPM) of the computed CTG output may not be as accurate when cross checked with the FECG signal. When an electrode is placed on the fetal scalp very accurate FECG signals can be extracted, this is called as an invasive procedure. This invasive procedure has a risk of infection to the fetus. However, the non-invasive FECG (NIFECG) method can be used to obtain FECG signals without causing risk to the mother and the fetus. Today, the NIFECG can be considered to be a vital information on the fetus well-being, to detect for twin pregnancies or any other irregularities with the fetus [4].

Biomedical researchers in this field have constantly improvised on the fetal extractions algorithms to detect the fetal information from the aECG signals and further reduced the MECG and other noise associated with it. Thus assuring the fetal health during the pregnancy period especially during the 3rd trimester and also during labor. There are various methods and techniques that are used by researchers over these years, some of the methods are listed here: Among the single channel signal source processing uses non adaptive methods such as auto or cross correlation, subtraction, averaging techniques, filtering techniques and wavelet transform based techniques. BSS (blind source separation) techniques such as ICA (independent component analysis), PCA (principle component analysis) and SVD (singular value decomposition) are non-adaptive multi-channel methods. Among the linear adaptive processing are LMS (least mean square) algorithm, Kalman filtering and RLS (recursive least square), while non-adaptive techniques include artificial neural networks (ANN) and ANFIS (adaptive-network-based fuzzy inference system). A detailed review of various techniques can be obtained from some of the following review papers such as Sameni et al [5], Hasan et al [13] and most recently, Behar et al [14].

II METHOD FOR MATERNAL ECG CANCELLATION

In this paper, we propose a technique to cancel the maternal ECG from the aECG using adaptive neuro-fuzzy inference system (ANFIS) based on Takagi–Sugeno fuzzy inference system [6]. Neural networks have an advantage of recognizing signals and configuring themselves to the fast changing scenarios. While the fuzzy inference systems (FIS) takes the task of decision making and verification process. Thus ANFIS is a perfect trade-off between the combination of neural network and fuzzy logic [6]. In our case, MECG is the main noise source which needs to be eliminated from the abdominal composite signal. Since ANFIS system is an adaptive noise cancellation system, it adjusts itself to filter the maternal ECG giving the estimated fetal ECG signal. Figure 1, shows the proposed fetal extraction method which extracts fetal R peaks using a fetal QRS detector to obtain accurate FHRs.

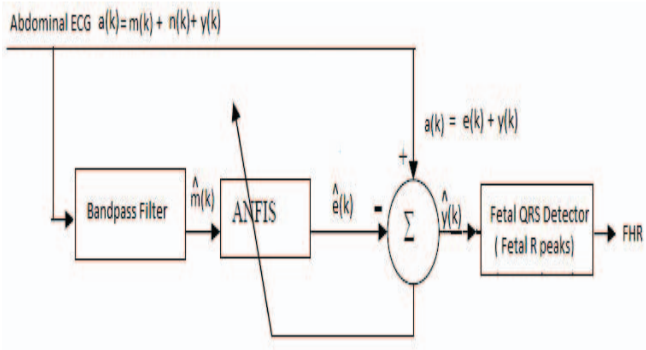

Fig.1. Schematic diagram of ANFIS with QRS detector for fetal R peaks.

In this technique, the abdominal ECG signal is represented by a(k) while, the signal y(k) represents the fetal ECG information, which needs to be obtained from the abdominal signal a(k). Two signals, m(k) is the MECG signal and n(k) is the composite of all other noise signals. The aim is to extract y(k) from the composite maternal abdominal signal a(k) which contains the desired FECG signal y(k) plus e(k), where e(k) is m(k) + n(k). To estimate the m(k) and n(k) signals, we need to first obtain a filtered MECG m(k) estimate signal as a reference signal. This is done by a band pass filter with 3Hz and 15Hz as the cut-off frequencies as shown in Figure 1. Our method is useful to compute the ê(k). When the two signals e(k) and the estimated ê(k) are identical, the signals cancel each other and we get the estimated fetal ECG output signal ŷ(k) which is very identical to the fetal scalp ECG signal.

A) *Maternal and Fetal QRS detections*

It is utmost important to detect accurate QRS complexes in electrocardiography and biomedical signal processing. In the presence of noise such as 50 Hz power line interference (PLI), low frequency noise such as baseline wandering due to mothers breathing, electromyogram (EMG) and electrode contact noise in the abdominal ECG deteriorates the performance of the QRS detector. Maternal and fetal QRS frequency bands overlap with the noise [5], thus increasing the complexity of the detection task of QRS complexes further. Among many approaches to detect QRS complexes, we used the Pan and Tompkins QRS detection algorithm [7] which is often used in real-time analysis as they do not require large computations and is based on analysis of the peak signal amplitude, the integrated window widths and the sharp slopes of QRS complexes.

We modified the algorithm and replaced the separate IIR low pass and high pass filters stages by two bandpass filters for effective linear filtering as shown in figure 2. The two stage elliptical IIR bandpass filters of order 8 and 2 respectively are used for a bandpass frequency of 10Hz to 35Hz. This two stage band pass filter effectively filters the higher frequencies of the EMG and PLI. This preprocessing band pass filter also attenuates the low frequencies especially noise due to baseline wandering. The next processing step is differentiation. This stage gives the information regarding the fast rising slopes of the QRS complex. We used the 5 point derivative with the transfer function which gives a linear range between 0 dc to 30Hz [7].

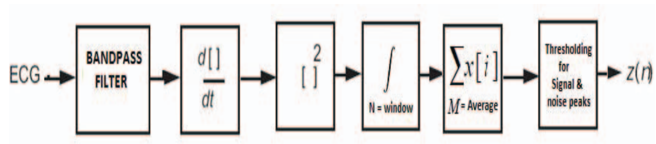

Fig.2. Modified FQRS detector for fetal R peaks.

The next stage includes an amplitude squaring stage which enables the desired peak signals to be further enlarged and small noise peaks to be reduced. The moving window integration uses a sampling frequency of 1000 Hz and a 152 samples wide window (152ms). Additionally a moving average filter (MAF) smoothens the integrated signal and computes a single output R signal peak. The adaptive threshold generated is automatically adjusted to float over the noise peaks. The peak value and peak index are obtained from the MAF output. The signal peak is adjusted as per the amplitude of each record. Figure 4 displays the simulations of the above stages using record r01 of the abdominal and direct fetal electrocardiogram database (adfecgdb).

B. *Adaptive Neuro Fuzzy Inference System*

The generalized structure of the ANFIS maps the input variables to the IF-part (layer 1), IF-part to rules (layer 2) and normalization (layer 3), while layer 4 is set by the THEN-part and finally the outputs (layer 5) [6] as shown in Figure 3. The detailed general architecture of Sugeno's ANFIS is given in [8].

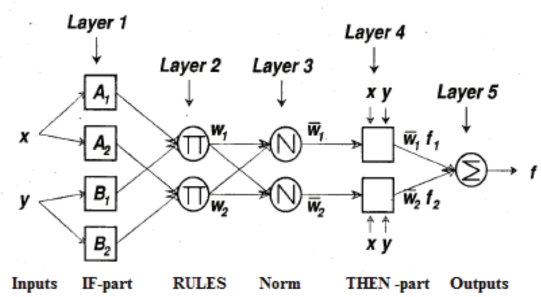

Fig.3. Equivalent ANFIS architecture [8]

The basic algorithm used to compute the estimated output FECG signal ŷ(k) using matlab is given below:

% Generating the initial FIS
Set the number of membership functions (mf) to 2
Set the number of step size (ss) to 0.2

% Bandpass filtered Abdominal ECG
d = m(k) estimate

% Abdominal ECG (aecg) = MECG + FECG + (Noise)
delayed_d = [0; d (1: length (d)-1)]
train_data = [delayed_d d aecg]

% Generate the initial fuzzy network
in_fismat = genfis1 (train_data, mf, mftype)

% Using ANFIS for fine tuning the FIS for 20 epochs
out_fismat = anfis (train_data, in_fismat, [20 nan ss])

% Testing the tuned model with training data
$\hat{e}(k)$ = evalfis(train_data(:, 1:2), out_fismat)
Estimated FECG [$\hat{y}(k)$] = aECG - estimate [$\hat{e}(k)$]

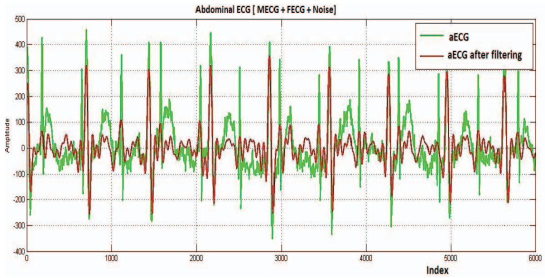

Fig 4(a)

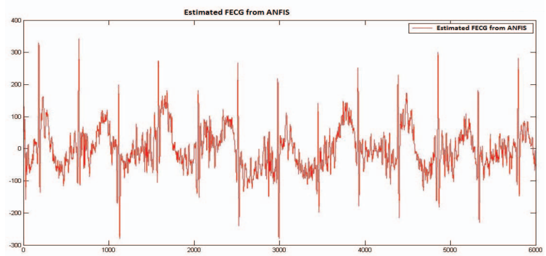

Fig 4b)

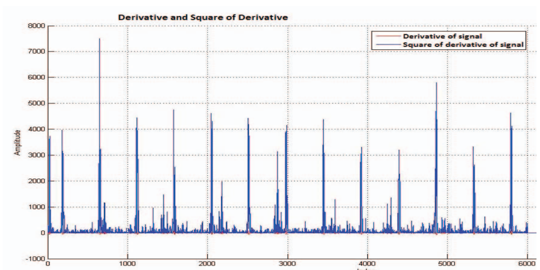

Fig. 4c)

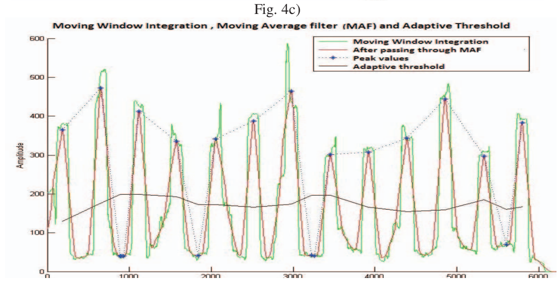

Fig. 4 Modified QRS detection algorithm for a FQRS of adfecgdb (file r01). Fig. 4(a) raw aECG signal with filtered aECG. Fig. 4(b) ANFIS: estimated FECG $\hat{y}$ (k) signal
Fig. 4(c) Output of the differentiator with the squaring process, Fig. 4(d) Output of moving window integration along with the moving average filter and the adaptive threshold.

III RESULTS

The Fetal ECG can be extracted by our proposed method using ANFIS and the adfecgdb database were used as the abdominal ECG signals hosted by PhysioNet online recordings [9]. The adfecgdb database contains multichannel FECG recordings with the sampling frequency of 1 KHz. These recordings were obtained from five various women which were in labor. The period of gestation for these women were from thirty-eight and forty-one weeks. The abdominal recordings had 4 channels (numbered as channel 2 to 5) and one golden reference channel as the scalp or direct fetal ECG (numbered as channel 1). This ECG is obtained from the fetal scalp.

a) Performance of the fetal QRS detetctor

As per the American National Standards [10] and Gari D. Clifford evaluations [11], we calculated the Sensitivity (Se) and Positive Predictivity (PP) for all the five records. The R wave peak index values computed from the modified fetal QRS detector is compared with the annotation provided by the physionet database [9]. If the difference is more than 30ms, then it will result into scoring for FN or FP. The FHR are calculated and the computed TP, FN, FP and Failed Detections (FD) for each record are listed below in Tables I.

TABLE I
EVALUATION OF THE MODIFIED QRS DETECTOR OF FHR USING ADFECGDB DATABASE

Record	TP	FN	FP	FD (%)	Se(%)	PP(%)	FHR_WL	FHR_A	FHR % error
r01	129	0	0	0	100	100	128.98	128.92	0.047
r04	125	14	0	11	90	100	124.98	144.2	-15.378
r07	127	3	4	5.51	98	97	127.09	125.79	1.023
r08	132	0	3	2.27	100	98	132.05	132.03	0.015
r10	128	8	0	6.25	94	100	128.48	126.33	1.673
5 patients									2.524

TP = True Positive; FN= False negative; FP = False positive; FD = Failed detections.
Sensitivity (se) % = (TP / TP + FN) *100 and Positive Predictivity (PP) % = (TP / TP + FP) *100
Failed detections = (FN + FP / TP) *100
FHR_WL: maternal and fetal heart rates computed from the physionet database [9]
FHR_A: maternal and fetal heart rates computed from our proposed algorithm

b) Training process of ANFIS

The estimated maternal ECG m(k) is fed to the ANFIS as a reference signal along with the MECG signal a(k) as shown in figure 5(a). The ANFIS tries to estimate the MECG present in the composite abdominal signal. When the desired epoch is obtained, ANFIS will stop training and output the new estimated MECG $\hat{e}(k)$.Once the estimated $\hat{e}(k)$ is computed using the matlab command "evalfis", the estimated fetal ECG is easily obtained by subtracting the composite MECG a(k) from the estimated MECG $\hat{e}(k)$. The estimated FECG signal shown in figure 5(d), is approximately the same as the direct fetal scalp ECG as show in figure 5(b). The average fetal heart rate of the scalp FECG for record r01 was 128.98 bpm while our method recorded 128.92 bpm as shown in figure 7b. The five records from the abfecgdb were evaluated for the fetal R peaks and FHR. A fair result was obtained from four records except from record r04. The fetal QRS detector failed to detect 14 fetal R peaks for record r04.

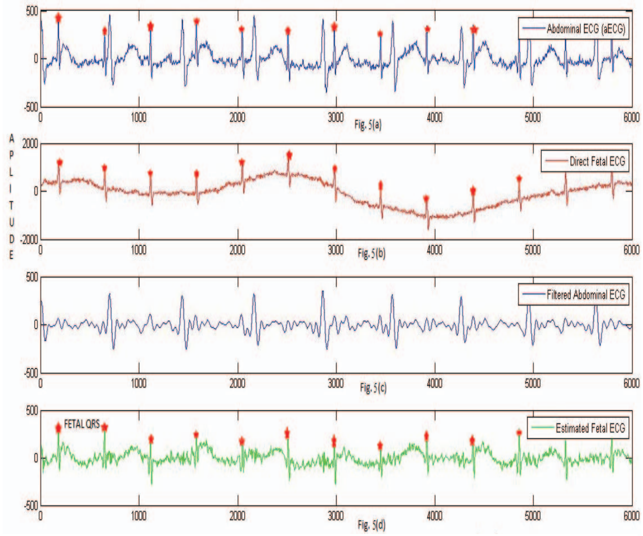

Fig. 5 ANFIS computations: Fig.5 (a) aECG a(k). Fig.5 (b) Direct scalp FECG. Fig.5(c) Filtered abdominal ECG and Fig 5(d) Estimated FQRS ŷ (k) shown by red dots are the fetal R peaks

c) Connecting to Android phone using MATLAB Mobile

In this paper, Matlab was used for software implementation. MATLAB Mobile is an application on your smartphone device which connects to a MATLAB session that is running on your laptop or desktop [12]. On the smartphone we can create a username and configure the IP address, while at the desktop or laptop we can use the command "connector on" to directly connect to the smartphone. This allows remote access to your scripts and also allows you to view the simulation plots, figures and results. Connecting to a Matlab session on your computer requires that you have the Matlab Connector running on that session. Additionally, the mobile device requires network access to the computer you are connecting it to. We connected our Android smartphone phone to Matlab via the Matlab Mobile as shown in Figure 6 to view the Matlab files of the QRS detector, ANFIS extracted FECG and the fetal heart rate.

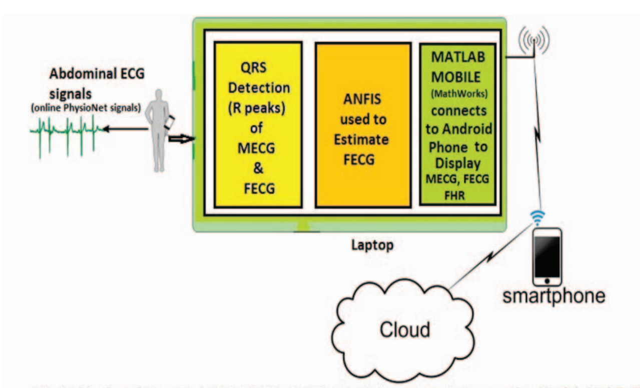

Fig. 6. Display of Abominal ECG , MECG , FECG with FHR on a smart phone using Matlab Mobile™

Figures 7(a) and 7(b) show the Matlab mobile screenshots of the FHR variability and the average FHR value respectively.

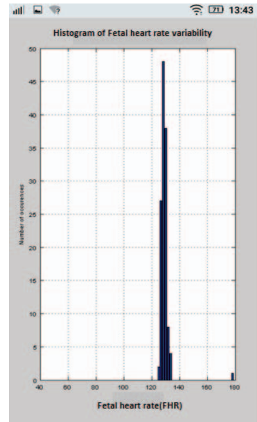

Fig.7 (a)

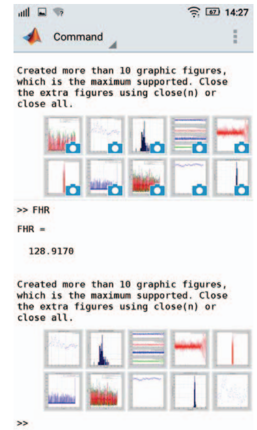

Fig.7 (b)

Fig.7 Matlab Mobile screenshots: Fig.7 (a) Histogram of the FHR variability. Fig.7 (b) Matlab command prompt showing the FHR value for the file r01 of database adfecgdb.

IV Conclusion

The proposed algorithm has been evaluated with the records of abdominal and direct fetal ECG database. ANFIS has advantages over other methods since it is suitable for nonlinear applications, has less mathematical analysis and requires less inputs to extract FECG due to the neutral network. The ANFIS module estimated the FECG output which was given to the modified QRS detector for fetal heart rate calculations. The modified algorithm adjusts the threshold for each record to obtain fetal heart rates giving a least average error of 2.52% for FHR. The average fetal heart rate of the direct scalp FECG (adfecgdb) for record r01 was 128.98 bpm while our method recorded 128.92 bpm. The FHR percentage error for most records were less than 2%.The failed detections for the fetal QRS detector of the record r04 was 11% due to the noisy abdominal signal and the adaptive threshold who could not detect some of its fetal R peaks. This algorithm could also be tested for other physionet databases such as nifecgdb and other real time maternal abdominal signals in the future. The Matlab simulation plots and FHR values were easily viewed on the smartphones using MATLAB Mobile.

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