AN EFFICIENT EXTRACTION OF FETAL ECG FROM ABDOMINAL ECG USING ANFIS TUNED WITH GA

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Abstract— **In this paper, the extraction of Fetal ECG from abdominal composite signals is proposed. With the help of soft computing techniques called Adaptive Neuro –Fuzzy Inference System (ANFIS) tuned with Genetic Algorithm. The thoracic ECG is 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. The abdominal ECG signal contains a nonlinearly transformed version of the MECG and FECG. In this paper an ANFIS system identifys the nonlinear relationship, and aligns the MECG signal with the reference to MECG in the abdominal ECG signal. It extracts the FECG by subtracting the aligned version of the MECG signal from the abdominal ECG signal. After that Genetic algorithm is applied to furthermore tune the output of the ANFIS and to extract FECG signal with more qSNR.**

***Keywords— Adaptive* Neuro-fuzzy inference system, Fetal ECG, Maternal ECG, Nonlinear transformation, Genetic Algorithm.**

1. INTRODUCTION

The abdominal ECG contains a weak fetal ECG signal, a relatively sound maternal ECG, maternal muscle noise and respiration, mains coupling, and thermal noise from the electronic equipment [1]. At present, many methods of signal processing are used for extracting FECG. ICA techniques are usually based on the maximization of some nonlinear criterion as a measure of component independence. These methods are, however, of the same order of complexity as conventional ICA algorithms, and are basically designed for signals having a constant fundamental period [2]. Many signal-processing-based techniques for FECG extraction have been introduced with varying degrees of success. These techniques include adaptive filters, correlation techniques, singular-value decomposition (SVD), wavelet transform, neural networks, and blind source separation (BSS). BSS via independent component analysis (ICA) is considered among the most recent and most successful methods used for FECG extraction.

However, in order for ICA to work properly, it requires multiple leads for collecting several ECG signals [5]. To enhance the extraction of FECG signal from the abdominal ECG signal, the Neural Network based FECG extraction has been proposed by many researchers. As the neural network is adaptive to the nonlinear and time-varying features of ECG signal therefore, the neural network has been used to extract the FECG signal. But the disadvantage is changing of the learning rate and the momentum also affects the output of the network [1]. In this paper, we aim to apply ANFIS for estimating the FECG component from one abdominal ECG recording and one reference thoracic MECG signal [5]. It shows results on both synthetic and real ECG data. The output of the ANFIS is further more tuned with GA.

II. PROBLEM FORMULATION

The problem is pictorially depicted in Fig. 1. The abdominal signal w(n), can be expressed as the sum of a deformed version of the maternal ECG, and a noisy version of the fetal ECG.

$$w(n) = x\hat{}(n) + s\hat{}(n) \quad (1)$$

$$x\hat{}(n) = T(x(n)) \quad (2)$$

$$s\hat{}(n) = s(n) + \eta(n) \quad (3)$$

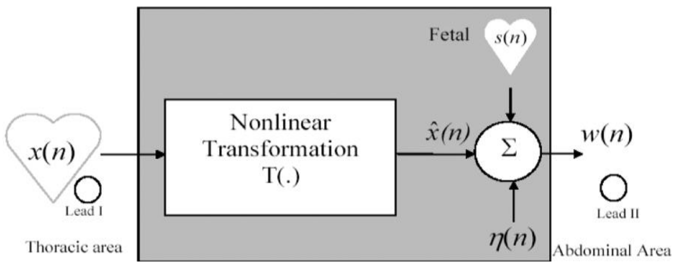

Fig.1 Depiction of the problem formulation

the deformation of the maternal ECG component in w(n) is due to the fact that the signal is measured far away from its source (the mother's heart), and consequently it encounters some nonlinear transformation as it travels to the abdominal area [5].

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS (ANFIS)

ANFIS are fuzzy Sugeno models put in the framework of adaptive systems to facilitate learning and adaptation. ANFIS combines the capabilities of both neural networks and fuzzy systems in learning nonlinearities. let us consider two-fuzzy rules based on a first-order Sugeno model [5].

Rule 1: if (x is A_1) and (y is B_1), then ($f_2=p_1x+q_1y+r_1$)

Rule 2: if (x is A_2) and (y is B_2), then ($f_2=p_2x+q_2y+r_2$)

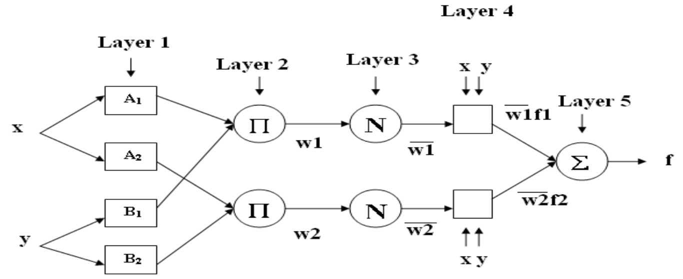

Fig.2 ANFIS Architecture.

Layer 1: Calculate Membership Value for Premise Parameter All the nodes in this layer are adaptive nodes; i is the degree of the membership of the input to the fuzzy membership function (MF) represented by the node.

Output $O_{1,i}$ for node i=1,2 $O_{1,i} = \mu_{Ai}(x2)$ (4)

Output

$O_{1,i}$ for node i=3,4 $O_{2,i} = \mu_{Bi-2}(x2)$ (5)

Layer 2: Firing Strength of Rule The nodes in this layer are fixed (not adaptive).These are labeled to indicate that they play the role of a simple multiplier. The outputs of these nodes are given by

$$O_{2,i} = w_i = \mu_{Ai}(x1)\,\mu_{Bi}(x2) \quad (6)$$

Layer 3: Normalize Firing Strength Nodes in this layer are also fixed nodes. These are labeled N to indicate that these perform a normalization of the firing strength from previous layer. The output of each node in this layer is given by

$$O_{3,i} = \overline{wi} = \frac{wi}{w1+w2} \quad (7)$$

Layer 4: Consequent Parameters All the nodes in this layer are adaptive nodes. The output of each node is simply the product of the normalized firing strength and a first-order polynomial

$$O_{4,i} = \overline{wi}fi = \overline{wi}\,(p_ix_1 + q_ix_2 + r_i) \quad (8)$$

Layer 5: Overall Output This layer has only one node labelled Σ to indicate that is performs the function of a simple summer. The output of this single node is given by

$$O_{5,1} = \sum_i \overline{wi}fi = \frac{\sum_i wifi}{\sum_i wi} \quad (9)$$

IV GENETIC ALGORITHM (GA)

The GA is a stochastic global search method that mimics the metaphor of natural biological evolution. GAs operates on a population of potential solutions applying the principle of survival of the fittest to produce (hopefully) better and better approximations to a solution. The recombination operator is used to exchange genetic information between pairs. Consider the two parent binary strings. The two offspring below are produced when the crossover point *i = 5* is selected,

P1 = 1 0 0 1 0 1 1 0, and P2 = 1 0 1 1 1 0 0 0.

O1 = 1 0 0 1 0 0 0 0, and O2 = 1 0 1 1 1 1 1 0.

A further genetic operator, called mutation, is then applied to the new chromosomes, again with a set probability, *Pm*. In the binary string representation, mutation will cause a single bit to change its state,0 to1 or 1 to 0.

So, for example, mutating the fourth bit of O1 leads to the new string, O1 = 1 0 0 0 0 0 0 0.

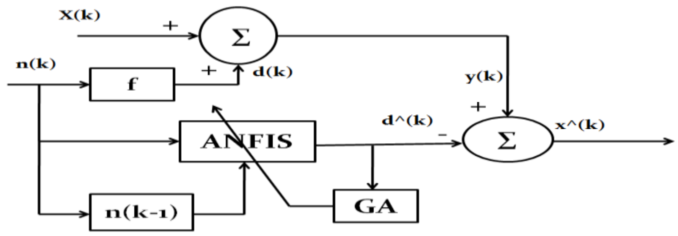

Fig.3 Schematic Diagram of ANC with GA

V.ECG DATA USED IN THIS STUDY

A. Synthetic ECG Data Generation

The shapes of the electrocardiogram for both mother and fetus signals(x(n) and s(n)) are simulated using MATLAB commands. The MECG signal x(n) is processed through the following expression to simulate the nonlinear and multipath effects it undergoes as it travels from the heart to abdomen [5].

$$x_e(n) = x(n) + a1x(n-1) + a2x(n-2) \quad (10)$$

$$\hat{x}(n) = sgn\left(x_e(n)\right)\left(mod\left(\tan^{-1}\left(x_e(n)\right)^{\propto}\right)\right) \quad (11)$$

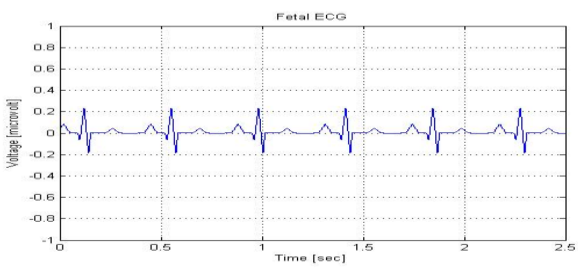

Fig. 4 Synthetic FECG signal

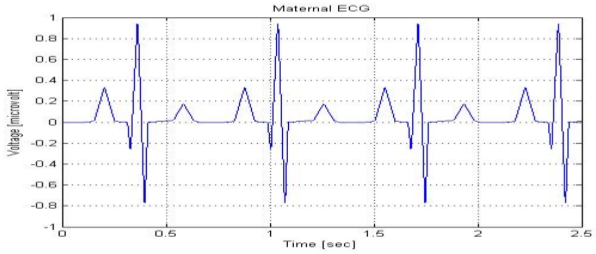

Fig.5 Synthetic MECG signal

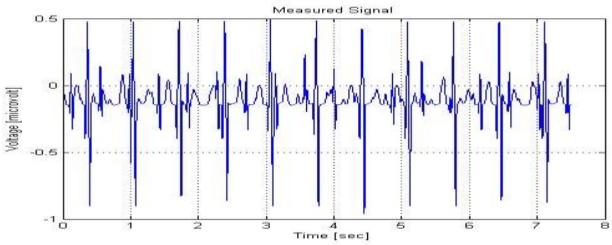

Fig .6 Composite signal

B. Real ECG Data

The real ECG data used in this project was a subset of a dataset contributed by Lieven De Lathauwer [8].The ECG signals in this dataset were recorded from eight different skin electrodes located on different points of a pregnant woman's body.

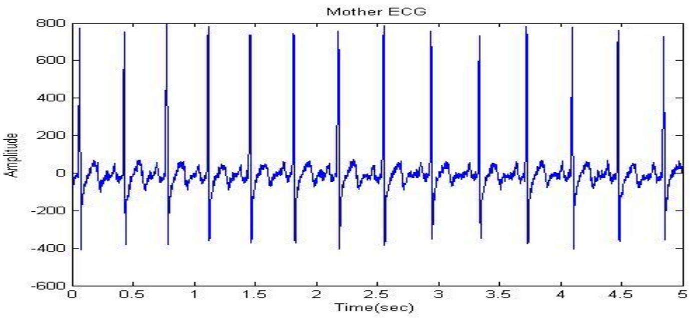

Fig.7 Real MECG signal

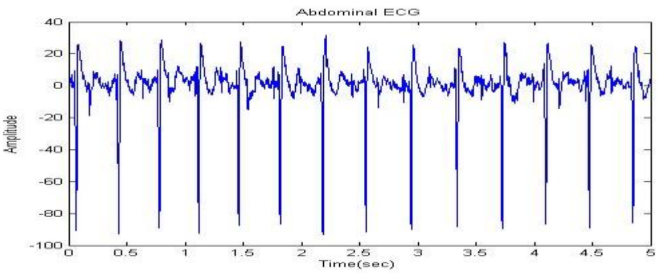

Fig.8 Real Abdominal signal

VI. EXPERIMENTAL RESULTS

A. Results on Synthetic ECG Data

Visually, the match between the two signals is clearly impressive. To quantify this match we calculate a quality signal to noise ratio qSNR and The mean square error between estimated FECG signal and original FECG signal (s^(n)and s(n)) [5].

$$qSNR = 10\log_{10}\frac{\sum_n(\hat{s}(n))^2}{\sum_n(s(n)-\hat{s}(n))^2} \qquad (12)$$

$$MSE = 10\log_{10}\frac{\sum_n(s(n)-\hat{s}(n))^2}{n} \qquad (13)$$

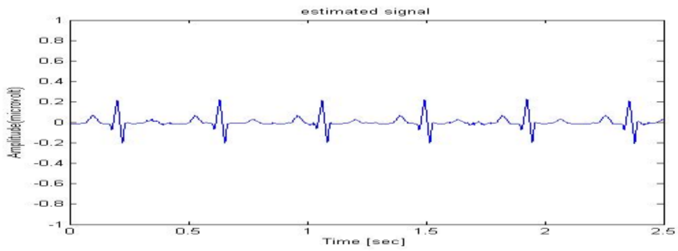

Fig.9 Estimated FECG using ANFIS

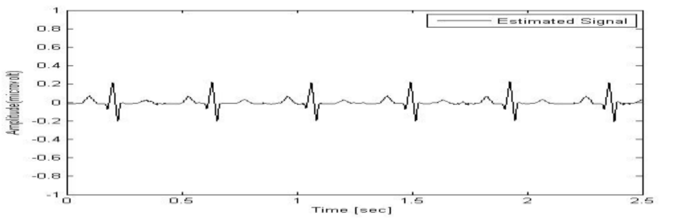

Fig.10 Estimated FECG using ANFIS tuned with GA

Table I Performance Analysis

SNR	qSNR		MSE	
	ANFIS	ANFIS+GA	ANFIS	ANFIS+GA
-26.12	1.63	0.78	0.005	0.975
-17.41	11.00	11.30	0.035	0.153
-11.76	11.10	11.32	0.032	0.036
-8.16	10.96	11.05	0.033	0.020
-6.07	11.01	11.30	0.035	0.013
-5.25	11.10	11.31	0.032	0.011

B. Results on Real ECG Data

The result of processing this data through the proposed algorithm where a suppression of the maternal component from the abdominal signal is accomplished. By visual inspection of the figure, both the proposed ANFIS method and the ANFIS tuned with GA method cancel the maternal component to a very good extent with a slight advantage to the ANFIS tuned with GA method.

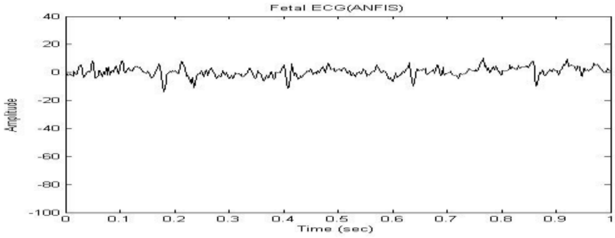

Fig.11 Estimated FECG using ANFIS

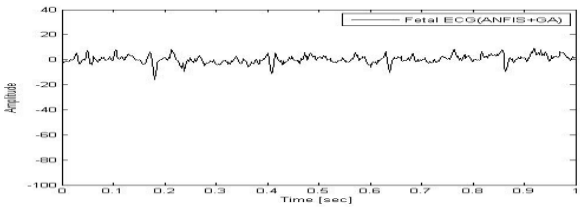

Fig.12 Estimated FECG using ANFIS tuned with GA

VII.CONCLUSIONS

In this paper, the removal of FECG from Abdominal ECG is solved by an adaptive neuro fuzzy inference system and ANFIS tuned with GA. Adaptive noise cancellation using ANFIS is performed on ECG signals with interference and their results are plotted. From the obtained results, It is concluded that ANFIS successfully removes the artifacts without affecting the ECG signal. In the next step, Along with the ANFIS method GA is used for optimizing the output of ANFIS. From the result it is concluded that ANFIS tuned with GA method performs better than ANFIS.

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