A Novel Approach for Fetal ECG Extraction –Blood Pressure Patient Using Adaptive Neuro-Fuzzy Inference Systems Trained With PSO

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Abstract- Fetal ECG is an important parameter in medical field. Fetal Electrocardiogram (FECG) identifies the congenital heart problems at the earlier stage. Fetal Electrocardiogram (FECG) signal is extracted from blood pressure mother's abdomen. FECG signal is recorded at the thoracic and abdominal area of blood pressure mother's skin. The thoracic ECG is considered to be completely maternal ECG (MECG) of blood pressure mother. The abdominal ECG is considered to be a combination of blood pressure mother's ECG signals and foetus's ECG signals and random noise. The maternal component of abdominal ECG is a nonlinear transformed version of the Maternal ECG. The method Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to identify the nonlinear transformation of maternal ECG. For identifying the nonlinear transformation and the FECG is extracted by subtracting the non linear version of the MECG signal from the abdominal ECG signal. ANFIS is trained with particle swarm optimization for better quality of signal. This method can be validated on both real and synthetic ECG signals. The results demonstrate the effectiveness of extracting the FECG from blood pressure mother's maternal ECG.

Index Terms- Fetal Electrocardiogram, Adaptive neuro fuzzy inference system, particle swarm optimization.

I. INTRODUCTION

During pregnancy period, mother having blood pressure, it can also affect the fetus. Care should be taken to prevent the fetus from mother's blood pressure. Fetal Electrocardiogram (FECG) signal is used to monitor the health condition of fetus by physicians. It is used to find heart problem at the early stage and take better action in critical situation. Fetal Electrocardiogram gives the electrical signal of fetal heart. There are two method to obtain Fetal Electrocardiogram signal such as invasive method and non invasive method. In invasive method, FECG signal is recorded from electrode which is placed on fetus head through mother's womb. This method may leads to problem for mother (bloodshed) and fetus (infection). Comparing to first method, second method is best and it can be used nowadays.

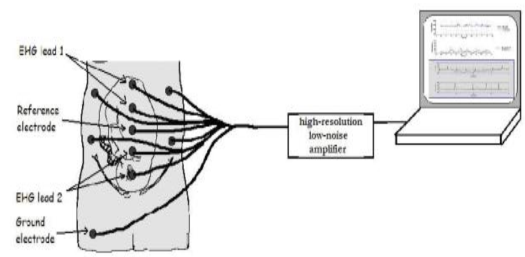

Figure 1: Non-invasive method recording of AECG signal

In non invasive method, two set of electrodes are placed on blood pressure mother's body. The first set of electrode is placed on the thoracic area. This gives the original maternal ECG (MECG). The second set of electrode is placed on the abdomen area of the blood pressure mother.

Figure 1 demonstrates the AECG signal recording. This AECG signal contains Fetal ECG with the altered MECG along with other contaminated noises. The other contaminated noises are maternal electromyogram (EMG) signal, baseline wandering, powerline interference, electrodes noise and recording system noise. Powerline interference, electrodes and recording system noises are eliminated by using low noise amplifier. The Electromyogram (EMG) signal can be eliminated by using classical low pass filtering techniques. The wavelet based methods are used to reduce the baseline wandering. Therefore, it is safe for eliminating altered maternal ECG component in the combined signal; estimated FECG signal can be obtained. Many signal-processing techniques are introduced to extract the FECG signal. These techniques include adaptive filters [2], correlation techniques [13], Adaptive noise cancellation [5], singular-value decomposition (SVD) [12], wavelet transform [8], [11], neural networks [7], blind source separation (BSS) [5] and independent component analysis (ICA) is considered among the most recent and successful methods used for FECG extraction [8]. ICA requires multiple electrodes for successful separation of the FECG. Practically, it is difficult to predict the signal components in the abdominal signals.

In this paper, we introduced ANFIS network trained with PSO method for estimating the FECG signal from one abdominal ECG signal and one thoracic

ECG signal. We use ANFIS network to identify the nonlinear align of thoracic MECG mixed with the abdominal ECG signal. This nonlinear transformation between the two signals allows for cancelling the maternal component from the abdominal signal and hence offers an estimate of the FECG signal. We show the results on synthetic ECG data and real ECG data.

This paper is organized as follows: The following section, we will analysis the schema of our work and theory of ANFIS

II. EXTRACTING FECG SIGNAL THROUGH NON-INVASIVE METHOD

The objective of non-invasive method is to extract FECG signal from signal recorded at blood pressure mother abdomen (AECG). AECG signal contains FECG signal, altered MECG signal and noises. The maternal components are distorted because it is travel from mother's heart to abdomen. This type of distortion can be taken as non-linear transformation of MECG signal. In order to improve the result of FECG signal, we need to weaken the power of MECG signal and decrease the effects of noises. We should able to recognize the altered MECG signal.

The aim purpose of proposed method is to identify the non-linear transformation. By indentifying the non-linear transform and it is applied on MECG signal which is recorded in thoracic region, we can obtain the estimation of MECG signal in blood pressure mother's abdomen region. By subtracting these MECG signal from AECG, we can get the FECG signal. Figure 2 shows the recording of thoracic and abdominal signals.

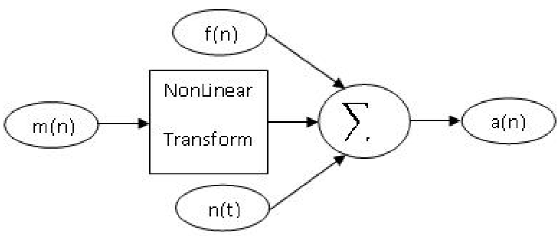

Figure 2. Recording of thoracic and abdominal signals

This method uses two recorded signal, one is recorded at thoracic region m(n) and another one is recorded at abdomen region a(n)of blood pressure mother. Figure 2 summarized the following equations:

$a(n)=\tilde{m}(n)+f(n)+n(n)$
$m\sim(n)=T\{m(n)\}$

where m(n) and a(n) are the signals recorded at thoracic and abdominal areas respectively. n(n) indicates the sum of noises in the recorded signal. m~ (n) is the distorted version of m(n) signal due to non-linear transformation T. m~ (n) represents altered MECG signal components in the recorded AECG signal. As mentioned above, the distortion resulted from non-linear transformation is created because the signal is recorded far away from the signal's source. We use ANFIS network trained with PSO for estimating the non linear transformation. This transform will operate on m(n) and produce the signal $\tilde{m}(n)$, which is aligned with distorted maternal component a(n).By removing the aligned maternal component in a(n) and then estimate the FECG signal from a(n).

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Adaptive Neuro-Fuzzy Inference System is the combination of artificial neural networks and fuzzy inference systems. The complex system requires more sophisticated tool to model the system behaviour. Mathematical tool is not an appropriate tool for modelling the system. By contrary, Fuzzy inference system can able to model the qualitative aspects of human knowledge by using fuzzy if-then rules. This type of fuzzy modelling was proposed by Takagi and sugeno. For better understanding, we need some basic aspects of this approach. Therefore, J.-S.R.Jang prescribed a new method called ANFIS. The purpose of ANFIS is to automatically realize the fuzzy system by using the neural network. In ANFIS, Fuzzy Sugeno models are involved in framework of adaptive system to facilitate the learning and adaptation method.

1) ANFIS *structure*

The ANFIS approach learns the rules and membership functions from data. ANFIS is an adaptive network. An adaptive network is network of nodes and directional links. Associated with the network is a learning rule. It's called adaptive because some, or all, of the nodes have parameters which affect the output of the node. These networks are learning a relationship between inputs and outputs. The ANFIS architecture is shown in Figure 3. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt.

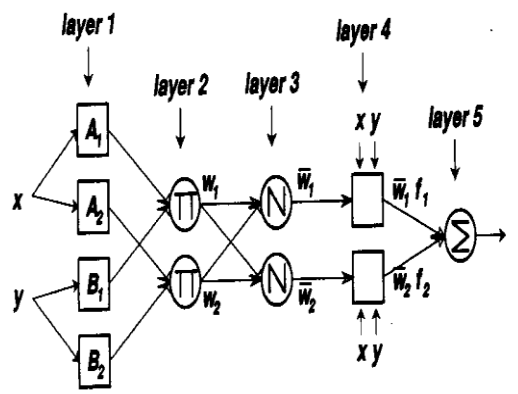

Figure 3 ANFIS architecture for first order Takagi-Sugeno model

Two fuzzy if-then rules under Takagi-Sugeno (TS) model are given as follows:

$$If\ x\ is\ A_1\ and\ y\ is\ B_1 \quad THEN\ f_1 = p_1x + q_1y + r_1$$
$$If\ x\ is\ A_2\ and\ y\ is\ B_2 \quad THEN\ f_2 = p_2x + q_2y + r_2$$

2) LAYER OF ANFIS STRUCTURE

Layer 1

The output of each node is:

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4$$

So, the $O_{1,i}(x)$ is essentially the membership grade for x and y

The membership functions could be anything but for illustration purposes we will use the bell shaped function given by

$$\mu_A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}}$$

Where a_i, b_i, c_i are parameters of membership function. These are the premise parameters.

Layer 2

Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades - for example the product: $O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), i = 1,2$

Layer 3

Layer 3 contains fixed nodes which calculate the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2$$

Layer 4

The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i)$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5

There is a single node here that computes the overall output:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

This then is how, typically, the input vector is fed through the network layer by layer. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules

3) ANFIS learning method

In ANFIS, training and updating the parameters is one of the main problems. There are number of possible approaches based on hybrid learning algorithm which uses a combination of gradient Descent and Least Squares Estimation (LSE). This provides a very high level description of algorithm. It can be shown that the network described if the premise parameters are fixed, the output is linear in the consequent parameters. Split the total parameter set into: set of total parameters(S) is the sum of set of premise (nonlinear) parameters ($S1$) and set of consequent (linear) parameters ($S2$).So, ANFIS uses two pass hybrid learning algorithm:

Forward pass: Here $S1$is unmodified and $S2$ is computed using a LSE algorithm.

Backward Pass: Here $S2$is unmodified and $S1$ is computed using a gradient descent algorithm such as back propagation.

So, the hybrid learning algorithm used to adapt the parameters in the adaptive network. ANFIS can be trained by hybrid learning algorithm, it has more complexity and slow convergence time. This complexity and convergence time can be reduced by using Particle swarm optimization (PSO) for training ANFIS.

IV. PARTICLE SWARM OPTIMIZATION

PSO is a robust stochastic optimization technique based on the simulation of the social behavior of birds within a flock. It was developed in 1995 by James Kennedy and Russell Eberhart . It uses a number of particles that constitute a swarm moving around in the search space looking for the best solution. Each particle is treated as a point in a N-dimensional space which adjusts its "flying" according to its own flying experience as well as the flying experience of other particles. The PSO algorithm is given as follows:

1. For initialization, at t = 0, the swam P(0) = { $P1$, $P2$, . . . , Pk }. For, i = 1, … k, the position of particle Pi € P(0), $\vec{x}_i(0)$ is random within the hyperspace and initial velocity $\vec{v}_i(0)$ of particle Pi is given for each i.(We assume that the swarm has k particles.)

2. Evaluate the performance of each particle, using its current position $\vec{x}_i(t)$. $F(\vec{x}_i(t))$is the fitness of particle i at time step t.

3. Compare the performance of each particle to its best Performance:

If $(\vec{x}_i(t)) < pbest$, then

$pbest_i = F(\vec{x}_i(t))$ and $\vec{x}_{pbest_i} = \vec{x}_i(t)$

4. Compare the performance of each particle to the global best particle:

If $(\vec{x}_i(t)) < gbest$, then

$gbest_i = F(\vec{x}_i(t))$ and $\vec{x}_{gbest_i} = \vec{x}_i(t)$

5. Change the velocity vector for each particle as follows:

$$\vec{v}_i(t+1) = \vec{v}_i(t) + \rho_1(\vec{x}_{pbest_i} - \vec{x}_i(t)) + \rho_2(\vec{x}_{gbest_i} - \vec{x}_i(t)$$

6. Move each particle to a new position

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{v}_i(t)$$

7. Go to step 2, and repeat until convergence is achieved.

The random numbers ρ_1 and ρ_2 are defined as $\rho_1 = r1c1$ and $\rho_2 = r2c2$, where $r1$, $r2 \in U(0, 1)$ and $c1$ and $c2$ are acceleration constants. The effect of the random variables ρ_1 and ρ_2 on the particle trajectories, and asserted that $c1 + c2 \leq 4$ [15]. If $c1 + c2 > 4$, velocities and positions explode toward infinity.

1) ANFIS Trained with PSO

Two parameters of ANFIS are premise and consequent parameters that are needs to be updated. Each parameter has three sets of values that is (a_i ,b_i,c_i) and (p_i,q_i,r_i).Each premise parameter has N genes and the consequent parameter has (I+1).R genes where N is the number of membership functions, R is the number of rules applied and I is the dimension of input data. Initially, parameters are considered randomly and then these values are applied to PSO algorithm for updating the values. Each iteration, one parameter is updated. In final stage, optimised value of parameters will be obtained for each training pair.

V. PROPOSED ALGORITHM FOR FECG SIGNAL EXTRACTION

In our proposed method, we uses two signals to extract FECG signal, one is m(n) another is a(n).These signals are segmented into N-samples along with overlapping frames for ANFIS training. The overlapping frames are considered as N/2 samples. The ANFIS inputs are vector whose values are obtained from m(n)framing process. The ANFIS output is the frame obtained from a(n).These parameters are adjusted separately for each pair of vector. After training each pair of vector is given as ANFIS input. The desired output is transformed version of m(n) that is m˜(n). Now, FECG is otained by subtracting a(n) from m~(n).

VI. RESULT AND DISCUSSION

To extract the FECG signal from our proposed algorithm. The result of proposed algorithm is tested on both synthetic and real signal. For constructing the training data, each of thoracic and abdomen signal can be framed with overlapping signal. We can synthesize the thoracic and abdominal signals for comparing the performance of proposed algorithm. Figure 4 and 5 shows the results of proposed algorithm on synthetic ECG and real ECG signals respectively.

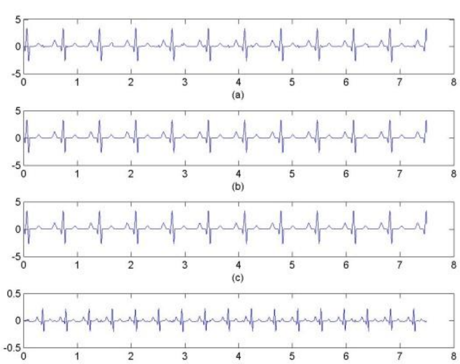

Figure 4. Proposed algorithm result for synthetic signal (a) synthetic abdominal ECG (b) synthetic thoracic MECG (c) synthetic estimated thoracic MECG (d) synthetic extracted FECG

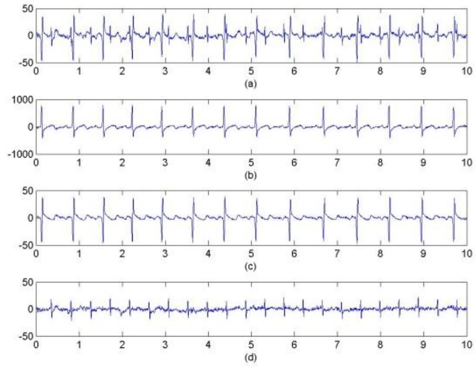

Figure 5 .proposed algorithm result for real signal (a) real abdominal ECG (b) real thoracic MECG (c) real estimated thoracic MECG (d) real extracted FECG.

The results of proposed algorithm can be compared based on quantity criterion which is Percentage Root –Mean Square Difference (PRD), is used to determine the similarity between original FECG and extracted FECG signal. Calculate the PRD values in the following equation:

$$PRD = \frac{\sum_{i=1}^{N}\{x_{ori}(i)-x_{rec}(i)\}^2}{\sum_{i=1}^{N}\{x_{ori}(i)\}^2} \%$$

where ori and rec is the parameter of original and extracted signal. Table 1 contain PRD values of proposed algorithm.

Table 1. Comparing the performance of the proposed algorithm using PRD values

ALGORITHM	PRD
ANFIS	0.5320
ANFIS+PSO	0.4734

VII. CONCLUSIONS

This paper presents ANFIS network for training PSO algorithm. It is used to extract fetal ECG signal from two recorded ECG signal at thoracic and abdomen region of blood pressure mother. Abdominal ECG contain nonlinear transform version of MECG This non linear transform of MECG can be determined by using ANFIS. The training method of ANFIS can affect the efficiency of signal. So, we can use PSO as a new tool for training ANFIS network. The result of using PSO is to reduce complexity and fast convergence. To find the non linear transform of MECG by removing the altered MECG from AECG and then get good approximation FECG signal.

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