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# Improvement of Fetal Electrocardiogram Extraction by Application of Fuzzy Adaptive Resonance Theory to Adaptive Neural Fuzzy System

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**ABSTRACT:** non-invasive fetal electrocardiogram (FECG) signal extraction from signals recorded at abdominal area of mother is a challenging problem for the biomedical and signal processing communities. In this paper, we improve the FECG extraction approaches which consist to find the relation-ships between the cardiac potentials generated at the heart level of mother and the potentials recorded on the abdominal area. We used an efficient signal processing method combining a hybrid learning algorithm based on the fuzzy adaptive resonance theory and the hybrid soft computing technique called Adaptive Neuro Fuzzy Inference System (ANFIS) trained with modified Particle Swarm Optimization (PSO) endowed with an initialization strategy to adjust the antecedent parameters of fuzzy rules. We implemented our algorithm and other algorithm on simulated signals, and we found that the proposed ANFIS with hybrid learning algorithm achieves superior performance in learning accuracy and allowed yielding best processing results to extract the FECG signal.

**KEYWORDS:** Fetal ECG, ANFIS, ART, PSO, AECG, MECG.

## 1 INTRODUCTION

Estimation of the fetal electrocardiogram signal is a classical problem in medical engineering. The signal FECG reflects the electrical activity of the fetal heart and contains information on the health status of the fetus. Consequently, its extraction can help children's heart disease specialist to evaluate the health and condition of the fetus during delivery or after birth.

Many active research projects explored FECG signal processing, and one of the early processing works is that of M. Cremer [1] who used galvanometric apparatus to observe fetal electrocardiogram signal, but with the developments in computer science and signal processing techniques, automatic signal processing and adaptive filtering techniques were used such as matched filtering [2], adaptive filtering [3], IIR adaptive filtering combined with genetic algorithms [4], and least square error fittings [5] have also been used for this purpose. Note that the existing adaptive filtering methods for maternal ECG artifact removal require a reference maternal ECG channel that is morphologically similar to the contaminating waveform, or require several linearly independent channels to roughly reconstruct any morphologic shape from the three references [6]. Also, the linear decomposition methods proposed wildly such as blind source separation [7], singular value decomposition [8], and wavelet transforms [9]. However, linear decomposition methods are limited for nonlinear or degenerate mixtures of signal and noise. In fact, fetal signals and other interferences and noises are not always linearly separable, Accordingly, an important aspect of non linear FECG signal processing exist such as fuzzy logic [10], dynamic neural network [11], polynomial network [12], adaptive neuro fuzzy logic technique [13].

In this paper, we suggest a method combining a hybrid learning algorithm based on the fuzzy adaptive resonance theory and the neuro fuzzy inference system trained with modified particle swarm optimization endowed with an initialization strategy to improve the performance of the traditional PSO.

The rest of the paper is organized as follows. Section 2, it details the FECG signal extraction model; Section 3 explains the methodology of the research including some subsections. Section 4 discusses the results of the performance of the proposed algorithm on simulated signals. Finally, section 5 summarizes the main conclusions and results of this work.

## 2 FECG Signal Extraction Model

In this work, the objective is to improve the approaches which consist to find relation-ships between maternal electrocardiograms (MECG) generated at the mother thorax and the maternal ECG measured at the abdominal area (AECG), because these relation-ships are the key to extract FECG signal from AECG signal by weakening the power of MECG signal components as far as possible. The MECG components travel from their source, i.e. mother's heart, to the abdomen, and this causes its distortion which it can be taken as unknown transformation applied on MECG signal components. By finding this transformation, we can extract a good approximation of FECG signal.

Fig. 1 can be summarized in the equations 1 and 2:

$$AECG = \overline{MECG} + FECG + Noise \tag{1}$$

$$\overline{MECG} = T(MECG) \tag{2}$$

Where the T models a path through which MECG signal passes from thoracic area to the abdominal area, where the signal is recorded.

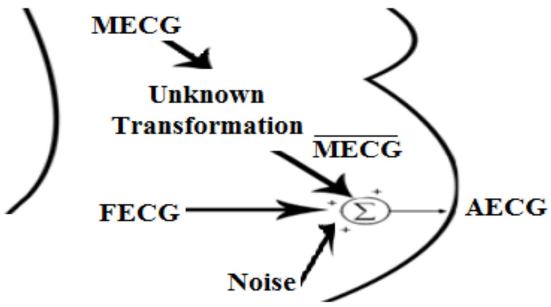



***Fig. 1. Recording and formation of thoracic and abdominal signals***

## 3 The Adaptive Neural Fuzzy System

The modeling systems based on general mathematical tools (like differential equations) is not an appropriate tool to model human knowledge. On the contrary, a fuzzy inference system, using if-then rules, is able to model qualitative aspects of human knowledge and rational process without using precise quantitative analyses. This fuzzy modeling or fuzzy diagnosis has been investigated by Takagi et al. in 1985, but implementing some of the basic aspects of this type of approaches needed a more complete understanding. Accordingly, Jang et al. in 1997 proposed a new architecture called ANFIS to implement a set of rules with appropriate membership functions for producing specific input and output pairs. In this section, the fundamental of ANFIS model is presented with some modification.

### 3.1 The Structure Of Anfis

There are many advantages in using ANFIS for training patterns and detection as compared to linear systems or neural networks. These advantages results from the combination of the capabilities of neural network and fuzzy systems in learning non-linear models. Moreover, the requirements and the primary assumptions of ANFIS structure are less and it is simpler than neural networks.

ANFIS based architecture is illustrated in fig. 2. It should be noted that, in this figure, the circle represents a stable node (the parameters do not change during training) and the square represents adaptive node (the parameters change during training).

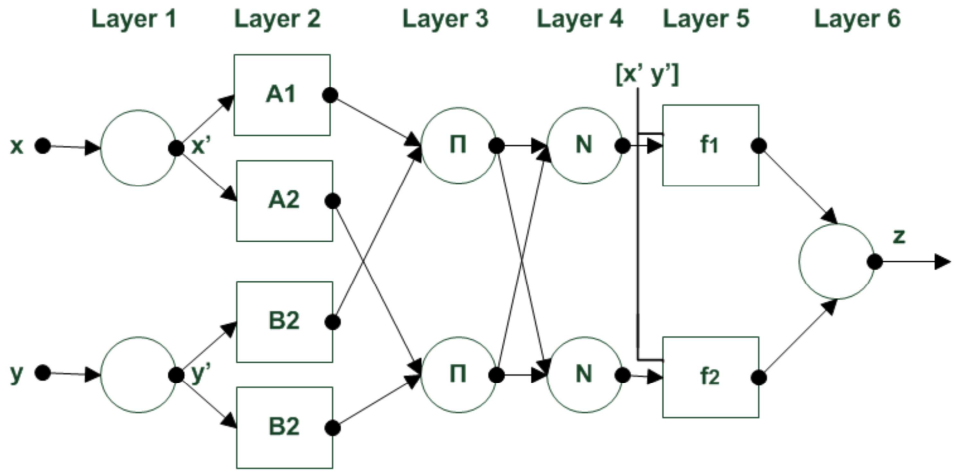



***Fig. 2. ANFIS Architecture***

Layer 1: This layer consists to use of the technique of complement coding to normalize the input training data and helps avoiding the problem of category proliferation for data clustering. The complement coding is a normalization process that rescales an N-dimensional vector in $\Re^n$ , x = ($x_1$, $x_2$, …,$x_n$) , to its 2N-dimensional complement coding form in $[0, 1]^{2n}$, x', such that

$$x' = [\bar{x}_1, 1-\bar{x}_1, \bar{x}_2, 1-\bar{x}_2, ..., \bar{x}_n, 1-\bar{x}_n] \text{ , with } [\bar{x}_1, \bar{x}_2, ..., \bar{x}_n] = \bar{x} = x/\|x\| \quad (3)$$

The output function of the first layer is noted as $O_{1,i}$ for i = 1, 2.

Layer 2: This layer (membership layer) receives the complement coded input values from the first layer and calculates the fuzzy sets of the respective input variables. Here we use trapezoidal membership function with parameters u and v. More details on how this membership function works on the real N-dimensional space combining the n inputs can be found in [14]. The output function of this layer is noted as $O_{2,i}$.

Layer 3: Each node in this layer performs a fuzzy-AND operations using the T-norm operator of the algebraic product. The result to each node's output being the product of all of its inputs and represents the level of each rule or the firing strength of the corresponding fuzzy rule. The output of the product layer is noted as

$$o_{3,i} = w_i \quad (4)$$

Layer 4: This layer normalizes the activation values of all fuzzy rules, the normalized output is computed for the ith node as the ratio of the ith rule's firing strength to the sum of all rule's firing strengths as follows

$$o_{4,i} = \frac{w_i}{w_1 + w_2} \quad (5)$$

Layer 4: This layer provides the output values resulting from the inference of rules; this represents another set of parameters for the neuro fuzzy network. The output of this layer is computed according to the formula

$$o_{5,i} = o_{4,i}.(f_i = p_i x + q_i y + r_i) \quad (6)$$

Where $p_i$, $q_i$ and $r_i$ are the linear or consequent parameters of the corresponding node i.

Layer 6: This layer is called as the output layer which sums up all the inputs coming from the layer 5 and returns the overall output using the following fixed function

$$o_{6,i} = \frac{\sum w_i f_i}{w_1 + w_2} \tag{7}$$

### 3.2 THE STRUCTURE LEARNING

Initial fuzzy rules are obtained in the phase of structure identification using fuzzy adaptive resonance theory. We have used the codes [15] and [16] to find the input membership function parameters u and v, and also to find proper input-space fuzzy clustering; the degree of association is strong for data within a fuzzy cluster and weak for data in different fuzzy clusters. Then, a fuzzy IF–THEN rule describing the distribution of the data in each fuzzy cluster is obtained.

Initially, for each complement coded input vector, the values of choice functions $T_j$ are computed by

$$T_j(x') = \frac{|x' \wedge w_j|}{\alpha + |w_j|} \quad , j = 1,\ldots, N \tag{8}$$

Where " $\wedge$ " is the minimum operator performed for the pair wise elements of two vectors, $\alpha \geq 0$ is a constant, N is the current number of rule nodes, and $w_j$ is the complement weight vector.

The choice function value indicates the similarity between the input vector x' and the complement weight vector $w_j$. We then need to find the complement weight vector closest to x'. This is equivalent to finding a category to which x' could belong. The chosen category is indexed by j where

$$T_j = \max \langle T_j : j = 1,\ldots, N \rangle. \tag{9}$$

Resonance occurs when the match value of the chosen category meets the vigilance criterion

$$\frac{|x' \wedge w_j|}{x'} \geq \rho \tag{10}$$

Where $\rho \in [0,1]$ is a vigilance parameter. If the vigilance criterion is not met we say mismatch reset occurs. In this case, the choice function value is set to zero for the duration of the input presentation to prevent persistent selection of the same category during search. A new index is then chosen using (9). The search process continues until the chosen satisfies (10). If no such is found, then a new input cluster is created by adding a set of new input-term nodes. More details on how this works can be found in [17].

### 3.3 PROPOSED TRAINING STRATEGY

The problem of parameter learning can be stated as: given the training input data [x, y] and the desired output value z, and we want to adjust the parameters of the membership functions optimally. Let the total set of parameters be S and let S1 denote the premise parameters which are known as nonlinear parameters and S2 denote the consequent parameters which are known as linear parameters. The proposed ANFIS uses a two learning algorithm: the Recursive Least Squares (RLS) algorithm which computation the consequent parameters, and the particle swarm optimization PSO which computed the premise parameters.

Particle swarm optimization is a method used to explore the search space of a given problem to find the settings or parameters required to optimize a particular objective. Consider an optimization problem of N variables, and let denote in the N-dimensional search area, the position x(t) and velocity v(t) of ith particle at time t are respectively shown with the following vectors:

$$x_i(t) = (x_{i1}(t), x_{i2}(t) \ldots x_{in}(t)) \tag{11}$$

$$v_i(t) = (v_{i1}(t), v_{i2}(t) \ldots v_{in}(t)) \tag{12}$$

At each time, particles are corresponded with an objective value and the best positions of the particles from the beginning to this moment have been stored by the algorithm. The best position for a particle, at time t, is a position which based on that the particle has the best objective value. The best position for the ith particle up to the time t is represented as:

(13)

$$P_{best,i}(t)=(P_{best,i1}(t), P_{best,i2}(t) \dots P_{best,in}(t))$$

The PSO also stores the best position that is obtained by all of particles up to the time t, which it can be shown as below:

$$g_{best}(t)=(g_{best,1}(t), g_{best,2}(t) \dots g_{best,n}(t)) \quad (14)$$

Where $x_{ij}$ and $v_{ij}$ are jth element of the velocity vector V and position vector X for the ith particle, respectively. Each particle position and velocity pair at time (t+1) is obtained as follows:

$$v_{ij}(t+1) = w.\, v_{ij}(t) + c_1 .\, rand1_{ij} .\, (P_{best,ij}(t) - x_{ij}(t)) + c2 .\, rand2_{ij} .\, (g_{best,j}(t) - x_{ij}(t)) \quad (15)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (16)$$

where i=1, 2,… n is particle index, $x_{ij}$ is the jth dimension of the ith particle position, $v_{ij}$ is the jth dimension of the ith particle velocity, $P_{best,ij}$ is the jth dimension of the best position of the ith particle at time t, $g_{best,j}$ is the jth dimension of the best position that so far achieved by all of the particles, W is the inertia weight. The $rand1_{ij}$, $rand2_{ij}$ ˜ U(0, 1) are two random numbers; $c_1$ and $c_2$ are training factors, where $C_1 + C_2 < 4$ [18].

The performance of this algorithm heavily relies on initialization of the algorithm parameters which is so important, because if they are not correctly selected, the PSO algorithm may never converge to the extremum point.

In Fig. 3 a method is proposed to obtain a better initial swarm. A fitness value is assigned to each particle in the swarm, where small values mean good fit. The objective function used in this work is defined as

$$\text{Objective function} = \frac{1}{s}\sum_{t=1}^{s}(y(t) - y'(t)) \quad (17)$$

Where y(t) is the output, y'(t) is the predicted output from fuzzy model, and s is the number of training data pairs.

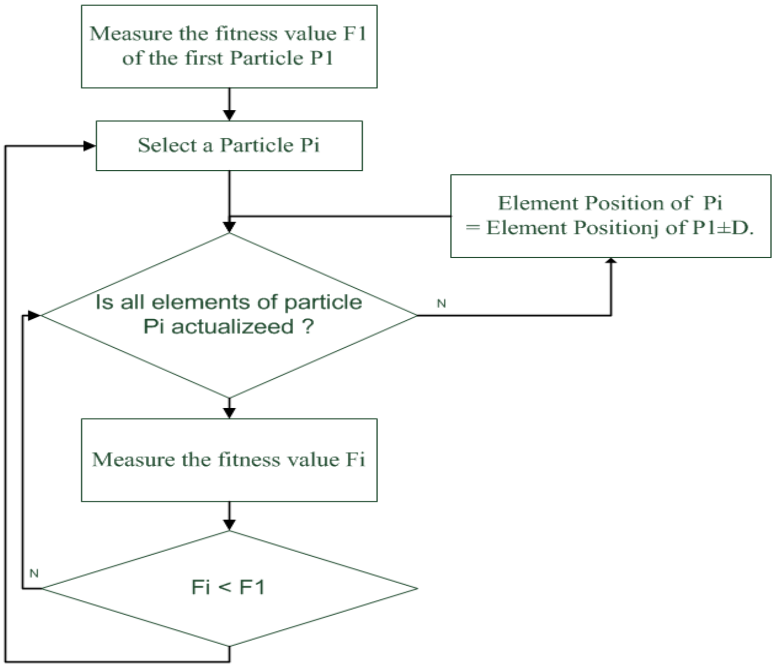



***Fig. 3. Typical flowchart illustrates the initialization steps***

In general, the PSO algorithm is used in accordance with the following steps:

1- Selecting the algorithm parameters and initializing particles $[x_i(t), v_i(t)]$.
2- Initializing the $P_{best}$ vectors for all of the particles using the initial values obtained in step 1 for the position vectors.
3- Calculate the fitness value for each particle and determining the $g_{best}$.
4- Updating the particles velocity vectors and position vectors according to (15) and (16),

5- Updating the parameters of the fuzzy system membership functions by the position vector of each particle and calculating the objective value for each particle,
6- Updating the $P_{best}$ , for each particle, if the fitness value of the new particle is good than those of local best, then the local best will be replaced with the new particle.
7- Updating the $g_{best}$ , If the fitness value of the new particle is good than those of global best, then the global best will be also replaced with the new particle.
8- If the stopping condition is met, algorithm is stopped and the optimal parameter values are achieved.

## 4 RESULTS AND ANALYSIS

In this part, we will compare the proposed method executed in LabVIEW software relatively to the most used technique to model the transformation of MECG signal which is ANFIS of Matlab fuzzy toolbox. In contrary to all the studies presented in literature which use more than an iteration to obtain a good linearization. We will show only the results of small iterations in both methods to understand the improvement presented in this work. We will use two recorded signals: one M(n) and one A(n). The two recorded signals are segmented so that they are prepared for ANFIS training. They are segmented in a way that each one is partitioned into N-sample segments. The i-th segment of the signal M(n) is the x input and the (i-1)-th segment of the second M(n) signal is the y input. Also, the i-th segment of the signal A(n) is the z output

### 4.1 RESULTS ON SIMULATED ECG SIGNAL

For generating the synthetic ECG signals we use the dynamical model developed by McSharry et al. [19]. Both fetal and maternal ECG signals are synthesized using this model using different parameters to account for different shapes and beat rates of the two signals. A model for generating the abdominal signal is proposed as shown in Fig. 4. The MECG signal is processed through a system to simulate the delays and the nonlinear effects it undergoes as it travels from the heart to the abdomen. The attenuation effects are reflected on the FECG signal before it is added to the nonlinearly transformed MECG. Additive noise effects can be modeled by adding white Gaussian noise; in this paper we will ignore the effect of noise. This is so because, as we mentioned earlier, we are interested in extraction which can be cleaned later via postfiltering if needed. The nonlinearity and multipath effects that undergoes the MECG until it reaches the abdomen are modeled as

$$M_e(n) = M(n) + a_1.M(n-1) \tag{18}$$

$$\overline{M}(n) = \alpha.\mathrm{sgn}(M_e(n))\left|\tan^{-1}(M_e(n))\right| \tag{19}$$

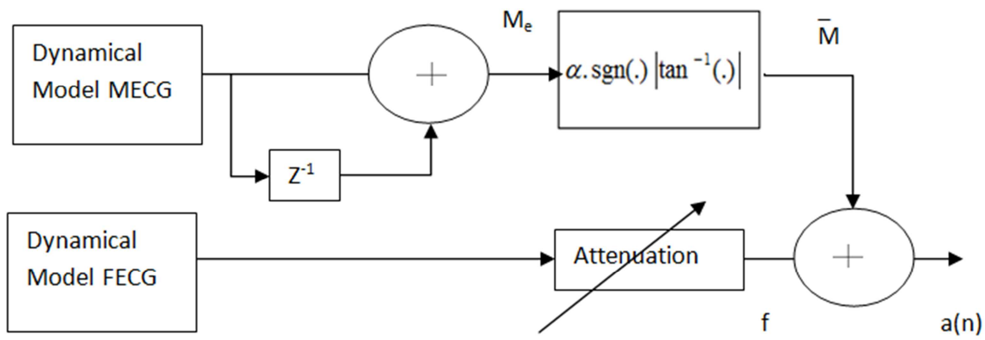



***Fig. 4. Block diagram for simulating the abdominal ECG signal***

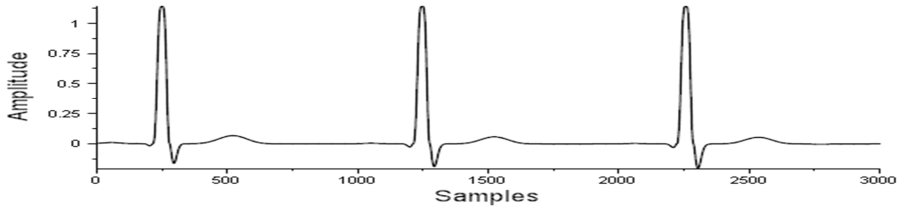
In algorithm comparisons, we have used not only visual (quality) criterion but also a quantity criterion, the signal-to-noise ratio (SNR) of the abdominal signal is adjusted with the different power levels of the FECG component. Where the inputSNR, outputSNR and the correlation coefficients R are defined as:

$$inputSNR = 10\log_{10}\left[\frac{\sum_n (f(n)^2)}{\sum_n ((a(n)-f(n))^2)}\right] \tag{20}$$

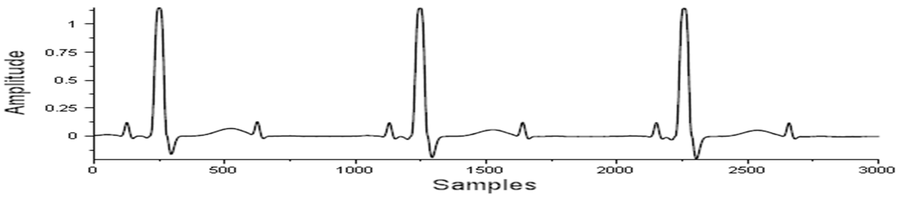
$$outputSNR = 10\log_{10}\left[\frac{\sum_n (f(n)^2)}{\sum_n ((f(n)-F(n))^2)}\right] \tag{21}$$

$$R = \frac{\sum_n (f(n)-\overline{F(n)})(F(n)-\overline{F(n)})}{\sqrt{\sum_n (f(n)-\overline{F(n)})^2 \sum_n (f(n)-\overline{F(n)})^2}} \tag{22}$$

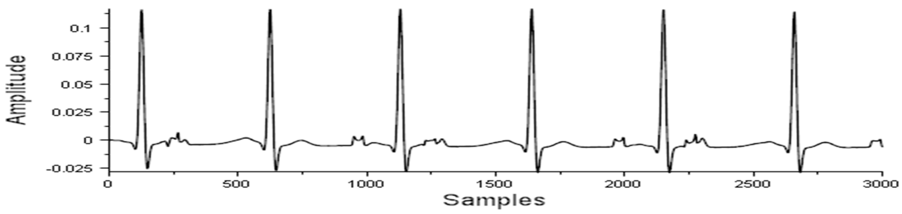
Fig. 5d shows the FECG extracted from the synthetic abdominal signal using our proposed method with the inputSNR=−20 dB.



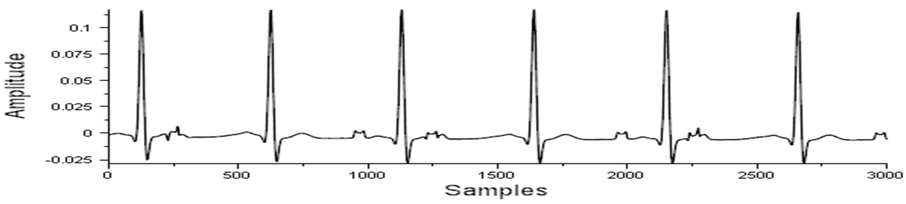

(a)




(b)




(c)




(d)

***Fig. 5. Synthetic ECG signal, (a) thorasic ECG, (b) abdominal ECG, (c) ANFIS extraction ECG, (d) proposed ANFIS extraction ECG***

The SNR and the correlation coefficients results are shown in table 1 and table 2, which illustrate the robustness of the proposed ANFIS-based technique as compared to the other techniques.

*Table 1. Effect of the fetal to maternal signal to noise ratio on the quality of FECG extraction using three different FECG extraction techniques*

| inputSNR | -10DB | -15DB | -20DB | -25DB | -30DB | -35DB |
|---|---|---|---|---|---|---|
| Proposed_ANFIS | 19,0862 | 19,0858 | 19,0852 | 19,0839 | 19,0816 | 19,0764 |
| ANFIS | 18,7527 | 18,7523 | 18,7518 | 18,7508 | 18,749 | 18,7452 |

*Table 2. The correlation coefficients between the extracted and the actual FECG frames using three different FECG extraction techniques.*

| SNR | -10DB | -15DB | -20DB | -25DB | -30DB | -35DB |
|---|---|---|---|---|---|---|
| Proposed_ANFIS | 0,9976169 | 0,9976160 | 0,9976145 | 0,9976116 | 0,9976062 | 0,9975939 |
| ANFIS | 0,9968066 | 0,9968058 | 0,9968045 | 0,9968020 | 0,9967975 | 0,9967879 |

## 5 Conclusion

This paper describes an algorithm to improve the linearization of MECG with AECG to separate the FECG using a combination of fuzzy adaptive resonance theory, particle swarm optimization and a neuro-fuzzy inference system. It should be noted that the implementation of this algorithm is independent of the period length of the maternal heart beat. In order to completely validate this FECG recovery technique and methodology, the results of the algorithm for different fetal to maternal ECG ratios are proposed and the correlation coefficients result demonstrates that the proposed algorithm works well.

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