

## Fetal Electrocardiogram Signal Extraction by ANFIS Trained with PSO Method

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### ABSTRACT

Studies indicate that the primary source of distress in pregnant mothers is their concerns about fetus's condition and health. One way to know about condition of fetus is non-invasive fetal electrocardiogram signal extraction through which the components of fetal electrocardiogram signal are extracted from a signal recorded at abdominal area of mother which is a combination of fetal and maternal electrocardiogram signal and noise source components. The purpose of this study is to propose an algorithm to boost this extraction. To this end, we decomposed electrocardiogram signal to its Intrinsic Mode Functions (IMFs) through Empirical Mode Decomposition algorithm; then, we removed the last and collected the other IMFs to reconstruct electrocardiogram signal without Baseline. Afterwards, we used Particle Swarm Optimization to train and adjust the parameters of Adaptive Neuro-Fuzzy Inference System to model the path that maternal electrocardiogram signal travel to reach abdominal area. Accordingly, we were able to distinguish and remove maternal electrocardiogram signal components from the recorded signal and hence we obtained a good approximation of fetal electrocardiogram signal. We implemented our algorithm and other algorithms on simulated and real signals and found out that, in most cases, the proposed algorithm improved the extraction of fetal electrocardiogram signal.

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## 1. INTRODUCTION

Birth is one of the most important stages in one's life. The infant should adapt itself with the new environment and problems like lack of oxygen and academia; and it should be able to feed and breathe independently. Infant's body is equipped with defense mechanisms that can even overcome lack of oxygen. In some cases, the pressures of parturition or lack of oxygen is so high or infant's body has some deficiency that the infant cannot overcome these problems. These would cause the infant to have birth defects, physically or mentally. An infant with birth defects is emotionally very painful; in addition, it is very costly in short and long terms. Accordingly, finding a way to prevent or solve these problems will be humane and economically effective.

Current statistics reveal that one of every 125 infant is born with heart deficiency [1]. There are different kinds of deficiencies and most of them begin to reveal themselves years after birth; in some cases they affect infant's development, a problem which is almost impossible to resolve. Fetus heart activity

produces electric current which is propagated in the peripheral tissues and produces potential difference. The value of this potential difference is very low and is simply mixed with noise. These signals can be recorded by needle electrodes. In this method, the electrodes pass through mother's abdomen into her womb until they are placed on fetus's head or hip. The recorded signal is called fetal electrocardiogram (FECG) signal. This method is called direct method which involves some risks both for mother (uterine rupture, bleeding, etc.) and for fetus (pressure, infection, etc.). Nowadays, another method called indirect method is used to record FECG signal. This method uses a recorded signal on mother's abdomen to extract FECG signal. Figure 1 illustrates the way abdominal electrocardiogram (AECG) signal is recorded.

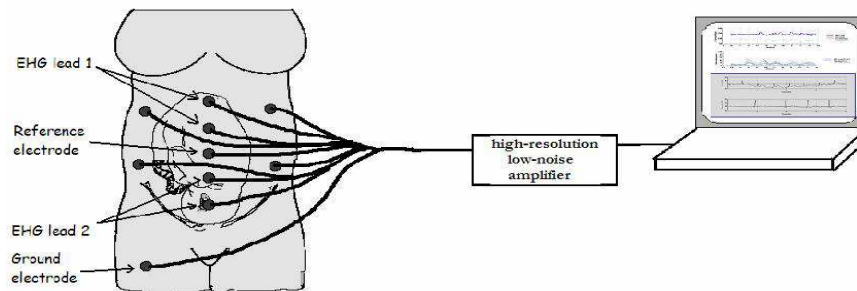


Figure 1. Indirect recording of AECG signal [11].

The recorded AECG signal includes maternal electrocardiogram (MECG) signal, FECG signal, and noise. The noise itself includes different noise sources among which baseline wandering [2], power line conflict, electrocardiography (EMG), and the noise related to recording electrode can be mentioned [11]. In this article, the method for extracting ECG's Intrinsic Mode Functions (IMFs) through screening algorithm is explained in the preprocessing section; then, after reviewing IMFs, the primary raw signal, and its baseline wandering, some IMFs at the end of the signal were considered as baseline or trend; the estimated trend signal and raw ECG signal were illustrated simultaneously and at the top of these two signals a signal whose baseline has been removed was shown.

The argument of extracting FECG signal through indirect methods goes back to about 40 years ago. One of the early processing works is that of Farvet who used Match filter to recognize the form of r wave [10]. The methods based on adaptive filters are among the oldest ways of extracting FECG signal; nowadays, these methods are mostly used to remove noise [3]. A large number of recursive algorithms have been presented to implement the concept of adaptive filters; one of these is Least Mean Squares (LMS) algorithm [4]. In [6], SVD method and Singular Value Ratio (SVR) were used to decompose signal components; in this article, they used SVR spectrum to estimate MECG and FECG signal frequency. The approaches based on Independent Component Analysis (ICA) have also used this algorithm to extract FECG signal; in [12] they used Joint Approximative Diagonalization of Eigenmatrices (JADE) algorithm to implement ICA and extract FECG from AECG. Zeng (2008) in [11] has used recursive least squares (RLS) algorithm based on adaptive noise cancellation (ANC) technique to remove MECG signal and, as a result, to extract FECG signal. Using this technique, he increased convergence speed and the capability to track FECG signal. In 1992 [8] has investigated the application of genetic algorithm (GA) in extracting FECG signal from AECG signal; the proposed theory is in the way that two signals are first recorded from thoracic and abdominal area; in addition, thoracic electrodes are placed in a spot where physician can hear FECG signal in the best way. Based on our findings, unlike other proposed methods, ANFIS based methods do not have a long record. In 2006, Vigila specifically used artificial intelligence (AI) and techniques based on fuzzy logic to extract FECG signals from AECG signals [14]; the basis of the proposed algorithm was ANC techniques with fuzzy logic to cancel conflicts, especially removing MECG signal from AECG signal. The objective of this study is a supplement to the proposed algorithm in [14].

SVD based methods have some limitations: AECG signal must be multi-channeled, if it is one-channeled, it should be transformed. This would lead to problems like selecting period and length, segmentation, irreversibility of some transformations, and increasing calculations because of transformation from one-dimensional to two-dimensional domain [5]. ICA based methods have also some limitations like independency of components; they also need much time because mixing matrix is selected randomly at first which is not desirable for non-static signals. Another problem of these methods is that they require multi-channel signals [5]. Although the methods based on wavelet transformation have been able to improve the speed of FECG signal extraction and they need to record only one channel to implement the algorithm, the

major problem is the fact that they remove the components of AECG signal to remove the components of MECG signal. Accordingly, in cases that MECG signal and FECG signal overlap, the algorithm will experience difficulty.

In this paper, we aim to apply a new ANFIS network trained with PSO method for estimating the FECG signal component from one abdominal ECG and one reference thoracic MECG signal. We use ANFIS trained with PSO to find nonlinear transformation between the MECG and the maternal component of AECG signal. Using this transformation, we can cancel the maternal component in AECG signal and then we can estimate the FECG signal. We show the results on both synthetic and real signals.

The rest of the article is organized as follows: A detailed methodology of the research including some subsections is presented in section 2; section 3 discusses the results and analysis of performance of the proposed algorithm on simulated and real signals; and section 4 concludes the paper.

## 2. RESEARCH METHOD

### a. Preprocessing to Remove Baseline wandering

Our surveys have revealed that since all components of FECG signal is important to diagnose a healthy fetus, and since the range of FECG signal in the recorded abdominal signal is next to a noise, preprocessing and removing conflicts in the extraction diagram block are very important matters.

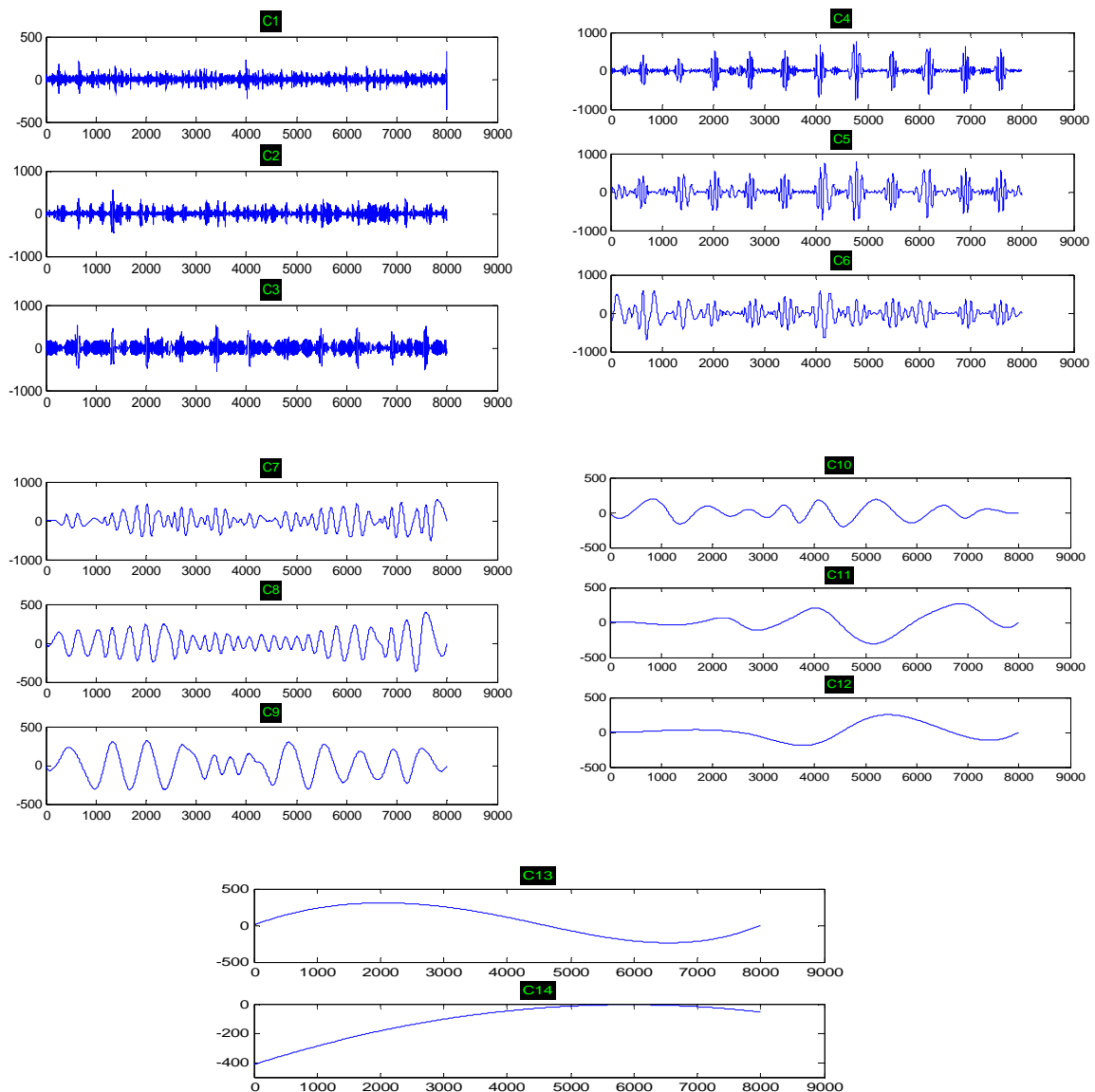


Figure 2. The result for the application of screening algorithm on the signal

Therefore, in order to remove baseline wandering from electrocardiogram (ECG) signal, the signal should be decomposed into related IMFs using screening algorithm. Frequencies of the obtained IMFs are in a descending order in a way that the last IMFs indicate low frequencies of the signal and illustrate baseline wandering. In Empirical Mode Decomposition (EMD) transformation, since the original decomposed signal can be only reconstructed through collecting IMFs, when we remove IMFs in the final aggregation for reconstructing the signal, the components related to those IMFs will be removed from the signal. Accordingly, by investigating the last IMFs we will remove some of them which indicate baseline wandering. By collecting other IMFs we will have a signal with no baseline wandering. After applying screening algorithm on the signal, the related IMFs have been changed according to Figure 2.

As illustrated above, the range of the last IMFs are considerable as compared to the signal range. By choosing the last 6 IMFs as baseline and removing them from ECG signal the result will be as shown in Figure 3.

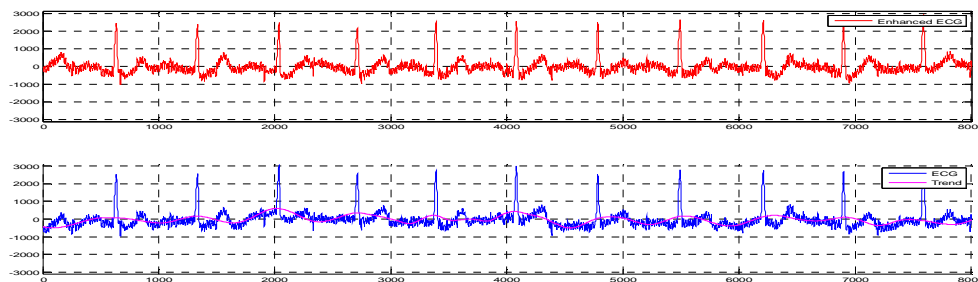


Figure 3. Removing the last IMFs from ECG signal

**b. The Proposed Algorithm for Extracting FECG Signal**

After preprocessing and removing noises and existing conflicts in the recorded AECG signals, it can be affirmed that if MECG signal components can be removed from the combined signal, an acceptable approximation of FECG signal could be obtained. Relying on the theory, we have used PSO-trained ANFIS in our proposed algorithm to remove MECG signal components from the recorded AECG signal.

**c. The Theory of Extracting FECG Signal through the Proposed Algorithm**

As mentioned, the objective of the indirect algorithm is to extract FECG signal from MECG abdominal signal. Accordingly, in order to improve the results of the extraction algorithm, one should be able to weaken the power of MECG signal components as far as possible; also, one should decrease the impact of conflicts. Now, we should be able to recognize MECG abdominal signal components. By removing these components from the combined signal, we can have a good approximation of FECG signal.

AECG signal is contaminated with MECG signals in the abdominal area. These components are distorted because they travel a path from their source, i.e. mother’s heart, to the abdomen where the signal is recorded. The cause of this distortion can be taken as a non-linear transformation applied on MECG signal components.

The purpose of the proposed algorithm in this article is to find this non-linear transformation. By finding this transformation and applying it on an MECG signal which is recorded in thoracic area, we can obtain an estimation of MECG signal components in mother’s abdominal area. Subtracting these components from AECG will result in extraction of FECG signal components. Figure 4 illustrates the way that these components are formed and recorded in the thoracic and abdominal areas.

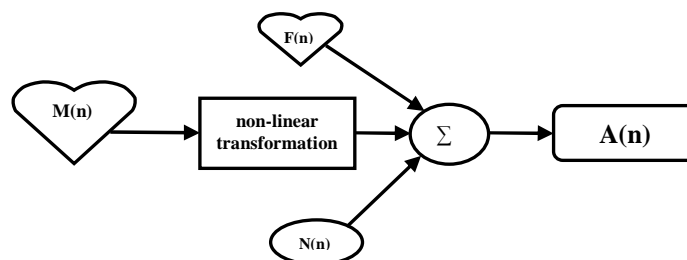


Figure 4. Recording and formation of thoracic and abdominal signals

M(n) and F(n) represent MECG and FECG signals respectively. A(n) signal represent the signal recorded at the abdominal area. The proposed algorithm uses two recorded signals to extract FECG signal. One is the signal recorded at thoracic areas, M(n), and A(n). In this method, we assumed that M(n) only contains MECG signal components. Due to strong MECG signals this assumption is a realistic one. Figure 4 can be summarized in the following two equations:

$$A(n) = \tilde{M}(n) + F(N) + N(n) \tag{1}$$

$$\tilde{M}(n) = T\{M(n)\} \tag{2}$$

where m(n) and a(n) are the signals recorded at thoracic and abdominal areas, respectively. N(n) indicates the sum of noises and conflicts in the recorded signal.  $\tilde{M}(n)$  is the distorted M(n) signal due to non-linear transformation T.  $\tilde{M}(n)$  represents MECG signal components in the recorded AECG signal. As mentioned, the above distortion resulted from non-linear transformation is created because the signal is recorded far away from the signal’s source (mother’s heart).

The objective of the algorithm is to model a path through which MECG signal passes from thoracic area to the abdominal area where the signal is recorded. By finding this signal and applying it on thoracic signal M(n), we can obtain  $\tilde{M}(n)$ . Using equation 1, we can extract a good approximation of FECG signal.

**d. Adaptive Neuro-Fuzzy Inference System (ANFIS)**

Modeling systems based on general mathematical tools (like differential equations) to use in uncertain systems is not an appropriate tool. On the contrary, by using if-then rules, a fuzzy inference system 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. [14], but implementing some of the basic aspects of this type of approaches needed a more complete understanding. Accordingly, Jang et al. proposed a new architecture called ANFIS to implement a set of rules with appropriate membership functions for producing specific input and output pairs.

**e. 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. Fuzzy techniques combine information sources as fuzzy rules. Moreover, the requirements and the primary assumptions of ANFIS structure are less and simpler than neural networks. Based on these characteristics, we determine ANFIS as a reliable tool for choosing non-linear transformation. In the proposed algorithm, the fuzzy model based on the first order of Sugeno [14] has been used as our structure.

ANFIS based architecture for implementing this model is illustrated in Figure 5. 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).

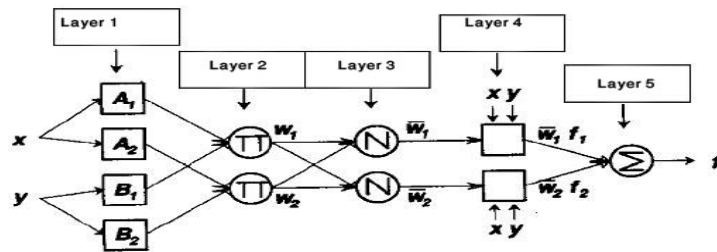


Figure 5. ANFIS architecture with two inputs and one output used in Sugeno rule

**Layer 1:**

The output of each node is

$$i = 1, 2$$

where  $x$  is the input to node  $i$  and  $A_i$  is the spoken label (small, large, ...) related to the function of this node. In other words,  $O_i^1$  is the value of membership function  $A_i$  and determines the input degree of membership for this function.

$$\mu_{A_i}(x) = \frac{1}{1 + \left[ \frac{(x - c_i)^2}{a_i} \right]^{b_i}}$$

$$\mu_{A_i}(x) = \exp\left\{-\left(\frac{x - c_i}{a_i}\right)^2\right\} \quad (3)$$

where  $a_i, b_i, c_i$  are parameters of membership function.

#### Layer 2:

The nodes in this layer are stable. These nodes multiply the input signals and then send the product to the next layer. The outputs of these nodes are as follows:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i=1,2 \quad (4)$$

#### Layer 3:

The nodes in this layer are also stable. These nodes are labeled as  $N$ . The output of each node in this layer is demonstrated through the following relation:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i=1,2 \quad (5)$$

#### Layer 4:

The nodes in this layer are adaptive, i.e. they have parameters that should be adjusted during the process. The output of each node in this layer is from the product of normalized firing strength in a degree 1 polynomial.

$$O_i^4 = \bar{w}_i = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y - r_i) \quad i=1,2 \quad (6)$$

where  $p_i, q_i$ , and  $r_i$  are design parameters.

#### Layer 5:

The only node in this layer sums the outputs of the previous layer.

$$o_i^5 = \text{overalloutput} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad i=1,2 \quad (7)$$

There are two horizontal layers (layers 1 and 4) in the mentioned architecture. Layer 1 has 3 adjustable parameters (antecedent part parameters). These parameters are the inputs of membership functions. Layer 2 has Also 3 adjustable parameters (conclusion part parameters).

#### f. ANFIS Training

In the architecture training algorithm, the purpose is to adjust the adjustable parameters to obtain outputs which are consistent with training information. Parameters  $a_i, b_i, c_i$  represent standard deviation, gradient, and the centre of bell functions, respectively.

In ANFIS training algorithm which is also known as hybrid training algorithm, functional signals first travel directly to layer 4 and conclusion parameters are determined by estimating least squares. On the way back, errors are propagated backwards and antecedent parameters are updated through reduced gradient. Therefore, given initial values for parameter set  $S_1$  (antecedent parameters), and applying training information on the network, for a straight path we will have the following matrix equation:

$$AX=B \quad (8)$$

where  $X$  is an undetermined vector including the parameters of set  $X^* = (A^T A)^{-1} A^T B$ . We use minimization  $a$ , which is the same as least squares minimization, to obtain  $X$ . Accordingly, the estimator of least squares will be as follows:

$$X^* = (A^T A)^{-1} A^T B \quad (9)$$

On the way back, errors signals are propagated backwards. Antecedent parameters are updated through gradient decrease (GD) and minimization of the following quadratic cost function according to each parameter of  $S_2$ .

$$C(X) = \frac{1}{2} \sum_{i=1}^N [B(i) - \hat{B}(i, X)]^2 \tag{10}$$

Therefore, updating the parameters of i-th node of L-th layer will follow the following equation:

$$\frac{\partial c(i)}{\partial \hat{X}_i^L(i)} = \epsilon_i^L \frac{\partial \hat{O}_i^L}{\partial \hat{X}_i^L(i)} \tag{11}$$

Gradient vector is defined as follows:

$$\frac{\partial c(i)}{\partial \hat{X}_i^L(i)} = \epsilon_i^L \frac{\partial \hat{O}_i^L}{\partial \hat{X}_i^L(i)} \tag{12}$$

where  $\hat{O}_i^L$  is the output of the node and  $\epsilon_i^L$  is the signal of returned error. In equation (11),  $\eta$  is training rate which is defined with equation (8).

$$\eta = \frac{k}{\sqrt{\sum_a \left(\frac{\partial C}{\partial a}\right)^2}} \tag{13}$$

$$\frac{\partial C}{\partial a} = \sum_{p=1}^P \frac{\partial C_p}{\partial a} = \sum_{o \in S} \frac{\partial C_p}{\partial o^*} \frac{\partial o^*}{\partial a}$$

where variable P is the number of training pairs.  $p^i$  is known as network parameter. K is gamut size which will be as the level of change in each transmission of gradient. Changing the value of K will change convergence speed of the algorithm. Two transmission of ANFIS training algorithm is summarized in table 1.

Table 1. Adjustment of parameters in ANFIS training algorithm

Return path	Straight path	
Gradient decrease	Stable	Antecedent parameters
Stable	Estimation of least squares	Conclusion parameters
Error rates	Nodes' outputs	Signals

**g. PSO Method for Training ANFIS Structure**

PSO algorithm is an optimization method based probability rules which is inspired by social behavior of birds and fish in search of food [15]. Each particle in the swarm is composed of three D-dimensional vectors, where D is the dimensions of search space.

The general PSO algorithm can be summarized as follows:

- Swarm's primary hypotheses
  - Primary hypothesis about the number of members in the swarm.
  - Particles are distributed randomly in the search space.

$$v_{K+1}^i = wv_{K+1}^i = C_1 rand \frac{(p^i - x_K^i)}{\Delta t} + C_2 rand \frac{(p_K^g - x_K^i)}{\Delta t}$$

- Estimation of the agreement of each particle with the record:  
Particle's best location so far (memory of  $p^i$  particle in  $x_0^i$  location)  
The best location in the entire swarm ( $p_0^g$ )
- The primary velocity hypothesis is also put randomly:

$$v_o^i = \frac{x_{\min} + rand(x_{\max} - x_{\min})}{\Delta t} = \frac{position}{time}$$

- Velocity update

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

w coefficient is known as inertia factor and its value is taken to be 0.4-1.4.  $C_1$  and  $C_2$  are known as security coefficients.  $C_1$  value takes 1.5-2 and  $C_2$  value takes 2-2.5.

- Location update  
Location is adjusted by velocity vector.
- The criterion to stop the algorithm

It is to be noted that reaching a specific number of repetitions can also serve as a condition to stop the algorithm.

**h. Training ANFIS with PSO**

ANFIS has two types of adjustable parameters which need to be updated, the antecedent and conclusion part parameters. There are three sets of parameters in antecedent part,  $\{a_i, d_i, c_i\}$ , and the conclusion part,  $\{p_i, q_i, r_i\}$ . In this article, the number of swarms has been selected to be 60 which are randomly scattered in the space of training parameters (6 parameters). The objective function is MES function (error of network output and actual output with training pairs). Initial assumptions about parameter values are first considered. Then, these values are given to PSO algorithm to be optimized and updated. Only one parameter is updated in each iteration. Finally, the optimized value of parameters for each training pair will be obtained. In the next part, we will explain the way ANFIS is used to extract FECG signal; the flowchart of the proposed algorithm will be also illustrated.

**i. Flowchart of the Proposed Algorithm to Extract FECG Signal**

Our method uses two recorded signals to extract FECG signal: 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. In the proposed algorithm, the overlapped segments are also considered; in other words, overlapping scale is  $N/2$  samples. The  $i$ -th segment of the signals is defined as follows:

$$M_i(m) = M(i(N - (\frac{N}{2})) + m) \quad m = 0, 1, 2, \dots, N - 1$$

$$A_i(A) = A(i(N - (\frac{N}{2})) + m) \quad m = 0, 1, 2, \dots, N - 1$$

In this way, the training vector in ANFIS algorithm is obtained. The structure of ANFIS used in Figure 6 has been repeated.

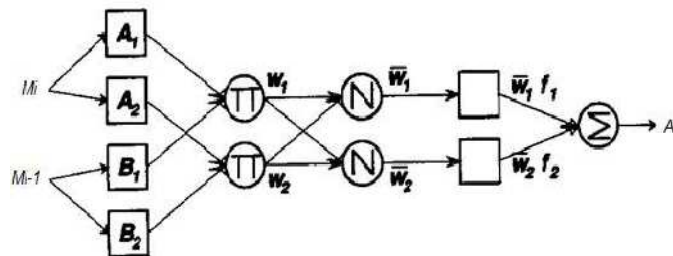


Figure 6. The structure of ANFIS used in the proposed algorithm.

As illustrated above, ANFIS inputs are one of the vectors obtained from segmentation of the thoracic signal and its delayed signal (the previous segment); the output of the network in training algorithm is the vector equivalent to the input vector in the set of the vectors obtained from abdominal signal segmentation. ANFIS parameters are separately adjusted for each pair of vector sets ( $M_i$  s and  $A_i$  s). After each training by one of paired vectors  $A_i$  and  $M_i$ ,  $M_i$  vector is submitted as ANFIS input. The obtained output is the transformed version of  $M_i$  vector in abdominal area which we call  $\tilde{M}_i$ . When all  $\tilde{M}_i$  s were obtained and the overlapping in segmentation process was taken into account, signal  $\tilde{M}$  (the transformed M signal at abdominal area) is created. Now we have fulfilled the predefined objective for we have been able to obtain MECG signal components after it has passed thoracic area to reach abdominal area. At this time, we can subtract the obtained signal from abdominal signal in order to obtain an approximation of FECG signal which is the desired one. The flowchart of the algorithm is illustrated in Figure 7. Figure 8 illustrates the extracted FECG and the transformed MECG signal resulted from application of the proposed algorithm on two thoracic and abdominal signals in [9].



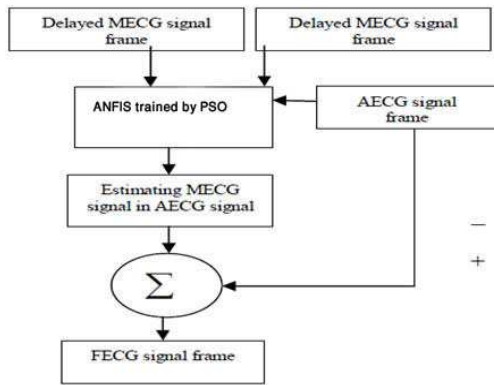


Figure 7. Flowchart of the proposed algorithm

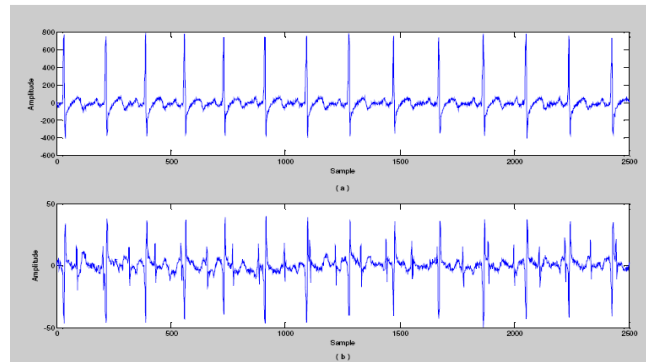


Figure 8. (a) The recorded signal at thoracic area, (b) the recorded signal at abdominal area.

### 3. RESULTS AND ANALYSIS

The proposed method uses ANFIS and PSO algorithm to model the transformation of MECG signal. It uses PSO to train ANFIS and to avoid the training algorithm from local minimums. Finding this transformation and applying it to MECG signal, one can obtain the transformed components of MECG signal in the combined signal.

We have tested the proposed algorithm, along with some other algorithms proposed in the literature (wavelet based algorithm, algorithm based on eigenvalue decomposition, ICA based algorithm, and ANFIS based algorithm using GD training algorithm), on both simulated signal and two signals chosen from real signal databases [17], [9].

- **Simulated ECG Signal**

In the simulated MECG signal, mother’s heart beat rate is 89 bpm. Fetal heart beat is considerably higher than mother’s. Fetal heart beat rate is normally 120-160 bpm. The range of FECG signal is considerably weaker than MECG signal. Moreover, AECG signal includes MECG signal which travels from thoracic area to abdominal area, FECG signal, and noises. FIR filter can be used to simulate the path through which MECG signal components pass. Moreover, Gaussian noise with SNR equal to 20 is added to the signal.

**a. The Results of Implementing the Proposed Algorithm on Simulated Signals**

We have applied the proposed algorithm on simulated abdominal and thoracic signals to extract FECG signal; this is illustrated in Figure 9.

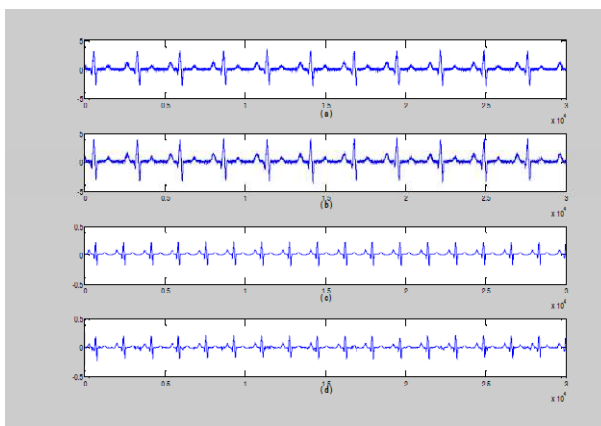


Figure 9. Extracting FECG signal with the proposed method from the simulated signal; (a) thoracic signal, (b) abdominal signal, (c) FECG simulated signal, (d) extracted FECG signal with the proposed algorithm.

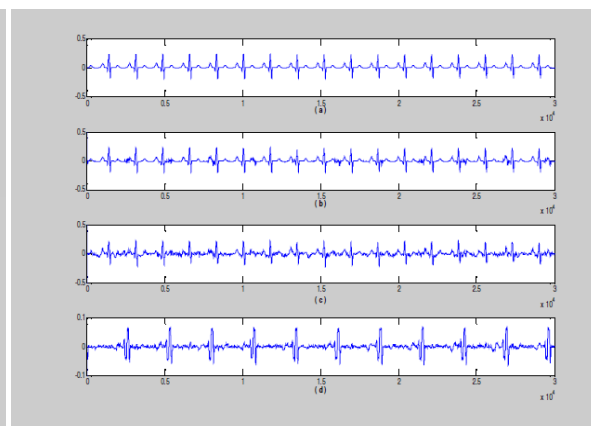


Figure 10. Visual comparison of FECG signal extraction by the proposed method with previous algorithms; (a) the original FECG signal, (b) FECG signal extracted by the proposed algorithm (ANFIS+PSO), (c) FECG signal extracted by simple ANFIS algorithm, (d) FECG signal extracted by wavelet based algorithm.

According to our studies, among the proposed methods for extracting FECG signal, only wavelet based methods, methods based on neural network, and ANFIS based methods are able to extract FECG signal by having only two signals, one thoracic and one abdominal. Our proposed method has shown greater success in extracting FECG signal than other methods. Figure 9 shows this comparison and illustrates the advantage of our proposed method over the other proposed algorithms.

As illustrated in Figure 10, the wavelet based algorithm [7] has not been able to do the extraction well. ANFIS based algorithms have been able to extract FECG signal well. However, as shown, the primary ANFIS based algorithms [13] have been able to extract only QRS complex locations of FECG signal; recognition of the other complexes (wave fragment P and wave fragment T which are effective in disease diagnosis) is done with difficulty. But, our proposed algorithm (ANFIS trained by PSO algorithm) has been able to extract all the components of FECG signal very well.

In algorithm comparisons, we have used not only visual (quality) criterion but also a quantity criterion, Percent Root-Mean Square Difference (PRD), to determine the extent of similarity between original FECG signal and FECG signal extracted with different algorithms. The above criterion is usually used in data compression problems and algorithms. The following equation illustrates how these two criteria are calculated:

$$PRD = \frac{\sum_{i=1}^N \{x_{ori}(i) - x_{rec}(i)\}^2}{\sum_{i=1}^N \{x_{ori}(i)\}^2} \tag{14}$$

The ori subscript refers to the parameters of the original signal. The rec subscript indicates the parameters related to the signal extracted by the extraction algorithm. PRD parameter reveals the scale of similarity between the extracted and the original signal in a way that is the closer the parameter is to zero, more similar are the signals. Table 2 contains the values of these criteria for the three algorithms in Figure 10. As observed, compared to other algorithms, the proposed algorithm has improved.

Table 2. Comparing the performance of the proposed algorithm using PRD criterion

The applied algorithm	RD
Algorithm based on wavelet transformation	0.1279
ANFIS based algorithm	0.5320
Our proposed ANFIS based algorithm using PSO algorithm	0.4734

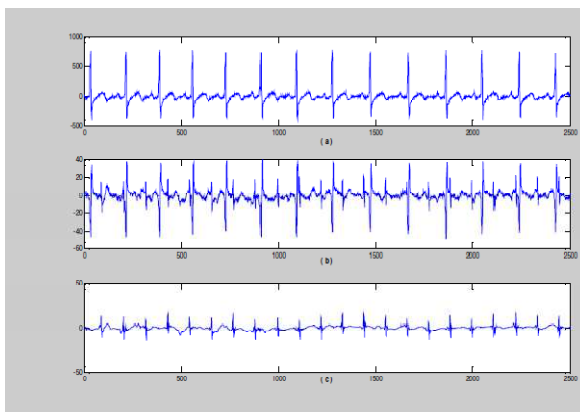


Figure 11. Implementing the proposed algorithm on the signals of Daisy database. (a) the signal recorded at thoracic area, (b) the signal recorded at abdominal area, (c) FECG signal extracted by the proposed algorithm.

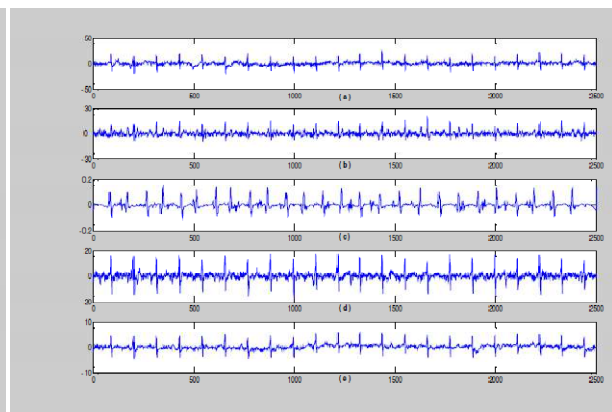


Figure 12. Comparing performance of the proposed algorithm with other algorithms in extracting FECG signal in Daisy database; (a) the resulted signal from the proposed algorithm, (b) the resulted signal from ANFIS based algorithm, (c) the resulted signal from the algorithm based on wavelet transformation, (d) the resulted signal from SVD based algorithm, (e) the resulted signal from ICA based algorithm.

As observed, PRD parameter for extracted signal resulted from the algorithm based on wavelet transformation equals 0.1279, for extracted signal resulted from ANFIS algorithm relied on GD training

algorithm it equals 0.5320, and for the resulted signal from our proposed algorithm it equals 0.4734. Consequently, the signal resulted from the application of our proposed algorithm has a considerable improvement.

#### b. The Results of Implementing the Proposed Algorithm on the Signals of Daisy Database

In this database, we have selected five signals recorded at abdominal area and three signals recorded at thoracic area. Unlike some other algorithms (like SVD based algorithms, ICA based algorithms, algorithms based on adaptive filters, and GA) the proposed algorithm needs only two signals: a thoracic signal as reference and an abdominal signal to extract FECG signal. We implemented the proposed algorithm on these signals. The result of this process is illustrated in Figure 11.

As observed above, the proposed algorithm has been able to extract FECG signal very well. Figure 12 illustrates a comparison between the performance of the proposed algorithm and the other algorithms in extracting FECG signal. Visual observation of this Figure reveals that only the result of SVD based algorithm can be compared to that of the proposed algorithm. However, the extracted signal components with SVD based algorithm are weak; in addition, one of the most important deficiencies of this algorithm and other blind source separation (BSS) based algorithms is the matter that the number of recorded signals should be more than the number of sources. When we are working with real signals, numerical comparison of algorithms' performance is not simple. In real signals, parameters like PRD cannot be measured because source signals are not specified. In fact, the objective is to find these sources.

In this study, in addition to visual criterion and PRD, two other parameters have been considered to compare the performance of algorithms. One is signal to noise ratio (SNR) [16] and the other is the number of signal channels necessary for implementing the algorithm. In this case, SNR parameter is defined as below. In using this parameter, it is assumed that the resulted signal from the algorithm only involves FECG signal components and uncorrelated noise.

Given the above hypothesis, at first we divide the signal into some pulses; then we take the pulses as columns of an imaginary matrix. Now, we obtain the eigenvalues of this matrix using Singular Value Decomposition (SVD) algorithm. We define SNR criterion as follows:

$$SNR_{svd} = \sqrt{\frac{\sigma_1^2}{\sum_{i=2}^N \sigma_i^2}} \quad (15)$$

In the above equation,  $\sigma_i$ s are eigenvalues corresponding to the matrix.  $SNR_{svd}$  parameter denotes the ratio of FECG signal components energy (first eigenvalue) to the energy of noise sources' components (second eigenvalue onward) in the extracted signal.

Now, if we apply normalization operation on matrix rows and if we define SNR parameter as a criterion to determine the level of correlation between two  $x(i)$  and  $x(j)$  pulses (columns of the imagined matrix), the above equation will be as follows:

$$SNR_{cor} = \sqrt{\frac{x(i)^T x(i)}{1 - x(i)^T x(i)}} \quad i \neq j \quad (16)$$

If we calculate this parameter for all pulses and then average the results, we will have equation (17)

$$SNR_{cor} = \sqrt{\frac{s}{1-s}} \quad (17)$$

$$s = \frac{2}{N(N-1)} \sum_{i=0}^{N-2} \sum_{j=i+1}^{N-2} x(i)^T x(j)$$

We used the parameters defined in equations (15) and (17), i.e.  $SNR_{cor}$  and  $SNR_{svd}$ , to evaluate the performance of the algorithms. Table 3 illustrates the values of these parameters for the algorithms. The two parameters indicate the quality of the extracted signal. The values of  $SNR_{svd}$  parameter for algorithms based on SVD, WT, ICA, ANFIS and the proposed algorithm is 0.1373, 0.1739, 0.2048, 0.1920 and 0.2141 respectively. According to these values and the curve of extracted signals, one can conclude that ICA based algorithm uses the information of multiple signals to extract FECG signal; indeed, this is one of the limitations of this method.

Table 3. SNRcor and SNRsvd parameter values for different algorithms

	SVD	Wavelet Transform	ICA	ANFIS	ANFIS+PSO
SNRsvd	0.3941	0.3943	0.4970	0.4697	0.4900
SNRcor	0.1373	0.1739	0.2048	0.1920	0.2141
No. of channels necessary for the algorithm	Multi-channeled	Multi-channeled	Multi-channeled	Single-channeled	Single-channeled

### c. The Results of Implementing the Proposed Algorithm on the Signals of Physiobank Database

This database contains ECG signals recorded at abdominal and thoracic areas in different stages of pregnancy. Using these signals, we have studied performance of the proposed algorithm in extracting FECG signal. Table 4 contains the values of SNRsvd and SNRcor parameters in different stages of pregnancy resulted from application of the above mentioned algorithms.

Table 4. SNRsvd and SNRcor values obtained for different algorithms in different stages of pregnancy

ANFIS+PSO		ANFIS		ICA		Wavelet Transform		SVD		
SNRcor	SNRsvd	SNRcor	SNRsvd	SNRcor	SNRsvd	SNRcor	SNRsvd	SNRcor	SNRsvd	
0.3065	1.1333	0.2749	1.0864	0.3977	1.5564	0.2183	1.0179	0.2005	0.8363	22 <sup>nd</sup> week
0.2115	0.9372	0.1906	0.9188	0.4732	2.7425	0.717	0.7603	0.2204	0.9845	29 <sup>th</sup> week
0.1900	0.9410	0.1710	0.9018	0.4165	3.0061	0.1320	0.7973	0.0984	0.8015	31 <sup>st</sup> week
0.1743	0.8921	0.1583	0.8559	0.1221	0.8195	0.1196	0.8516	0.1139	0.8308	38 <sup>th</sup> week
0.1714	0.7488	0.1556	0.6712	0.1618	0.9884	0.1471	0.7184	0.2013	0.9738	40 <sup>th</sup> week
0.2107	0.9305	0.1901	0.8868	0.3143	1.8226	0.1368	0.8291	0.1669	0.8854	Average values

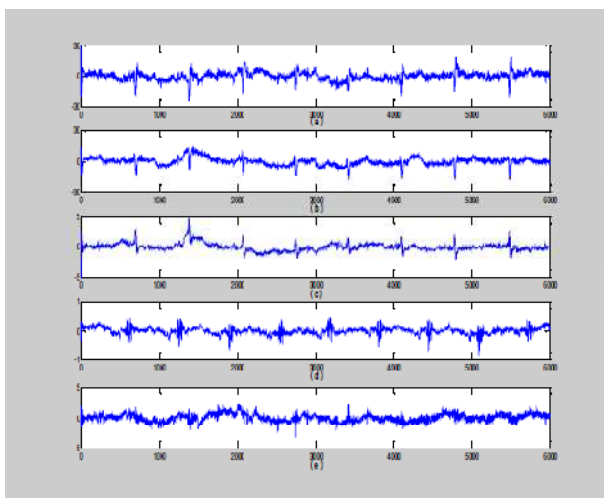


Figure 13. Comparing the performance of the algorithms in FECG signal extraction in 22<sup>nd</sup> week of pregnancy; (a) the signal resulted from the proposed algorithm, (b) the signal resulted from ANFIS based algorithm, (c) the signal resulted from ICA based algorithm, (d) the signal resulted from the algorithm based on wavelet transform, (e) the signal resulted from SVD based algorithm.

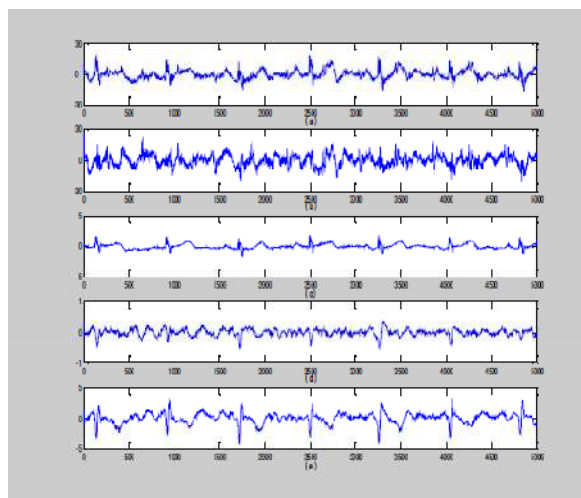


Figure 14. Comparing the performance of the proposed algorithm with other algorithms in FECG signal extraction in 40<sup>th</sup> week of pregnancy; (a) the signal resulted from the proposed algorithm, (b) the signal resulted from ANFIS based algorithm, (c) the signal resulted from ICA based algorithm, (d) the signal resulted from the algorithm based on wavelet transform, (e) the signal resulted from SVD based algorithm.

Concerning Physiobank database signals, the average value of SNRsvd parameter for the algorithms based on SVD, WT, ICA, ANFIS and the proposed algorithm is 0.8854, 0.8291, 1.8226, 0.8868 and 0.9305 respectively. Also, the average value of SNRcor parameter for algorithms based on SVD, WT, ICA, ANFIS and the proposed algorithm is 0.1669, 0.1368, 0.3143, 0.1901, and 0.2107 respectively. However, as mentioned above, one advantage of the proposed method over ICA based algorithm is the fact that the

proposed algorithm needs only two recorded signals; not only this reduces the calculation time, it also makes the mother more comfortable when signal is recorded. Moreover, less recorded signals means less recording electrodes, hence less noise sources and less costs. Figures 13 and 14 illustrate the extraction of FECG signals from the recorded signals in 22<sup>nd</sup> and 40<sup>th</sup> weeks of pregnancy, respectively.

The illustrated signal in Figure 13 belongs to a recording in 22<sup>nd</sup> week of pregnancy. One problem in using different algorithms to extract FECG signal is the fact that some algorithms are not able to appropriately separate FECG signal in early stages of fetal life. However, as illustrated in Figure 13, compared to that of other tested algorithms, the signal extracted with the proposed algorithm has been well able to extract FECG signal components.

#### 4. CONCLUSION

The proposed method in this article to extract FECG signal components uses two signals: one recorded at the thoracic area and the other at the abdominal area of mother. MECG signal components in the recorded signal at the abdominal area are transformed versions of MECG signal. This transformation occurs because these components are recorded in some distance from their source (mother's heart). Indeed, it should be noted that this is a nonlinear transformation. The proposed method uses ANFIS and PSO to model this transformation. The method uses PSO to train ANFIS and to avoid the training algorithm from local minimums. By finding this transformation and applying it to MECG signal, one can obtain the transformed version of MECG signal components in the combined signal. Removing these components from the combined signal, and assuming that preprocessing techniques have removed the impact of noise sources, we could have a good approximation of FECG signal.

We have tested the proposed algorithm, along with some other algorithms proposed in the literature (wavelet based algorithm, algorithm based on eigenvalue decomposition, ICA based algorithm, and ANFIS based algorithm using GD training algorithm), on both simulated signal and two signals chosen from real signal databases.

For the simulated signals, in addition to visual criterion as a quality criterion, we have used PRD to quantitatively compare performance of the proposed algorithm with other algorithms. This parameter reveals the scale of similarity between the extracted and the original signal; more close the parameter to zero, more similar are the signals. PRD parameter for extracted signal resulted from the algorithm based on wavelet transformation equals 1.1279, for extracted signal resulted from ANFIS algorithm relied on GD training algorithm it equals 0.5320, and for the resulted signal from our proposed algorithm it equals 0.4734. So, the resulted signal from the application of our proposed algorithm has a considerable improvement.

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