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Extraction of Fetal ECG from the composite abdomen signal by ANFIS with different learning algorithm

[1]Pradeepa Manickam and [2]Helen Prabha

[1]Pradeepa Manickam, Associate Professor, Department of ECE, C.Abdul Hakeem College of Engineering and Technology, Melvisharam, Tamil Nadu, India.
[2]Helen Prabha, Professor,Department of ECE, RMD Engineering College, Kavaraipettai,, Tamil Nadu, India.

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Address For Correspondence:
Pradeepa Manickam, C.Abdul Hakeem College of Engineering and Technology, Department of ECE, 632509, Melvisharam, Tamil Nadu, India
E-mail: pradeepamrch@gmail.com

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ABSTRACT

Background: Fetal ECG extraction is still a challenging task for diagnosis. **Objective:** Finding a better method in extraction process and also a method to improve the quality of extracted fetal ECG. **Results:** ANFIS algorithm is used to identify the maternal component present in the abdomen ECG signal and removed from the composite abdomen signal. The resultant signal contains baseline wandering noise and other high frequency noises. The moving average filter is used to identify the baseline wander noise and then removed from the extracted signal. Finally the other noises are removed using wavelet denoising technique. ANFIS structure has two sets of parameters such as premise parameters and consequent parameters. These parameters are initialized and then updated at each iteration of the algorithm. This article compares the different learning algorithm such as hybrid learning, particle swarm optimization and genetic algorithm used to optimize the parameters of ANFIS. These learning algorithms are developed to achieve the desired performance function. The performance function used to extract the fetal ECG is to minimize the mean square error. The average percentage reduction in variance from initial stage to last stage is 48.6% is achieved. **Conclusion:** The need of identifying the fetal ECG from the abdomen signal is required in clinical analysis. The proposed method of ANFIS with hybrid learning or PSO or GA based learning is able to extract the fetal ECG, and also the clarity of extraction is improved by the post processing techniques such as moving average filtering for removal of base line wandering noise and wavelet denoising for other high frequency noises.

KEYWORDS: ECG, ANFIS, Hybrid Learning, Particle Swarm Optimization, Genetic algorithm

INTRODUCTION

The fetal ECG imitates the electrical activity of the fetus heart. Normally, the fetal heart rate lies between 120 and 180 beats per minute. Fetal arrhythmia may be classified based on heart rate as fetal bradycardia where the heart rate is low (<100 bpm) and Tachycardia where the heart rate is high (>180 bpm) [1] [2]. Hence the signal provides the information about heart rate, duration of P-R interval, R-R interval and dynamic performance which have been used to identify the problems associated with fetal development [3]. There are several practical problems associated with the non-invasive method of recording of fetal ECG. The signal is actually recorded at the abdomen of the mother. Hence the signal is interfered with many sources of interference. From this composite signal the extraction is critical due to the low power of the fetal ECG signal. The sources of hindrance include the maternal ECG, the maternal electromyogram (EMG), 50 Hz power line

interference, baseline wander and random electronic noise [4]. Abolition of these unwanted components from the composite signal results the fetal ECG signal.

A numerous methods have been proposed for extracting the fetal ECG signal from the abdominal ECG signal. Those proposed techniques include adaptive filter [4] [5], singular value decomposition [6], wavelet transform [7], neural network [8], independent component analysis [9], periodic component analysis (πCA) [10], blind source separation [11] [12] and template subtraction method [13]. This paper applies the ANFIS algorithm used to identify the maternal component present in the abdomen ECG signal and the maternal component is eliminated which is the major noise present in the abdomen ECG signal. The resultant signal is the extracted fetal ECG. Different learning algorithms such as hybrid learning, particle swarm optimization and genetic algorithm are used to optimize the parameters of ANFIS. This paper analyzes and compares the performance of these learning algorithms which have been designed to achieve the desired performance function. The performance function used to extract the fetal ECG is to minimize the mean square error. The result is further improved by moving average filter which identifies the baseline wander noise and removed from the extracted fetal ECG. Finally the other noises are removed using wavelet denoising technique.

MATERIAL AND METHODS

ANFIS:

Adaptive Neuro-Fuzzy Inference System (ANFIS) is hybrid intelligent system which merges the fuzzy logic approach and adaptive neural network competence towards enhanced performance. The ANFIS structure is presented below [14].

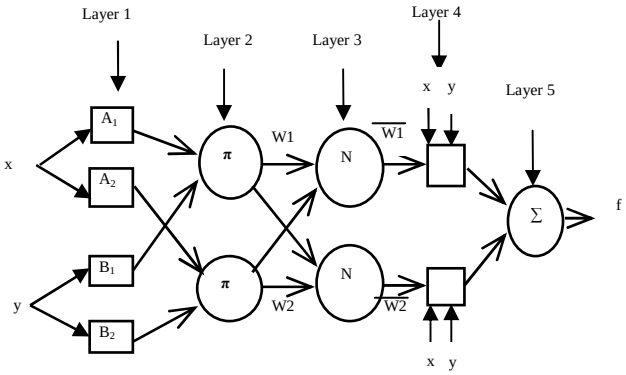


Fig. 1: ANFIS structure

A rule set and the functions of each layer with fuzzy system are listed below.

x is A_1 and y is B_1, then

$$f_{n1} = a_1 x + b_1 y + c_1 \quad (1)$$

x is A_2 and y is B_2, then

$$f_{n2} = a_2 x + b_2 y + c_2 \quad (2)$$

Layer 1:

$$O_{1,i} = \mu A_i(x) \quad for\ i = 1,2 \quad or \quad (3)$$

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

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - r_i}{p_i}\right|^{2qi}} \quad (5)$$

Layer 2:

$$O_{2,i} = w_i = \mu A_i(x)\, \mu B_i(y) \quad for\ i = 1,2 \quad (6)$$

Layer 3:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad for\ i = 1,2 \quad (7)$$

Layer 4:

$$O_{4,i} = \overline{w}_i f_{ni} = \overline{w}_i (a_i x + b_i y + c_i) \quad for\ i = 1,2 \quad (8)$$

Layer 5:

$$O_{5,i} = \sum \overline{w}_i f_{ni} = \frac{\sum w_i f_{ni}}{\sum w_i} \quad for\ i = 1,2 \quad (9)$$

In layer 1 every node is an adaptive node, where x and y are the input to node, A and B are the linguistic label associated with the node, $O_{1,i}$ is the membership grade of fuzzy set. The membership function may be of

any parameterized membership function where the generalized bell function is used in this implementation. $\{p_i, q_i, r_i\}$ are the parameters of the generalized bell function. When these value changes, the bell-shaped function differ accordingly, thus produce various forms of membership functions for fuzzy set. Parameters in layer 1 are referred to as premise parameters. In layer 2, every node is a fixed node, whose output is the product of all the incoming signals. The node output represents the firing strength of the rule. In layer 3, every node is a fixed node. The node calculates the ratio of its rule's firing strength to the sum of all rules' firing strengths. In layer 4, every node is an adaptive node and $\{a_i, b_i, c_i\}$ are the parameters of this node and are referred as consequent parameters. Layer 5 contains a single, fixed node, which computes the overall output as the summation of all incoming signals [14].

Learning Algorithm:

Hybrid learning algorithm:

Many learning algorithms were proposed to learn the ANFIS network like Back Propagation (BP), Least Square Estimator (LSE) and hybrid learning algorithm. Hybrid learning algorithm was used to learn the network because it converges much faster than other methods [14]. In the ANFIS architecture, the values of premise parameters are kept fixed, and then the output can be presented as a linear grouping of the consequent parameters. The output function as

$$f = \frac{w_1}{w_1 + w_2} f_{n1} + \frac{w_2}{w_1 + w_2} f_{n2} \quad (10)$$

$$= \overline{w}_1(a_1 x + b_1 y + c_1) + \overline{w}_2(a_2 x + b_2 y + c_2)$$

$$= (\overline{w_1}x)a_1 + (\overline{w_1}y)b_1 + (\overline{w_1})c_1 + (\overline{w_2}x)a_2 + (\overline{w_2}y)b_2 + (\overline{w_2})c_2 \quad (11)$$

The function is linear in the consequent parameters a_1, b_1, c_1, a_2, b_2 and c_2.

During the forward pass of the learning algorithm, node outputs are calculated until layer 4 and the consequent parameters are identified by the LSE. During the backward pass, the error signals are propagated backward and the premise parameters are updated by gradient descent method. The identified consequent parameters are optimal under the premise parameters are fixed. The advantage of the hybrid learning algorithm is that it converges much faster because it reduces the search space dimensionality back propagation method [14].

Particle Swarm Optimization:

The particle warm optimization technique is based on the principle of survival of the fittest; PSO is motivated by the imitation of the social behavior of flocks. The PSO algorithm is used as optimizer in a wide range of applications. In PSO, particles are initialized randomly and the population of individuals is updated according to the fitness information. Hence the individuals of the population move towards better solution. Each individual particle in the search space, whose position and velocity are dynamically updated according to its own experience and its travel companion's experience. The PSO works under different cases, first is the individual best, each individual compares its position to its own best called personal best. The second case is the global best; the social knowledge is used to update the movement of particles by considering the position of the best particle from the entire swarm. In addition, each particle uses its history of experience in terms of its own best solution [15] [16]. This algorithm is presented below.

1. Initialize the swarm of particles where the position $\overrightarrow{x_i}(t)$ is chosen randomly.
2. Calculate the performance F of each particle, with its current position $\overrightarrow{x_i}(t)$
3. Compare the performance of each individual to its best performance
   If $F\left(\overrightarrow{x_i}(t)\right) < pbest$
   Then $pbest_i = F\left(\overrightarrow{x_i}(t)\right)$ (12)
   $\vec{x}_{pbest_i} = \overrightarrow{x_i}(t)$ (13)
4. Compare the performance of each individual to global past particle
   If $F\left(\overrightarrow{x_i}(t)\right) < gbest$
   Then $gbest_i = F\left(\overrightarrow{x_i}(t)\right)$ (14)
   $\vec{x}_{gbest_i} = \overrightarrow{x_i}(t)$ (15)
5. Update the velocity for each particle
   $\overrightarrow{v_i}(t) = w * \overrightarrow{x_i}(t-1) + \rho_1\left(\vec{x}_{pbest_i} - \overrightarrow{x_i}(t)\right) + \rho_2\left(\vec{x}_{gbest_i} - \overrightarrow{x_i}(t)\right)$ (16)
   Where w is the inertia weight, ρ_1 and ρ_2 are random variables.
6. Change each particle position to its new position
   $\overrightarrow{x_i}(t) = \overrightarrow{x_i}(t-1) + \overrightarrow{v_i}(t)$ (17)
   $w = w * wdamp$, where w is an inertia weight damping ratio

These steps are repeated till the convergence is reached.

The random variables, ρ_1 and ρ_2 are defined as $\rho_1 = r_1 c_1$ and $\rho_2 = r_2 c_2$ with $r_1, r_2 \sim U(0, 1)$, c_1 and c_2 are positive acceleration constant. The stability of PSO is guaranteed if $c_1 + c_2 \leq 4$. [15] [16].

Genetic Algorithm:

The genetic algorithm is a stochastic global search method that imitates the symbol of natural biological evolution. It works on a population of potential solutions by the principle of survival of the fittest to make better estimate of the solution. At each generation, a new set of population is created by selecting the individuals according to their level of fitness. This process provides better population of individuals suited to their environment in the next generation [17].

Initially, all individuals in the population are encoded into binary bits called a chromosome and each individual is associated with the fitness value. Other encoding streams may also be used such as gray coding. The encoding scheme provides a path to transform the problem in to GA structure. Then the fitness function is to be designed, whether it is a maximization or minimization function. The fitness of each individual is calculated according to the fitness function derived. After the evaluation of the fitness, the selection process decides which parents participate in creating the off spring for the next generation. The members with higher fitness are surviving and participate in crossover process. The selection probability is calculated as $f_i/\sum_{k=1}^{k=n} f_k$. This selection procedure permits the members with above average fitness values to reproduce and replace members with who have the fitness below the average. Crossover is applied to the selected pairs of parents with probability equal to a given cross over rate. One point or two points cross over is used. The chromosome between the two points is swapped to generate children. If the population does not contain all the encoded bits of information needed to solve the particular problem, do not provide acceptable solution. Hence mutation is preferred and is implemented by flipping a single bit with a probability equal to a mutation rate. It can prevent the population struck at local optima [14] [17].

The following outline summarizes how the genetic algorithm works:

1. Create a random initial population.
2. Find the level of fitness of each population by computing its fitness value.
3. Select two members from the population with probability proportional to their fitness value.
4. Apply crossover with the probability equal to the crossover rate.
5. Apply mutation with the probability equal to the mutation rate.
6. Repeat these steps until the required members are generated.
7. Calculate the fitness value and repeat the selection, crossover and mutation until the desired criteria is satisfied [14].

RESULTS AND DISCUSSION

The proposed method to extract fetal ECG is shown in Figure 2.

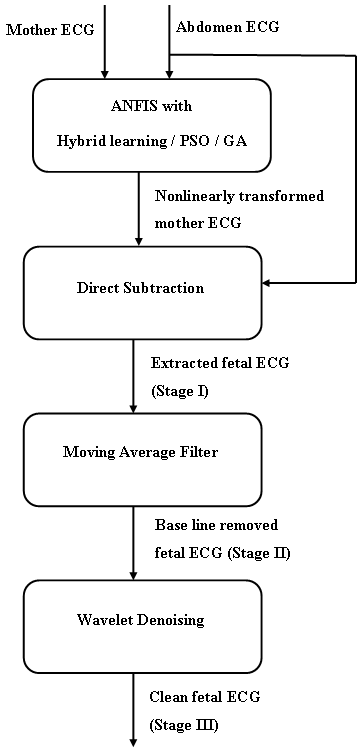


Fig. 2: Flow diagram of the proposed method

The input to the ANFIS network is the mother and abdomen ECG. The abdomen signal consists of maternal ECG component, fetal ECG component and other interferences. The maternal component present in the abdomen signal is the non linear version of the mother ECG which is taken at thorax. Hence the mother ECG cannot be directly subtracted from the abdomen signal. ANFIS performs the nonlinear mapping, which maps the mother ECG into an abdomen ECG. Once the maternal components in abdomen is identified by this non linear mapping, then direct subtraction is performed to extract fetal ECG, thus the major source of interference is eliminated. While implementing ANFIS algorithm, the parameters are assigned as, number of membership function is 5, membership function type is generalized bell function, the number of iteration is 2500 and the inputs to train the ANFIS network are mother and abdomen ECG. The objective function is minimization of mean square error. In order to optimize the performance of the extraction different learning procedure is applied to tune the ANFIS parameters. Initially hybrid learning is applied to update the ANFIS parameters such as premise parameter and consequent parameters. During the forward pass the consequent parameters are identified by the LSE. During the backward pass, the error signals are back propagated and the premise parameters are restructured by gradient descent method. In PSO optimization, the population size is chosen as 50, the constrain coefficients are chosen as, inertia weight is 1, inertia weight damping ratio is 0.99, personal learning coefficient c_1 is 1 and global learning coefficient c_2 is 2. In GA optimization the parameters are chosen as, crossover percentage is 0.4, mutation percentage is 0.7, mutation rate is 0.15, and selection pressure is 8.

In order to validate the proposed method, the data's are taken from Daisy dataset provided by De.Moore [18]. This database contains two ECG recorded signal, one ECG is recorded at the thorax and the other is recorded at abdomen of the pregnant women.

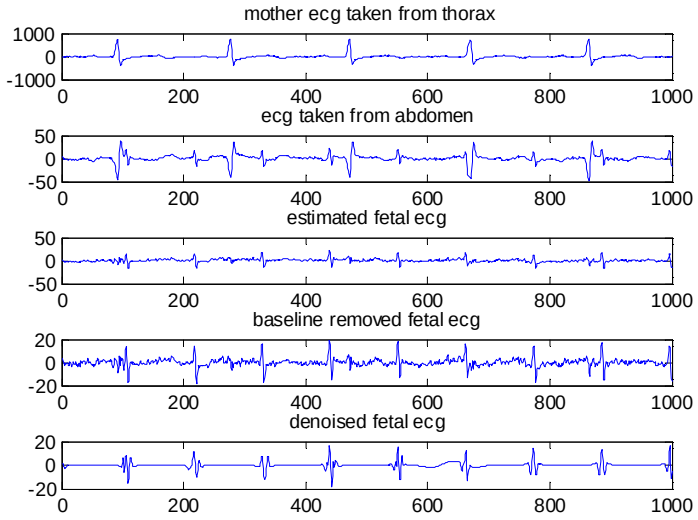


Fig. 3: Results of ANFIS with Hybrid learning

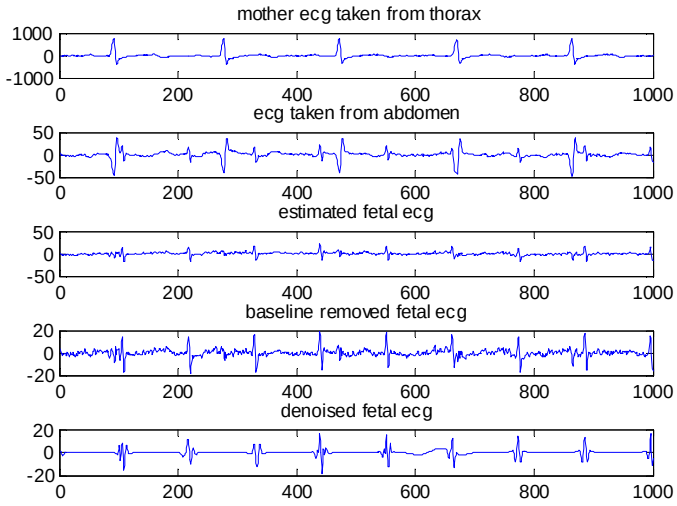


Fig. 4: Results of ANFIS with PSO optimization

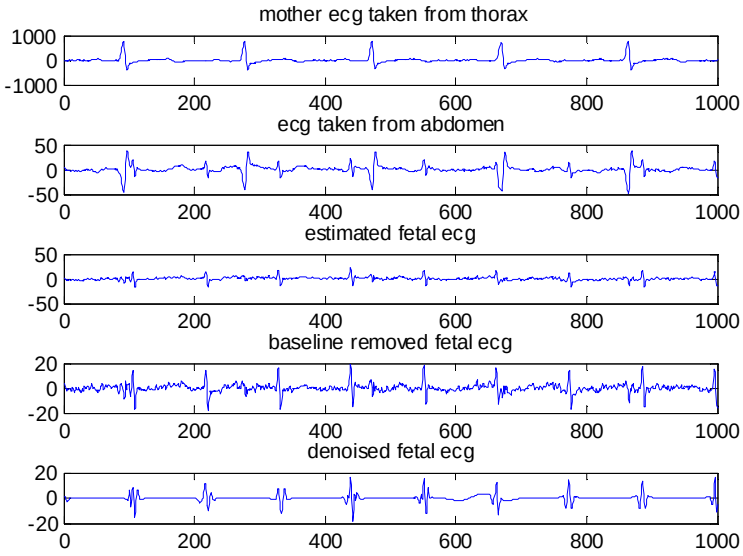


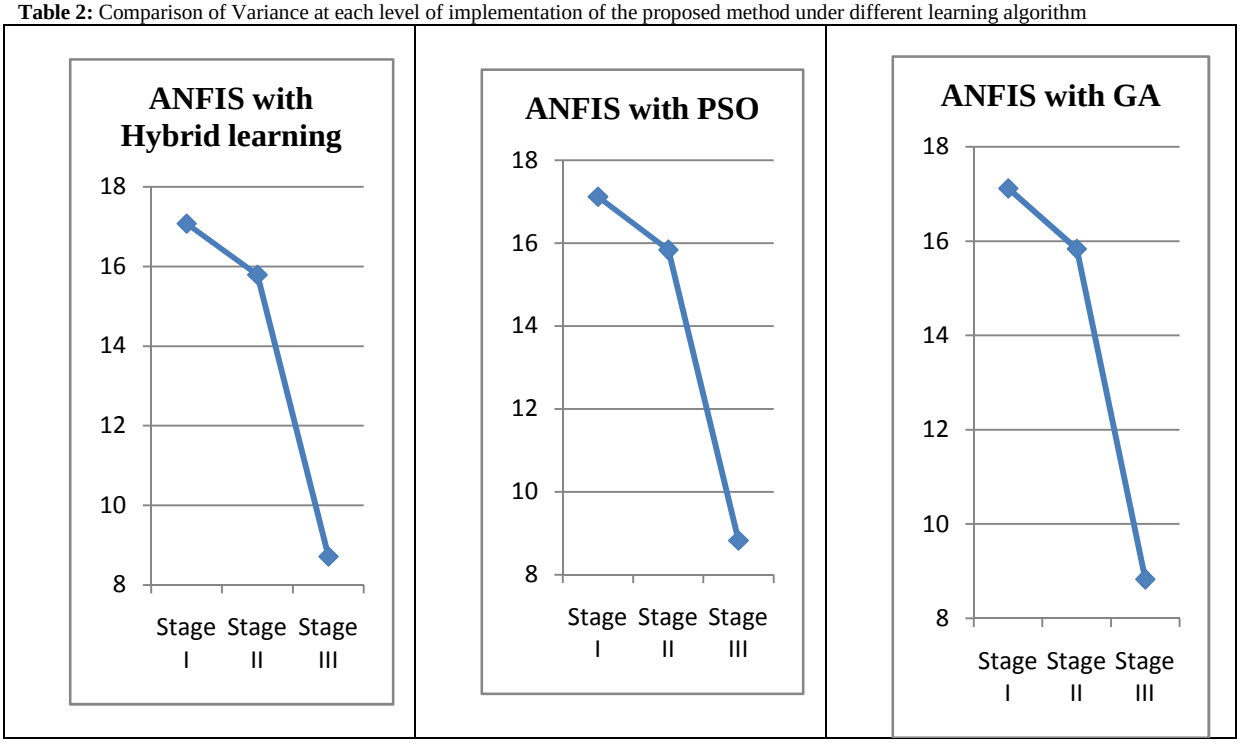
Fig. 5: Results of ANFIS with GA optimization

The Variance parameter is calculated at each level of implementation of the algorithm proposed and tabulated below.

Table 1: Comparison of Variance of different algorithms with the proposed method

Algorithm	Stage I	Stage II	Stage III
ANFIS with Hybrid learning	17.0745	15.7875	8.7177
ANFIS with PSO	17.1158	15.8318	8.8260
ANFIS with GA	17.1158	15.8318	8.8259

Table 2: Comparison of Variance at each level of implementation of the proposed method under different learning algorithm



The graph shows that at each level of extraction, the variance is reduced but the learning algorithm doesn't produce much difference on extraction.

Contribution of the study:

In clinical applications, due to the problems present in the extraction of fetal ECG, other methods such as Doppler echocardiography and Fetal magnetocardiography are used to diagnose the abnormality present in fetus even though there are limitations in those methods. Hence the improvement in quality extraction of fetal ECG is vital in diagnosis. This study provides is improving the quality of extraction of fetal signal by the application of ANFIS based method along with moving average filtering and wavelet denoising techniques.

Conclusion and future work:

The fetal ECG is an important tool to analyze the health status of the fetus. The need of identifying the fetal ECG from the abdomen signal is required in clinical analysis. The proposed method of ANFIS with hybrid learning or PSO or GA based learning is able to extract the fetal ECG, and also the clarity of extraction is improved by the post processing techniques such as moving average filtering for removal of base line wandering noise and wavelet denoising for other high frequency noises. The average percentage reduction in variance from initial stage to last stage is 48.6% is achieved. The database used for this research is based on DeMoore database [18]. The study need to be tested with varies database for its reliability. The authors recommend online processing of fetal ECG and applied to tele-medicine applications. The obtained results may be used for hardware designs.

REFERENCES

1. Weber, R., D. Stambach and E. Jaeggi, 2011. Diagnosis and management of common fetal arrhythmias. Journal of the Saudi Heart Association, 23(2): 61-66.
2. Hornberger, L., D. Sahn, 2007. Rhythm abnormalities of the fetus. Heart, 93(10): 1294-1300.
3. Panigrahy, D., M. Rakshit, P.K. Sahu, 2015. An Efficient Method for Fetal ECG Extraction From Single Channel Abdominal ECG. In the proceedings of the 2015 International Conference on Industrial Instrumentation and Control (ICIC), pp: 1083-1089.
4. Ferrara, E.R., and B. Widrow, 1982. Fetal electrocardiogram enhancement by time-sequenced adaptive filtering. IEEE transactions on bio-medical engineering, 29(6): 458-460.
5. Behar, J., A. Johnson, G.D. Clifford and J. Oster, 2014. A Comparison of Single Channel Fetal ECG Extraction Methods. Annals of biomedical engineering, 42(6): 1340-53.
6. Callaerts, D., B. De Moor, J. Vandewalle, W. Sansen, G. Vantrappen and J. Janssens, 1990. Comparison of SVD methods to extract the foetal electrocardiogram from cutaneous electrode signals. Medical & biological engineering & computing, 28: 217-224.
7. Khamene, A., and S. Negahdaripour, 2000. A new method for the extraction of fetal ECG from the composite abdominal signal. IEEE transactions on bio-medical engineering, 47: 507-516.
8. Camps, G., M. Martinez and E. Soria, 2001. Fetal ECG extraction using an FIR neural network. Computers in Cardiology, 28: 249-252.
9. Sameni, R., F. Vrins, F. Parmentier, C. Hérail V. Vigneron, M. Verleysen, C. Jutten and M. B. Shamsollahi, 2006. Electrode Selection for Noninvasive Fetal Electrocardiogram Extraction using Mutual Information Criteria. In the proceedings of the 26th International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering, pp: 97-104.
10. Sameni, R., C. Jutten and M.B. Shamsollahi, 2008. Multichannel electrocardiogram decomposition using periodic component analysis. IEEE transactions on bio-medical engineering, 55(8): 1935-1940.
11. Zarzoso, V., A.K. Nandi and E. Bacharakis, 1997. Maternal and foetal ECG separation using blind source separation methods. IMA journal of mathematics applied in medicine and biology, 14: 207-225.
12. Zarzoso, V., and A.K. Nandi, 2001. Noninvasive fetal electrocardiogram extraction: blind separation versus adaptive noise cancellation. IEEE transactions on bio-medical engineering, 48:12-18.
13. Vullings, R., C.H.L. Peters, R.J. Sluijter, M. Mischi, S.G. Oei and J.W.M. Bergmans, 2009. Dynamic segmentation and linear prediction for maternal ECG removal in antenatal abdominal recordings. Physiological measurement, 30(3): 291-307.
14. Jang, R.J., C. Sun, E. Mizutani, 1997. Neuro-Fuzzy and Soft Computing. Prentice Hall New Jersey.
15. Aliyari Shoorehdeli, M., M. Teshnehlab, A.K. Sedigh, 2007. Novel Hybrid Learning Algorithms for Tuning ANFIS Parameters Using Adaptive Weighted PSO. In proceedings of the 2007 IEEE International Fuzzy systems Conference, pp: 1-6.
16. Sargolzaei, A., K. Faez, S. Sargolzaei, 2011. A new method for Foetal Electrocardiogram extraction using Adaptive Nero-Fuzzy Interference System trained with PSO algorithm. In the proceedings of 2011 IEEE International Conference, pp: 1-5.
17. Chipperfield, A., P. Fleming, H. Pohlheim and C. Fonseca, 1994. Genetic Algorithm TOOLBOX For Use with MATLAB. University of Sheffield.
18. http://homes.esat.kuleuven.be/~smc/daisy/