A Novel Hybrid Soft Computing Technique for Extracting Fetal ECG from Maternal ECG Signal

Saranya.S
PG Student, Applied Electronics
Anna University,Tirunelveli,India

Suja Priyadharsini.S
Lecturer, Dept of ECE
Anna University, Tirunelveli,India

ABSTRACT
The fetal electrocardiogram (FECG) signal reflects the electrical activity of the fetal heart. It contains information about the health status of the fetus and therefore, an early diagnosis of any cardiac defects before delivery increases the effectiveness of the appropriate treatment. The proposed approach extracts the FECG from two ECG signals recorded at the thoracic and abdominal areas of the mother's skin, with the help of a hybrid soft computing technique called Adaptive Neuro-Fuzzy Inference System (ANFIS). The thoracic ECG is assumed to be almost completely maternal (MECG) while the abdominal ECG is considered to be composite as it contains both the mother's and the fetus' ECG signals. The principle used for the elimination of artifacts is ANC. The results demonstrate the effectiveness of the proposed technique in extracting the FECG component from abdominal signals of very low maternal to fetal signal-to-noise ratios. Finally, a pure FECG is obtained with higher SNR. Also, we apply one of the swarm intelligent branches, namely particle swarm optimization (PSO) to furthermore tune the ANFIS parameters and to extract the pure FECG signal with higher SNR and lower error rate.

Keywords
Adaptive neuro-fuzzy inference system, fetal ECG, maternal ECG, Particle swarm optimization.

1. INTRODUCTION
ECG records carry information about abnormalities or responses to certain stimuli in the human heart. Some of the characteristics of these signals are the ion frequency and the morphology of their waves. The analysis of the fetal heart rate (FHR) has become a routine procedure for the evaluation of the well-being of the fetus. Factors affecting FHR are uterine contraction, baseline variability, hypoxia and oxygenation. It has many drawbacks such as position-sensitivity, signal drop out, frequent confusion between maternal heart rate and fetal heart rate, failure in obese patients which in turn increases the rate of cesarean sections due to over diagnosis of fetal distress misinterpretation of cardiotocogram traces and failure to act in time. FECG measurement is used to overcome all these limitations. FECG is useful to get reliable information on fetal status, the detection of abnormalities and monitorization task during labor, to enable the adoption of measures for assuring fetal wellbeing, to detect whether the fetus is alive or dead, and to determine twin pregnancies. The diagnostic tests of fetal well-being can be categorized as invasive and noninvasive. During delivery, accurate recordings can be made by placing an electrode on the fetal scalp. However, as long as the membranes protecting the child are not broken, one should look for noninvasive techniques.There are several technical problems associated with the noninvasive extraction of FECG from ECG signals recorded at the abdominal surface. These problems are mainly due to the low power of the FECG signal which is contaminated by various sources of interference. Therefore, it is safe to say that if one is able to eliminate the maternal ECG component in the composite signal, a reasonable estimate of the FECG signal can be obtained. Due to the presence of artifacts, it is difficult to analyze the ECG, for they introduce spikes which can be confused with neurological rhythms. Thus, noise and undesirable signals must be eliminated or attenuated from the ECG to ensure a correct analysis and diagnosis. Therefore, adaptive neuro-fuzzy inference systems (ANFIS) is applied for extracting the FECG component from abdominal ECG recording which is considered to be composite as it contains both the mother's and the fetus' ECG signals

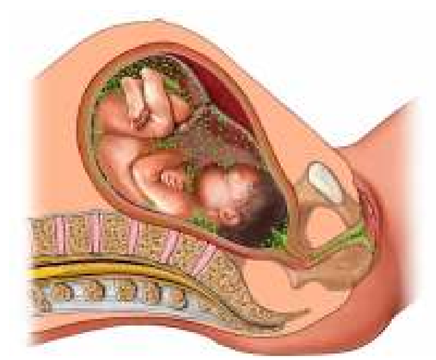


Figure 1. Fetus inside Mother's stomach

2. RELATED WORK
The fetal electrocardiogram (FECG) signal reflects the electrical activity of the fetal heart. It contains information on the health status of the fetus and, therefore, an early diagnosis of any cardiac defects before delivery increases the effectiveness of the appropriate treatment [1].There are several technical problems associated with the noninvasive extraction of FECG from ECG signals recorded at the abdominal surface. These problems are mainly due to the low power of the FECG signal which is contaminated by various sources of interference. These sources include the maternal ECG, the maternal electromyogram EMG, 50 Hz power line interference, baseline wander and random electronic noise [2], [3]. Assuming that we are using state of the art low noise electronic amplifiers with high common mode rejection ratio, the effect of the 50 Hz interference and electronic random noise can be eliminated. The EMG noise can also be reduced but not necessarily eliminated with the use of classical low pass filtering techniques.

Therefore, it is safe to say that if one is able to eliminate the maternal ECG component in the composite signal, a reasonable estimate of the FECG signal can be obtained. To further enhance this FECG estimate, especially its P and T waves, one needs to apply post filtering techniques. These techniques include nonlinear filtering via wavelet denoising [4].Many signal-processing-based techniques for FECG extraction have been introduced with varying degrees of success. These techniques include adaptive filters [3], correlation techniques [5], singular-value decomposition (SVD) [6], wavelet transform [7], [8], neural networks [9], [10], blind source separation (BSS) [11],[13] and ANFIS[17]. BSS via independent component analysis is considered among the most recent and successful methods used for FECG extraction [14].Two leads, as we are proposing in this work, are certainly not enough for satisfactory FECG extraction via ICA. This is so because of the nonlinear relationship between the thoracic ECG and the maternal ECG component in the abdominal ECG signals. ICA assumes that composite signals (abdominal) are obtained via linear mixing of the thoracic and fetal components and other interfering signals. Other techniques [3], [7], [9] that can use two leads have their limitations especially when the fetal beats overlap with the QRS wave of the maternal beats. In other words, one can see remnants of the maternal component in the extracted FECG especially when the R wave of maternal and fetal QRS overlap. ICA also requires multiple leads for successful separation of the FECG. It can be overcome by polynomial network which is based on nonlinear mapping between the abdominal and the MECG signal [16]. In [16], authors have chosen 2 signals for analyses based on the visual observations made on the signals, such as whether the signals have stronger FECG or MECG components. Practically, it is difficult to predict the signal components in the abdominal signals. Comparison is made between polynomial network and ANFIS in [18]. [19] produces 28.2397 SNR value after applying ANFIS training during its 10 epoch.

In this paper, we aim to apply ANFIS for estimating the FECG component from one abdominal ECG recording and one reference thoracic MECG signal. We use ANFIS to nonlinearly align the thoracic MECG with the abdominal ECG signal. This nonlinear alignment between the two signals allows for canceling the maternal component from the abdominal signal and hence offers an estimate of the FECG signal. We show results on synthetic ECG data and estimate higher SNR than [19] with lesser error rate by combining ANFIS with Particle Swarm Optimization.

This paper is organized as follows: The following section, we will analysis the schema of our work and theory of ANFIS. In Section IV, we describe the particle swarm optimization. In Section V, we report the experiment results, and we draw the conclusions in section VI.

3. METHODOLOGY

3.1 MECG Cancellation

The method used in this paper is adaptive noise cancellation (ANC) based on neuro fuzzy logic technique. ANC is a process by which the interference signal can be filtered out by identifying a non linear model between a measurable noise source (MECG) and the corresponding immeasurable interference. This is an extremely useful technique when a signal is submerged in a very noisy environment. Usually, the MECG noise is not steady; it changes from time to time. So the noise cancellation must be an adaptive process: it should be able to work under changing conditions, and be able to adjust itself according to the changing environment. The basic idea of an adaptive noise cancellation algorithm is to pass the corrupted signal (abdominal) through a filter that tends to suppress the MECG while leaving the signal unchanged. As mentioned above, this is an adaptive process, which means it does not require prior knowledge of signal or noise characteristics. Figure 2 shows noise cancellation with ANFIS filtering.

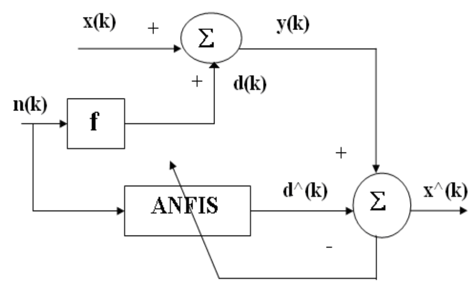


Figure 2. Schematic Diagram of ANC

The principle used for the elimination of artifacts is ANC. It is a process by which the interference signal can be filtered out by identifying a linear model between a measurable noise source (artifact) and the corresponding immeasurable interference. Fig.2 shows noise cancellation with ANFIS filtering. In this paper, x(k) represents the FECG signal which is to be extracted from the noisy signal. n(k) is the MECG which is the noise source signal. The noise signal goes through unknown nonlinear dynamics (f) and generates a distorted noise d(k) ,which is then added to x(k) to form the measurable output signal (abdominal) y(k).The aim is to retrieve x(k) from the measured signal y(k) which consists of the required signal x(k) plus d(k) , a distorted and delayed version of n(k) i.e. the interference signal.

The function f(.) represents the passage dynamics (mother's body) that the noise signal n(k) goes through. If f(.) was known exactly, it would be easy to recover x(k) by subtracting d(k) from y(k) directly. However, f(.) is usually unknown in advance and could be time- varying due to changes in the environment. Moreover, the spectrum of d(k) may overlap with that of x (k) substantially, invalidating the use of common frequency domain filtering techniques. To estimate the interference signal d(k) , we need to pick up a clean version of the noise signal n(k) that is independent of the required signal. However, we cannot access d(k) directly since it is an additive component of the overall measurable signal y(k) .

In Figure 2, ANFIS is used to estimate the unknown interference d^(k) .When d^(k) and d(k) are close to each other, these two get cancelled and we get the estimated output signal x^(k) which is close to the required signal (FECG).Thus by this method, the MECG is Completely removed and the required FECG is obtained.

3.2 ANFIS (Adaptive Neuro-Fuzzy Inference Systems) Overview

The acronym ANFIS derives its name from Adaptive Neuro-Fuzzy Inference System. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows your fuzzy systems to learn from the data they are modeling.Fuzzy inference systems incorporate human knowledge and perform inference and decision making. The basic idea of combining fuzzy systems and neural networks is to design an architecture that uses a fuzzy system to represent knowledge in an interpretable manner, in addition to possessing the learning ability of a neural network to optimize its parameters. ANFIS cancels out the interference and gives better performance even if the complexity of the signal is very high.

ANFIS application to synthesize:

1 controllers (automated FC tuning)
2 models (to explain past data and predict future behavior)

Adaptive Neural Fuzzy Inference System (ANFIS) Characteristics:

Creates a fuzzy decision tree to classify the data into one of 2^n (or p^n) linear regression models to minimize the sum of squared errors (SSE):

$$SSE = \sum_j e^2{}_j \qquad [1]$$

Where, e_j is the error between the desired and the actual output. Fuzzy Logic has been widely used in the design and enhancement of a vast number of applications. It is conceptually simple and straightforward. However, its proper use is heavily dependent on expert knowledge, which may not always be available. The proper selection of the number, the type and the parameter of the fuzzy membership functions and rules is crucial for achieving the desired performance and in most situations, it is difficult. Yet, it has been done in many applications through trial and error. This fact highlights the significance of tuning fuzzy system. ANFIS are fuzzy Sugeno models put in the framework of adaptive systems to facilitate learning and adaptation. Such framework makes fuzzy logic more systematic and less relying on expert knowledge. There are many benefits to using ANFIS in pattern learning and detection as compared to linear systems and neural networks. These benefits are centered on the fact that ANFIS combines the capabilities of both neural networks and fuzzy systems in learning nonlinearities. Fuzzy techniques incorporate information sources into a fuzzy rule base that represents the knowledge of the network structure so that structure learning techniques can easily be accomplished. Moreover, ANFIS architecture requirements and initializations are fewer and simpler compared to neural networks, which require extensive trails and errors for optimization of their architecture and initializations.

3.3 ANFIS architecture

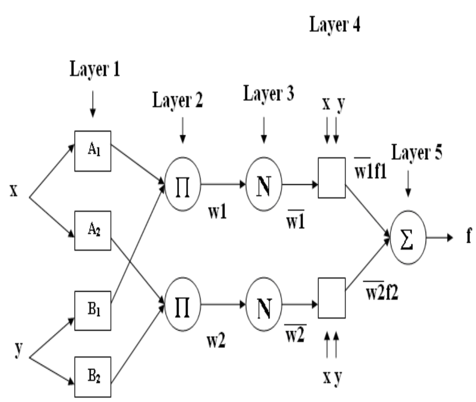


Figure 3. General Equivalent ANFIS Architecture.

There are many benefits to using ANFIS in pattern learning and detection as compared to linear systems and neural networks. These benefits are centered on the fact that ANFIS combines the capabilities of both neural networks and fuzzy systems in learning nonlinearities. Moreover, ANFIS architecture requirements and initializations are fewer and simpler compared to neural networks, which require extensive trails and errors for optimization of their architecture and initializations.

To present the ANFIS architecture, let us consider two-fuzzy rules based on a first-order Sugeno model,

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

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

One possible ANFIS architecture to implement these two rules is shown in Fig. 3. Note that a circle indicates a fixed node whereas a square indicates an adaptive node (the parameters are changed during training.

Layer 1: Calculate Membership Value for Premise Parameter

All the nodes in this layer are adaptive nodes; is the degree of the membership of the input to the fuzzy membership function (MF) represented by the node,

Output $O_{1,i}$ for node i=1,2

$$O_{1,i} = \mu_{A_i}(x_2) \qquad [2]$$

Output $O_{1,i}$ for node i=3,4

$$O_{1,i} = \mu_{B_{i-2}}(x_2) \qquad [3]$$

Layer 2: Firing Strength of Rule

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

$$O_{2,i} = w_i = \mu_{A_i}(x_1)\mu_{B_i}(x_2) \qquad [4]$$

(for i=1,2)

The output of each node is this layer represents the firing strength of the rule.

Layer 3: Normalize Firing Strength

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

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad [5]$$

(for i=1,2)

Layer 4: Consequent Parameters

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

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x_1 + q_i x_2 + r_i) \qquad [6]$$

Where p_i, q_i and r_i are design parameters (consequent parameter since they deal with the then-part of the fuzzy rule).

Layer 5: Overall Output

This layer has only one node labeled ∑ indicate that is performs the function of a simple summer. The output of this single node is given by

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad [7]$$

The ANFIS architecture is not unique. Some layers can be combined and still produce the same output. In this ANFIS architecture, there are two adaptive layers (1 and 4). Layer 1 has three modifiable parameters (a_i, b_i and c_i) pertaining to the input MFs. These parameters are called premise parameters. Layer 4 has also three modifiable parameters (p_i, q_i and r_i) pertaining to the first-order polynomial. These parameters are called consequent parameters.

3.4 Membership Function Used in ANFIS

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1.In this paper, we have used generalized bell type MF for tuning the FIS parameters. It has the advantage of smoothness and concise notation.

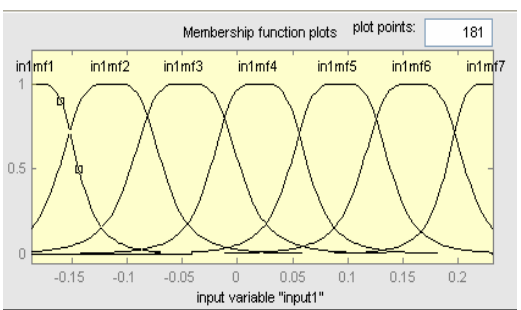


Figure 4. Bell shape membership function

3.5 Computations in ANFIS

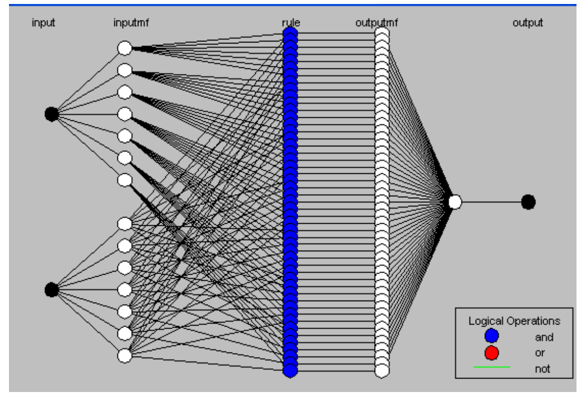
The basic steps used in the computation of ANFIS are given below.

• Generate an initial Sugeno-type FIS system using the matlab command *genfis 1*. It will go over the data in a crude way and find a good starting system.

• Give the parameters like number of epochs, tolerance error, number of MF, type of MF for learning.

• Start leaning process using the command *anfis* and stop when goal is achieved or the epoch is completed. Anfis applies the least squares method and the back propagation gradient descent for identifying linear and nonlinear parameters respectively.

• The *evalfis* command is used to determine the output of the FIS system for given input. In this paper, we have taken the MECG as the reference signal and the abdominal signal as the desired signal. These two signals act as training pair for ANFIS training.



Fig\ure 5. ANFIS Architecture. ANFIS info:

Number of nodes: 131
Number of linear parameters: 147
Number of nonlinear parameters: 42
Total number of parameters: 189
Number of training data pairs: 30000
Number of checking data pairs: 0
Number of fuzzy rules: 49

Start training ANFIS

1 8.37757e-006
2 9.52879e-006
3 8.32715e-006
4 7.05682e-006
5 7.25749e-006
6 6.77896e-006
7 6.72859e-006
8 7.03534e-006
9 6.73443e-006
10 7.14229e-006

Designated epoch number reached: ANFIS training completed at epoch 10.

Jang [15] is introduced four methods to update the parameters of ANFIS structure, as listed below according to their computation complexities:

1. Gradient decent only: all parameters are updated by the gradient descent.
2. Gradient decent only and one pass of LSE: the LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the gradient decent takes over to update all parameters.
3. Gradient decent only and LSE: this is the hybrid learning.
4. Sequential LSE: using extended kalman filter to update all parameters.

These methods have high complexity. [12] Compares several popular training algorithms in tuning parameters of ANFIS membership functions (MFs). In this paper we introduced a method which has less complexity and fast convergence.

ANFIS:

• SNR is high
• Noise present in the estimated FECG signal is less
• Less epoch number is sufficient to get the fine result
• Less convergence time.

4. PARTICLE SWARM OPTIMIZATION (PSO)

The Particle Swarm Optimization (PSO) is a new technique for finding optimal region of complex search space through the interaction of individuals in a population of particles. Unlike evolutionary algorithms, which are based on the principle of survival of the fittest, PSO is motivated by the simulation of the social behavior of flocks. The PSO algorithm has been shown to be a successful optimizer over a wide range of functions and attracted wide attention from several scientific and engineering communities.PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO applies the concept of social interaction to problem solving. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution.

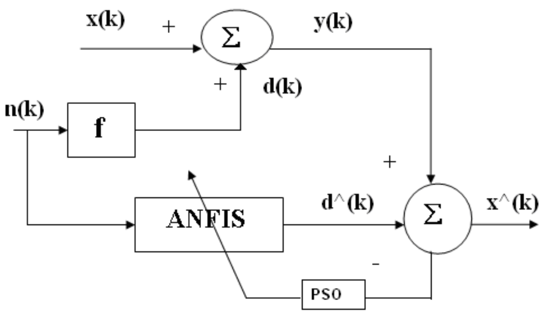


Figure 6. Schematic Diagram of PSO

In PSO, particles work in the same way, which is, updating the population of individuals by applying some kind of operators according to the fitness information obtained from the environment so that the individuals of the population can be expected to move toward better solution areas. In the PSO each individual flies in the search space with velocity which is dynamically adjusted according to its own flying experience and its companion flying experience, each individual is a point in the D- dimensional search space. Generally, the PSO has three major PSO algorithms available. The first is the individual best. This version, each individual compares position to its own best position, pbest, only. No information from other particles is used in these type algorithms. The second version is the global best. The social knowledge used to drive the movement of particles includes 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 thus far.

5. RESULTS AND DISCUSSION

After training, the estimated MECG is calculated using the command *evalfis*. The result obtained through the proposed technique is shown.For generating the synthetic ECG signals the dynamical Model is used. Both fetal and maternal ECG signals are synthesized using different parameters for different shapes and beat rates of the two signals.

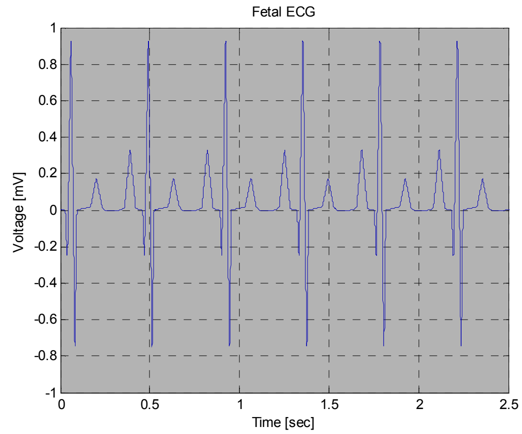


Figure 7. Synthetic FECG Waveform

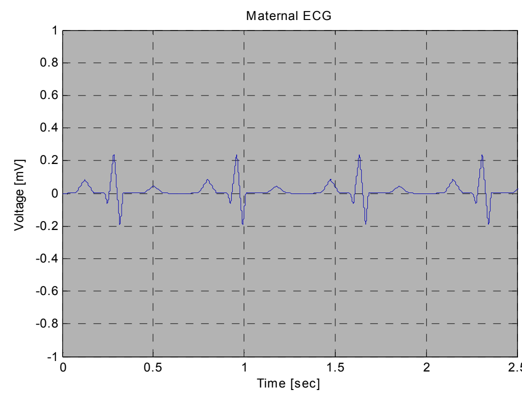


Figure 8. Synthetic MECG Waveform

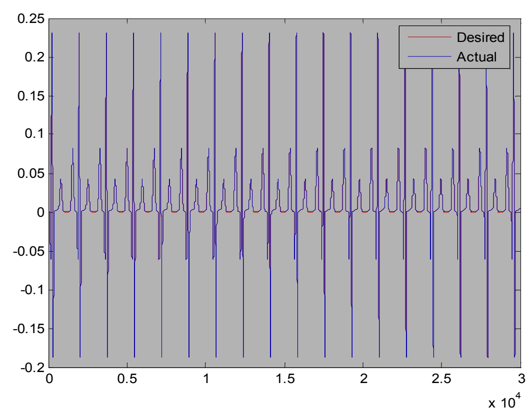


Figure 9. Mixing FETAL ECG and MATERNAL ECG signals

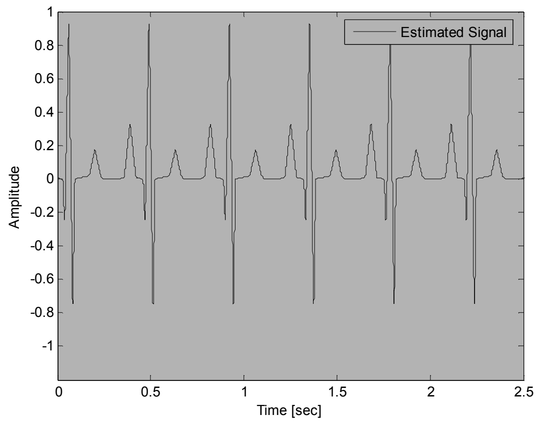


Figure 10. Estimated Signal(Output FECG Signal)

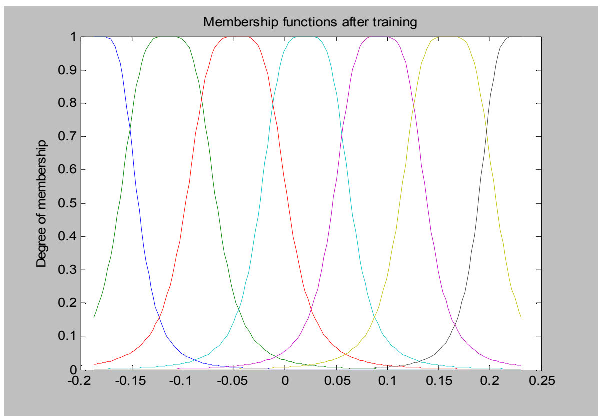


Figure 11. Membership function after training

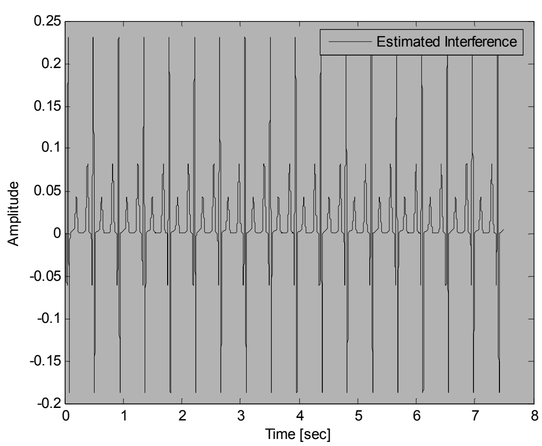


Figure 12. Estimated interference

Table 1. Performance Analysis

Epoch 10	Error rate	SNR
ANFIS	0.1018	27.7259
PSO	0.0720	28.067

Fetal ECG waveform and Maternal ECG waveform are synthetically generated and that is shown in fig 7,8. The FECG and MECG signal are added and given as the mixed signal (The thoracic ECG is assumed to be almost completely maternal (MECG) while the abdominal ECG is considered to be composite as it contains both the mother's and the fetus' ECG signals. After applying ANFIS, the estimated output signal is shown in fig 10 and the estimated interference is obtained and shown in fig. 12. Normally the FECG signal will not be a pure signal. Since the fetus is present inside the mother's stomach, it will be in the form of composite signal. To identify the health status of the fetus, there is a need of pure FECG signal.

6. CONCLUSION

In this paper, we propose neuro fuzzy logic technique namely ANFIS to cancel the MECG. It combines the advantages of neural network and fuzzy logic technique. Due to the adaptation capability of neural network, even if we have a single reference signal without considering the sensitivity of the electrode position, it is possible to estimate the MECG present in the abdominal signal. Since neural network takes longer time for convergence, we have combined the fuzzy logic technique for decision making and verification purposes. Experiments were carried out with the simulated signals using conventional methods of LMS filter, adaptive neural networks and ANFIS in order to prove the efficiency. From the results obtained through these techniques, we infer that ANFIS cancels out the interference and gives better performance even if the complexity of the signal is very high. The characteristics of the synthetic MECG and abdominal signals are different from the simulated signals like sine wave and random wave. Hence, the results obtained with this method are visually compared with the previous methods and we have found that we could extract the FECG signal with less computational time and higher signal to noise ratio.

The various artifacts mixed in the ECG signal cannot be filtered directly because they pass through the human body and turn into an interference component. Adaptive noise cancellation using ANFIS is performed on ECG signal to removal FECG from MECG and their results are plotted. Also, along with ANFIS, an optimization technique namely Particle Swarm Optimization (PSO) is applied for tuning and updating the ANFIS parameters. The complexity of this new approach is less than other training algorithms and free of derivative which is more convenience for fuzzy- neural net structure such as ANFIS.In our proposed method the SNR value is improved and there is a reduction of error rate from 0.1018 to 0.0720 by applying PSO.

7.REFERENCES

[1] S. Abboud, A. Alaluf, S. Einav, and D. Sadeh. 1992.Real time abdominal fetal ECG recording using hardware correlator: *Comput. Biol. Med.*, vol. 22, pp. 332–335.

[2] K. Assaleh and H. Al-Nashash. Jun. 2005.A novel technique for the extraction of fetal ECG using polynomial networks: *IEEE Trans. Biomed. Eng.*, vol. 52, no. 6, pp. 1148–1152.

[3] D.Callaerts, B. D. Moor, J. Vandewalle, and W. Sansen. 1990.Comparison of SVD methods to extract the fetal electrocardiogram from coetaneous electrode signals: *Med. Biol. Eng. Comput.*, vol. 28, pp. 217 224.

[4] G. Camps, M. Martínez, and E. Soria. 2001.Fetal ECG Extraction using an FIR Neural Network: in *Computers in Cardiology*, pp. 249–252.

[5] G. Camps-Valls, M. Martínez-Sober, E. Soria-Olivas, R. Magdalena- Benedito, J. Calpe-Maravilla, and J. Guerrero-Martínez. 2004.Foetal ECG recovery using dynamic neural networks: *Artif. Intell. Med.*, vol. 31, no. 3, pp. 197–209.

[6]A. Deam. Jan.1994.The use of fetal electrocardiogram: *J.Obstet. Gynecol.*, pp.101:9–17.

[7] E.R.Ferrara and Widrow.1982.Fetal electrocardiogram enhancement by time-sequenced adaptive filtering: *IEEE Trans. Biomed. Eng.*, vol. BME-29:pp. 458–460.

[8] Goddard.Mar.1966.A clinical fetal electrocardiograph: *Med. Biol. Eng.*vol. 4, pp. 159–167.

[9] Jyh-Shing Roger Jang. May/June 1993.ANFIS: Adaptive-Network-Based Fuzzy Inference System: IEEE Trans. Sys.,Man and Cybernetics., Vol. 23, No. 3.

[10] A. Khamene and Negahdaripour. Apr. 2000.A new method for the extraction of fetal ECG from the composite abdominal signal: *IEEE Trans. Biomed. Eng.*, vol. 47, no. 4, pp. 507–516.

[11]Khaled Assaleh. Jan.2007. Extraction of Fetal Electrocardiogram Using Adaptive Neuro-Fuzzy Inference Systems: *IEEE Trans. Biomed. Eng.*, vol. 54, no. 1.

[12]L. D. Lathauwer, B. D. Moor, and J. Vandewalle. 1995.Fetal electrocardiogram extraction by source subspace separation:in *Proc. IEEE SP/ATHOS Workshop HOS*, Girona, Spain, pp. 134–138.

[13] F. Mochimaru, Y. Fujimoto, and Y. Ishikawa. 2002.Detecting the fetal electrocardiogram by wavelet theory-based methods: *Prog. Biomed. Res.*, vol. 7, no. 3, pp. 185–193.

[14] Mu-Song Chen, "A Comparative Study of Learning Methods in Tuning Parameters of Fuzzy Membership Functions", IEEE SMC '99 Conference Proceedings, 1999,P.40-44vol.3

[15] C. K. Selva Vijila, P. Kanagasabapathy and S.Johnson .2006.Fetal ECG extraction using softcomputing technique: Journal of Applied Sciences, 251-256.

[16] C. K. Selva Vijila, P. Kanagasabapathy.2008. Intelligent Technique of canceling Maternal ECG in FECG extraction: *Iranian Journal of Fuzzy Systems* Vol. 5, No. 1, pp. 27-45.

[17]V.Vigneron,A.Paraschiv-Ionescu,A.Azancot,O.Sibony and C.Jutten. Jul. 2003.Fetal electrocardiogram extraction based on non-stationary ICA and wavelet denoising: presented at the Int. Symp. Signal Processing and its Applications (ISSPA), Paris.

[18] V. Zarzoso, A. K. Nandi, and E. Bacharakis, 1997, Maternal and fetal ECG separation using blind source separation methods: *MA J. Math. App. Med. Biol.*, vol. 14(, no. 3).

[19] V. Zarzoso and A. Nandi. Jan. 2001.Noninvasive fetal electrocardiogram extraction: Blind separation versus adaptive noise cancellation: *IEEE Trans. Biomed. Eng.*, vol. 48, no. 1, pp. 12–18.