Network and Complex Systems
ISSN 2224-610X (Paper) ISSN 2225-0603 (Online)
Vol.4, No.1, 2014
www.iiste.org

Extraction Of Fetal Electrocardiogram Using An Adaptive Neuro-Fuzzy System

Emuoyibofarhe J. O.,
Department of Computer Science and Engineering,
Faculty of Engineering and Technology,
Ladoke Akintola University of Technology, Ogbomoso, Nigeria;
eojustice@gmaill.com
Alamu F.O
Department of Computer Science and Engineering,
Faculty of Engineering and Technology,
Ladoke Akintola University of Technology, Ogbomoso, Nigeria;
femialamu@gmail.com

Opiarighodare D. K.,
Department of Computer Science and Engineering,
Faculty of Engineering and Technology,
Ladoke Akintola University of Technology, Ogbomoso, Nigeria;

And
Adewusi E A
Department of Computer Science and Engineering,
Faculty of Engineering and Technology,
Ladoke Akintola University of Technology, Ogbomoso, Nigeria;

ABSTRACT

In this paper, adaptive neuro fuzzy inference system (ANFIS) was used for the cancellation of maternal electrocardiogram (MECG) in fetal electrocardiogram extraction (FECG) from the composite abdominal electrocardiogram (AECG). This technique is used to estimate the MECG present in the abdominal signal of a pregnant woman. The FECG is then extracted by subtracting the estimated MECG from the abdominal signal.

In the furtherance of extraction, MATLAB (version 7.6) was used to code the system in order to generate the maternal heartbeat signal and the fetal heartbeat signal which were added to form the measured signal. For the fetal heartbeat signal to be recovered from the interference (maternal heartbeat) signal, a reference signal (which is a clean version of the original maternal heartbeat signal) was introduced in the system. It is this signal that cancelled the maternal heartbeat signal in the measured signal, thereby leaving the fetal heartbeat signal as an error signal.

However, though the recovered signal still contained some traces of the maternal heartbeat signal, performance of the soft computing technique applied is in terms of the capability of adaptive neuro fuzzy inference system in removing the overlapping between the MECG and the FECG signals. The results obtained show that this method is a simple and powerful means for the extraction of Fetal Electrocardiogram.

Keywords: Fetal Electrocardiogram Extraction (FECG), Neuro-fuzzy system, Noise Cancellation

1. INTRODUCTION

Fetal electrocardiogram (FECG) signal extraction is an interesting but difficult problem in biomedical engineering. The analysis of the FECG signal has become a common procedure for evaluating the well-being of the fetus. There are many factors that affect the FECG signal. These include baseline variability, uterine contraction, hypoxia and oxygenation etc. The analysis of the FECG signal has many setbacks such frequent confusion MECG signal and as position-sensitivity, signal drop out, frequent confusion between MECG signal and FECG signal, 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 signal measurement is used to overcome all these limitations. FECG signal is useful in getting reliable information about the fetal status, the detection of abnormalities and monitoring task during labour, to enable the adoption of measures for assuring fetal well-being, to detect whether the fetus is alive or dead, and to determine twin pregnancies (Assaleh, 2007). The diagnostic tests of fetal well-being can be categorized as invasive and non-invasive (Camps-Valls et al, 2001). 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, the diagnostic tests technique to look out for should be the non-invasive type (Mazzeo, 1994).

Over the years, many different methods and/or techniques have been developed for detecting and extracting the FECG signal. Blind Source Separation (BSS) is one of the methods that were recently investigated to measure the FECG signal. This is because the method involves the separation and the estimation of the original source of waveforms from a sensor array, without knowing the transmission channel characteristics and sources which may include diaphragm and uterus besides the FECG and the maternal electrocardiogram (MECG) signals (Lathauwer et al, 2000). This method fails in precise extraction of the FECG signal, since the contamination from the MECG signal is easily recognizable in the extracted FECG signal (Jang, 1993). Besides the BSS – base methods, various non-invasive signal processing techniques have been developed, such as fuzzy – logic, polynomial networks as well as wavelet theory based methods which can also be used to remove any ECG – noise signal from the FECG signal etc.

However, neuro-fuzzy logic soft computing technique has been proposed for the cancellation of the MECG signal which is the major interference signal, in order to extract the FECG signal. This technique combines the advantages of neural network and neuro-fuzzy logic technique (Jang, 1993). 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 signal present in the abdominal electrocardiogram signal. And this is what will be demonstrated in this project.

2. METHOD AND CONCEPT OF MECG CANCELLATION

The method used in this project 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 (which is MECG in this case) and the corresponding immeasurable interference (Assaleh, 2007). 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 1 shows noise cancellation with ANFIS filtering (Swarnalatha et al, 2009)

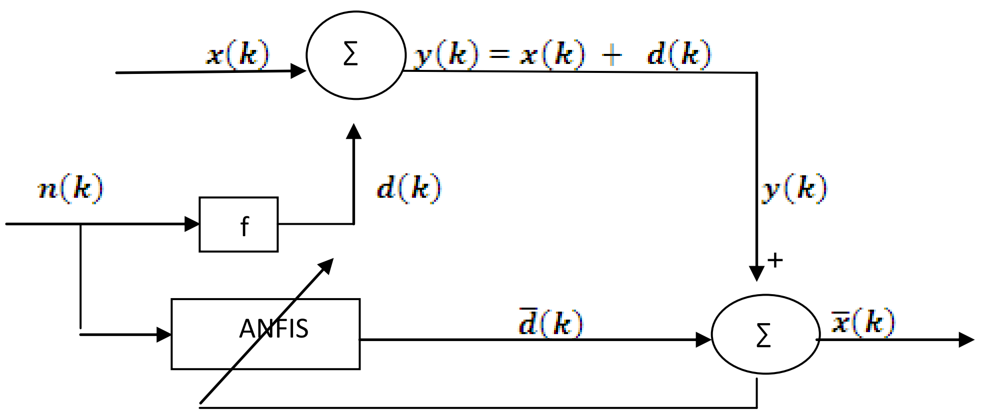

Figure 1: Schematic Diagram Of Adaptive Noise Cancellation Using Neuro Fuzzy Technique.

In this project, $x(k)$ represents the FECG signal that is to be extracted from the noisy signal. $n(k)$ is the MECG which is the noise source signal. The noise signal goes through an unknown nonlinear dynamics (f) and generates a distorted noise $d(k)$, which is then added to $x(k)$ to form the measurable output (abdominal) signal $y(k)$. The aim is to retrieve $x(k)$ from the measured signal $y(k)$ which consists of the required signal

$x(k)$ and $d(k)$, which is a distorted and/or delayed version of $n(k)$ i.e. the interference signal. In symbols, the measured signal is expressed as

$$y(k) = x(k) + d(k) = x(k) + f(n(k), n(k-1), n(k-2), \cdots) \cdots (2.1)$$

The function $f(\cdot)$ represents the passage dynamics (which may be the mother's body) that the noise signal $n(k)$ goes through (Selva et al, 2006). If $f(\cdot)$ was known exactly, it would be easy to recover $x(k)$ by subtracting $d(k)$ from $y(k)$ directly. However, $f(\cdot)$ is usually unknown in advance and could be time-varying due to changes in the system environment. Moreover, the spectrum of $d(k)$ may overlap with that of $x(k)$ substantially, which makes difficult to apply 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.**1, ANFIS is used to estimate the unknown interference $\bar{d}(k)$. When $\bar{d}(k)$ and $d(k)$ are close to each other, these two get cancelled if negative is assigned to the unknown interference signal. Thus we get the estimated output signal $\bar{x}(k)$ which is close to the required signal (FECG).

2.1 Adaptive Neuro Fuzzy Inference System

Adaptive Noise Cancellation using linear filters have been used successfully in real world applications such as interference canceling in Electrocardiograms, Echo elimination on long distance telephone transmission lines, and antenna side lobe interference canceling. This concept of linear adaptive noise cancellation can be extended to non-linear realms by using nonlinear adaptive systems. Thus, ANFIS, which is one of such nonlinear adaptive systems is applied in this project, to estimate the unknown interference present in the FECG signal.

Over the last few decades, neural networks and fuzzy systems have established their reputation as alternative approaches to signal processing. Both have certain advantages over conventional methods, especially when vague data or prior knowledge is involved. However, their applicability suffered from several weaknesses of the individual models. Neural networks recognize patterns and adapt themselves to cope with changing environments of the system. Fuzzy inference systems (FIS) incorporate human knowledge and perform inferencing and decision-making. ANFIS takes the advantages of the combination of neural network and fuzzy logic (Assaleh et al, 2005). 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. The drawbacks of both of the individual approaches - the black box behavior of neural networks, and the problems of finding suitable membership values for fuzzy systems - could thus be avoided**.**

2.2 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 (Swarnalatha et al, 2009). In this project, generalized bell shape type MF was used to tune the FIS parameters. This is shown in Figure 32. It is specified by three parameters namely a_i, b_i and c_i which represents the width, centre and slope of the curve, and it is given by

$$\mu_A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b}} \qquad \cdots \ (2.2)$$

As the values of these parameters change, the bell shaped functions vary accordingly. It has the advantage of smoothness and concise notation.

2.3 ANFIS Architecture: Sugeno's ANFIS

The general architecture of ANFIS (Selva et al, 2006) is shown in Figure 3 It has two inputs *x* and *y* and one output *z.* Assume the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type.

Rule1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$.

Rule2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$.

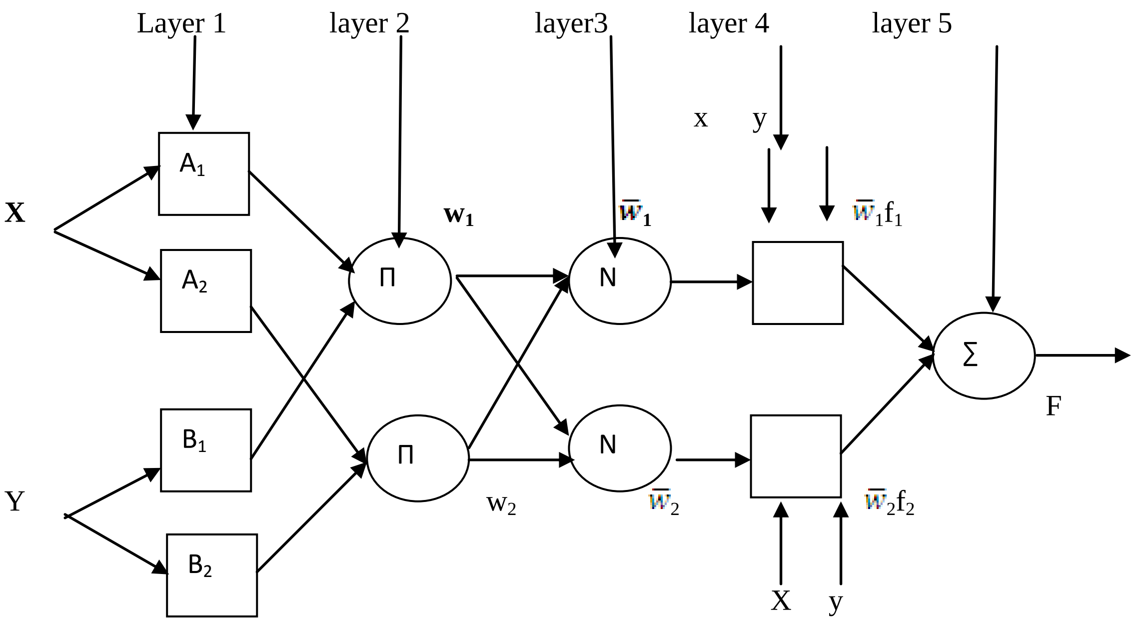

Figure 2 ANFIS Architecture

$$O_{1,i} = \mu_{Ai}(x), \text{ for i = 1, 2 or} \ldots\ldots \quad \textbf{2.3}$$
$$O_{1,i} = \mu_{Bi-2}(y), \text{ for i = 3, 4}$$

Where x is the input to node I, and A_i is the linguistic label associated with this node function. Parameters in this layer are called premise parameters.

- Layer 2: Every node in this layer is a fixed node labeled Π, whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y), i = 1, 2 \ldots\ldots \quad \textbf{2.4}$$

Where each node output represents the firing strength The architecture consists of five layers excluding the inputs and the output. The node functions in the same layer are of the same function family as described below (Assaleh, 2007).

- Layer 1: in this layer, every node i is an adaptive node with a node function

of a rule.

- Layer 3: Each node in this layer is a fixed node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strength:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2 \ldots\ldots \quad \textbf{2.5}$$

Where the outputs of this layer are called normalized firing strengths.

- Layer 4: Every node i in this layer is an adaptive node with a node function

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i \,(p_i\, x + q_i y + r_i), \text{ .... } \mathbf{2.6}$$

where $\overline{w}_i$ is a normalized firing strength from layer 3 and {p_i , q_i, r_i qi ri } is the parameter set of this node. Parameters in this layer are called consequent parameters.

- Layer 5: The single node in this layer is a fixed node labeled $\sum$, which computes the overall output as the summation of all incoming signals:

$$\text{Overall output} = O_{5,1} = \sum \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum_i w_i} \text{ .... } \mathbf{2.7}$$

The structure of this adaptive network is not unique. We can combine layers 3 and 4 to obtain an equivalent network with only four layers.

2.4 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 learning 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 a given input.In this project, the MECG was taken as the reference signal and the abdominal signal as the desired signal. These two signals act as training pair for ANFIS training. An alternative procedure is to use the ANFIS Editor to generate the various interfaces required for implementation as shown in the following figures:

3. RESULTS

During the extraction of the fetal heartbeat signal, the system input parameters (of both the maternal and the fetal heartbeat signals) were generated by codes written in matlab (version 7.6). These parameters were then passed to the adaptive neuro fuzzy inference system (ANFIS) for training. In the process of training, the parameters (i.e. membership function parameters) of each system input signal continues to map each other until the adaptive noise canceller (ANC) reaches a point of convergence. This is the point of complete overlap between the maternal heartbeat signal and the fetal heartbeat signal. The following are the results obtained:

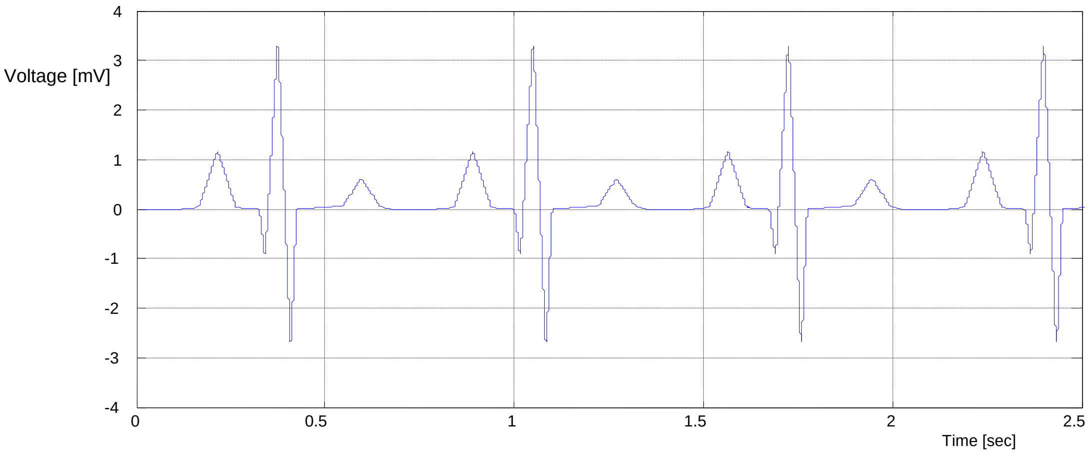

Figure 3: MECG Signal: d(k)

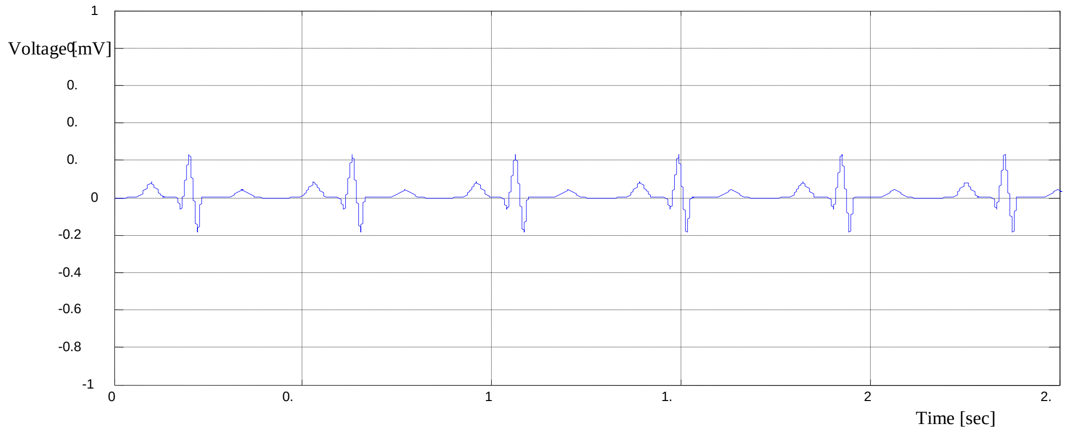

Figure 4: FECG Signal: x(k)

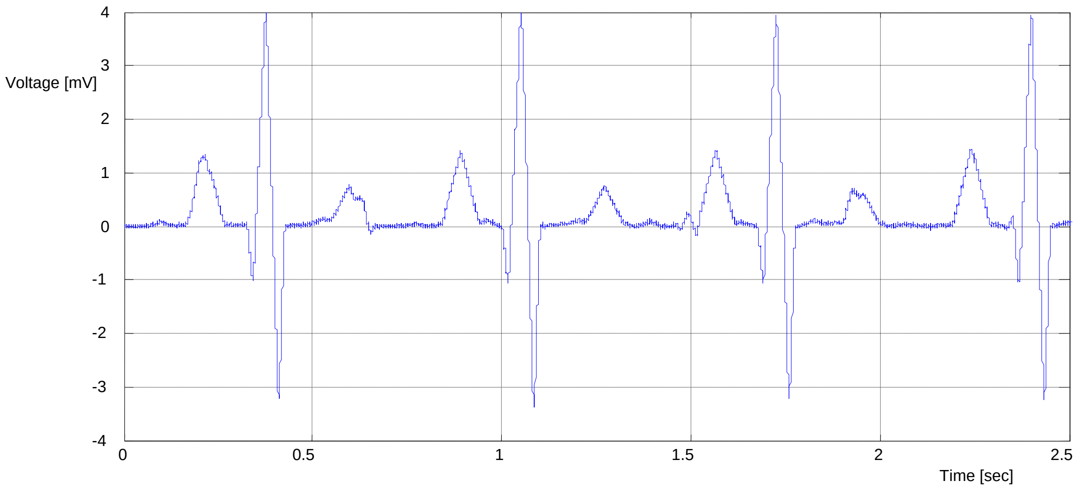

Figure 5 Measured Signal: y(k)

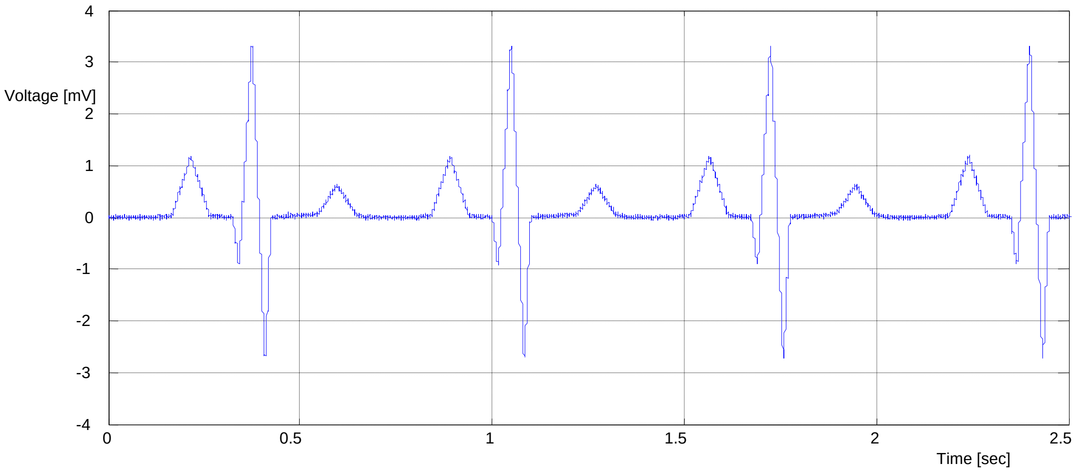

Figure 6: Reference Signal: n(k)

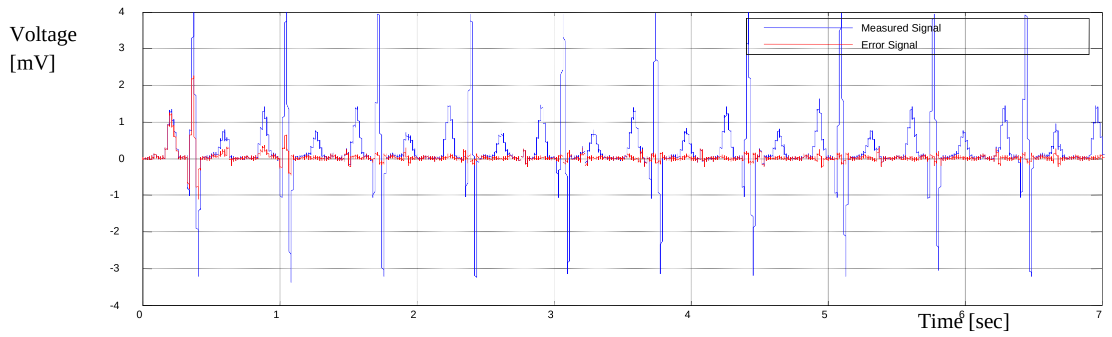

Figure 7: Convergence of Adaptive Noise Canceller

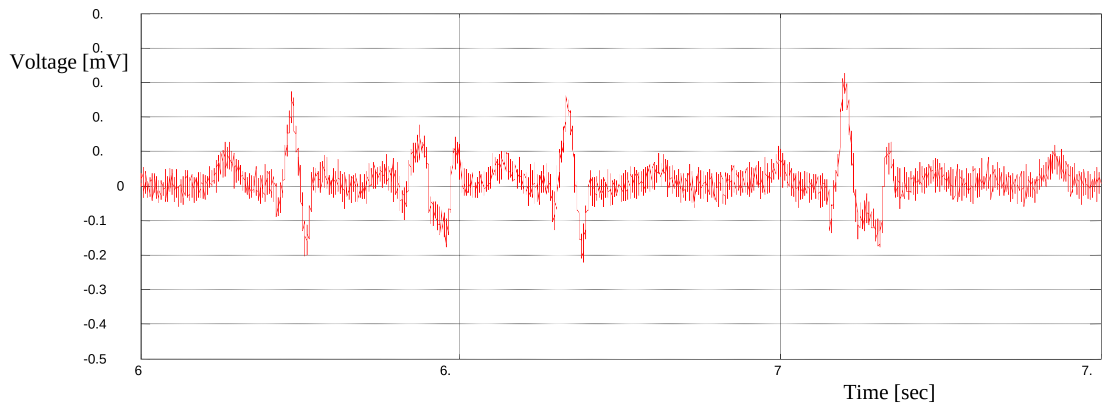

Figure 8 Recovered FECG Signal: $\overline{x}(k)$

4. DISCUSSION

A careful observation of the ECG wave morphologies and parameters above revealed the following:

4.1 Maternal Heartbeat Signal

In figure 3, we have the maternal heartbeat signal. And in this signal, the P wave which is usually produced as a result of atria contraction is about 6mm wide (slightly out of the range of a normal heartbeat of 89bpm i.e. 4mm). A P wave that exceeds 4mm will be an indication of hypertrophy i.e. enlargement. And this is exactly what we observed.

Next, is the PR interval which is measured from the start of the P wave to the start of the Q wave. It is a representation of the duration of atria depolarization. Here, it is 0.20 seconds, 10mm wide which is within the range of 0.12 to 0.20 seconds of a normal maternal heartbeat. Any PR interval that exceeds 0.20 seconds will be an indication of atrioventricular (AV) block.

Following the PR interval is the QRS complex which is measured from the start the Q wave to the end of the S wave. This represents the duration of ventricle depolarization. In our result (figure 3), we observed that the QRS complex is 0.12 seconds, 6mm wide, which is within the range of 0.08 to 0.12 seconds and 2mm to 6mm wide for a normal maternal heartbeat signal. Any duration of QRS complex greater than the larger value of the normal range is an indication of presence of bundle branch blocks. And this is what our results illustrated in figure 3.

Next, is the QT segment (also referred to as QT_c) which is measured from the start of Q wave to the end of T wave. And this interval represents the duration of activation and recovery of the ventricular muscle. In our result, it is 0.40 seconds which is slightly different from the approximate value of 0.44 seconds of a normal maternal heartbeat signal.

Next to the QT segment is the ST segment which is measured from the end S wave, J point, to the start of T wave. This segment is important in identifying pathology such as myocardial infarction.

4.2 Fetal Heartbeat Signal

In figure 4, we have the fetal heartbeat signal. And in this signal, the P wave which is usually produced as a result of atria contraction is about 4mm wide less than that of the maternal heartbeat signal.

Next, is the PR interval which is measured from the start of the P wave to the start of the Q wave. It is a representation of the duration of atria depolarization. Here, it is 0.12 seconds, 6mm wide which is less than that of the normal maternal heartbeat.

Following the PR interval is the QRS complex which is measured from the start the Q wave to the end of the S wave. This represents the duration of ventricle depolarization. In our result (figure 3.), we observed that the QRS complex is 0.08 seconds, 4mm wide, which is half of the value of the normal maternal heartbeat signal.

Next, is the QT segment (also referred to as QT_c) which is measured from the start of Q wave to the end of T wave. And this interval represents the duration of activation and recovery of the ventricular muscle. In our result, it is 0.24 seconds less than the approximate value of 0.41 seconds of a normal maternal heartbeat signal.

Next to the QT segment is the ST segment which is measured from the end S wave, J point, to the start of T wave. This segment is important in identifying pathology such as myocardial infarction.

4.3 Measured Signal

In figure 5, we have the measured signal which is a combination of both maternal and fetal electrocardiograms (i.e. y(k) signal) illustrated. This figure shows a complete overlap between the fetal ECG and the maternal ECG beats. In our results, For example, at time t= 0.20, 0.62, 1.11 and 2.00 seconds, we can see that the FECG is mixed with the MECG. This represents the extreme case where the FECG beat is completely dominated by the MECG component to the extent that the FECG beat is no longer visually distinguishable. However, figure 8 shows that the proposed technique for the extraction of the FECG is capable and efficient.

4.4 Reference Signal

Figure 6 the reference signal which is a clean version of the noise signal n(k) that is independent of the required signal in order to aid the system in estimating the interference signal d(k). This signal is slightly different from the MECG signal referred to as d(k) which was made to passed through the unknown nonlinear dynamics which was in turn referred to as the mother's body.

4.5 Convergence of Adaptive Noise Canceller

Figure 7 illustrates the outcome of the adaptive noise canceller at the point of convergence. It shows the state of the signal where the error signal that is to be recovered as the FECG beat is completely masked by the measured signal.

4.6 Recovered FECG Signal

Figure 8 illustrates the recovered FECG as error signal, the ultimate goal achieved. This shows that neuro fuzzy technique is capable of extracting FECG by cancelling the MECG.

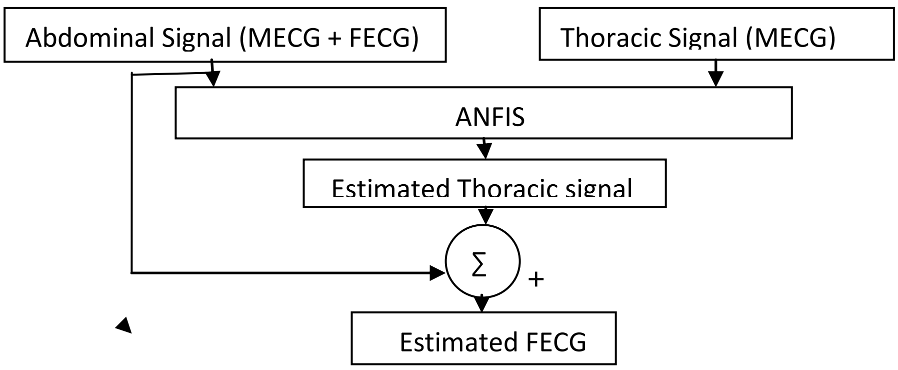

Figure 9: Flowchart for the Cancellation of MECG and the Extraction of FECG

ANFIS takes the thoracic signal as the reference signal and abdominal signal as the desired signal and tries to estimate the MECG present in the abd1 signal. Once the designated epoch is reached or the goal is reached, it stops training and gives the estimated thoracic signal. Then FECG is extracted by simply subtracting the estimated thoracic signal from the abdominal signal. In this project, Matlab version 7.6 was used for the software implementation. Since there was no any idea of what the initial Membership Function parameters (MFs) would look like, one can use the command called genfis1 which will examine the training data set and generate a single-output Sugeno-type Fuzzy Inference System (FIS) that can be used as the starting point for the training of the Adaptive Neuro Fuzzy Inference System (ANFIS).

Fuzzy model with 2 inputs and one output generated by this command is shown in Figure 10 below, where Thr3 and delayed thr3 represent the inputs to the fuzzy model.
Each input contains 5 MFs. Infismat represents the system name and has 25 fuzzy rules. Estimated MECG represents the system output. Since we are using the Sugeno type, defuzzification is not required at the output.

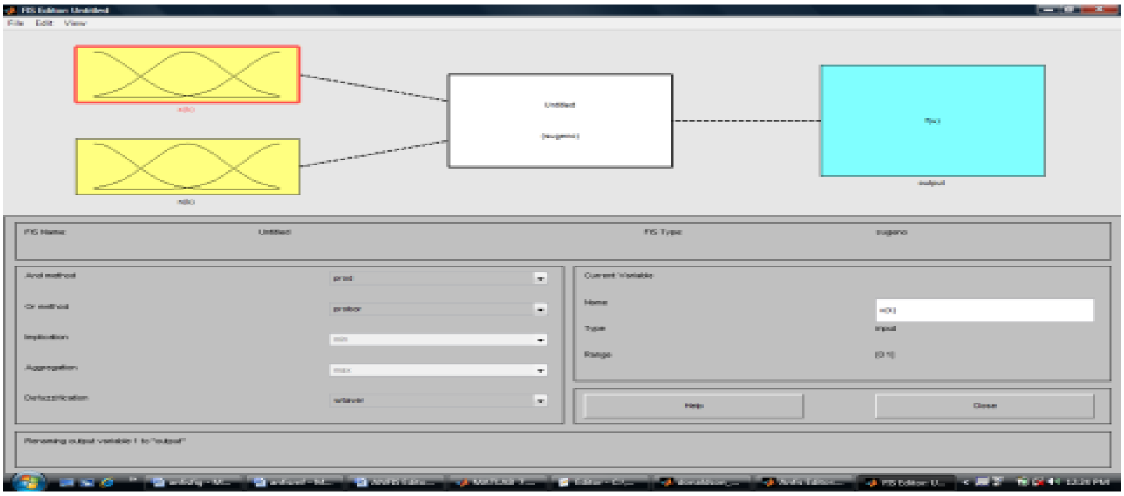

Figure 10 Fuzzy Model Generated by GENFIS in FIS Editor Interface

After generating the fuzzy model, ANFIS requires number of epochs, training pair, and number of MFs for training. The function used for training is anfis. In our analysis, we applied the generalized bell shape (gbellmf) Membership Function (MF) in the training of the ANFIS. The structure of ANFIS used in the extraction of FECG is shown in Figure 11 below. Two nodes are present under input layer and represent the inputs. Fuzzification is done by layer 1 (inputmf) which allocates 5 MF's to each input. Totally 25 rules are used and are usually found in layer 2. Normalization layer (layer 3) is not included in this architecture.
While layer 4 is the defuzzification layer (outputmf). Layer 5 performs summation operation.

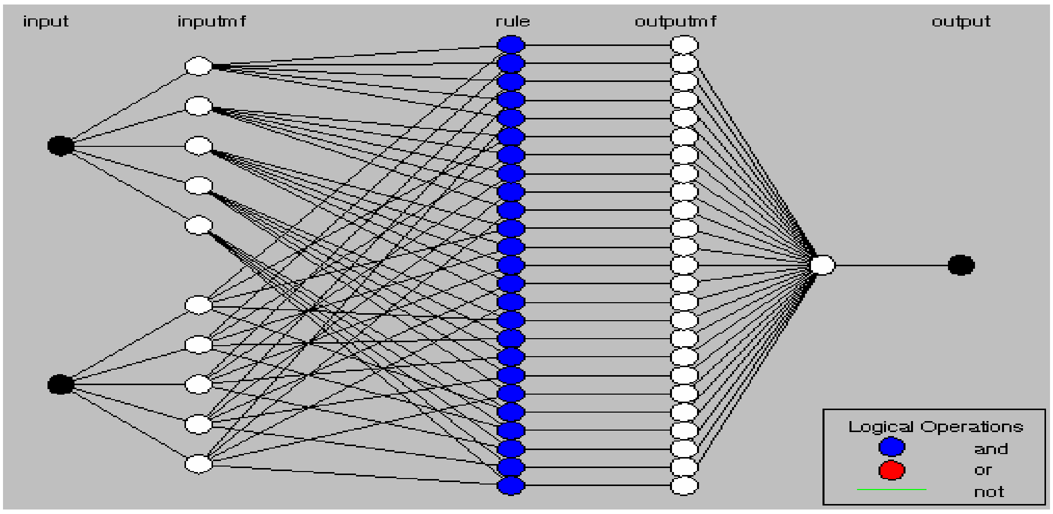

Figure 11 ANFIS Structure.

5. CONCLUSION

Adaptive Neuro Fuzzy Inference System (ANFIS) was the proposed technique for the extraction of Fetal Electrocardiogram (FECG) signals from composite abdominal ECG recordings. The advantage of this technique over other methods is that it requires only one abdominal signal and one thoracic signal. But the other methods require many signals to validate their results. Compared to other methods, ANFIS is well suitable for non linear applications. Mathematical analysis is very less in this method because of the qualitative aspect of the artificial intelligence. Since this technique uses neural network it requires fewer inputs to extract the FECG signal. Convergence time is less compared to methods using neural network alone due to the hybrid rule used in the ANFIS technique. ANFIS can separate the FECG without dividing the signals into different frames. After removing the major interference (MECG) from the FECG, it is easier to cancel the high frequency noise using digital filters. Since the morphology of the extracted FECG using this technique remains same, it can be used by the medical doctors and/or physicians to diagnose.

6. RECOMMENDATIONS

Following the results attained, although the morphology of the FECG beat recovered is fairly same as that of the original, a closer observation of the FECG beat recovered, still shows some traces of the MECG beat. Since the spectrum of the MECG present in the overall result do not substantially overlap with the FECG beat, we therefore recommend that common frequency domain filtering techniques be used along side with the ANFIS in order to completely remove every trace of the MECG from the overall result.

REFERENCES

Al-Zaben A. et al. (2006). Extraction of Foetal ECG by Combination of Singular Value Decomposition and Neuro Fuzzy Inference System, Phys. Med. Biol., 51:137-143.

Assaleh K. et al. (2005). A Novel Technique for the Extraction of Fetal ECG Using Polynomial Networks, IEEE Trans. Biomed. Eng., 52: 1148-1152.

Assaleh K. (2007). Extraction of Fetal Electrocardiogram Using Adaptive Neuro-Fuzzy Inference Systems, IEEE Trans. Biomed. Eng., 54: 59-68.

Azad K. (2000). Fetal QRS Complex Detection from Abdominal ECG: A Fuzzy Approach, Proceeding Symposium, (NSPS00), Kolmarden, Sweden, pp: 275-278.

Camps G. et al (2001). Fetal ECG Extraction Using an FIR Neural Network, Computer Society Press, Rotterdam, Netherlands, pp: 249-252.

Camps-Valls G. et al. (2004). Foetal ECG Recovery Using Dynamic Neural Networks, Artif. Intell. Med., 31: 197-209.

Horner S. et al. (1995). A Robust Real Time Algorithm for Enhancing Non-Invasive Foetal Electrocardiogram, Digital Signal Proc., 5: 184-194.

Ibahimy M. et al. (2003). Real Time Signal Processing For Fetal Heart Rate Monitoring, IEEE Med Biol. Eng. Comput., 50: 258-261.

Jang J. (1993). ANFIS: Adaptive –Network- Based Fuzzy Inference Systems, IEEE Trans. Syst. Man Cybern, 23: 665-683.

Jang J. et al (1995). The Fuzzy Logic Toolbox For Use With MATLAB, The Mathworks Inc, USA.

Jang S. et al. (1997). Neuro-Fuzzy and Soft Computing, Prentice – Hall, USA.