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Extraction Of Fetal ECG From Maternal ECG

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Abstract— Recording and observing fetal electrocardiogram assumes an important task in the therapeutic field. The fetus ' electrocardiogram signal, i.e. FECG displays clear data that helps specialists and physicians to determine the appropriate and planned pregnancy choice. FECG is isolated from composite signals of the stomach using innovative techniques and assumes critical work in fetal monitoring. The FECG signal in pregnant women can be determined from the mid-region of the body. The ECG of the pregnent lady itself is recorded from the mid-section of the body and known as maternal ECG (MECG). The extraction of the fetal ECG from the maternal ECG is one of the the greatest test with the help of signal acquisition and processing. The algorithm uses the method of Artificial Neural-Based Fuzzy Inference System(ANFIS) and a database is implemented for FECG extraction on MATLAB. Therefore, the FECG signal obtained is a noise-free signal.

Keywords—Fetal ECG, Maternal ECG, Abdominal ECG, Finite Impulse Response(FIR) Algorithm, ANFIS

1 INTRODUCTION

A portion of the medical records show that a large portion of abnormal or disturbed condition in the fetus' condition is brought about by the

pressure and uneasiness of the maternal. Cardiac abnormalities may occur due to inherited disease, genetic syndrome, or environmental factors such as pregnancy infections or misuse of drugs In certain cases, due to the fetal distress, a meconium aspiration syndrome occurs where the fetus forcefully gasps the amniotic liquid and breathes it into the lungs. If the baby inhales the amniotic liquid it poses a great threat to even fatal to the newly born child. The outcome of this sort of weight is discharged in the pregnancy time of the maternal. . Other researchers have raised questions about whether these findings may be due to contamination after sample collection and that meconium is, in fact, sterile until after birth. Further researchers have hypothesized that there may be bacteria in the womb, but these are a normal part of pregnancy and could have an important role in shaping the developing immune system and are not harmful to the baby. Hence, exactness in the fetal rate helps in determining the current fetal condition during the pregnancy of a woman.

Fetal ECG monitoring is providing all the vital information necessary for the assessment of the fetal wellbeing.Invasive and non-invasive procedures are performed to obtain the fetal ECG signal. Considering the risks of invasive measurement like womb break, indoor womb disease, and fetal protection risk, the trend of fetal ECG monitoring is in non-invasive methods of data acquisition. It is still in infancy to use soft computing methods in signal processing of the fECG signal. So far, a few soft computing-based fECG extraction concepts have been added. These include ADALINE and Adaptive neuro-fuzzy interference (ANFIS) device equipped to manage particle swarms.[9].

II. ADAPTIVE NEURO FUZZY INTERFERENCE SYSTEM

The rationale for implementing these new methods in the last three decades was a rapid development of processor technology. ANFIS is a Sugeno-type Fuzzy Interference System (FIS) hybrid adaptive network implemented in the ANN feedforward framework. To evaluate the relationship between input and output data set, it uses neuro-adaptive learning algorithm. [9]. This learning algorithm can be propagated hybridly and backwards. There are many benefits to using ANFIS in pattern learning compared to linear models and neural networks. Such strengths are due to the fact that in studying nonlinearities ANFIS combines the capacities of both neural networks and fuzzy systems. Fuzzy techniques incorporate information sources into a fuzzy rule base that represents network structure knowledge so that structure is learned.

To order for the program to function properly, a few basic features must be maintained:

- ANFIS single production.
- FIS must be a zero or first-order Sugeno model.
- The number of rules is the number of membership features.
- The membership function of the output is constant or linear.

ANFIS Architecture: In the algorithm, we have used first-order Sugeno fuzzy model as the structure. The first layer is running the process of fuzzification. All nodes are adaptive nodes in this layer. Second layer nodes multiply the performance of previous layer optimization signals. In the third layer, the normalized layer labelled N contains a function to calculate normalized firing strength. The fourth layer, all nodes in this layer are adaptive. Last and fixed layer calculates total output of the system. In order to model complex nonlinear systems, ANFIS uses MFs to divide each input dimension into many local regions. The output space is filled by overlapping MFs, which means that a single input can activate multiple local regions simultaneously. Typically used as MFs are Bell-shaped with a maximum of 1 and a minimum of 0. To represent the ANFIS architecture, two-fuzzy Rules are considered based on a first-order Sugeno model,

Rule 1: if (x is A1) and (y is B1), then (f2=p1x+q1y+r1).

Rule 2: if (x is A2) and (y is B2), then (f2=p2x+q2y+r2). [9].

FECG elimination using ANFIS: ANFIS inputs are (1) abdominal signal (MECG+FECG) acting as the reference signal (2) direct fetal ECG signal (fECG) acting as the target signal. ANFIS uses the method of hybrid learning to calculate linear, non-linear parameters. The ANFIS output is the approximate estimated fetal ECG signal from the abdominal signal. The ANFIS transforms the fuzzy inference engine into an adaptive network that learns the input-output relationship. FECG extraction using ANFIS was successful. Generalized bell shape (gbellmf) MF is used in the proposed methods for ANFIS learning. It is necessary to select a suitable number of membership functions to boost convergence speed of the ANFIS Algorithm.

The ANFIS transforms the fuzzy inference engine into an adaptive network that learns the input-output relationship. Error between required and projected direct fECG provides us with the estimated fECG signal. For the development of ANFIS, we use three MATLAB functions:

1) genfis1 to create the initial Sugeno FIS structure.
2) anfis to start ANFIS learning process. There is a possibility to change learning algorithm or number of epochs,
3) evalfis to evaluate output of the system for given input.

The number of membership functions varied between 2 and 9 and the number of epochs between 10 and 30 (after hundreds of epochs). We evaluated the efficiency of ANFIS filtration for four specific membership types, namely triangular, trapezoidal, bell-shaped and gaussian membership features.

III. Materials And Methodology

Continuous signal processing of the abdominal ECG i.e. (mECG + fECG) and the direct fetal ECG signal may seem to be a promising technique for the fetal monitoring due to its technical feasibility. At the centre of this signal processing challenge, there is a need for an adaptive system to be adopted that allows extracting the desirable fECG component from the abdominal ECG signals without cancelling the maternal ECG during the process. This can be done by using the neural fuzzy network system i.e. the ANFIS (Adaptive Neuro-Fuzzy Interference System. The distinctive strides of the proposed calculation are quickly portrayed underneath :

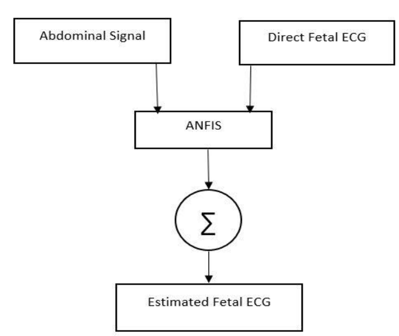

Fig. Algorithm Implementation

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IV. Algorithm

The proposed extraction technique in this proposal is used by MATLAB code which incorporate four general strides as depicted in the flowchart of the proposed calculation demonstrated beneath in Figure 1.3. The flowchart clearly explains how the ANFIS training is carried on in determining the estimated fetal ECG from the given abdominal ECG and the
direct fetal ECG.

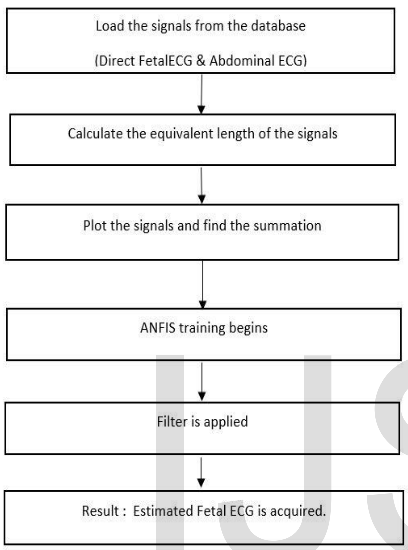

Fig. Flowchart for extraction of Fetal ECG

Firstly, the signal was acquired from the Physionet database which comprises of both the fetal ECG, the Maternal ECG i.e. the Abdominal ECG. A standard Direct Fetal ECG is also taken for comparison. The signals were pre-processed by filtering and normalization to eliminate fair amount of noise and baseline wander and the equivalent length of the signals are also calculated.

Secondly, the abdominal ECG signals are loaded and set up for the ANFIS training and testing. On the other hand, the Direct ECG are loaded as well for the ANFIS training.

Lastly, the ANFIS training and testing begins in three stages; the genfis, the anfis and the evalfis where the membership function and the epoch has been declared. Thus, after the training is over the acquired estimated fetal ECG is plotted and the error is also calculated.

Thus, training of the abdominal ECG for the required fetal extraction has been accomplished.

Significant Parameters :

The ECG signal parameters used for the experiment is described as follows:

Direct FECG Signal : Sampling frequency: 250 Hz, Sampling interval: 0.004, Base : 3000; which is constant for all the ECG signals. Also, there has been an alteration in the length of the FECG signal which has been done in MATLAB for making its size equivalent to the size of the other signals.

AbdECG Signal : Sampling frequency: 250 Hz, Sampling interval: 0.004, Base : 3000; which is constant for all the ECG signals.

Sampling frequency: 250 Hz, Sampling interval: 0.004, Base : 3000; which is constant for all the ECG signals.

V. Results & Discussions

The Maternal ECG generated, as shown in the figures below and the Fetal ECG along with the noises is combined to make it as the mixture of maternal and fetal ECG. When this mixture signal is passed through the LMS filter, the abdominal ECG is then acquired. After this, the maternal ECG is then cancelled. With the weights added to the filter the FECG signal is not destroyed. Hence the fetal ECG is separated from the MECG. The following are the output acquired after the ANFIS training has been performed on various datasets.

Sample 1:

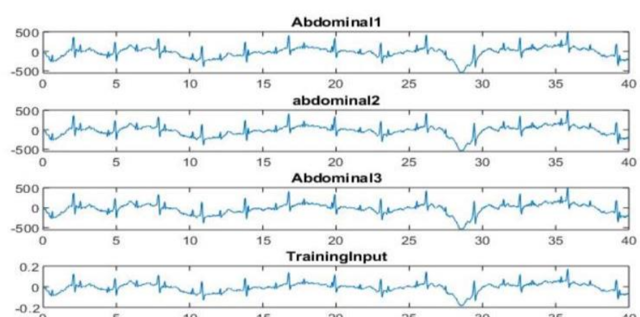

Fig. Abdominal ECG acquired from the dataset

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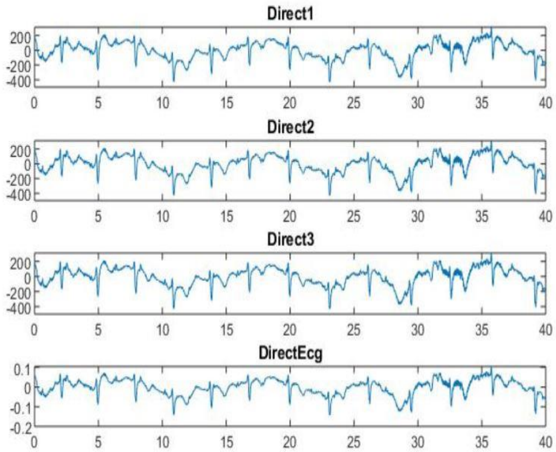

Fig. Direct Fetal ECg acquired from the dataset

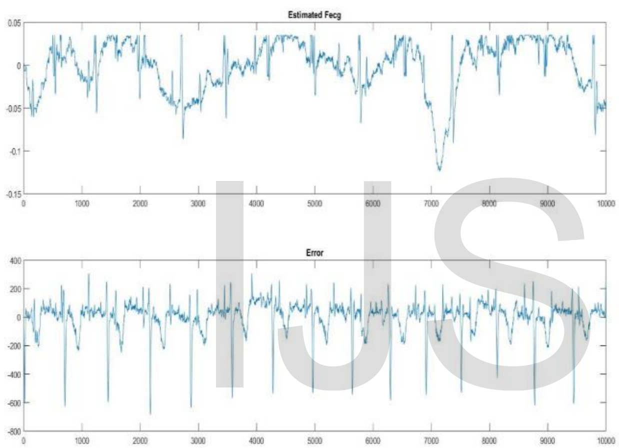

Fig. Acquired Fetal ECG along with errors

Sample 2:

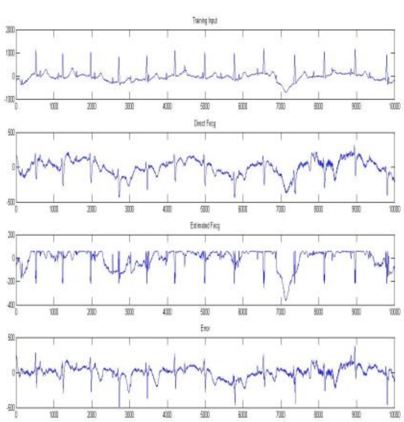

Fig. Estimated Fetal ECG with the acquired error

Analysis were also made where the signals were passed through a simple lowpass filter as well as without a filter. During this process, the mean and the percentage error were calculated. The results have been analysed in the table I and II below. The signal information has been obtained from the Physionet data.

TABLE 1.
ANALYSIS OF SIGNAL USING A FILTER

SAMPLE	EPOCH	MEMBER FUNCTION	MEAN	PERCENTAGE ERROR(%)
1.	500	3	1.194E-13	1.194E-11
2.	500	3	-1.174E-07	-1.174E-05
3.	500	3	-1.53E-07	-1.53E-05
4.	500	3	-2.131E-07	-2.131E-05
5.	500	3	-9.0E-10	-9.0E-08
6.	500	3	-1.33E-06	-1.33E-04
7.	500	3	5.03E-06	5.03E-04
8.	500	3	5.03E-07	5.03E-05

TABLE 2.
ANALYSIS OF SIGNAL WITHOUT THE FILTER

SAMPLE	EPOCH	MEMBER FUNCTION	MEAN	PERCENTAGE ERROR(%)
1.	500	2	7.678E-09	7.678E-07
2.	500	2	-4.053E-11	-4.053E-09
3.	1500	2	5.470E-12	5.470E-10
4.	1500	2	2.821E-08	2.821E-06
5.	200	2	2.85E-09	2.85E-07
6.	200	3	3.2E-08	3.2E-06
7.	800	3	1.45E-07	1.45E-05
8.	900	3	4.63E-11	4.63E-09

TABLE 3.
SIGNAL INFORMATION

SAMPLES	SIGNAL GAIN	BASE	UNITS
DIRECT 1	9.9998741211	-1	Uv1
ABDOMINAL 1	9.9998741211	-1	UV3
ABDOMINAL 2	9.9998741211	-1	UV4
ABDOMINAL 3	9.9998741211	-1	UV5
ABDOMINAL 4	9.9998741211	-1	UV6

VI. CONCLUSION

In comparison between the simple FIR filter and the least mean square (LMS) algorithm, according to our study we have come to the conclusion that the LMS gives better extraction of fetal ECG signal from Maternal ECG signal. Precise and accurate results are observed where the diagnosing of diseases by the specialists will not be a problem. The simple FIR filter does not help much for this kind of extraction since it is a basic simple filter and it wears off only the noise present and cannot be used for extraction purpose. Other filters like ANFIS filters can also be implemented in the fetal extraction and comparison studies can be made amongst the filters used to show which filter does the job well.

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