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## FETAL ELECTROCARDIOGRAM EXTRACTION USING BFOA-BASED ADAPTIVE FILTER

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### ABSTRACT

*In this paper, a new bacterial foraging optimization algorithm (BFOA)-based adaptive filter is proposed for the extraction of fetal electrocardiogram (ECG) signal. A noninvasive two-point method is used to record thoracic and abdominal ECG signals from the mother's body. The abdominal ECG (AECG) signal consists of fetal heart signal, the distorted maternal heart signal and noise. The thoracic signal contains the undistorted maternal heart signal. The two signals are applied to an adaptive filter whose coefficients are optimally determined by the conventional least means square (LMS) algorithm and BFOA. Simulation results using both synthetic signals and real data from Physionet shows the superiority of the new approach over conventional methods.*

### INTRODUCTION

Many health-related problems that occur during a human's lifespan (particularly in the first few months of life) can be reduced if related signs and symptoms are noticed during pregnancy. Since heart rate is one of the most important physiological indicators of health, accurately determining the heart rate of a fetus is an important task. One important low-cost non-invasive method for deriving the heart rate is by recording and processing the electrocardiogram (ECG). Electrocardiogram (ECG) is a popular diagnostic method for various heart diseases or electrical heart activities. Fetal ECG (FECG) signal reflects the electrical activity of the fetus heart and provides valuable information of its physiological state (Jeweski et al 2012, Ferrara & Widrow 1982).

Non-invasive FECG has been used to obtain valuable clinical information about the fetal heart

condition during pregnancy by using skin electrodes placed on the maternal chest and abdomen (Ferrara & Widrow 1982). The abdominal leads pick up a composite signal, consisting of the contributions from maternal electrocardiogram (MECG) and the fetal electrocardiogram (FECG) while the chest leads contains maternal ECG (MECG) only. However, abdominal ECG (AECG) is always corrupted with power line interference, maternal ECG (MECG), electromyogram (EMG), baseline wandering, skin impedance etc (Ferrara & Widrow 1982, Khawaja 2007). The method is illustrated in Fig. 1. Two leads, one in the maternal region and the other in abdominal region of a pregnant woman were used; the mapped maternal ECG is subtracted from the abdominal ECG signal (AECG) and the result would be a noisy fetal ECG signal. These signals are denoted as  $x(n)$  and  $A(n)$  to correspond to the maternal and abdominal ECG signals respectively. Embedded in  $A(n)$  are three signals; one is a deformed version of the maternal ECG

signal, i.e.  $\hat{x}(n)$ , another is the fetal ECG  $s(n)$ . The

third is additive noise from other sources. The abdominal signal is described in the equation (1).

$$A(n) = \hat{s}(n) + \hat{x}(n) \tag{1}$$

$$\hat{x}(n) = T(x(n)) \tag{2}$$

$$\hat{s}(n) = s(n) + \gamma(n) \tag{3}$$

where the deformation of the maternal ECG component is due to the fact that the signal is measured far away from its source (the mother’s heart), and consequently it

encounters some nonlinear transformation as it travels to the abdominal area as shown in Fig 1.

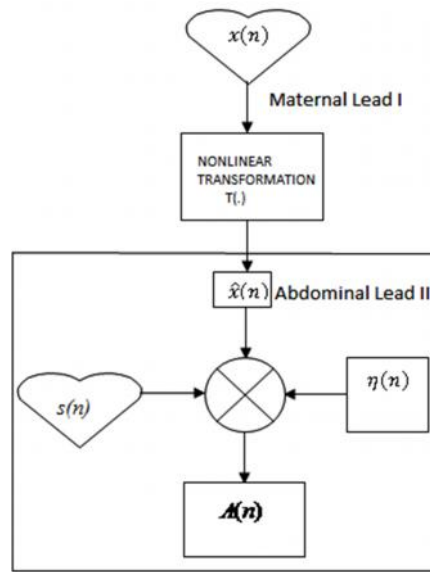


Fig. 1 Fetal ECG Monitoring

Research is ongoing on methods of extracting FEEG from AECG. The most dominant unwanted signal in the AECG is the MEEG which has been removed by various researchers using adaptive filters (Ferrara & Widrow 1982, Khawaja 2007) and wavelet transform (Nagel (1984), Karvounis et al 2004), Wu et al 2013) among other methods (Kholdi et al 2007), Karvounis et al (2007).

In this paper, another approach to the use of adaptive filter in the extraction of FEEG is presented. This is a modification of the procedure proposed by Ferrara and Widrow (1982). Bacterial Foraging Optimization algorithm (BFOA) (Passino (2002)) is used to find the best set of filter coefficients.

### THE PROPOSED EXTRACTION ALGORITHM

The structure of the proposed algorithm is shown in Fig. 2. The abdominal lead data and the chest lead data are fed into the algorithm as shown.

The diagram illustrates the two methods used in this paper, viz. the BFOA and the conventional least means squares (LMS) method. Each of two algorithms is used to select the best set of filter coefficients.

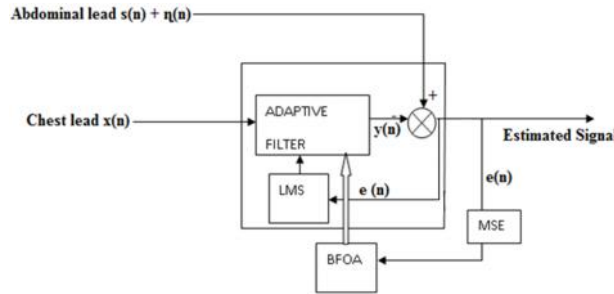


Fig. 2 Block diagram of LMS/BFOA-based adaptive filter

### The Adaptive Filter

The configuration of the adaptive filter, operating in the discrete-time domain  $n$  is shown in Fig. 3.

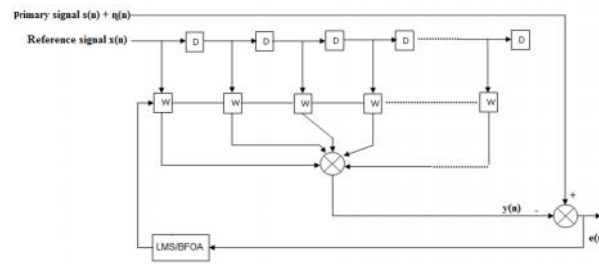


Fig. 3 Adaptive filter structure

From Fig 3 the primary signal is  $s(n)$ , the primary noise is  $y(n)$  and this noise is uncorrelated with  $s(n)$ . The reference signal is  $x(n)$  which is  $e(n) = s(n) + y(n) - y(n)$

uncorrelated with  $s(n)$  but strongly correlated with  $y(n)$ . The output error  $e(n)$  is given by

$$(4)$$

The error signal is used by the adaptation algorithm to update the adaptive filter coefficient vector  $W(n)$  according to some performance criterion. The whole adaptation process is aimed at minimizing some metric error signal, forcing the adaptive filter output

signal to approximate the reference signal (Widrow & Sterns 1985, Lee & Lee 2005, Douglas 1999).

The mean square error (MSE) is a metric indicator of how well a system can adapt to a given solution. A small minimum MSE is an indication that the adaptive system has accurately modeled, predicted,

adapted or converged to a solution for the system. A very large MSE usually indicates that the adaptive filter cannot accurately model the given system or the initial

state of the adaptive filter is an inadequate starting point to cause the adaptive filter to converge (Widrow & Sterns 1985, Lee & Lee 2005, Douglas 1999).

The mean square error is defined or given by

$$v(n) = E[e^2(n)] = E[|s(n) + y(n) - y(n)|^2] \tag{5}$$

Where E denotes expectation operation

In noise canceling systems a practical objective is to produce a system output  $e(n) = s(n) + y(n) - y(n)$  that is best fit, in the

least squares sense of signal  $s(n)$ . The mean square of error is of interest and can be obtained as follows

$$e^2(n) = s^2(n) + (y(n) - y(n))^2 + 2s(n)(y(n) - y(n)) \tag{6}$$

Taking expectation of both sides

$$E[e^2(n)] = E[s^2(n)] + E[(y(n) - y(n))^2] + 2E[s(n)(y(n) - y(n))] \tag{7}$$

Since  $s(n)$  is uncorrelated with both  $y(n)$  and  $y(n)$ ,

$$E[e^2(n)] = E[s^2(n)] + E[(y(n) - y(n))^2] \tag{8}$$

Adapting the filter minimizes the mean square of error. This has no effect on the input signal  $s(n)$ .

$$\min E[e^2(n)] = E[s^2(n)] + \min E[(y(n) - y(n))^2] \tag{9}$$

Minimizing the mean square error, causes the filter output  $y(n)$  to be a best least square match to  $x(n)$ .

Equation (4) can be rewritten as

$$(e(n) - s(n))^2 = (y(n) - y(n))^2 \tag{10}$$

Minimizing the mean square error of equation (10)

$$\min E[(e(n) - s(n))^2] = \min E[(y(n) - y(n))^2] \tag{11}$$

Minimizing the mean square of error causes  $e(n)$  to be a best least squares match to the primary signal  $s(n)$ .

requiring any prior knowledge of the signal and noise statistics.

This result is obtained by the adaptive process without

**Least Mean Square Algorithm**

The LMS algorithm is popular because of its simplicity, robustness, ease of implementation, low From Fig 3

$$y(n) = W(n)x(n) \tag{12}$$

$$y(n) = \sum_{i=0}^M w(n)x(n-i) \tag{13}$$

where

$$y(n) = [x(n), x(n-1), x(n-2) \dots \dots x(n-(N-1))] \tag{14}$$

$$W(n) = [w_0(n), w_1(n), \dots \dots w_{N-1}(n)] \tag{15}$$

The estimate for ideal cost or error function is

$$w(n+1) = W(n) - \sim e(n)x(n) \tag{16}$$

where

$$e(n) = s(n) + y(n) - y(n) \tag{17}$$

$\sim > 0$  is called the step-size,  $w(n+1)$  represents the new coefficient values for the next time interval,  $x(n)$  is the filter (reference) input signal,  $y(n)$  represent the filtered output,  $s(n)$  is the desired response and  $e(n)$  is the error function. The convergence of  $W$  to the optimum solution and the convergence speed depend on the value of step-size parameter  $\sim$ .

**BFO Extraction Algorithm**

Bacteria Foraging is an evolutionary algorithm which estimates cost function after each iterative step of the program as the program execution proceeds and leads to progressively better fitness (less cost function).

computational complexity, stability and unbiased convergence (Lee & Lee (2005)).

The parameters to be optimized represent coordinates (position) of the bacteria.

After each progressive step the bacteria move to new positions (new coordinate values) and at each position cost function is calculated and then, with this calculated value of cost function, further movement of bacteria is decided by decreasing direction of cost function. This finally leads the bacteria to a position (set of optimization parameters) with highest fitness.

The foraging strategy of E Coli bacteria are governed by four processes. These are chemotaxis, swarming, reproduction and elimination and dispersal. Chemotaxis is achieved by swimming and tumbling. When the bacterium meets favorable environment (rich in nutrients and noxious free), it continues swimming in the

same direction. Decrease in cost function represents favorable environment, while increase in cost function represents unfavorable environment. When it meets unfavorable environment it tumbles (changes direction). In swarming, the bacteria move out from their respective places in ring of cells by bringing mean square error to the minimal value.

$w_1(n), w_2(n), w_3(n), \dots, w_{N-1}(n)$  are the parameters to be optimized. They represent axis of

$$f^{i,j+1,k,l}(W(n)) = f^{i,j,k,l}W(n) + C(i) \frac{del(i)}{\sqrt{del^T(i)del(i)}} \tag{18}$$

where  $W(n) = [w_0(n), w_1(n), \dots, w_{N-1}(n)]$  (19)

## SIMULATION, RESULTS AND DISCUSSION

### Generation of Synthetic Signals

The various shapes of ECG signals were generated using MATLAB function `ecg`. Specifically,

$$[M1, T1] = ecg(fs, h1, p1) \tag{20}$$

Where  $fs$  is the sampling frequency. The sampling frequency was carefully pegged at 4000Hz in order to have almost accurate display of the waveform.  $h1$  is the maternal heart rate which is normally 89 bpm and  $p1$  is the maternal ECG peak amplitude which is always at 3.5 millivolts. To generate fetal ECG waveform, similar MATLAB model and sampling frequency were used but at different heart rate and peak amplitude. The fetal

$$M2 = filter(b / 30, 1, M1) \tag{21}$$

space coordinates. Now let  $f^{i,j,k,l}(W(n))$  represent position of  $i^{th}$  bacterium at a point in  $W(n)$  coordinate system, in  $j^{th}$  Chemotaxis,  $k^{th}$  reproduction and  $l^{th}$  elimination and dispersal step.  $C(i)$  Represents unit run-length of a bacterium,  $del(i)$  is ten elements direction vector. Each element of  $del(i)$  is a random number lying between  $[-1, 1]$ . Then movement of  $i^{th}$  bacterium in  $j^{th}$  chemotaxis step can be represented by following equation

maternal ECG, fetal ECG, abdominal ECG and cumulative noise signals were generated. The maternal ECG signal was generated using the following function

heart has peak amplitude of 0.25 millivolt and heart beats noticeably faster than that of the mother's ranging between 120 to 160 bpm. The abdominal ECG signal was generated through the addition of deformed maternal ECG signal which propagates from the mother's chest cavity to the abdomen. This propagation path is described as a linear FIR filter with 10 randomized coefficients. The MATLAB model for the propagation path is

where  $b$  is the 10 randomized coefficients and  $M1$  is the original maternal ECG signal. Also added to form abdominal ECG is fetal ECG signal and some noises (i.e

$$PL = p * \sin(2 * \pi * f * t) \tag{22}$$

where  $p$  is the noise power, and  $f$  the power line frequency which is normally 50Hz. The white Gaussian noise was generated using

$$N = p * randn \tag{23}$$

Finally, the abdominal ECG signal was generated using equation (24)

$$A1 = F1 + PL + N + N2 \tag{24}$$

Fig. 4 through Fig. 6 show the plot of Maternal, Fetal and abdominal ECG signals respectively.

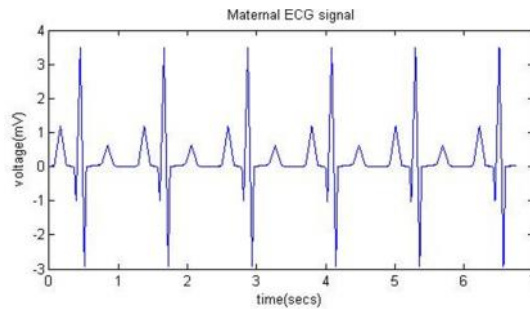


Fig. 4 Maternal ECG signal

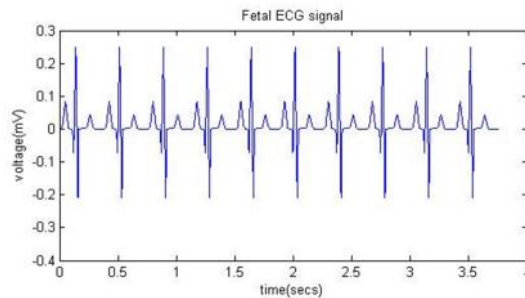


Fig. 5 Fetal ECG signal

**Simulation Using Synthetic Signals**

Figure 7 to Figure 11 show the extracted fetal ECG signal waveform. In each case, (a) is the output of error signal without BF optimization while (b) with BF optimization at different fetal heart rate (i.e between 120-160 bpm). The figures show that before the application

$$Hr = (rv * 60) / t \tag{25}$$

where  $rv$  is the r - r interval and  $t$  is the time interval.

of BFO algorithm, the first P-wave is missing or not clearly defined but after the application of BFO algorithm the P-wave is recovered with all other waves and R-R interval clearly seen. Also the expected different fetal heart rates were equally recovered. The fetal heart rates were obtained using equation (25).

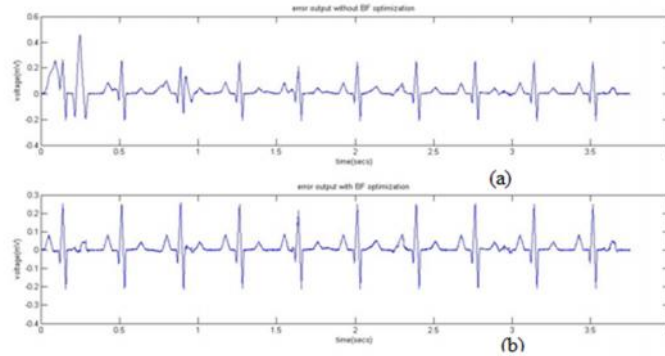


Fig. 6 Fetal ECG waveform at 160bpm heart rate

Table I shows the results of magnitude of Mean Square Error (MSE) and Signal to Noise Ratio (SNR) obtained at different fetal heart rate (i.e 120-160 bpm).

$$SNR = 10 \log_{10} \left( \frac{P_s}{P_n} \right) \tag{26}$$

where  $P_s$  is the signal power, in this case the power of fetal ECG signal  $s(n)$  which was obtained using  $ps = \text{var}(F1)$  and  $Pn$  is the noise power which  $Nt = \hat{x}(n) + y(n)$

The signal to noise ratio (SNR) is calculated using equation (26)

represents the power of both deformed maternal ECG and white Gaussian noise. It was obtained using  $Pn = \text{var}(Nt)$  where

$$\tag{27}$$



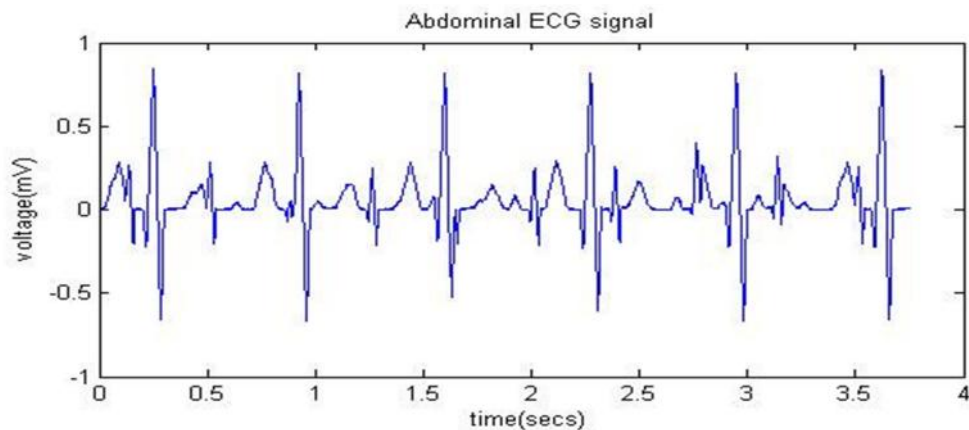


Fig. 7 Abdominal ECG signal

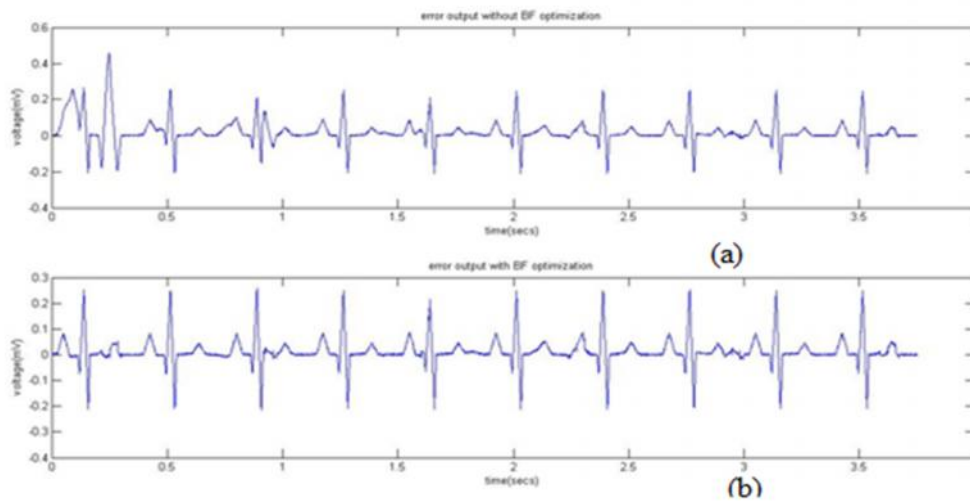


Fig. 8 fetal ECG waveform at 160bpm heart rate

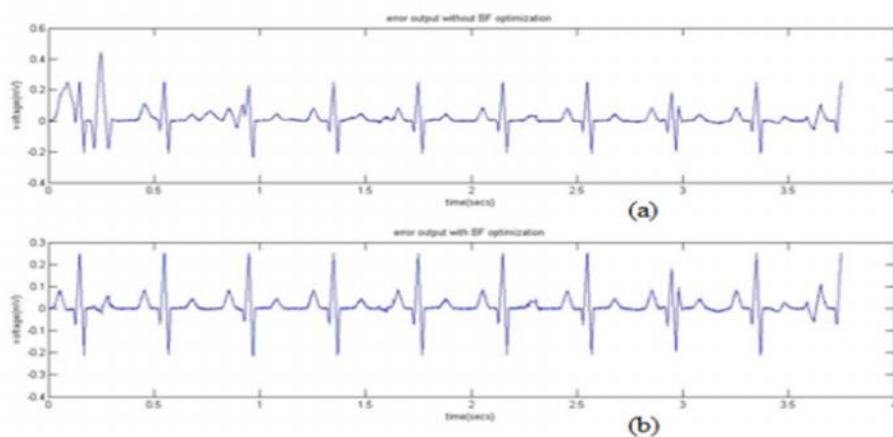


Fig. 9 Fetal ECG waveform at 150bpm heart rate

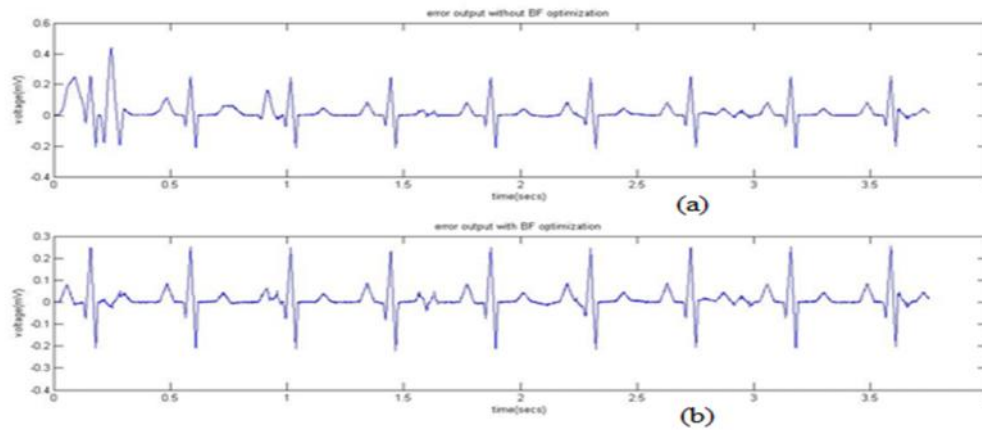


Fig. 10 Fetal ECG waveform at 140bpm heart rate

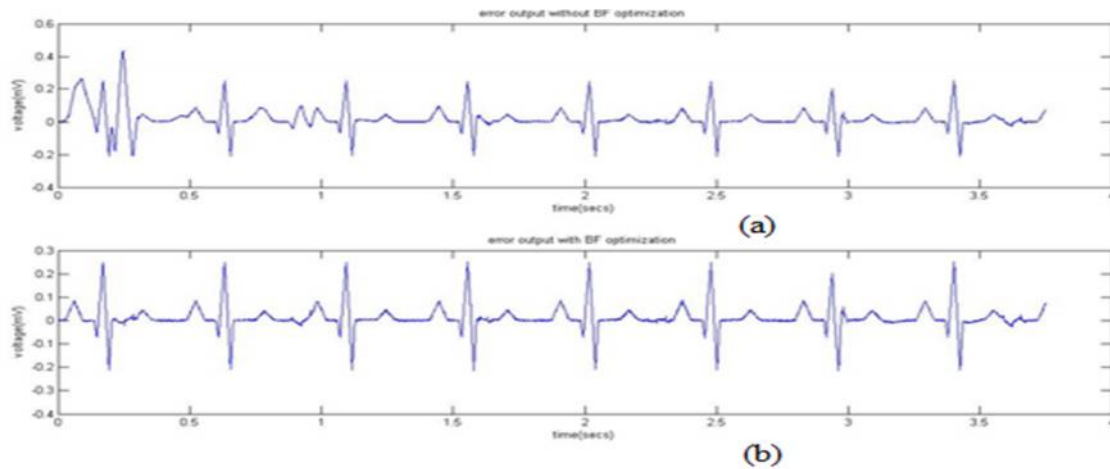


Fig. 11 Fetal ECG waveform at 130bpm heart rate

**Table I:** Signal to Noise Ratio (SNR) and Mean Square Error (MSE) Values at different heart rates

Heart Rate (bpm)	SNR (dB)	MSE
160	4.7481	0.0045
150	4.8051	0.0045
140	4.8730	0.0045
130	4.8933	0.0045
120	5.0083	0.0045

The result shows that, the SNR is better at 120 bpm. But the values of mean square error (MSE) remain the same with change in fetal heart rate. The obtained mean square error values show that system has been

accurately modeled, predicted, adapted and converged to a solution for the system.

### ***Analysis Using Real ECG Signal***

A real abdominal ECG signal was obtained from the physionet database developed by MIT-BIH and was used to validate the effectiveness of the proposed algorithm. Simulation was carried out in MATLAB environment. The obtained signal has a sampling frequency of 5000Hz.

The BFOA-based algorithm was used to extract the fetal ECG signal from signal obtained from MIT-BIH database and the SNR of the signal was calculated using equation (26). Fig. 12 shows the obtained abdominal ECG signal from MIT-BIH database, Fig. 12 the estimated maternal signal and Fig. 13 the extracted fetal ECG signal using the proposed algorithm with R-R intervals clearly seen.

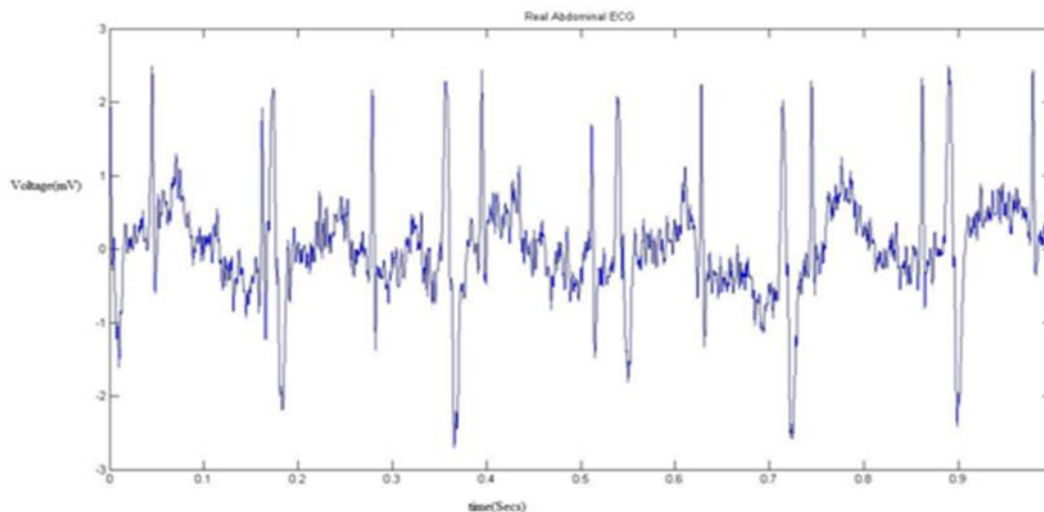


Fig. 12 Abdominal ECG signal from MIT-BIH database (r01.edf)

### ***Comparison with Existing Methods***

The results obtained using BFOA-based extraction method was compared with selected existing methods and the result is summarized in Table II.

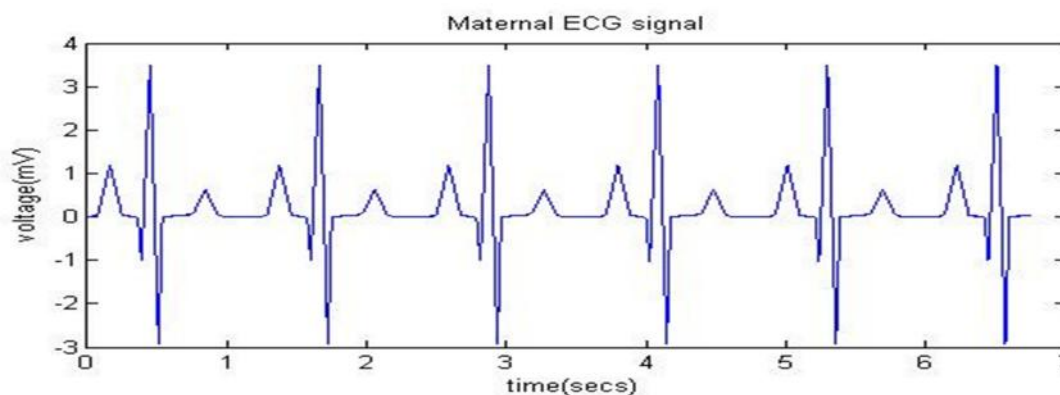


Fig. 13 Estimated Maternal ECG signal

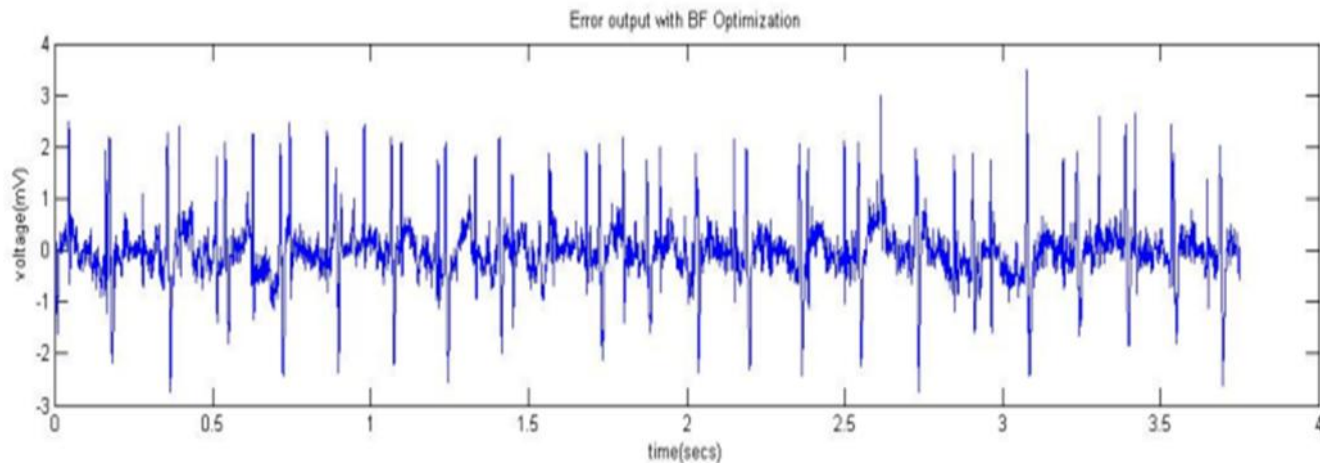


Fig. 14 Extracted Fetal ECG Signal using BFOA

**Table 2:** Performance comparison

Extraction Algorithms	Extracted Components						
	Heart Rate(bpm)	P-wave	QRS Complex	R-R Interval	T-wave	SNR(db)	R-peak
Wavelet Transform (Bokher and Gawande (2013))	454 Not Extracted	Not clearly Recovered	Recovered	Recovered	Recovered	-2.457	0.09mV Not normal
Wiener Method (Kommareddy (2013))	154 Extracted	Not clearly Recovered	Recovered	Recovered	Not clearly Recovered	-10.9838	1.7mV Not normal
ICA (Kushwaha (2013))	159 Extracted	Not fully Recovered	Recovered	Recovered	Not fully Recovered	-3.1313	4.0mV Not normal
SVD (Kommareddy (2013))	154 Extracted	Not clearly Recovered	Not Recovered	Not Recovered	Not clearly Recovered	-12.7980	No uniform Extraction Level
BFOA	160 Extracted	Recovered	Recovered	Recovered	Recovered	4.7481	0.25mV Normal level

## CONCLUSION

The BFOA-based adaptive filter was applied in the extraction of fetal ECG from composite abdominal ECG signal from both the real abdominal ECG signal as obtained from MIT-BIH database and synthetic abdominal ECG signal generated using some MATLAB and mathematical models. The procedure was performed on both the signals and the result shows very impressive performance. Comparison with existing methods reveals the superiority of the proposed approach.

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