"Towards Intelligent Fetal ECG Signal Extraction and Abnormal Heart Rate Detection from Maternal Signals"

Mohammed Saifuddin Munna

[1] Assistant Professor, Department of EEE, Premier University, Chittagong, Bangladesh

ABSTRACT

In monitoring fetal health, accurately assessing the fetal heart rate is crucial. However, extracting clear fetal ECG signals from the maternal abdomen, where electrodes are typically placed, presents challenges due to interference from maternal ECG signals and noise. This paper presents a straightforward method to overcome this challenge and obtain high-quality fetal ECG signals. The proposed method utilizes an LMS adaptive filter to effectively extract fetal ECG signals, resulting in accurate estimation of the fetal heart rate with minimal error. By setting appropriate threshold values and detecting R-R peaks, the fetal heart rate can be reliably determined, enabling the classification of abnormalities. The Pan & Tompkins algorithm is employed to detect QRS complexes, further refining the accuracy of the heart rate calculation. Through this approach, the fetal heart rate can be promptly assessed, allowing for immediate identification of both regular and irregular heart rhythms. This method offers a practical solution for real-time fetal monitoring, facilitating timely intervention when abnormalities are detected.

Keyword: - *Least mean square adaptive filter (LMS); R-R peaks; Pan & Tompkins algorithm; QRS complex.*

1. INTRODUCTION

In pediatric treatment, one of the difficulties in determining the fetal heart rate. It is critical for observing the condition and well-being of a fetus, as it can help diagnose arrhythmias or other problems in this manner. Fetal heart rate calculation and control are most commonly used at or near the onset of labor. One of the most important data that this gives is whether the infant obtains adequate oxygen. A Doppler ultrasound is widely used during childbirth to monitor the fetal heart rhythm. As the name suggests, this approach uses ultrasound waves expressed by the fetal heart rate, changing the wave frequency. This is converted by the doppler into a tone so that the heart rhythm can be heard and reflected on a computer [1]. However, owing to restricted accessibility, this approach is not ideal for long-term tracking and is not as accurate [2].

Electrocardiograms, or ECGs, are used to record electrical activity in the heart. Signals containing maternal and fetal ECG signals can be obtained by placing electrodes on the maternal abdomen. However, there are difficulties in seeking to isolate the fetal ECG signal from a signal containing both maternal and fetal ECG signals as well as noise. The magnitude of the fetal signal QRS is much lower (order of microvolts) than the maternal signal (order of millivolts) [3]. Fetal heart rate helps doctors detect fetal cardiac arrhythmias such as sinus Bradycardia, sinus Tachycardia, Atrial flutter, Ventricular flutter [4]. Chronic fetal arrhythmia may also influence heart failure development and may be related to other neurological injuries [5].

2. LITERATURE REVIEW

Current approaches to fetal ECG (FECG) extraction are categorized based on methodology into linear, non-linear, and adaptive filtering techniques [6]. These methodologies encompass a range of methods such as adaptive filtering, blind source separation, wavelet analysis, adaptive neural networks, neuro-fuzzy inference schemes, independent component analysis (ICA), and support vector machines (SVM) [7]. One common approach involves using cross-correlation features to obtain the fetal ECG signal [8]. Maternal ECG interference is addressed by extracting the

mean maternal ECG waveform and generating a maternal ECG prototype signal [8]. Wavelet transform is then employed for denoising purposes, akin to Fourier analysis but with wavelets decomposing the signal into "wavelets" for internal product comparison [9]. Wavelet-based methods further refine FECG observation, employing multi-resolution analysis (MRA) with Daubechies4 wavelets up to the 12th level to reduce baseline fluctuations and noise [10]. Genetic algorithms are utilized for separating pure maternal ECG from abdominal signals, aiding in FECG extraction [8]. Additional techniques include Pan-Tompkins analysis, employing various filters, amplification strategies, and signal search algorithms [11]. The primary goal of these methods is to isolate fetal pulse signals with minimal error, remove noise using MATLAB, and detect fetal heart rhythm. Depending on the heart rate, abnormalities such as Bradycardia, Tachycardia, Atrial flutter, Ventricular flutter, Asphyxia, and Hypoxia can be identified [12]. This model serves as a screening tool to aid physicians in early prediction of multiple fetal abnormalities.
The main objective is to overcome the limitations mentioned above to isolate the fetal pulse signal with a deficient percent error to remove noise by using MATLAB, detect the fetal heart rhythm, and, depending on heart rate, identify Bradycardia, Tachycardia, Atrial flutter, Ventricular flutter, Asphyxia and Hypoxia abnormality in the fetus. This model can be used as a screening technique to help doctors to predict multiple abnormalities early.

3. METHODOLOGY

The methodology is shown in Figure 1.

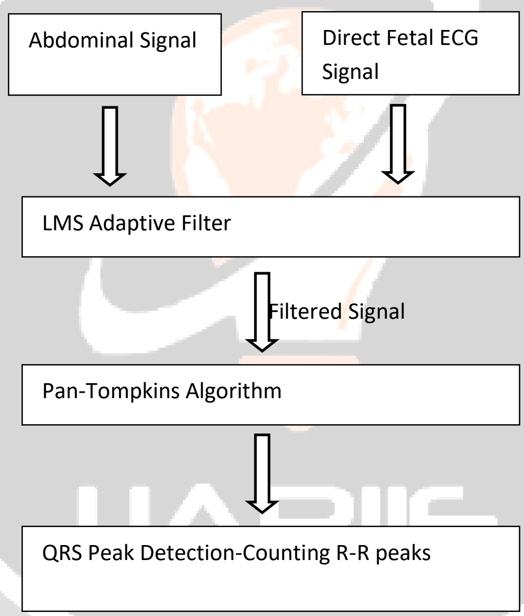

Fig-1: Block Diagram of Suggested Method

Our proposed method, seen in Fig. 1, would use an adaptive Least Mean Square (LMS) filter to extract only the fetal ECG signal, which will then be put into the Pan and Tompkins algorithm to find the QRS complexes and therefore produce the fetal heart rate signal. Each recording includes four signals taken from the maternal belly as well as the direct fetal ECG recorded from the fetal head. Four electrodes were put around the navel, and one over the pubic symphysis.
A reference electrode was placed on the left leg to ground the signal. The signal bandwidth was 1-150 Hz, with a sampling rate of 1 kHz and a resolution of 16 bits.

3.1 Dataset

The Suggested method was developed and tested with the Physio-Net database of Abdominal and Direct Fetal Electrocardiograms. The database includes fetal ECG multichannel records from 38 distinct women. Each woman was in labor and between 38 and 41 weeks of gestation when the recordings were obtained.

3.2 Least Mean Square Adaptive Filter

The fundamental idea of adaptive filtering is to reduce the fluctuation between the variable filter output and the intended signal by adjusting the variable filter (shown as w(n) in fig. 2). The block diagram for the adapter filter is shown in Fig. 2. The abdominal signal, a(n), is run through a variable filter, which modifies a(n), through the use of w(n), a weighted vector that controls the filter [11]. Next, the desired output, denoted by d(n), is compared to the output of the modified signal, denoted by f(n). What separates f(n) from d(n) is the mean-square error, or e(n). The adaptive algorithm then processes the error signal and a(n), updating the filter coefficients in an effort to further minimize the error.
The adaptive algorithm relies on the parameter μ in order to update the filter coefficients w(n). This represents the adaptive filter's step size. This is the adapter filter's step size. Due to the imperfection of the adaptive filter, the error may not converge exactly to zero, which impacts the error of steady-state and the speed of convergence (the rate at which the error signal is decreased) [12]. A modest steady-state error is correlated with a short step size. When the abdominal signal is used to determine the fetal ECG signal, the measured steps ranged from 0.40 to 0.85. From this range, the fetal heart rate step size with the lowest predicted percent error was selected [13].

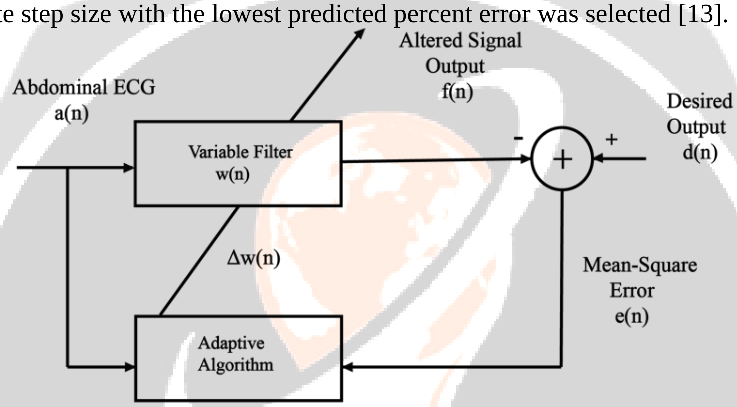

Fig 2: Least Mean Square Adaptive Filter Block diagram

To update the filter coefficients w(n), the adaptive algorithm depends on the parameter μ. This is the step size of the adaptive filter. This is the step size of the adapter filter. It affects the speed of convergence (how rapidly the error signal is minimized) and the error of steady-state (because the adaptive filter is not perfect, the error may not converge exactly to zero) [12]. A small step size corresponds to a small, steady-state error. The steps measured varied from 0.40-0.85 when the fetal ECG signal is derived from the abdominal signal. The step size of the fetal heart rate that was estimated to have the least percent error was chosen from this range [13].
Another parameter that affects the adaptive filter is the weight vector's order or length [14]. While there might be less noise if the order is increased, the magnitude of the fetal heartbeat might be more difficult to detect. Additionally, the filter takes longer to process an order the larger it is. When the order exceeded about 800, the mean error remained constant and was compared to the order to determine which order to utilize. The 1000 order was the one that was used.

3.3 QRS peak detection

The concern of QRS Complex Identification and Categorization has been severely monitored over the last three decades. Robust ECG systems face a problem in the exact identification of the QRS complex, a significant aid in monitoring ECG datasets [15]. In order to extract the fetal heart rate, the FECG signal R-peaks must be counted. The QRS complex wave shape is shown in Figure 3. There are different types of methods for detecting the R-R intervals. The Pan-Tompkins algorithm was found to be the most efficient in finding the R-R peaks.

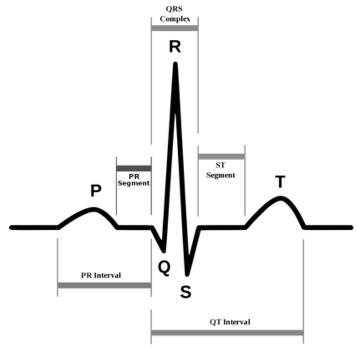

Fig-3: QRS Complex

3.4 Pan-Tompkins Algorithm

The algorithm block diagram is given below:

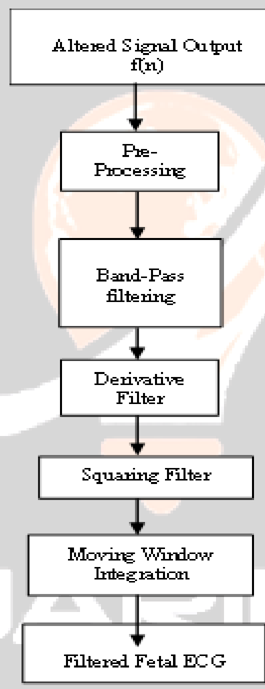

Fig-4: Pan–Tompkins Algorithm Block diagram

As shown in Figure 4. this algorithm uses the same pre-processing technique. Initially, a low pass and a high pass filter pass over the ECG signal. The bandpass filter (low pass + high pass) eliminates noise in the ECG signal by matching the average QRS complex spectrum[16].

The low pass filter is given by:
$f(n) = 2f(n-1)-f(n-2)+a(n)-2a(n-6)+a(n-12)$……………(1)

The high pass filter is described by:
$f(n) = f(n-1) - \frac{1}{32} a(n)+a(n-16)-a(n-17) + \frac{1}{32} a(n-32)$……….(2)

After filtering, the signal is differentiated by using derivative filter for slope information using the following equation:
$f(n) = \frac{1}{8} [2a(n)+a(n-1)-a(n-3)-2a(n-4)]$……………….(3)

In order to make all data points positive, the signal is then squared point by point.
$f(n) = a^2(n)$…………………….. (4)

The algorithm performs moving window integration after squaring to obtain waveform feature information.
$f(n) = \frac{1}{N}$ [a(n-(N-1))+a(n-(N-2))+………+a(n)]………..(5)

Where N is moving window size and depends on the sampling rate.

The Pan & Tompkins approach is used to find the R waves once the fetal ECG signal has been separated from the abdominal signal (fig. 3 shows the block diagram). The signal is prepared for 200 Hz of the sampling frequency by the first algorithm. Next, a bandpass filter with a frequency range of 5–15 Hz is utilized to filter out noise. The additional filtering can aid in removing any residual noise from the frequency spectrum because the adaptive filter has already filtered the signal.

Then, a derivative filter is employed. The signal will be smoothed and the signal-to-noise ratio will be increased using differentiation. It will aid in peak detection as well. To limit the influence of noise, potential signal peaks can be found by specifying the places where the signal crosses the x-axis (zero crossings) and determining whether the peak is higher than the established peak threshold. Next, the current signal is squared to get positive values, which emphasize higher frequencies more precisely.

It is critical to supply an integrator following differentiation. The Pan and Tompkins algorithm employs a moving-window integration to obtain additional waveform information. When the location of the R waves is known, the heart rate (beats per minute) can be calculated as 1000*(60)/(RR interval (milliseconds)). This process is applied to the four signals generated by the four electrodes and compared to the direct fetal ECG signal of the electrode on a fetal scalp in the calculated heart rate. The system's precision is determined by measuring the percentage error.

4. RESULTS

Fig-4, shows the Maternal ECG signal & Figs. 6, 7, 8, and 9 show an abdominal signal, the desired output, the output signal, and the same patient's error signal. The signal in the figure is shown. 7 is similar to the output shown in fig.6. Also, the low-percentage errors in the Calculation indicate the efficiency of the filtering process.

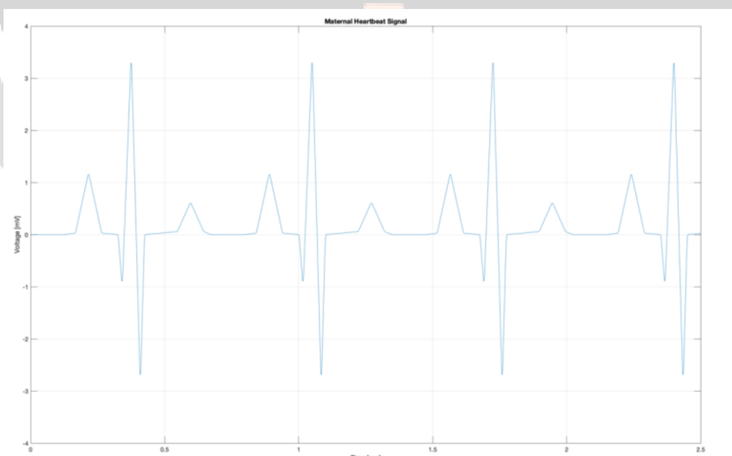

Fig-5: Maternal Heart beat signal.

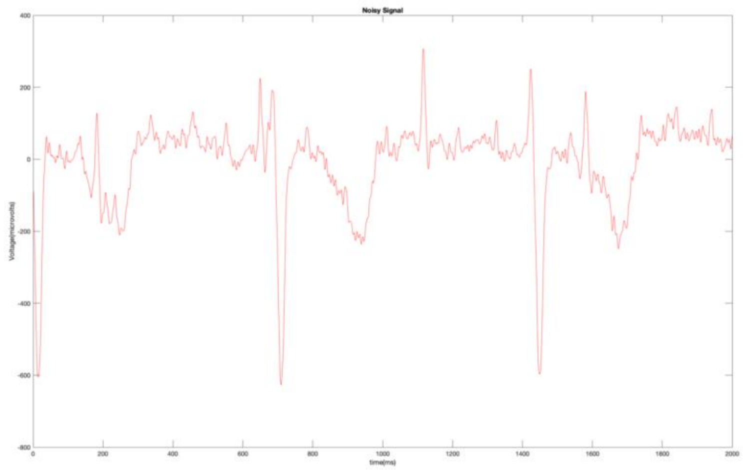

Fig-6: The abdominal signal obtained from patient 01

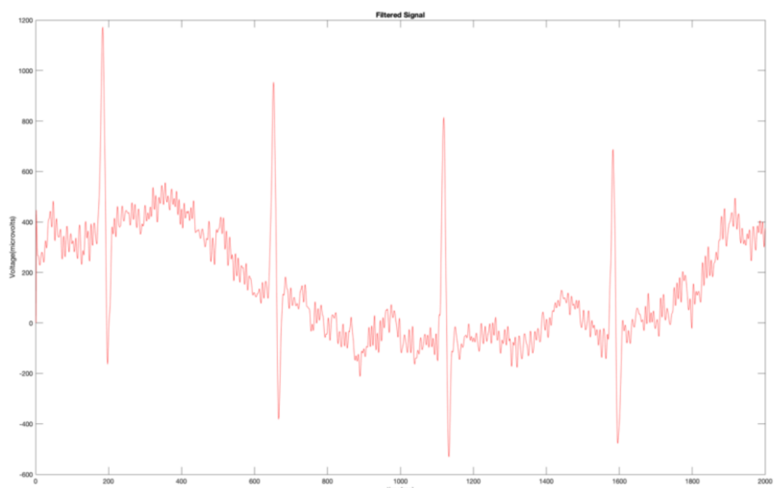

Fig-7: Signal obtained from the direct fetal scalp electrode from patient 01.

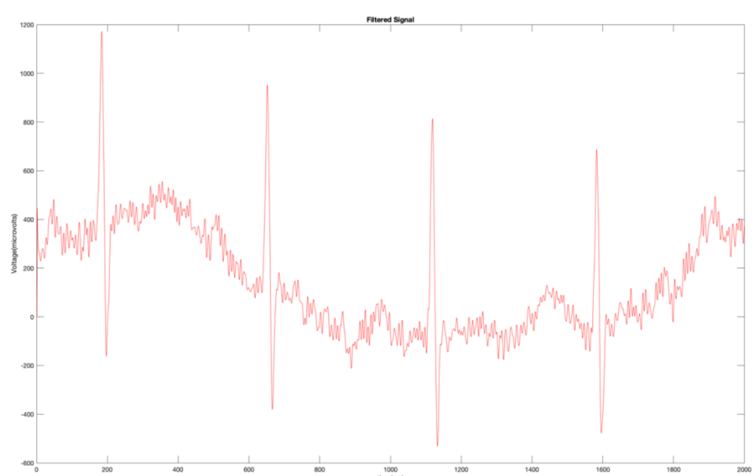

Fig-8: Output signal after applying LMS adaptive filter for patient 01.

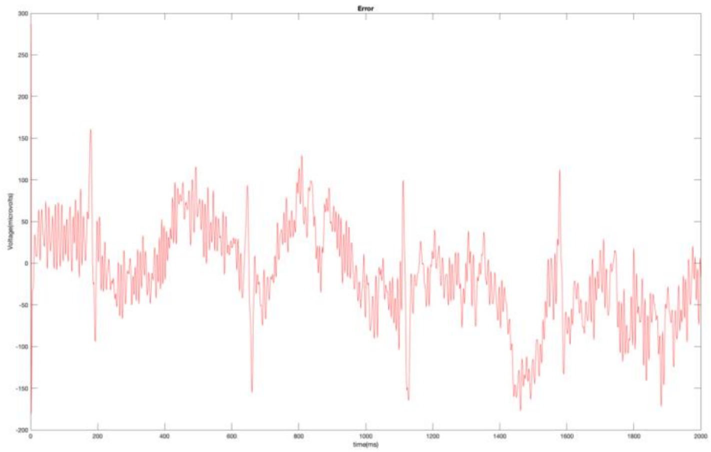

Fig-9: The signal error for patient 01

4.1 Calculation of Percentage Error (Single Abdominal Signal and Direct fetal):

Reference Heart Rate: 128.3285 (direct heart rate)
While the Step Size was 0.71
Calculated Heart Rate: 129.9264

We know that,

$$\text{Percentage Error} = \frac{\text{Calculated Heart Rate} - \text{Reference Heart Rate}}{\text{Reference Heart Rate}}$$

$$\text{So, Percentage Error} = \frac{129.9264 - 128.3285}{128.3285} = 1.245\%$$

Similarly, while the Step Size was 0.83 and Calculated Heart Rate was 128.4659
Percentage Error = 0.107%

while the Step Size was 0.43 and Calculated Heart Rate was128.9662
Percentage Error = 0.496%

while the Step Size was 0.63 and Calculated Heart Rate was 128.3011
Percentage Error = 0.021%

The heart rate computed using the direct signal, the fetal heart rate calculated using each abdominal signal, the step size of each heart rate, and the percentage inaccuracy between the calculated heart rate and the reference heart rate for a single patient are all displayed in this calculation.

The images in this study provide a detailed visual representation of the signal processing and analysis procedures involved in obtaining fetal ECG signals and detecting aberrant heart rate. Figures 10 and 12 show the usefulness of averaging data from numerous electrodes and using LMS adaptive filtering techniques on patients 01 and 04, respectively. Meanwhile, Figure 11 illustrates the direct fetal scalp electrode signal for patient 04. Moving on to section 4.2, the following figures demonstrate the use of the Pan-Tompkin algorithm. From the raw signal in Fig. 13 to the final QRS detection in Fig. 20, each figure depicts an important step in the signal processing pipeline. Whether filtering, differentiation, or QRS detection, these images aid in grasping the complexities of neurobiology

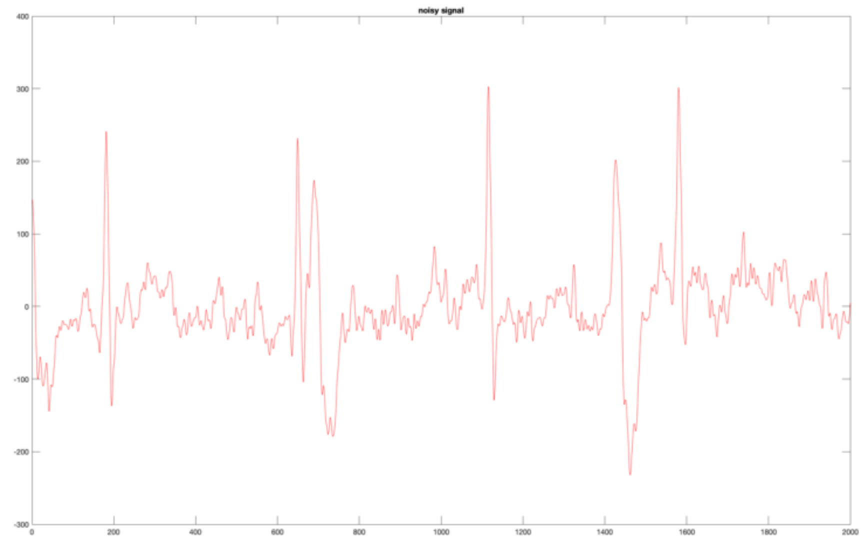

Fig- 10: Output signal after the average of 4 electrodes and applying LMS adaptive filter for patient 01

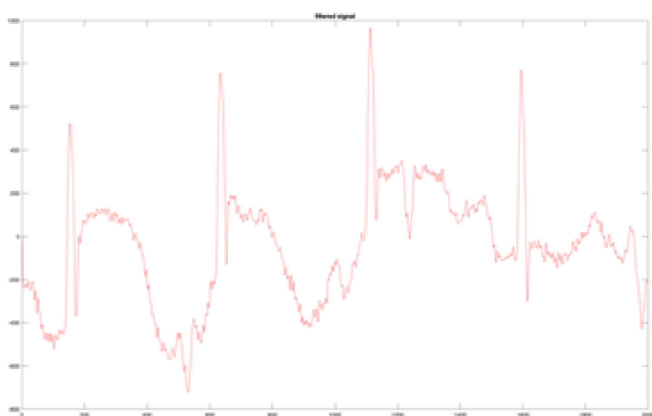

Fig-11: Signal obtained from the direct fetal scalp electrode from patient 04

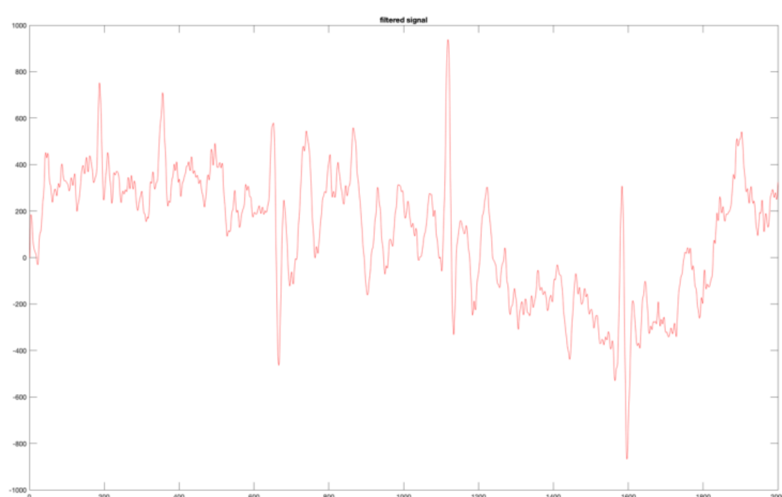

Fig-12: Output signal after the average of 4 electrodes and applying LMS adaptive filter for patient 04

4.2 Output Figures after applying Pan-Tompkin's algorithm

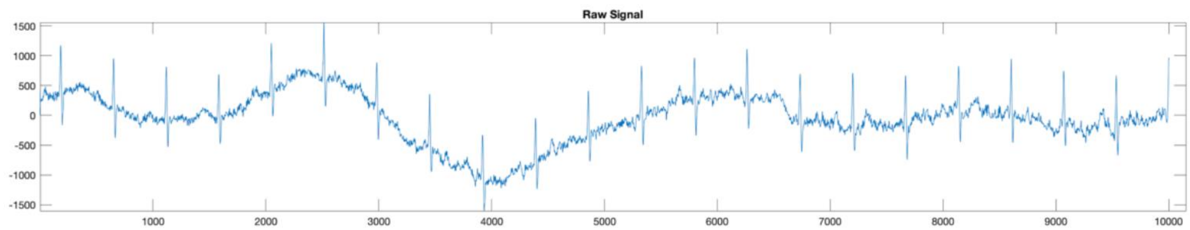

Fig-13: Raw Signal

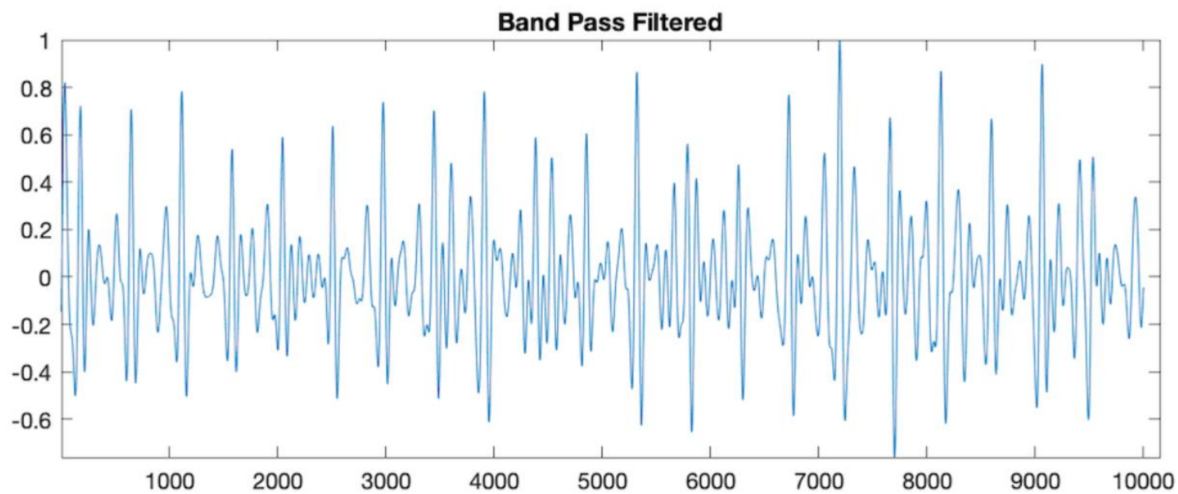

Fig-14: Band Pass Filtered Signal.

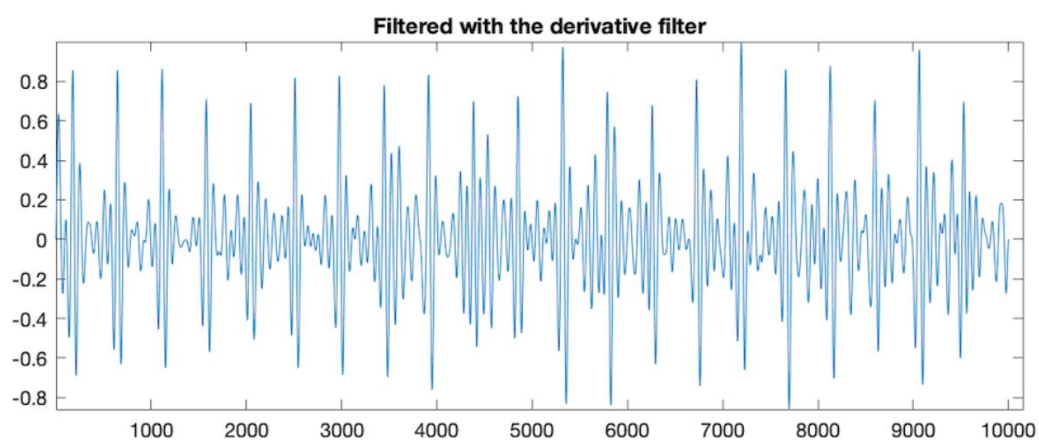

Fig-15: Signal after differentiation

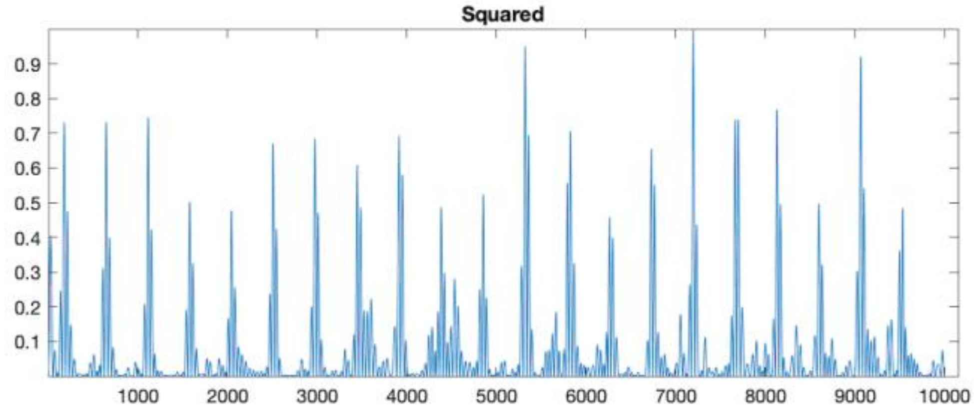

Fig-16: Squaring the signal from point to point.

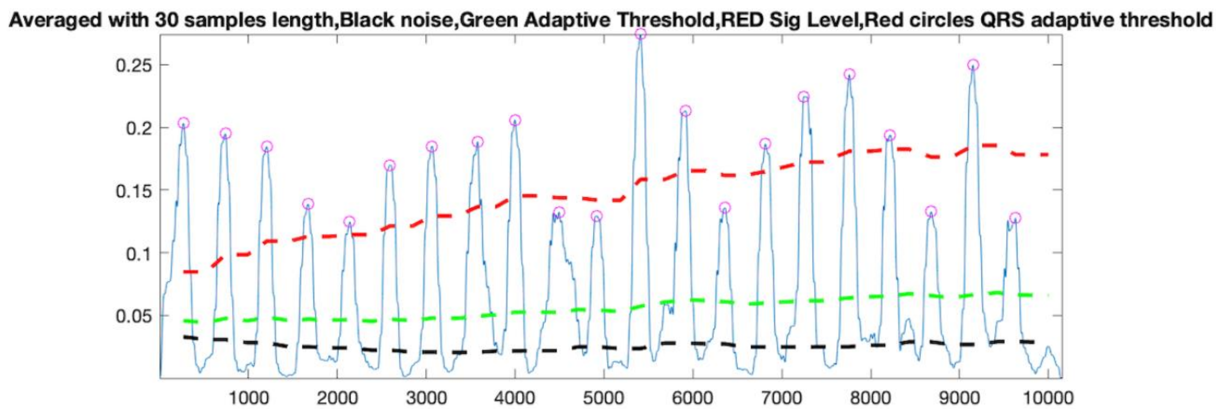

Fig-17: Averaged with 30 samples length, Black noise, Green Adaptive threshold, red signal level, red circles QRS adaptive threshold.

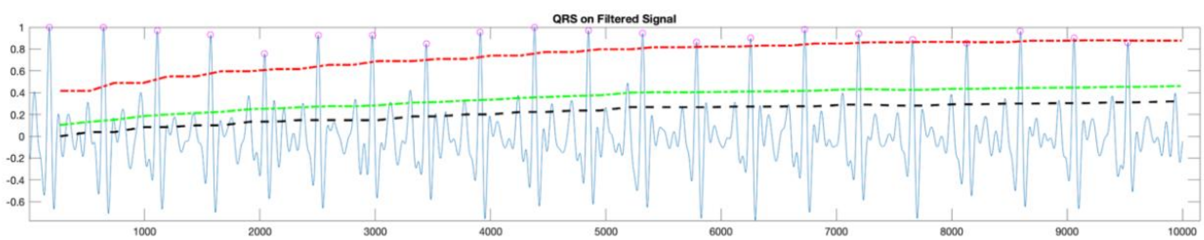

Fig-18: QRS detection on the filtered signal.

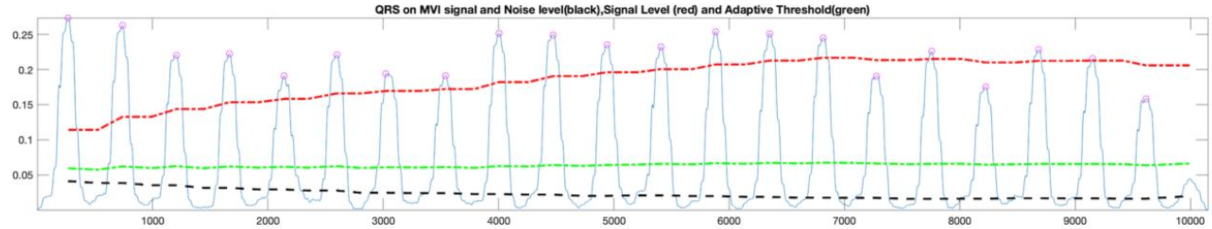

Fig-19: QRS on signal and Noise level(black), Signal level (Red), Adaptive threshold(green).

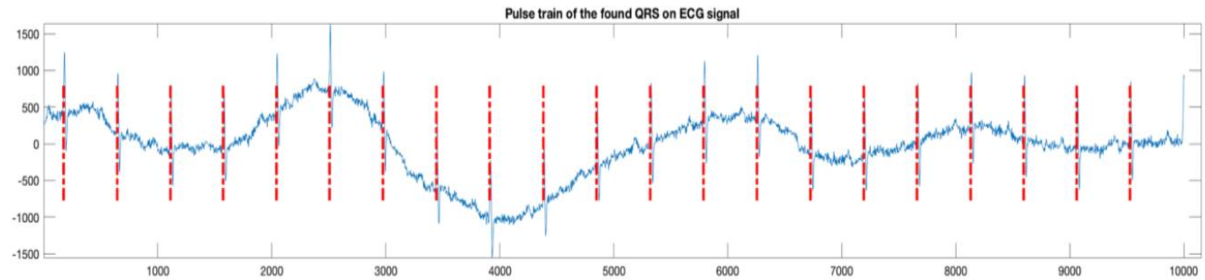

Fig-20: The final result of QRS in ECG signal.

4.2 Calculation of percentage Error (Averaged Abdominal Signal and Direct fetal):

For the patient 01:
While the Step Size was 0.43 and Calculated Heart Rate was 130.8044
Percentage Error = 1.929%

For the patient 04:
Reference Heart Rate: 123.9285 (direct heart rate)
While the Step Size was 0.43 and Calculated Heart Rate was 122.3825
Percentage Error = 1.247%

The average of four abdominal signals decreased the time required to measure the fetal heart rate. As a result, only one step size needed to be found. The estimate shows data from two patients. Overall, the percentage error was 5.71% for a patient, while the remaining four patients were under 5% error.

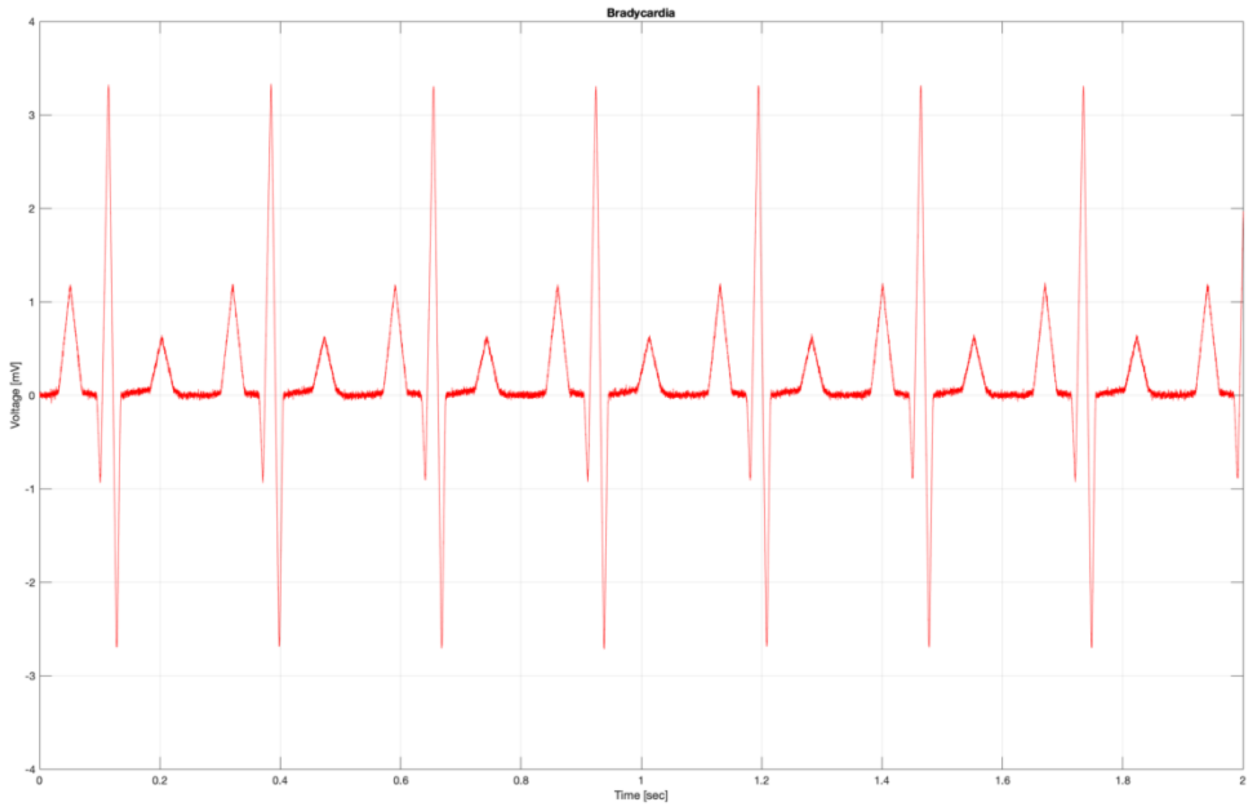

Fig-21: Fetal heart beat signal showing Bradycardia

In Figure 21 below, a fetal heart beat signal is shown. It reveals Bradycardia which is an abnormally slow heart rate in the fetus. Bradycardia in fetuses is usually described as a heart rate less than 110 beats per minute “bpm”. From the figure below, the fetal heart rate is shown to be significantly lower than normal. It may be an indicator of some problems with the well being and optimal oxygenation of a fetus. Several- minutes monitoring and possible intervention to eliminate the cause may be required to prevent adverse development.

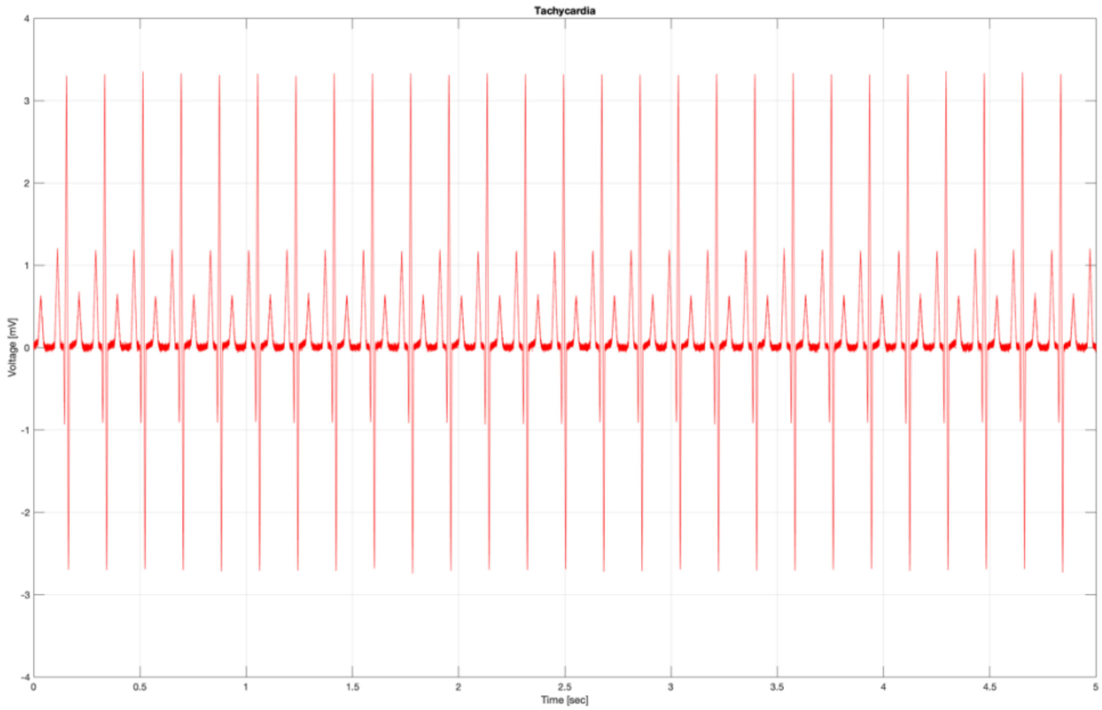

Fig-22: Fetal heart beat signal showing Tachycardia

This is a figure showing a fetal heart beat signal characterized by Tachycardia. Tachycardia refers to a situation where the fetal heart rate becomes abnormally high. A frequent definition of the conduction disease is a rate greater than 160 bpm. In Figure 22, the FHR appears to be raised implying enhanced cardiac activity. Tachycardia in fetuses is symptomatic of fetal distress, maternal pyrexia, FHR <120 themoregulation, or fetal arrhythmias. Rapid assessment and intervention are important since they can harm the fetus.

5. CONCLUSION

It has been shown that the LMS adaptive filter is efficient in determining fetal heart rate in combination with the Pan & Tompkins algorithm. Finally, measuring R-R peaks finds heart rate. Furthermore, the fetus' heart rate is used to differentiate between Bradycardia and Tachycardia groups, where Bradycardia determines fetal heart rate below 110 bpm and Tachycardia determines fetal heart rate above (160-180) bpm. This abnormality is automatically detected; we can also detect Atrial flutter (200-250) bpm, Ventricular flutter (200-210) bpm, Asphyxia, and Hypoxia easily by the heart rate. The method can automatically classify between abnormality groups and diagnosis of the thoracic aortic defect in fetuses on a real-time abdominal ECG signal and detect cardiovascular disorder early in pregnancy.

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BIOGRAPHIES

	**Mohammed Saifuddin Munna** is assistant professor at Department of Electrical and Electronic Engineering, Premier University, Bangladesh. He received the B.Sc. in electrical and electronic engineering from Premier University, Bangladesh & M.Sc. in Electrical & Electronic Engineering from Chittagong University of Engineering & Technology (CUET). Now Pursuing PhD from CUET. His research areas are Bio Medical Engineering, Machine Learning, and Renewable Energy. He can be contacted at email: munna.puc@gmail.com.