

Monitoring of Vital Signs in Fetuses and Neonates

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Abstract: The goal of this paper is to create a fetal heart rate (FHR) extraction application that can be used to analyse fetus activities in the mother's uterus. FHR can be detected using a variety of ways, including the fetal electrocardiogram (FECG), which is generated by the fetus' heart. While the fetus is inside the mother's uterus, extracting FECG signals is considered a serious issue. The Normalized Least Mean Square (NLMS) method is one of the adaptive filters used to generate FECG. The Pan Tompkins algorithm is used to track R-peaks of FECG signal cardiac pulses. After detecting the RR interval, the bpm (beats per minute) of the FECG is calculated using a formula. Because it provides a reference signal, the abdominal and direct FECG (ADFECG) database will be used to evaluate the implemented approaches. The computed FHR ranged from 125.4 to 130.3 bpm at the conclusion of the study. The inaccuracy of FHR is 0.1 percent when comparing abdominal ECG (AECG) with direct FECG (DFECG). R-peaks extraction is 100 percent accurate, as all R-peaks are detected by the techniques used. For signal simulations, MATLAB is employed. This system will be able to analyse and compute the non-invasive FECG (NIFECG) database's FHR.

Keywords: NLMS Algorithm, Pan Tompkins Algorithm, Fetal Heart rate Extraction

I. INTRODUCTION

Doppler ultrasound is now routinely utilized in clinic for FHR monitoring. Ultrasound use, on the other hand, has not been proven to be completely safe for the fetus. As a result, in addition to doppler ultrasound, there are a variety of ways to monitor the FHR. The non-invasive fetal electrocardiography (NIFECG) method, for example, involves placing electrodes on the thorax to record the maternal electrocardiography (MECG) signal and the belly to capture the abdominal electrocardiography (AECG) signal. The NIFECG recorded signals can be utilized to estimate the FHR, making it a viable alternative to Doppler ultrasound for FHR monitoring.

The AECG signal is made up of the sum of many impacts that overlap the FECG signal. The majority of the affects originate from the MECG signal. In the AECG recordings, the FECG signal is barely discernible. It is impossible to extract usable information from an AECG signal without suitable signal processing. The major feature that needs to be extracted from the AECG signal is the location of fetal R- peaks, which is needed for FHR computation. Detecting the R-peaks from the AECG, on the other hand, remains a difficult task.

As a result of these impacts, detecting the FHR in the AECG signal may be challenging, and as a result, the NIFECG placement approach cannot be employed in clinic. Extracting FECG signals while the fetus is still in the mother's uterus is a difficult task. The AECG signal is mingled with the MECG signal and ambient noise. In most cases, the FECG signal is weaker than the MECG signal. The MECG signal is normally approximately 3.5 millivolts, while the FECG signal is between 0.1-0.25 millivolts. Furthermore, a range of undesirable sounds will unavoidably influence the AECG signals. The MECG signal and the FECG signal were previously indistinguishable due to high-frequency noise. This could have an impact on the FHR calculation. Filters can be used to minimize undesired noise and boost SNR, making it easier to identify QRS complexes. The detection of fetal R-peaks is a crucial step in obtaining FHR data. However, the drawback of this strategy is that the R-peaks are defined solely by a threshold, resulting in poor anti-interference performance. The main goal of this project, as stated in the problem statement above, is to extract R peak on FECG signal for FHR computation.

II. METHODOLOGY

A. Project Implementation Flow

Figure 1 depicts the overall project implementation sequence. The project implementation path for the FHR detection system is depicted in this flowchart. The first step is to create an adaptive filter to eliminate the MECG signal from the AECG signal. The next stage is to create a Pan Tompkins algorithm for the FECG signal in order to eliminate noise and track R-peaks. Physionet's abdominal and direct FECG (ADFECG) database is used to test the functionality of the designed procedures. For further investigation, the developed methodologies are applied to the non-invasive FECG (NIFECG) database.

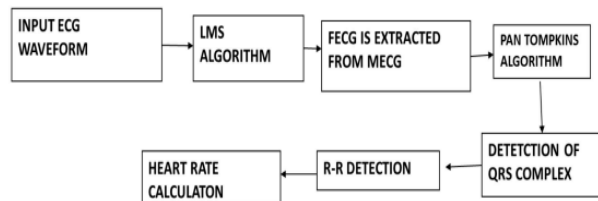


Fig 1: Flowchart of the project implementation flow on FHR detection system

B. Project Requirement

In this project, there is only one software is required which is version MATLAB R2014a. There is also required DFECG signal, AECG signals and MECG signal to develop FHR detection system. Physionet is one of the famous websites which stores many types of ECG signal. ADFECG database is chosen to do experiment on implemented techniques as the recording information contains: Signals recorded from 5 different women in labour, between 38 and 41 weeks of gestation, four signals acquired from maternal abdomen and Direct electrocardiogram recorded simultaneously from fetal head. NIFECG database is chosen for further analysis of implemented technique. The database recording contains: 2 thoracic signals, 3 or 4 abdominal signals (most records include 4) and signals are taken from a single subject between 21 to 40 weeks of pregnancy.

III. EXPERIMENT PROCEDURE

First and foremost, the input signal from the Physionet Database is processed through the ADFECG database before being applied to the NIFECG database. This is because the NIFECG database does not contain any FECG signal truth data, whereas the ADFECG database does. The recovered FECG signal from the AECG signal will be compared to the DFECG signal as a reference. The '.mat' format will be used to save all databases. The database is plotted as a voltage (µV) vs time graph (ms). In MATLAB, the sample data is transformed into a readable file. Because the sample data file contains numerous abdomen data, the mean is calculated independently for each data set. Finally, these data will be used in the subsection that follows

A. Normalised LMS Algorithm

Another sort of adaptive filtering is the NLMS algorithm, which involves modifying filter parameters (coefficients) over time to respond to changing signal characteristics. Every iteration of the LMS algorithm has a fixed step size parameter, which is suited for constant signal. The NLMS algorithm is a modification of the LMS algorithm that avoids this problem by choosing a different step size value, (n), for each iteration of the process. The current input values are used to determine the step size parameter.

The NLMS algorithm is extremely similar to the LMS algorithm since it is an extension of the LMS algorithm. These equations are required for each iteration of the NLMS algorithm. The adaptive filter's output is calculated using a formula.

$$y(n) = W^T(n) x(n)$$

Where (n) is input signal and $W^T(n)$ is transpose of weight vector.

As error signal is calculated based on formula

$$e(n) = d(n) - y(n)$$

Where (n) is desired signal and (n) is output of the adaptive filter.

The step size values for the input vector is calculated using formula

$$\mu(n) = \frac{1}{x^T(n)x(n)}$$

Where x(n) is input signal and $x^T(n)$ is transpose of input signal.

The filter tap weights are updated in preparation for the next iteration. The formula of filter tap weights is

$$w(n) = w(n-1) + \mu(n)e(n) \frac{x^*(n)}{\varepsilon + x^H(n)x(n)}$$

Where $w(n-1)$ is previous of filter tap weight vector, $\mu(n)$ is step size of filter, $e(n)$ is error signal and $x^*(n)$ is complex conjugate of input signal, ε is a constant, and $x^H(n)$ is transpose of conjugate of input signal and $x(n)$ is input signal. When process ADFECG database, the input signal, x is AECG signal and desired signal, d is direct FEGC (DFECG) signal. When the AECG signal is moved into adaptive filter, the signal is processed. Then, the output of adaptive filter, y is filtered AECG signal which also known as extracted FEGC signal. A subtraction is done between d and y signal left over residue signal named error signal. The error signal should be zero as both extracted FEGC signal and DFECG signal are same. A block diagram is shown in Figure 2 for easy understanding. Extracted FEGC signal and DFECG signal is bring forward to Pan Tompkins algorithm for removing noise and track R-peaks.

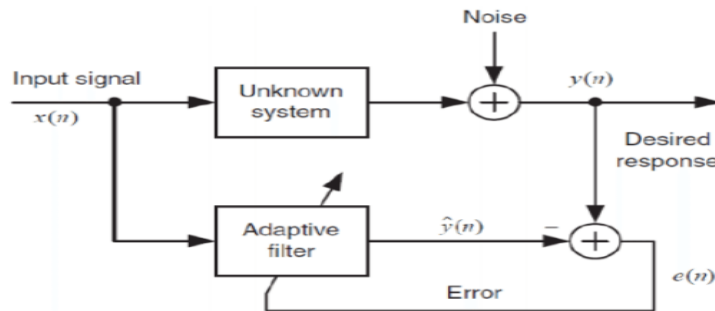


FIG 2: BLOCK DIAGRAM OF NLMS ALGORITHM

B. Pan Tompkins algorithm

Pan Tompkins algorithm is one of the methods for the detection of PQRST points and R-R peak on FEGC signal. Pan Tompkins algorithm was achieved by linear filtering, non-linear transformation, and decision rule algorithm. Pan Tompkins algorithm consists of the following steps: band pass filtering, derivative filtering, squaring function, moving window integration and adjusting the thresholds.

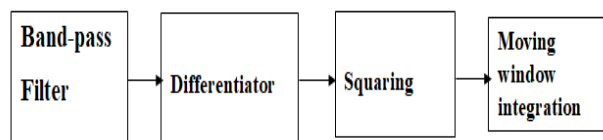


FIG 3: BLOCK DIAGRAM OF PAN TOMPKINS ALGORITHM

Band-Pass filtering

The main function of band-pass FIR with Hamming Window filter is reduce the influence of muscle noise, baseline wander, 60Hz interference and T-wave interference from the original signal. The desirable pass band to maximize the QRS energy is approximately 5-15Hz and used to increases the signal to noise (SNR) ratio of ECG signal

Derivative Filtering

A derivative filter is used to find the high slopes information in the ECG signal. QRS complex tends have a larger variation in its slope in the ECG wave. The derivative procedure suppresses the low-frequency components of P and T waves

A five points derivative is used with the transfer function:

$$H(z) = \frac{-z^{-2} - 2z^{-1} + 2z^1 + z^2}{8T}$$

The amplitude response is

$$|H(\omega T)| = \frac{\sin(2\omega T) + 2\sin(\omega T)}{4T}$$

The difference equation is

$$d(nT) = \frac{x(nT-2T) - 2x(nT-T) + 2x(nT+T) + x(nT+2T)}{8T}$$

Squaring Function

After derivative filtering, the signal is squared point by point.

The equation of this operation is

$$s(nT) = [(d(nT))]^2$$

This equation makes all data points positive and does non-linear amplification of the output amplification of the output of the derivative emphasizing the higher frequencies.

Moving Window Integration

The purpose of moving-window integration is to obtain waveform feature information in addition to the slope of the R wave. It is calculated form

$$m(nT) = \frac{s(nT-(N-1)T) + s(nT-(N-2)T) + \dots + s(nT)}{N}$$

where N is the number of samples in the width of the integration window.

The number of samples N in the moving window is important. The width of the window should be the same as the width of QRS complex. If the window is too wide, the T wave will merge the QRS complex together. In opposite, if the window is too narrow, QRS complexes will produce several peaks which can cause difficulty in subsequent QRS detection processes.

Adjusting the Thresholds

The thresholds are automatically adjusted in the ECG signal by computing running estimates of signal and noise peaks. A peak is said to be detected whenever the final output changes direction within a specified interval.

Pan Tompkins algorithm contains many steps. Each step has formula and parameter required. Since this algorithm was designed for adult, then R-peaks in MECG signal can be detected with original parameter. This algorithm can be used to detect R-peaks in FECG signal with different parameters. The FHR is in range of 110 bpm to 160 bpm and maternal heart rate (MHR) is in range of 60 bpm to 90 bpm. This means the FHR is 1.8 times of MHR. Therefore, the parameters apply on FECG signal should be about 1.8 times of MECG signal. The cutoff frequency of FECG and MECG used in bandpass filter step is 9Hz-27Hz and 5Hz-15Hz respectively. The window width of FECG and MECG signal is 80ms and 150 respectively.

FETAL HEART RATE

The value of average RR interval after Pan Tompkins algorithm will be used in this section to calculate the FHR.

The formula of FHR is:

$$FHR = \frac{(60 \text{ seconds} \times \text{sampling frequency})}{\text{Average of RR Interval}} \text{ (bpm)}$$

where sampling frequency of input source is 1kHz. The FHR will interpret into three condition which are normal condition (110-160 bpm), abnormal condition (<110 bpm) and dangerous condition (>160 bpm).

C. PROJECT REQUIREMENT

FHR Detection System," was created using MATLAB R2014a. This application is designed to calculate FHR using a non-invasive database. The main page activity is the only activity in this application. The main page's layout comprises of two buttons: "Upload AECG" and "Load." Two graphs for the original ECG data are also included in the layout: one for AECG and FECG, and another for MECG. For both FECG and MECG, there are two screens that show the heart rate. There are also many radio buttons that are used to display the many graphs that have been processed for analysis. When you tap the "Upload AECG" button, a list of AECG files will appear.

III. RESULT AND DISCUSSION

A. Sample Data from Physionet

In MATLAB, the ADFECG database is converted from a ".mat" file to a readable format. As can be seen, the FECG signal influenced various peaks in the AECG signal. The AECG signal will be utilised as the input signal and the DFECG signal will be the intended signal to verify the functionality of the implemented techniques. The NLMS algorithm works by scaling the AECG signal to match the DFECG signal.

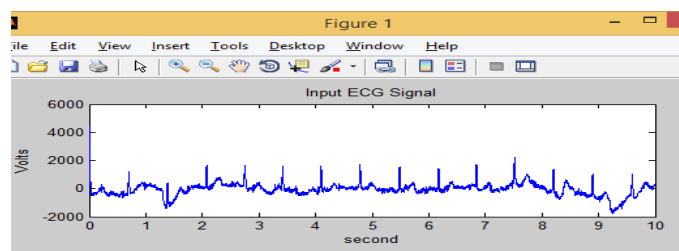


Figure 4: Input ecg signal from Physionet

B. NLMS Algorithm

The NLMS algorithm is used to process the original AECG signal. Then, using the NLMS algorithm, a subtraction between the filtered AECG signal and the DFECG signal is performed. To reduce noise and track the R-peaks, the filtered AECG and DFECG signals are sent via the Pan Tompkins algorithm.

C. Pan Tompkins Algorithm

Figure 5 shows the results of the Pan Tompkins algorithm. After being put into a bandpass filter, the undesired noises are decreased. After the derivative filtering process, the P and T waves of the filtered AECG signal are also suppressed. To show the substantial difference in QRS complexes, the signal is squared. The squared signal is smoothed down using a moving window integrator, allowing for improved tracking of R-peaks. By adjusting the threshold, the signal peaks were categorised and the noise peaks were ignored.

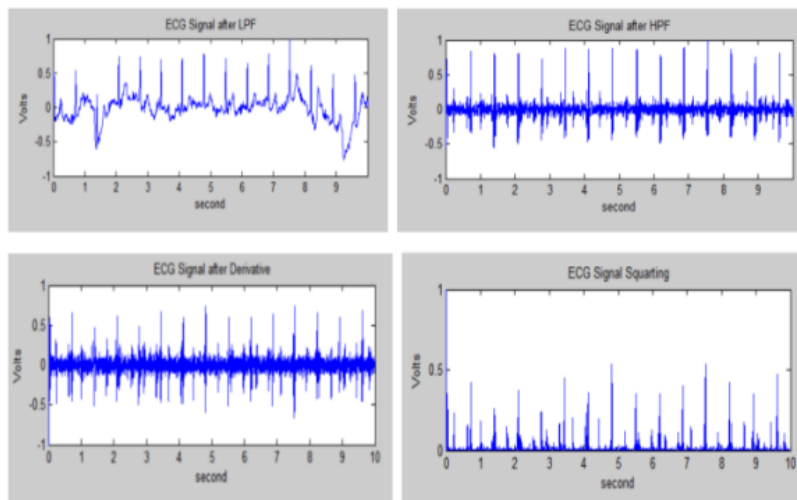


Figure 5: Result of Pan Tompkins Algorithm

D. Fetal Heart Rate

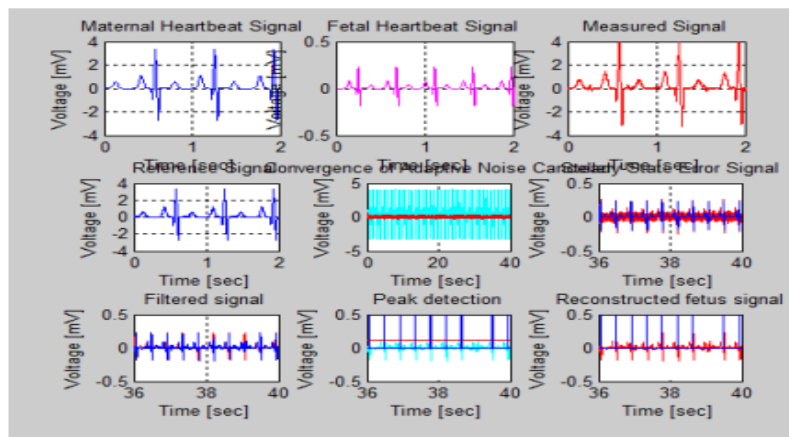


Fig 6: Fetal Heart rate

For calculation of FHR, the formula of FHR is applied to both ECG signals. The computed of FHR in filtered AECG signal is 126 bpm which are same as DFECG signal. The implemented techniques are also applied to r01, r07, r08 and r10, the FHR computed is varied from 125.4 – 130.3 bpm. The percentage error of FHR between DFECG and filtered AECG signal is 0.1%. This indicates the extraction of FECG signal in AECG signal is 99.9%.

IV CONCLUSION

Finally, the MECG signal was suppressed and the FECG signal was matched to the DFECG signal. When signals are band pass filtered, the Pan Tompkins method reduces unnecessary noise. The calculated FHR ranges from 125.4 to 130.3 beats per minute. The difference between the AECG and DFECG signals reveals a 0.1 percent FHR inaccuracy.

R-peaks extraction is 100 percent accurate, which means that all R-peaks are extracted using the technique. The software for the FHR detection system was successfully built in this project.

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