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Adaptive Rule Based Fetal QRS Complex Detection Using Hilbert Transform

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***Abstract*— In this paper we introduce an adaptive rule based QRS detection algorithm using the Hilbert transform (adHQRS) for fetal magnetocardiography processing. Hilbert transform is used to combine multiple channel measurements and the adaptive rule based decision process is used to eliminate spurious beats. The algorithm has been tested with a large number of datasets and promising results were obtained.**

I. Introduction

THE fetal heart experiences a substantial amount of growth during early stages of pregnancy. Using ultrasound, a heartbeat can be detected as early as 5-6 weeks of gestation. Detection and analysis of fetal cardiac signals are essential components of fetal health monitoring and have various applications, e.g. fetal monitoring during labor [1], identification of fetal state [2,3], monitoring of fetal arrhythmia[4], and automatic detection of fetal movement [5]. As the heart develops changes occur in the morphology and amplitude of the fetal cardiac signal (FCS). Also, electrophysiological recordings of FCS are ten-fold weaker in amplitude than maternal heart signal which makes the detection a challenging task.

Conventionally, Doppler sonography and fetal electrocardiogram (fECG) are used to observe the fetal heart. However, maternal and fetal movements decrease the sensitivity of ultrasound systems and fECG may require the repositioning of the electrodes. fECG signal strength decreases after about 27-28 weeks of gestation and cannot be captured reliably between 30 and 34 weeks because of the insulating effects caused by *vernix caseosa*. Doppler heart rate monitors can provide only average information about the heart rate, and hence it is not possible to understand the fine details such as firing of the sinus, conduction velocities, etc. from the heart rate data. With the advent of bio-magnetic recordings, using high sensitive sensors, it is possible to measure the fetal magneto-cardiogram (fMCG) successfully starting from 14 weeks of gestation.

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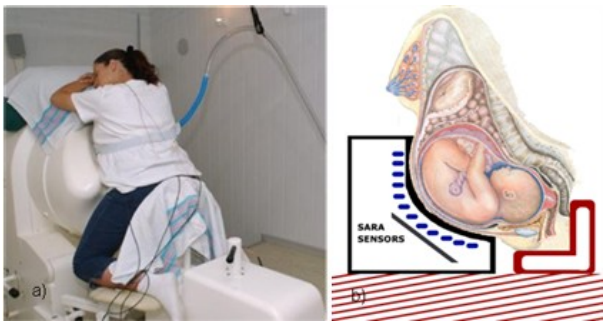

Fig. 1. Fetal MEG System a) Mother sits on and leans against the SARA system. b) Fetus and SQUID sensors.

A unique instrument called SARA (Fig. 1) an acronym for SQUID Array for Reproductive Assessment, has been devised and installed at the Department of Obstetrics and Gynecology, University of Arkansas for Medical Sciences. SARA has 151 channel array of SQUID gradiometers with diameter of 2 cm and baseline of 8 cm and can capture maternal cardiac signal, fetal cardiac signal, fetal brain signal and other biological signals pertinent to fetal development. The sensors are distributed evenly on a concave surface and spaced approximately 3cm apart. They cover an area greater than 850cm^2 spanning the maternal abdomen longitudinally from the symphysis pubis to the uterine fundus and a similar distance laterally. SARA is completely non-invasive and provides a higher signal to noise ratio than fetal electrocardiogram (fECG). Compared to SARA, single channel SQUID systems, ultrasound and other fetal monitoring systems require repositioning of the sensors to capture FCS during fetal movements.

With the large spatial distribution of SARA sensors, it is possible to develop algorithms that can process multiple channel signals to improve signal to noise ratio for FCS. However, only the sensors close to the fetal heart record the fMCG signal with high signal to noise ratio and different sensors obtain fMCG signal with different amplitude and polarity. Maternal and fetal movements can also alter the fMCG signal amplitude and morphology.

Generally, heart beat detection is a two step approach. The first step involves preprocessing the data using appropriate filtering. The second step involves a threshold detection scheme to distinguish and identify the R-wave from other components of the cardiogram which we call decision step in this work. A well designed first step greatly improves the

signal to noise ratio and provides a reliable baseline for the decision step which is essential to obtain noise free results.

Cardiac signal extraction has been studied by other researchers. Hamilton used a rule based system to detect the QRS complex [6]. The use of Hilbert transform to detect the QRS complex has been attempted by Benitez *et al.* [7] and Wilson *et al.* [8]. While Benitez e*t al.* based their approach on the single channel ECG, Wilson *et al.* used the cardiac signals from multiple sensors and have shown that Hilbert transform can be utilized to combine multiple sensor measurements to improve the signal to noise ratio. During fetal motion FCS undergoes amplitude changes that result in spurious (missed/extra) beats. Though Wilson *et al.* approach identifies the spurious beats this approach does not provide methods to correct them.

In this paper, we introduce the adaptive rule based QRS detection algorithm using the Hilbert transform (adHQRS). The adHQRS algorithm, similar to the Hilbert approach [8], uses the Hilbert transform and multiple sensor information to improve the signal to noise ratio. Additionally, it addresses the weaknesses of the Hilbert approach by using an adaptive threshold and QRS complex decision process. The adHQRS algorithm has been tested with 485 fMCG datasets and results were compared with the Hilbert approach.

II. Methodology

A. Data Collection

485 datasets from 223 pregnant women between 28 and 37 weeks of gestation were collected using the SARA device. Data were sampled at a rate of 312.5 Hz using a bandwidth set for 0-100 Hz. Each recording lasted for 11-30 minutes depending on maternal comfort.

B. First Stage: Filtering

The maternal cardiac signal was removed by the orthogonal projection technique [9]. The data were band-pass filtered between 1-60 Hz using a 4th order Butterworth digital filter with zero phase distortion.

A subset of the available channels associated with the fetal heart is selected as follows: i) power spectral density of the channels is estimated by using the fast Fourier transform (Fig. 2). ii) ten channels with highest power at the frequency bandwidth between 1 to 60Hz are used for further calculations.

For a real-time function x(t), the Hilbert transform is defined as:

$$h(t) = \frac{1}{\pi} P.V. \int_{-\infty}^{\infty} x(\tau) \frac{1}{t-\tau} d\tau$$

where P.V. denotes Cauchy Principal Value. In practice, we compute h(t) using the 'hilbert' function in Matlab which

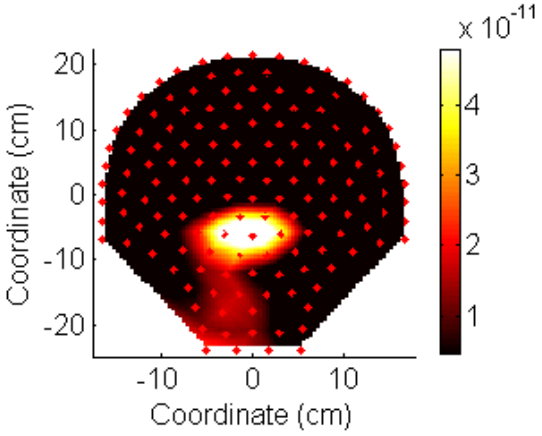

Fig. 2. Estimated power for channels for the frequency bandwidth between 1 to 60Hz. Red dots show channel locations.

provides r(n)=x(n)+ih(n), where t=n/samplefrequency.

Next, the rate of change of the Hilbert amplitude (RHA), $R_{m,n}$ of the analytic signal $r_{m,n}$ is defined as follows:

$$R_{m,n} = \sqrt{(x_{m,n+1} - x_{m,n})^2 + (h_{m,n+1} - h_{m,n})^2}$$

Where m is the channel number and n is the data point. Finally, $R_{m,n}$ are summed up for the selected ten channels.

$$S(n) = \sum_{m} R_{m,n}$$

S, cumulative Hilbert amplitude (cRHA), is always positive.

C. Second Stage: Decision

Heart rate is defined in beats per minute (BPM). Decision stage takes two input parameters, expected minimum and maximum heart rate (EminBPM , EmaxBPM). For a healthy fetus this range is usually between 90- 210 bpm. These values are converted to minimum R-R interval (EminRR) and maximum R-R interval (EmaxRR), respectively. The R-R values detected in the data that are not in this range are defined as outliers. There is a provision for the users to provide their own range of values, to deal with arrhythmic/bradycardia situations.

The algorithm involves the following four steps.

Step 1: Find Global Threshold

Step 1.1: Multiple threshold values are defined starting from Smin = min(S) to Smax=max(S) with 5% step size.

Step 1.2: Local maxima points (R peaks) above each threshold are identified.

Step 1.3: Time between consecutive local maxima points are identified as R-R interval.

Step 1.4: For each threshold, the number of outlier is calculated and the threshold with the minimum outlier is assigned as global threshold and used for further processing.

Step 2: R Peak Detection

A peak detection algorithm (Fig. 3) with hysteresis

proportional to the threshold is used.

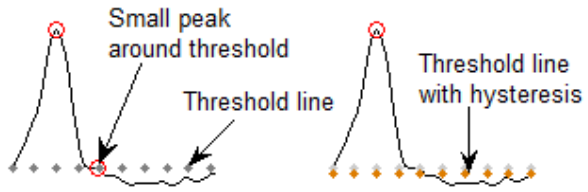

Fig. 3. Local maxima points above threshold.

Step 2.1: Starting from the first point above the threshold and continuing until a data point which is ten percent below the threshold value is found or the end of data is reached, search for the maxima as follows:

Compare amplitudes of each successive value. If it is larger than the current maximum, designate this as the maximum value. The maximum points are taken as R time points. A matrix V with time and amplitude of R peaks is generated for further processing.

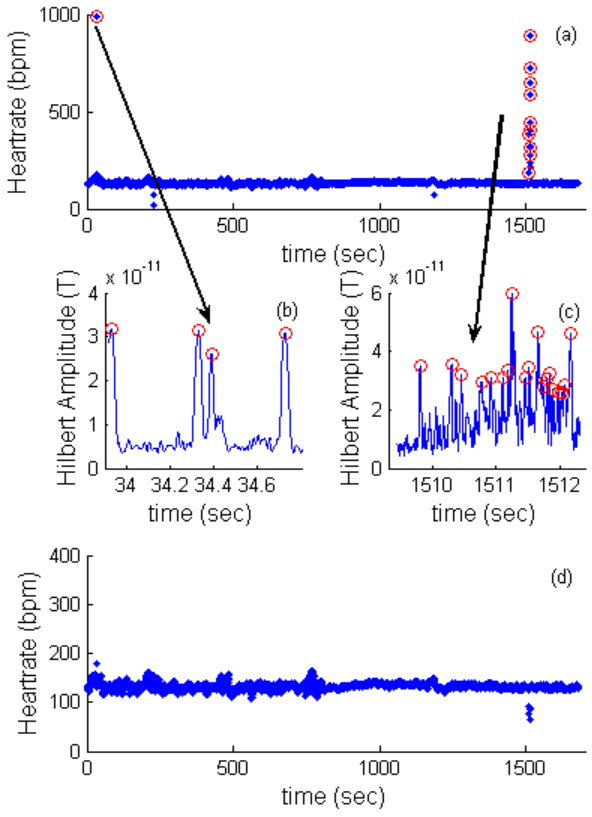

Fig. 4. a) Heart rate obtained by using the global threshold R peak detection (after step 2). Outliers (extra beats) are shown with red circles. The corresponding RHA signals are shown in b) and c). d) After decision step (step 4) spurious beats are eliminated.

Step 3: Missed Beats

Outliers are classified into two groups; missed beats and extra beats. Missed beats are the R-R intervals above EmaxRR indicating the global threshold value must be lowered for detection. Extra beats are the R-R intervals below EminRR indicating the possible presence of noise. The algorithm first checks for the missed beats.

Step 3.1: For a missed beat calculate the local average amplitude of the previous 10 R peaks. (If 10 R peaks are not available, use the average amplitude of all identified R peaks)

Step 3.2: Adjust the threshold to the half of the local average amplitude and process the data between these two R points and find the maximum points above threshold.

Step 3.3: If new peaks are found, update vector V (R peak index) with newly found peaks.

Step 4: Extra Beats

Extra beats are usually generated by R-R intervals which are physiologically impossible such as 0.1sec (600 BPM) and are corrected as follows:

Step 4.1: Starting from the second R-R interval for all the R-R intervals, if the current or the previous R-R interval is identified as an extra beat go to step 4.2.

Step 4.2: Define d1 as the absolute value of the difference between the local average and the sum of the previous and current R-R intervals. Similarly, d2 and d3 are the absolute values of the difference between the local average and the current R-R interval and the previous R-R interval respectively. If d1 is less than d2 or d3 then the R peak between the current and previous R-R is eliminated.

Figure 4 demonstrates the application of the adHQRS. Figure 4a shows the heart rate obtained after the filtering stage with the global threshold. It has extra beats at two different instances (shown in circles). In Figure 4b and 4c, the corresponding signals (S) are plotted. Figure 4d shows the heart rate obtained after step 4. In this case, there is no extra beat left.

Figure 5 illustrates the step 4.2. RR_{32} is identified as an outlier. The difference between RR_{21} and the local average has less value than RR_{31} therefore the algorithm does not eliminate the R_2 peak. However, the difference between RR_{42} and local average is less than RR_{43} and the algorithm eliminates the R_3 and assumes RR_{42} as single RR interval.

TABLE I
PERFORMANCE OF THE ALGORITHMS

	Hilbert	adHQRS
Number of datasets	485	485
Total Error	12003	3231
Total Extra	5913	556
Total Missed	6090	2675
Total Est. Beats	1118091	1117796
Efficiency	0.989	0.997
Total Without Error	156	249

III. Results

The results obtained for the datasets are given in the Table 1. To assess the performance of this approach we used the

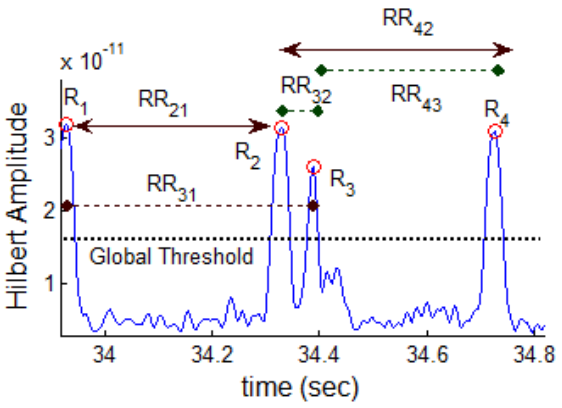

Fig. 5. R to R interval between 3rd and 2nd peak is identified as an extra beat and eliminated by the step 4.2.

set of metrics in ref [8]. The efficiency of the Hilbert and adHQRS are 98.9% and 99.7%, respectively. In 156 datasets both algorithms captured all the beats correctly. In 297 of the remaining 329 datasets, the adHQRS had a better performance based on the statistics given in Table 1, compared to the Hilbert approach. In the rest of 32 datasets, both methods had the same number of errors (maximum 10 and minimum 1) and for 1 dataset the adHQRS performed worse (14 vs. 13 errors).

IV. Conclusion

The adHQRS detection algorithm has shown significant performance and established a good signal to noise ratio. In addition to its proven performance, adHQRS's ability to select and combine SQUID channels indicates a possible use for fetal cardiac signal analysis that could be implemented for fetal health monitoring.

Fetal movements during the recordings may induce amplitude and morphology change for the signals. The Hilbert amplitude is insensitive to morphological changes such as monopolar to bipolar cardiac signals. However, the signal to noise ratio may affect the detection process. With bio-magnetic modeling approaches such as dipole fit, it is possible to estimate the fetal heart location for individual beats within a certain error range. Empirical results indicate that cardiac signals obtained by using sensors in the vicinity of the fetal heart have higher signal to noise ratio. Incorporating a fetal heart tracking based sensor selection algorithm for the Hilbert amplitude calculation may improve the detection rate.

In future work, we will address some of the pertinent issues mentioned above. Also the fetal heart extracted using this approach will be used for the behavioral state estimation [3], actocardiogram [10] calculation and HRV studies.

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