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Fetal Heart Rate Monitoring Based on Adaptive Noise Cancellation and Maternal QRS Removal Window

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Abstract

In this paper a new method to extract the fetal signal from the abdominal electrocardiogram (ECG) is presented. A three-stage method for fetal heart rate detection from abdominal ECG recordings is proposed. After preprocessing, adaptive noise cancellation (ANC) is used to extract the fetal ECG. Then in the third stage maternal QRS complex removal window is applied to eliminate or scale down the maternal residual peaks. The method is validated using 30 recorded data and compared with another three stage method using independent component analysis (ICA) for the fetal ECG extraction. The average sensitivity and average positive predictivity of the ANC based method is 85.8 % and 67.6 % respectivly compared to 74.4% and 64.1% of the ICA based method. These show that the ANC based method was more successful in detecting the FHR than ICA.

Keywords: Adaptive noise canceller, independent component analysis, fetal heart rate monitoring and QRS Removal Window.

1. Introduction

Fetal heart rate (FHR) monitoring is one of the methodologies to test fetal well being and diagnose for possible abnormalities. Fetal monitoring throughout the pregnancy enables the clinician to diagnose and recognize the pathologic condition especially asphyxia [1].

Although Doppler ultrasound device is currently used for FHR monitoring, it is not suitable for long term monitoring due to its sensitivity to movement and its safety for long term exposure has yet to be established [2]. Besides ultrasound, non-invasive electrocardiography has been used to obtain valuable clinical information about the fetal well being during pregnancy. The extraction of the fetal electrocardiogram (ECG) can be carried out via skin electrodes attached to the maternal abdomen. However, the abdominal ECG (AECG) is always corrupted with power line interference, maternal ECG (MECG) and electromyogram where its variability is influenced by the gestational age, position of the electrodes and the skin impedance [3]. Therefore, appropriate signal processing techniques are required to reveal the fetal ECG (FECG) from the AECG.

Various research efforts have been proposed to extract the FECG from the AECG such as adaptive filtering [4], correlation techniques [5], blind source separation [6] and a combination of wavelet analysis and blind source separation methods [7]. FHR can be calculated by determining the R-R intervals from the extracted FECG. However, the extracted FECG is still corrupted by the residual peaks of MECG (especially its QRS complexes) hence the FECG detection remains difficult.

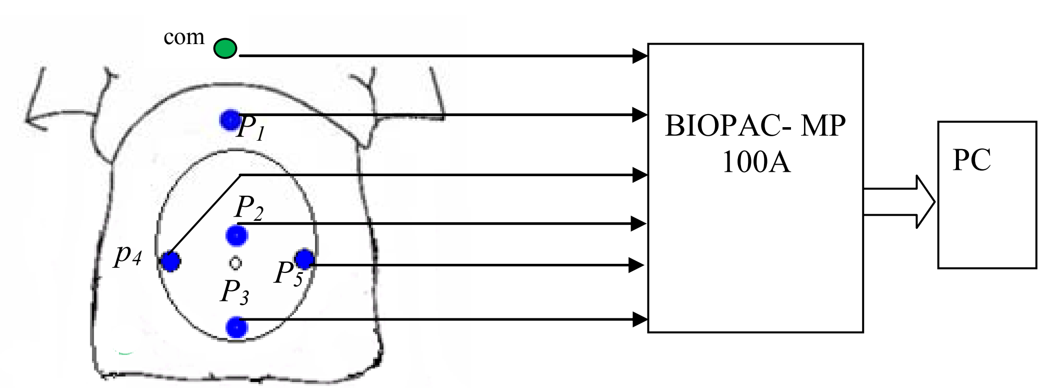
In this paper, an adaptive noise canceller (ANC) is proposed to extract the FECG from the AECG. A QRS removal window (a window for removing the maternal QRS (MQRS) complex), algorithm is developed to eliminate the MECG residual peaks in the extracted FECG. The performance of the proposed algorithm is evaluated and compared with the well-known independent component analysis (ICA) algorithm by using recorded data from the Universiti Kebangsaan Malaysia Medical Center (PPUKM).

2. Methodology

2.1. Data Acquisition

AECG signals were recorded from 30 healthy pregnant women (at 35 to 38 weeks of gestation), most of which are corrupted with different levels of noises, using the lead system as shown in Fig. 1. The experimental protocol was approved by the PPUKM Research and Ethical Committee prior to commencement of the study and informed consents were obtained from all subjects.

Figure 1: Locations of the abdominal electrodes.



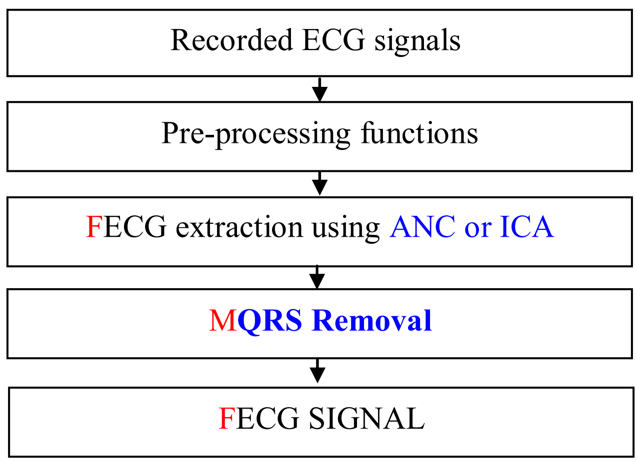
The AECG signals, $\mathbf{X(n)} = [X_1(n), X_2(n), ..., X_p(n)]^T$ where n denotes a discrete-time index, and T is the transpose operator, were simultaneously recorded from maternal abdomen using six electrodes (five electrodes, $p \in$ [l, 2, 3, 4, 5], with a single common) using high gain amplifiers (BIOPAC- MP 100A). The AECG signals were digitized at 1000 Hz with 12 bit resolution. The total recording time during each session was about one minute.

Electrode p_1 is located in such a way that only MECG signals are acquired while the electrodes p_2, p_3, p_4 and p_5 acquired the mixture of MECG and FECG. Therefore, $X_1(n)$ is defined as the reference input and $X_2(n)$ and $X_3(n)$ are the primary input signals to the adaptive filter. As for ICA, four of the acquired AECG signals, $\mathbf{X(n)} = [X_2(n), X_3(n), ..., X_p(n)]$ $p \in$ [2, 3, 4, 5], are fed into the ICA algorithm as $X_1(n)$ contains only MECG signal

2.2. Algorithms

The block diagram of the proposed algorithm is shown in Figure (2). It consists of the pre-processing stage, FECG extraction using ANC or ICA and the MQRS removal window.

Figure 2: The block diagram of the proposed algorithm.



2.2.1. Preprocessing Stage

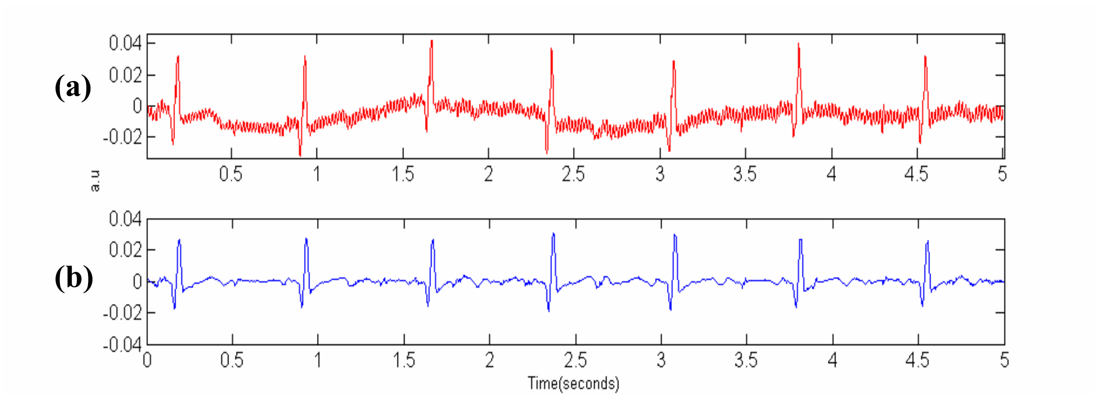
The preprocessing stage consists of the removal of the DC signal, baseline wander and the power line interference. Each observation signal is made zero mean by subtracting its mean as follows:

$$X(n) = X(n) - mean(X(n)) \tag{1}$$

Baseline wander is caused by the patient's breathing or movements during recording. The frequency of the baseline wander due to breathing is in the range of 1 Hz and the EMG noise (artifacts of muscular contractions) is characterized by relatively high frequency noise, hence the recorded signals were filtered by a FIR band-pass filter with cut-off frequencies at 4 Hz and 90 Hz.

The power line interference consists of 50 Hz sine wave and its harmonics. A notch filter centered at 50 Hz is used to eliminate this interference. An example of an AECG signal and the pre-processed signal are shown in Fig. 3.

Figure 3: (a) **AECG** signal and (b) pre-processed signal



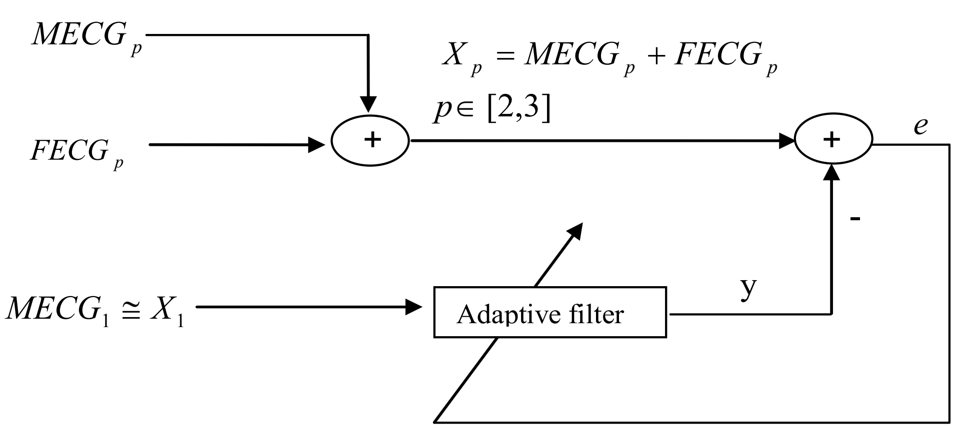
2.2.2. FECG Extraction Technique

Two algorithms namely ANC and ICA have been implemented in this work to evaluate their performance for FECG extraction.

A. Adaptive Noise Canceller

ANC is a method of estimating a signal ($FECG_p$), contaminated by additive noise, $MECG_p$, $p \in [2,3]$ with the primary input to the ANC becoming X_p using a reference input, $MECG_1 \cong X_1$ [8]. The noise $MECG_1$ is uncorrelated with the $FECG_p$ but correlated in some unknown way with the noise $MECG_p$ as shown in Figure (4). The X_1 and X_p are the signals acquired from the maternal abdomen.

Figure 4: Adaptive noise canceller system



The noise $MECG_1$ is filtered to produce an output y that is as close a replica as possible of $MECG_p$. This output is subtracted from the primary input X_p to produce the system output

$$e = MECG_p + FECG_p - y \tag{2}$$

Where y is the output of the adaptive filter Squaring both sides of Equation 2, we obtain

$$e^2 = FECG_p^2 + (MECG_p - y)^2 + 2FECG_p(MECG_p - y) \tag{3}$$

Applying expectations on both sides of Equation 3, we get

$$E[e^2] = E[FECG_p^2] + E[(MECG_p - y)^2] + 2E[FECG_p(MECG_p - y)] \quad (4)$$

As FECG is uncorrelated neither with $MECG_p$ nor with y then $2E[FECG_p(MECG_p - y)] = 0$. Finally, we obtain

$$E[e^2] = E[FECG_p^2] + E[(MECG_p - y)^2] \quad (5)$$

The goal of the adaptive filter is to minimize the mean square error (MSE) of $E[MECG_p - y] = 0$ This can be obtained iteratively, to give the optimal solution when $y = MECG_p$.

B. Independent Component Analysis

ICA is a method to find underlying factors or components from multivariate (multidimensional) statistical data. It looks for components that are both statistically independent and non-gaussian. Although an excellent review has been given by Cichocki & Amari [9], a brief description is given here.

Given a set of p mixed signals $X(n) = [X_1(n), X_2(n), \ldots, X_p(n)]^T$ which are linear mixed with q $(p \geq q)$ unknown mutually statistically independent, zero-mean source signals $S(n) = [s_1(n), s_2(n), \ldots, s_q(n)]^T$ and noise contaminated. This can be written as

$$X_i(n) = \sum_{j=1}^{q} A_{ij} s_j(n) + g_{ci}(n), \; i = 1,2,\ldots,p \quad (6)$$

or in the matrix notation

$$\mathbf{X} = \mathbf{AS} + \mathbf{g_c} \quad (7)$$

where $\mathbf{X} = X(n)$ is the vector of sensor signals, $\mathbf{S} = S(n)$ is the source signal vector, $\boldsymbol{g_c} = [g_c(n), g_c(n), \ldots, g_{cp}(n)]^T$ is the additive noise vector, $\mathbf{A}$ is an unknown $p \times q$ mixing matrix and n is the discrete-time index. The noise vector, $\boldsymbol{g_c}$ is assumed Gaussian and independent.

The mixing matrix **A** is determined by the body geometry and conductivity, as well as the electrode-source relative positions [12]. Criteria based on maximization of non-gaussianity [13], maximum likelihood, minimization of mutual information [14], tensorial methods [15] and non-linear decorrelation [16] may be used to estimate the mixing matrix **A** and the source signal vector **S**.

In the noise-free model, $\mathbf{g_c} = \mathbf{0}$, the identification of the mixing matrix **A** and the sources signal, **S** can be estimated if the sources are independent and non-Gaussian, and the number of sensors is equal or larger than the number of independent sources to be estimated. However, a noisy estimates of the sources signal may obtain, $\mathbf{S} = \mathbf{A}^{-1}(\mathbf{X} - \mathbf{g_c})$, if $\mathbf{g_c} \neq \mathbf{0}$. Therefore, pre-processing before applying ICA may improve the performance of the ICA.

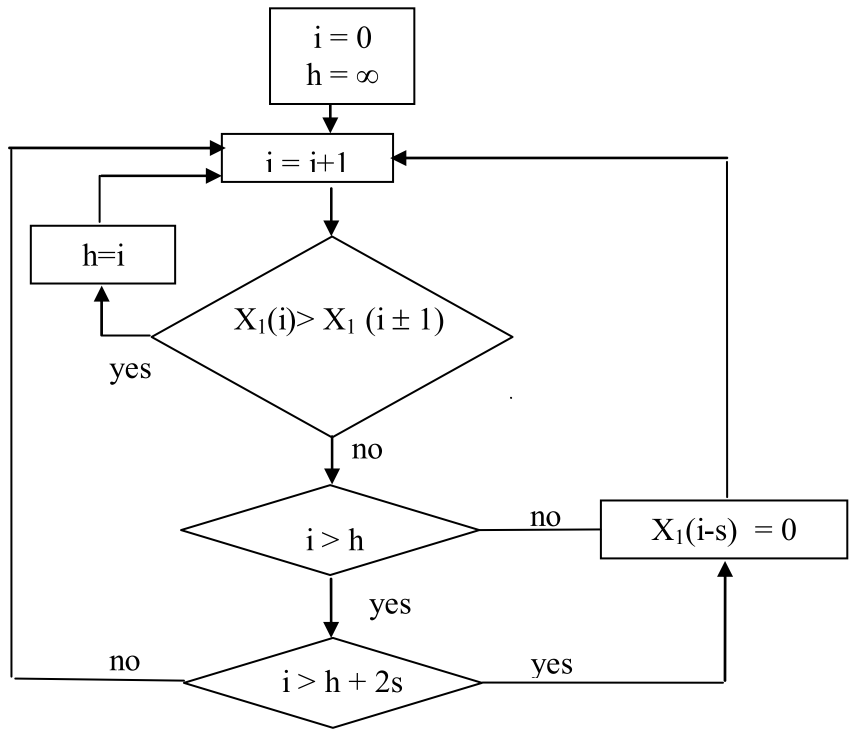
In this paper, Second Order Blind Identification (SOBI) algorithm has been utilized to extract the FECG from the AECG. SOBI is a robust algorithm to separate the noises especially EMG and electrode artifacts.

2.2.3. Maternal QRS Removal

In the post processing stage two steps are implemented which are the MQRS removal to eliminate the maternal residual peaks, and finally a 1 Hz notch filter to attenuate the residual baseline wander in the FECG.

MQRS signal is captured within a window which is defined by taking 50 samples before and after every peak found in the input signal X_1 with the condition as shown Fig. 5.

Figure 5: Flow Chart of the MQRS Removal Window



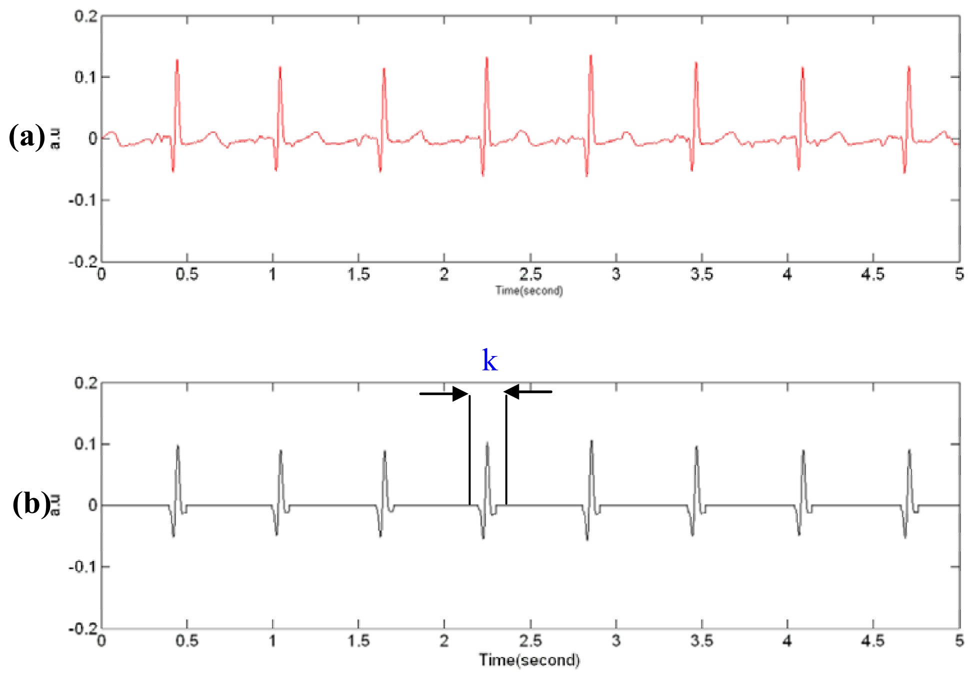
The QRS complex interval is given by

k = (i – s) : (i + s); (8)

where i is the sample index and s =50 is the number of samples. All samples that do not fall within this window will be zero padded as shown in Figure 6(b).

The MQRS window of Figure6(b) is used to eliminate or scale down the maternal residual peaks from the extracted FECG. A small amount of baseline wander was observed at this extracted signal. Therefore, a notch filter centered at 1 Hz is used to attenuate this baseline wander.

Figure 6(a): Pre-processed AECG signal X1 and (b) MQRS interval definition.



2.3. Evaluation

The proposed algorithms have been implemented in Matlab codes using Matlab-7.4 (The Math-works Inc.). The performances of the algorithms were then evaluated based on their sensitivities and positive predictivities [15], when applied to AECG signal acquired from the PPUKM. The sensitivity is the fraction of real events that are correctly detected and it is defined by,

$$Se = \frac{TP}{TP + FN} \tag{9}$$

The Positive Predictivity is the fraction of detections that are real events and it is defined by,

$$+P = \frac{TP}{TP + FP} \tag{10}$$

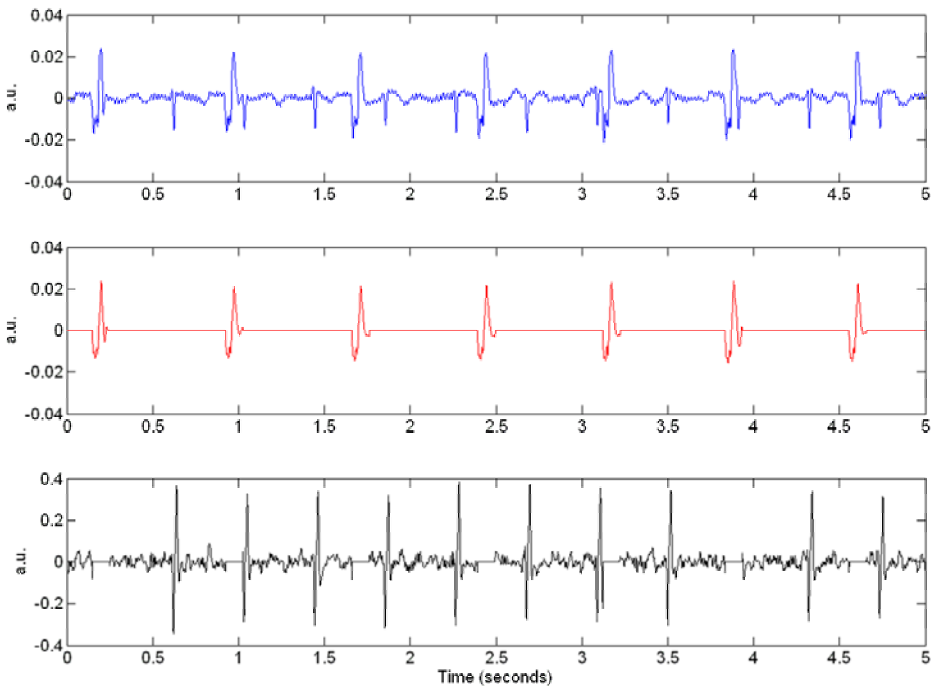
where FN (False Negatives) denotes the number of missed detections, FP (False Positives) represents the number of extra detections and TP (True Positives) is the number of correctly detected QRS complexes.

3. Results and Discussions

3.1. Adaptive noise canceller extraction technique

Examples of the extracted FECG using ANC, maternal QRS and FECG signal after applying maternal QRS removal window are shown in Figure (7). It is noted that the maternal residual peaks are still observed after the ANC and only eliminated after applying the maternal QRS removal window. After maternal residual peaks have been eliminated from the extracted FECG signal, a small amount of baseline wander has been observed. Therefore, notch filter centered at 1 Hz is adequate to attenuate this baseline wander.

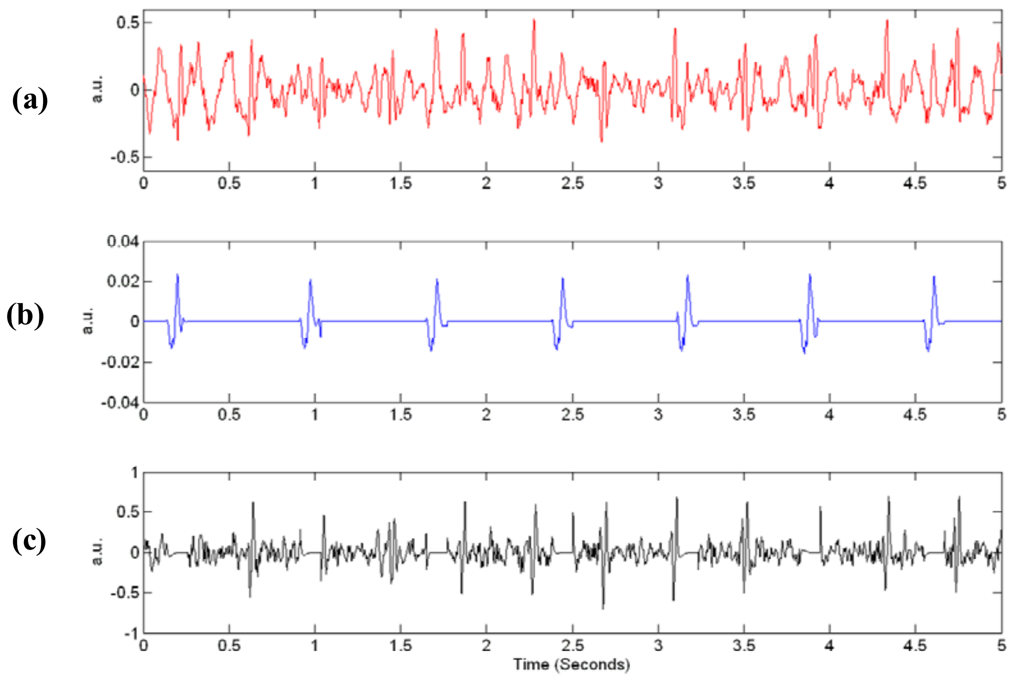
Figure 7: (a) Extracted FECG using ANC, (b) MQRS and (c) FECG signal after applying MQRS removal window.



3.2. Independent Component Analysis Extraction Technique

Figure (8)shows examples of the result using ICA. The maternal residual peaks are still observed in the extracted FECG signal using ICA. The QRS Removal Window was then applied to remove the maternal residual peak from the FECG. After maternal residual peaks have been eliminated from the extracted FECG signal, a small amount of baseline wander has been observed. Therefore, notch filter centered at 1 Hz is adequate to attenuate this baseline wander.

Figure 8: (a) Extracted FECG using ICA, (b) MQRS window and (c) FECG signal after applying MQRS removal window



With this improvement on the extracted signal, the performance of the FECG extraction techniques (ANC and ICA) is compared in terms of FHR detection. The FHR is calculated from the RR interval after peak detection [16].

3.3. Performance Evaluation

In this section, the ANC and ICA methods are evaluated using sensitivity and positive predictivity. The effect of the lead position in the primary input of the ANC is also evaluated.

Table 1 shows the performance using ICA and ANC based methods at signal extraction stage. The average sensitivity of the ANC based method is 85.5 % (X_2 as primary signal) as compared to 74.4% of the ICA based method. The average positive predictivity of the ANC based method is 67.6% (X_2 as primary signal) as compared with that of the ICA based method which is 64.1%. It shows that the ANC based method was more successful in detecting the FHR than ICA. The QRS Removal window was employed to improve this detection.

Table 1: Performance of ICA and ANC based method

Weeks	**No Signals**	**ANC method**				**ICA method**	
		X_2 as primary signal		**X_3 as primary signal**			
		Se **(%)**	$+P$ **(%)**	Se **(%)**	$+P$ **(%)**	Se **(%)**	$+P$ **(%)**
35	2	79.0	54.5	77.5	53.1	66.6	48.8
36	13	88.4	77.8	86.2	70.4	74.8	72.2
37	6	91.1	68.9	78.4	67.9	79.9	70.1
38	9	84.8	69.6	87.9	75.5	76.4	65.4
		85.5(%)	**67.6(%)**	**82.5(%)**	**66.7(%)**	**74.4(%)**	**64.1(%)**

With the availability of the multi-lead system for the ICA used in this work, it is possible to evaluate the lead position for the primary signal of the ANC that gives optimum results. Hence a comparison is made between X_3 as the primary signal and X_2 as also shown in Table 1.

The average sensitivity of the proposed algorithm from the primary signal X_2 is 85.8 % as compared to 82.5 % with primary signal X_3. Also the average positive predictivity of the proposed algorithm is 67.6% with primary signal X_2 as compared to X_3 with 66.7%.

The performance of the algorithm was better than ICA for both locations, although electrode location p_2 (associated with X_2) is better than p_3. This shows that the location of the electrode plays an important role in FHR detection.

4. Conclusion

The proposed algorithm (ANC with the QRS Removal Window) has been demonstrated to have better performance to extract the fetal signal. This method can use only two leads and a common. By using the MQRS removal window it is shown that it is possible to control the amplitude of the maternal QRS complex in the extracted signal or eliminate it. This facilitates detection of the fetal peaks and therefore the determination of FHR.

The limitation of the proposed algorithm is that only signals which acquired later than 35 gestation weeks are tested. Farther improvement is required to implement the algorithm on ECG signal earlier than 35 gestation week.

Current work is in progress towards realizing an online FHR detection using 24 bit high resolution multi-channel bio-amplifier and finally the proposed algorithm will be fully tested in the clinical environment.

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