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An Efficient Method for Fetal Electrocardiogram Extraction from the Abdominal Electrocardiogram Signal

[1]Muhammad Asraful Hasan, [1]Muhammad Ibn Ibrahimy and [2]Mamun Bin Ibn Reaz
[1]Department of Electrical and Computer Engineering,
International Islamic University Malaysia, Gombak, 53100 Kuala Lumpur, Malaysia
[2]Department of Electrical, Electronic and Systems Engineering,
University Kebangsaan Malaysia, 43600 UKM, Bangi, Selangor, Malaysia

Abstract: Problem statement: FECG (Fetal Electrocardiogram) signal contains potentially precise information that could assist clinicians in making more appropriate and timely decisions during pregnancy and labor. **Approach:** Conventional techniques were often unable to achieve the extraction of FECG from the Abdominal ECG (AECG) in satisfactorily level. A new methodology by combining the Artificial Neural Network (ANN) and Correlation (ANNC) approach had been proposed in this study. **Results:** The accuracy of the proposed method for FECG extraction from the AECG signal was about 100% and the performance of the method for FHR extraction is 93.75%. **Conclusions/Recommendations:** The proposed approach involved the FECG extraction even though the MECG and FECG are overlapped in the AECG signal so that the physician and clinician can make the correct decision for the well-being of the fetus and mother during the pregnancy period.

Key words: FECG, AECG, artificial neural network, QRS complex

INTRODUCTION

During the pregnancy and labor, Fetal Heart Rate (FHR) monitoring is a technique that can give the substantial message about the condition of a fetus. It is being performing by detecting the ECG signal that is generated by the heart of the fetus[1]. The features of the FECG, such as pulse rate, wave shape and dynamic conduct are convenient in defining the fetal life, fetal growth, fetal maturity and existence of abnormal condition of fetus or congenital cardiopathy. FHR or MHR monitoring can recognize conditions, which may extend to fetal and/or maternal mortality or morbidity. From these conditions, the status of the fetus can be found along with the abnormally high acidity, irregularity of cardiac rhythm, cardiac arithmia and the activity of the Automatic Nervous System (ANS). The FHR may vary any time as the fetus responds to circumstances in the uterus. An unnatural FHR or pattern may mean that the fetus is not getting enough oxygen or there are other problems. Sometimes an abnormal pattern also may mean that an emergency or abdominal delivery is needed. However, FHR abnormalities are unpredictable and it may occur at any time. To monitor such abnormalities, ambulatory monitoring has been established a useful approach[2] with use of long-term monitoring of FHR, where, the mother can keep normal daily activities, work and keep away the unnecessary hospital stays.

Accurate finding of the QRS complex, in particular, accurate detection of the R-peak, is essential in computer-based FECG signal analysis especially for a correct measurement of FHR and Fetal Heart Rate Variability (FHRV)[3]. However, this is often hard to achieve, since several sources of existing noise contraction[4] are frequently found, such as baseline drifts, power line interferences, motion artifacts and muscular activity. Many clinical applications require accurate heartbeat monitoring systems including intensive care units, operating rooms, implantable pacemakers and defibrillators. Machine-driven algorithms notice a QRS complex for R-peak detection when ECG amplitude exceeds a threshold level. A true beats can be missed when the threshold is too high. Similarly, if the threshold is too low, false detection can result during EMG artifact and external interference[5]. As the magnitude of the noise can become greater than the signal during these artifacts, based on amplitude thresholding alone is not satisfactory for the detection of R-peak in the ECG signal. Benitez *et al*.[4] focused Hilbert Transform to detect the R-peak by zero-crossing point in its first differential waveform. P and T waves

Corresponding Author: Muhammad Asraful Hasan, Department of Electrical and Computer Engineering, International Islamic University Malaysia, Gombak, 53100 Kuala Lumpur, Malaysia

are minimized in relation to the relative peak corresponding to the peak of QRS complex in Hilbert sequence. This Hilbert Transform needs complex equation of calculations. Besides, looking at zero crossing point alone is not enough in determining QRS complex of the Maternal ECG (MECG) and FECG. Because, P, QRS complex and T waves can have similar differential values.

To solve the above problems and to extract the FECG signal from AECG for FHR monitoring, in this study, Artificial Neural Network and Correlation method has been used. Artificial neural network is chosen primarily since it is adaptive to the nonlinear and time-varying features of ECG signal. The Neural Network can be trained to recognize the normal waveform and filter out the unnecessary artifacts and noises while detecting the R-peak of QRS complex for MECG in the AECG. Likewise, the Correlation method has been selected as the correlation factor can be used for scaling the MECG to subtract from the AECG to get the FECG signal.

Clinical significance of FECG morphology: Biomedical signal implies a collective electrical signal acquired from any organ that represents a physical variable of interest where the signal is considered in general a function of time and is describable in terms of its amplitude, frequency and phase. FECG is a biomedical signal that provides electrical representation of FHR to get the vital information about the condition of fetus during gestation and labor from the recordings on the mother's body surface. Sometimes the FECG is the only information source in early stage diagnostic of fetal health and status. The FECG signal is very much related to the adult ECG, containing the same basic waveforms including the P-wave, the QRS complex and the T-wave. The PQRST complex as shown in Fig. 1 is an electric signal produced by the contraction of the heart's muscle called myocardium. It is composed of three parts; firstly, The P-wave reflects the contraction of the atriales. Secondly, the QRS-complex is related with the contraction of the ventricles. Due to the magnitude of the R-wave, it is extremely reliable. Finally, the T-wave, which corresponds to the re-polarization phase, which follows each heart contraction.

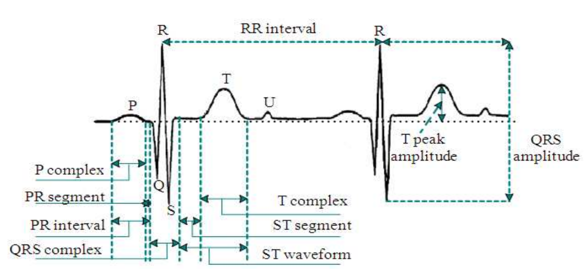

Fig. 1: FECG is showing key features: The PQRST complex

MATERIALS AND METHODS

Artificial neural network and correlation: The algorithm is an essential part for processing the AECG to detect the MECG and extract FECG for measuring the FHR and MHR respectively. Some different techniques have been developed for FECG enhancement and detection from the AECG signal. In this research, it has been presented the continuous work where the QRS complex of MECG signal in the AECG had already been detected proficiently in the previous research[3]. The primary flow of the work has been shown in Fig. 2. The input signal has been conceived the raw AECG signal. From the raw AECG signal, some features is collected such as amplitude, differentiation, duration, approximate RR interval and zero-crossing flag, first-element flag. These features are used to train the neural network to recognize R peak in the QRS complex for MECG and remove the noises along with the raw AECG[3].

The Back-propagation multilayer feed forward network has been used shown in Fig. 3. According to the Fig. 3, as inputs, 6 different features has been used in the input layer and 13 neurons in the hidden layer and one output neuron in the output layer considered.

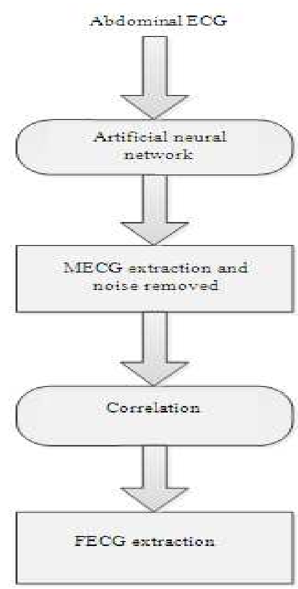

Fig. 2: Overall flow of algorithm for FECG extraction

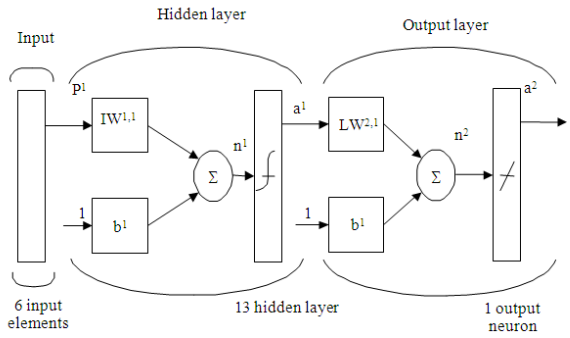

Fig. 3: Back propagation multilayer feed forward network

There is no definite way of determining the right number of neurons in hidden layer. It is chosen based on Kolmogorov's theorem[6]. The network is trained to output 1 for R peak and 0 to non-R peak.

The network is initialized with the following settings:

$$\text{net.TrainParam.show} = 100 \tag{1}$$

$$\text{net.TrainParam.epochs} = 800 \tag{2}$$

$$\text{net.TrainParam.goal} = 1\text{e-}3 \tag{3}$$

Every 100 iteration, the error is displayed once. The maximum epoch for training is 800 and the goal is to reach error at 1e-3. For each training session, the training stops when reaches either maximum epochs or goal error. The network is trained with 20 signals[3]. The total points fed into the network are around 1000 input-target pairs. The signals are with different amplitudes, heart rate and noise level. The weight and bias values are saved for each training session. When the simulations are not satisfactory, the network is trained one more time with the last saved weight and bias values. This can improve the network and reduce the number of time of training. The efficiency of the designed algorithm was 99.09% where the different types of raw signals have been used to validate of the algorithm. After this, the correlation approach has been applied for the extraction of FECG from the AECG signal. The flow of the work has been showed in the Fig. 4, where R-peak detection assumed the R-peak of the maternal ECG. The MECG QRS template had been found by using the averaging technique where, two samples of the MECG template are averaged and subtracted within each sampling interval. This means, the subtraction of the 480 ms is being completed within 240 ms.

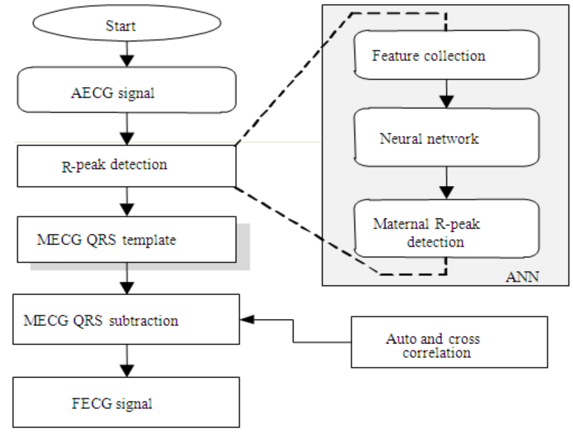

Fig. 4: Flow chart of FECG extraction

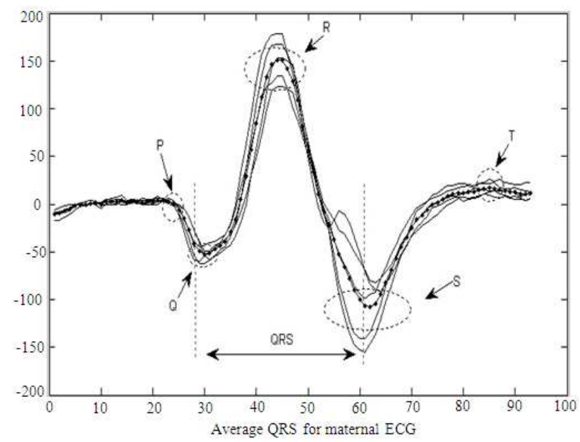

Fig. 5: QRS complex for MECG in AECG

The average Maternal QRS template has been shown in Fig. 5. According to Fig. 5, P, Q, R, S, T each peak point was circled and the average QRS for the MECG template was used diamond line that it can be different from the other QRS in the signal.

Indeed, the subtraction of the MECG template from the abdominal signal is a very critical routine, since any slight shift in the subtracting template will produce residuals that obscure the fetal complex and may cause serious difficulties in the fetal QRS detection and extraction. The care is taken to subtract the MECG template by fine aligning the peaks. The MECG template is matched with actual MECG in the AECG signal by scaling with the factor K, which is given by the equation 4[7]:

$$k = \sqrt{\frac{C_{MECG}}{A_{MECG}}} \tag{4}$$

where, $C_{MECG} < A_{MECG}$, these are obtained from the cross-correlation of abdominal signal with maternal template

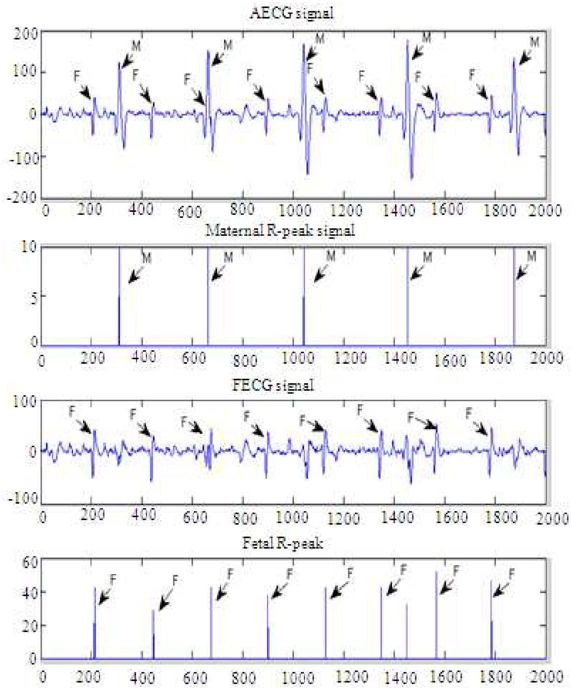

Fig. 6: Fetal ECG extraction

and auto-correlation of maternal template itself. The cross-correlation value of the Eq. 4 is obtained by the cross correlating the maternal template with abdominal signal when the template peak coincides with the signal peak. The auto-correlation value is obtained by summing the squares of each maternal QRS template sample. After finding the scaling factor K, the maternal template has been subtracted from the original abdominal ECG so that the FECG can be extracted. The factor K is working as a scaling coefficient. That means, when the difference between original abdominal signal and average QRS MECG template signal is high, the factor multiplied in such a way that the average QRS goes near to the original abdominal signal.

RESULTS AND DISCUSSION

The algorithm tested using the several AECG signals. One of the tested signals has been shown in the Fig. 6.

Maternal and fetal QRS complexes are overlapped at around 700 sample point. The algorithm is able to extract the FECG signal from the AECG even the fetal QRS is overlapped with that of maternal. There is a maternal QRS at around 1500 sample point, which is relatively higher than the average QRS of maternal ECG. Therefore, the maternal contribution was not totally suppressed at the point in the FECG signal. It constructed a similar but small QRS with negative side. From the tested output signals, it can be said that the FECG is extracted efficiently from AECG signal.

Table 1: Accuracy compassion for FHR detection method

Researcher	Description	Accuracy (%)
Mooney *et al*.[9]	Adaptive algorithm	85.00
Azad[7]	Fuzzy approach	89.00
Pieri *et al*.[10]	Matched filter	65.00
Ibrahimy *et al*.[11]	Statistical analysis	89.00
This research	Artificial intelligence and correlation	93.75

In order to analyze and compare the detection performances of the detection scheme shown in Table 1, several sets of AECG signals were tested using the following equation defined by Azevedo *et al*.[8]:

$$\text{Performance} = \frac{\text{No.fetal R wave} - (\text{No.miss} + \text{No.false})}{\text{No.fetal R wave}} \times 100 \quad (5)$$

CONCLUSION

An efficient method for FECG Extraction from AECG has been developed successfully in this research. The result obtained from the simulation in MATLAB tools shows that the developed system can extract the FECG from the AECG more efficiently. FECG are being extracted perfectly even though, the FECG and MECG is overleaped in the AECG. This research is also totally noninvasive approach. It can be used as a reference for other researches who involved in FHR monitoring research area.

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