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To derive fECG for Monitoring Fetal Health

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Abstract: *Recent trends in biomedical engineering research of analyzing maternal and fetal heart activity via the extraction of non-invasive maternal abdominal ECG (aECG) brings clinical researchers to effectively monitor the well-being of the fetus especially in the third trimester of pregnancy. Thus closely monitoring fetal distress using non-invasive fECG along with the conventional ultrasound method is the best method. The biggest challenge lies in the poor amplitude of fECG signal as contrasted to the maternal ECG (mECG). The other challenges are the existence of the predominant noises such as the baseline wander, measuring electrodes, power line interference and maternal Electromyogram (EMG) among others. The focus of this paper provides a concise review of the comparisons and performance of some of the methods used by researchers to extract fECG signal for fetal heart rate monitoring systems. The proposed technique using FIR filters gave precise fetal heart rates even when the fECG and mECG existed in close proximity or partially overlapped in the time domain. Our methodology displayed fHR close to the invasive fetal index as compared to techniques such as ANFIS, Correlation and ICA.*

Keywords: *fetal ECG, maternal ECG, abdominal ECG, fetal heart rate, FIR filters, ANFIS, ICA, correlation.*

I. Introduction

In recent times, the experiments in biomedical engineering of analyzing fetal heart activity via the extraction of non-invasive maternal aECG brings clinical researchers together to study and assist doctors to monitor the well-being of the fetus while still in the womb. It is reported that one in thirty-three infants have birth defects each year and the infant Mortality Rate (IMR) in India is about 42 deaths per 1000 live births (2012) [1]. It is further reported that the IMR fluctuated around 38 deaths per 1000 live births from 2012 to 2017 [2]. The early observation of the decelerations of the fHR can save the fetus from getting into fetal distress. Hence when we monitor the fetal heart rate electronically apart from the other classical methods such as ultrasound etc, we eliminate the possibility of the fetus getting asphyxia and hence save the fetus [3].

FECG signals extracted from the maternal abdomen have very poor amplitude ECG signals as contrasted with the maternal complexes. There are other artifacts such as the maternal respiration effects which give rise to the baseline wander (BW), the 50Hz power line interferences (PLI), maternal electromyogram (EMG) among other artifacts. Invasive fECG obtained using the fetal scalp electrode have much larger amplitudes but at the risk of infection to the fetus [3]. In recent years, research in biomedical signal processing has been accelerated towards algorithms and techniques that can detect and extract fECG from mother's abdomen signals

II. Fecgsignal Extraction And Processing Techniques

The noninvasive fECG can be extracted from the aECG by using either a multichannel or single channel source and are processed by using either non-adaptive or adaptive techniques. The former technique being time invariant is disadvantages compared to the later method [4]. Over the decades, the biomedical researchers have contiuously improvised in their detection and extraction algorithms which further mitigated the artifacts in the aECG. This progressive research have obtained predictable fECG and thus made known the health status of the fetus before labour.

Some of the well-known methods of adaptive processing are Kalman filtering, Artificial intelligence (AI) and adaptive noise cancellation algorithms such as ANFIS (adaptive-network-based fuzzy inference system). Among the non-adaptive multi-channel techniques include methods of BSS (blind source separation) such as ICA (independent component analysis), PCA (principle component analysis) and SVD (singular value decomposition). Techniques such as correlation, averaging techniques, subtraction, finite impulse response (FIR), infinite impulse response (IIR) filtering and wavelet transform form the single channel source non-adaptive methods [5]. The taxonomy of techniques for non-invasive fECG extraction are shown in figure 1 while the table 1 summaries the list of fECG extraction techniques with their accuracy.

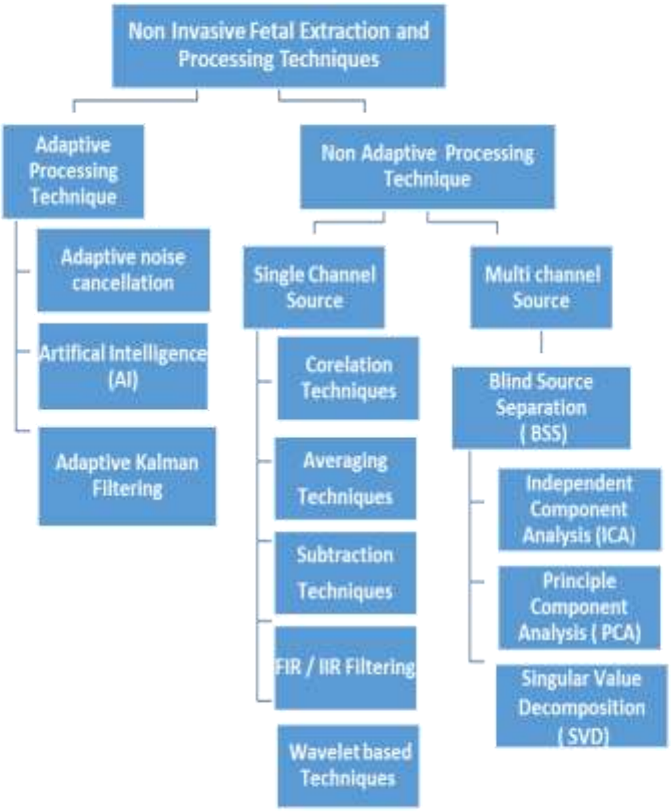

Fig. 1 Taxonomy of techniques for non-invasive fECGextraction.

TABLE I: SUMMARY OF EXISTING FECG EXTRACTION TECHNIQUES

Author	Technique	Database	Accuracy (%)
Mooney et al.,1995 [73]	Adaptive	5 abdominal leads	85
	Algorithm	(several records)	
Azad et al., 2000 [18]	Fuzzy approach	3 abdominal leads	89
		(5 records)	
Khamene et al.,2000 [45]	Quadratic spline	5 abdominal &	100
	wavelet	3 thoracic	
Pieri et al., 2001 [74]	Matched Filter	3 abdominal leads	65
Camps et al.,2001 [20]	FIR neutral network	Synthetic & real	91
	Statistical Analysis	Registers	
Ibahimy et al.,2003 [76]	Complex wavelets	One abdominal lead	89
	Time Frequency	5 records, 20 min	
Karvounis et al., 2004 [38]	methods	3 abdominal leads	99.5
	Time frequency	15 records,1 min.	
Karvounis et al., 2006 [39]	Analysis	4 long records	96
	Time frequency	15 minutes	
Karvounis et al., 2007	Analysis	3 abdominal leads	99.19
[76]	Wavelet adaptive	8 short records	
Karvounis et al., 2007	filter	3 abdominal leads	97.35
[76]	Multistage Adaptive	10 short records	
Swarnalatha et al.,2009 [77]	Filter	SISTA/DAISY &	90
Swarnalatha et al.,2010	ANFIS & Wavelet	Physionet data	
[5]	method	SISTA/DAISY &	89
Swarnalatha et al.,2010			
[78]		Physionet data	
		5 different subjects	100

A. *Adaptive processing technique*

Adaptive filters are self-adjusting filters whose transfer function acts according to an optimization algorithm driven by an error signal. Adaptive noise canceller (ANC) requires a reference input that should be uncorrelated with the signal of interest and closely correlated with the interference. The adaptive filter learns and adapts the characteristics of reference signal and modifies it similar to the influencing interference. These methods train an adaptive or matched filter for either removing the mECG using one or many maternal thoracic as reference channels to extract the fECG. Amalgamation of different adaptive techniques and training algorithms are replaced to overcome limitations of individual techniques giving rise to a large number of new intelligent systems. Nasiri et al [6] and Assaleh et al [7] respectively used adaptive neuro-fuzzy inference System (ANFIS) to nonlinearly align the maternal ECG signal with the components of maternal ECG in the abdominal ECG signal. Identified maternal components were cancelled from the abdominal ECG signal and finally fECG signal is extracted [8]. In the following ANFIS system [9] shown in figure 2, an initial Sugeno-type FIS system is generated using the matlab command genfis1 with the membership function (mf) set to 2. Using ANFIS to fine tune the intial FIS, the number of epochs is set to 20.We could start the learning process using the command anfis and stop when the epoch is completed. The evalfis command is used to determine the output of the FIS system for a given input.

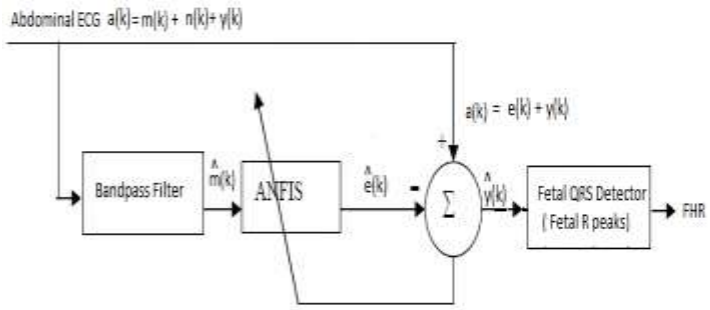

Fig. 2 ANFIS model to extract fECG [9].

B. Correlation technique

In this technique a correlation function is subtracted from the aECG to yield the desired fECG. However, correlation techniques are not very efficient and effective in the detection of non-stationary signals like ECG. Van Bemmel, 1968 [10] proposed a method using auto correlation and cross correlation techniques for detecting the presence of a fetal heart signal in an aECG signal corrupted by noise. In the paper described in [11], the filtered aECG pulses x1(k) was multiplied with the proposed customized synthesized pulses x2(n-k) as shown in equation (1). The output pulses represented the fetal QRSsignal.

$$y(n) = \frac{1}{N}\sum_{n=0}^{N-1} x_1(k)\, x_2(n-k) \quad (1)$$

C. Independent Component Analysis

Independent Component Analysis (ICA) has become a promising tool and developing work in recent biomedical signal processing research works. ICA aims at the direct reconstruction of the different statistically independent bioelectric source signals, as well as the characteristics of their propagation to the electrodes. ICA, using higher order statistics to decompose the signal into statistical independent components, has already been used in single pregnancies to distinguish between maternal and fECG signals [12]. Estimated maternal signals were subtracted from aECG, however this approach fails when fECG is weaker than the residual noise. The work described in [11], has a two stage ICA system wherein aECG is composed of the mECG m(k), fECG f(k) and artefact noise signals, denoted by n(k). After the implementation of the 2nd ICA stage, a strong mECG is obtained on one channel, a strong fECG on 2nd channel along with mECG spikes of moderate amplitudes. Channels 3 and 4 contain the noise signals as shown in figure 3.

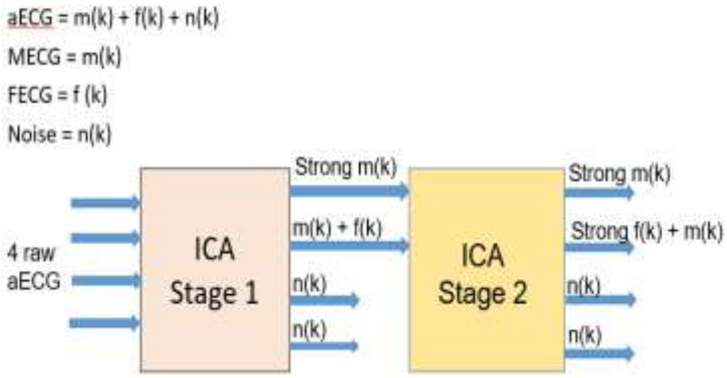

Fig. 3 ICA algorithm to extract fECG[11].

D. Filter method

Since fECG is our signal of interest, all other noise including mECG are considered as artefact. The fECG signals are filtered by using various filtering methodologies such as FIR or IIR filters. Commonly filters can be used in the form of low pass, high pass, band pass and notch filters [13]. Kam. A and Cohen. A, 1999 [14] proposed two distinct techniques. The first method used the IIR filter with genetic algorithm adaptation while the other IIR filter without the adaptation. The resulted fECG was good compared to methods using genetic algorithm alone.

III. Proposed Methodology

We proposed a novel method of using FIR filters using its important features such as linearity and sharp transition characteristics. We proposed to use these sharp FIR filters to extract the maternal and fetal signals knowing the approximate QRS frequency bands of the mother and fetus [15]. If we truncate the frequency band according to the required QRS range we aim to achieve an appreciable transition range of about 2Hz using these linear phase FIR band pass filters. The proposed methodology is shown in figure 4.

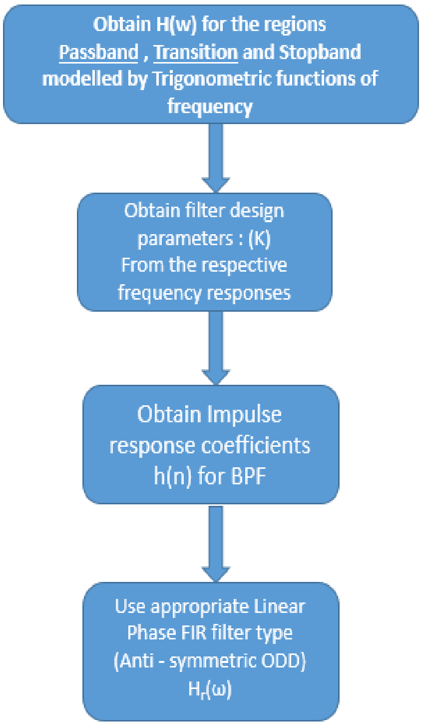

Fig 4. Proposed methodology using anti-symmetric odd type to obtain linear FIR BPF.

The magnitude response of the BPF is obtained for three main regions, namely one passband region, transition bands (two regions) and stopbands (two regions). Using the novel technique of modelling the five regions (curve approximations) the H (ω) is obtained. The filter design parameters can be easily obtained from the respective frequency responses. The next step was to compute the impulse response coefficients h (n) for the BPF. Using the linear phase FIR filter theory, the BPF falls in the category of anti – symmetry odd [16-17]. Once we are certain with the maternal and fetal fiduciary band edges we can apply the band edges to the proposed BPF to effectively obtain fHR and mHR.

IV. Results

The proposed methodology used linear phase FIR band pass filter [15] and the same was compared with the other methods such as ANFIS, correlation with synthesized QRS pulse and ICA method. The simulation was carried out using Matlab simulation and used Physionet database (adfecgdb) [18] to compare the above techniques. Each of the above methods used a common QRS detector based on Pan Tomkins [19]. The difference of the fetal index obtained for the record by each of the methods were compared with the invasive fetal index (annotations given by Physionet).

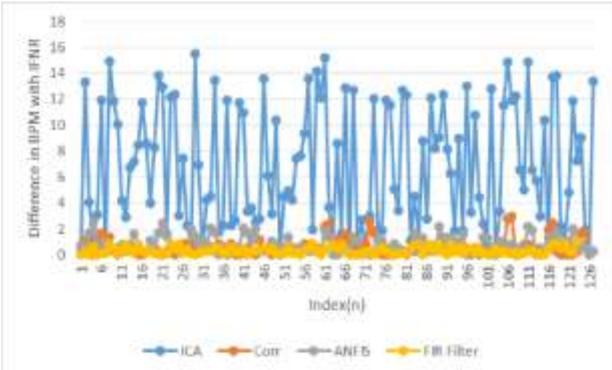

Fig. 5 Computing fHR using various methods

It is observed in figure 5, that the difference in the beats per minute (BPM) compared to the invasive fHR using our linear phase FIR filters is the least as compared with the other techniques. It is also noticed that in spite of mECG and fECG stay sometimes in (a) close proximity or (c) partially overlap as seen in figure 6, we obtain valid and correct fHR and mHR.However when the aECG signals are (b) corrupted during acquisition as seen in figure 6, then it becomes nearly impossible to extract correct heart rates. Figure 7 indicates the difference in the index between fetal and maternal R-peaks when the two signals are in close proximity in time domain. While figure 8,shows the difference in heart rate between fetal and maternal R-peaks when the two signals overlap in time domain.

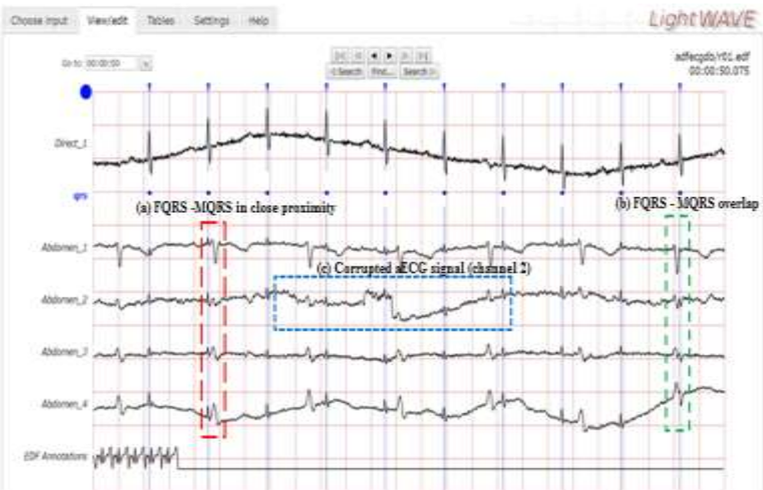

Fig. 6 fQRSand mQRS signals in time domain [18].

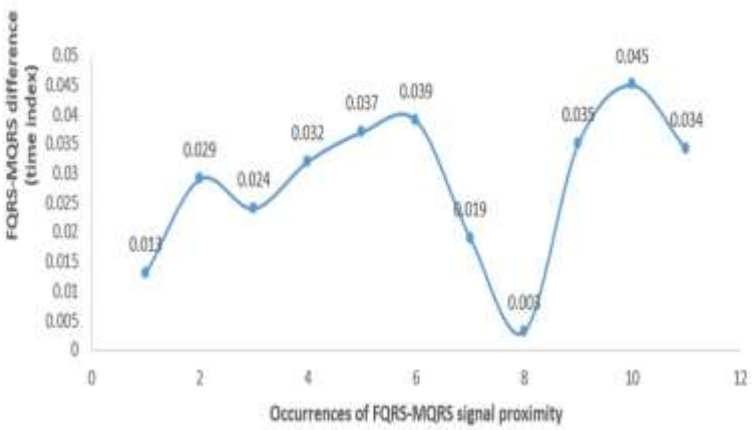

Fig. 7 Difference in the index between fetal and maternal R-peaks when the two signals are in close proximity in time domain.

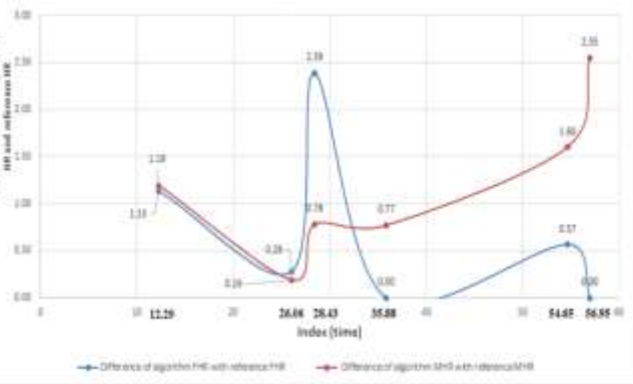

Fig. 8 Difference in heart rate between fetal and maternal R-peaks when the two signals overlap in time domain.

V. Conclusion

The proposed technique using FIR filters gave precise fetal heart rates as compared with the techniques such as ANFIS, Correlation and ICA. The next best method for computing fHR seen from the simulation was ANFIS followed by Correlation technique. The two stage ICA exhibits the worst fHR computations, giving a maximum difference of up to 15 BPM as compared to 0.2 to 1 BPM for our proposed method. It is also concluded that our sharp FIR filter method computed precise mHR and fHR in spite of the noisy aECG and when the mECG and fECG existed in close proximity or partially overlapped in time domain. The biggest challenge was to compute fHR for signals which were corrupted during acquisition. With proper ECG electrode instrumentation in abdomen placement configurations, suppressions of power line frequency (50Hz) and removals of other artifacts such as baseline wandering we may achieve to get better composite aECG signals to extract precise fECG so as to derive fetal morphological analysis and thereby estimate the fetal health status throughout the third trimester in pregnancy.

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