A concise review of NIFECG extraction techniques to monitor fetal distress

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Abstract—**Non-Invasive Fetal Electrocardiogram (NIFECG) obtained from the abdominal Electrocardiogram (aECG) of a pregnant woman is an efficient clinical tool for supporting and evaluating the fetal distress along with the conventional ultrasound method. FECG signal is often masked by the maternal Electrocardiogram (MECG) partly due to the relatively low signal-to-noise ratio of the fetal ECG compared to the maternal ECG. The predominant noises are baseline wander, measuring electrodes, power line interference, maternal Electromyogram (EMG) etc. The other challenge is that the maternal and fetal signals overlap in time as well as frequency. Over the years, biomedical researchers have used various powerful and advanced techniques to extract and detect NIFECG from abdominal signals, which is become an important step towards fetal monitoring. The focus of this paper provides a concise review of the comparisons and performance of the various methods used by researchers to extract NIFECG signal for applications such as fetal heart rate monitoring systems.**

***Keywords* —NIFECG, maternal ECG, abdominal ECG, fetal heart rate.**

I. Introduction

Five years later after Einthoven first discovered the presence of electrical activity in an adult heart, Cremer identified FECG from a combination of viginal and abdominal electrodes. Six year later, Winckel [1] suggested that a fetal heart rate (FHR) of less than 120 beats per minute (bpm) or greater than 160 bpm were signs of fetal distress. It is reported in WHO Media Centre 2012 that Congenital anomalies (also referred to as birth defects) affect approximately 1 in 33 infants and result in approximately 3.2 million birth defect related disabilities every year. The infant Mortality Rate (IMR) of 2012 in India is 11 deaths per 1000 live births [2]. It was observed that decelerations of the fetal heart rates predicted fetal hypoxia. Monitoring of FHR is therefore sensitive and can detect fetal asphyxia early in the evolution to acidosis. Electronic FHR monitoring was introduced in an attempt to reduce or eliminate the potentially disastrous consequences of fetal asphyxia. Currently, CTG and Ultra sound transducer are the main methods by which the fetal's wellbeing is monitored.

Fetal distress, now commonly known as non-reassuring fetal status is a complication during pregnancy or labor. It is occurs mostly due to placenta abruption, umbilical cord prolapse, breathing problems etc. The various non-reassuring patterns seen on a cardiotocography to mark fetal distress are increased or decreased fetal heart rates especially during and after a contraction, decreased variability in FHR and late decelerations among other signs. However fetal's beat-to-beat changes obtained using CTG are not accurate compared to those obtained from the electrocardiogram (ECG) signal [3].

FECG signals extracted from the abdominally placed ECG electrodes of the mother are very low-voltage amplitude signals buried in maternal complexes, baseline wander, power line interferences, maternal electromyogram and other artifacts. Invasive FECG obtained using the fetal scalp electrode directly applied to the skin allows easy detection of fetal QRS complexes. These signals have much larger amplitudes than abdominally obtained signals, however with the risk of infection to the foetus. Detection of NIFECG signal and its analysis is becoming a very powerful and advanced method in clinical diagnosis and biomedical applications. The FECG which contains potentially valuable information would assist clinicians in making more appropriate and timely decisions during labor. However there exists a limitation for perfectly monitoring the fetal heart rates improving the SNR of the FECG. Latest technologies in digital signal processing have been developed over the years towards advanced FECG detection, extraction, and analysis methods.

II. NIFECG Signal Extraction and Processing Techniques

The NIFECG can be extracted from the aECG by using either a single channel or a multi- channel signal source. These signals are processed by means of adaptive and non-adaptive methods to extract FECG. The drawback of non-adaptive techniques is that they are time invariant in nature, which has been overcome by the adaptive methods [4]. Researchers in this biomedical field have continuously strengthened the extraction algorithms and improved the detection techniques which has led to further reduce noise and thus acquire reliable FECG signals assuring the fetal health during pregnancy period and labor. They have put in extensive work to effectively and efficiently separate FECG from maternal ECG using single and multichannel signal sources. Some of the methods of linear adaptive processing are Kalman filtering, LMS (least mean square) algorithm, RLS (recursive least square) algorithm and adaline neural networks, while non-adaptive techniques include techniques like artificial neural networks and ANFIS (adaptive-network-based fuzzy inference system). Methods of BSS (blind source separation) – ICA (independent component analysis), PCA (principle component analysis) and SVD (singular value decomposition) are non-adaptive multi-channel. Conversely single channel signal source processing uses non-adaptive methods like correlation, auto correction methods, subtraction, averaging techniques, wiener filtering, finite impulse response (FIR), infinite impulse response (IIR) filtering and wavelet transform based techniques.

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 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. Various adaptive filters have been used in the past for MECG cancellation as noise and to extract FECG. 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. The adaptive filtering methods require a reference MECG channel or involve numerous linearly independent channels to approximately restructure the morphologic profile from the references. These methodologies include least mean square (LMS) algorithms, recursive least square (RLS) algorithms, artificial intelligence techniques, fuzzy inference systems, genetic algorithms and Kalman filters [4].

1. Adaptive Noise Cancellation (ANC)

R. Swarnalatha et al., 2010 [5] used multistage adaptive filtering for FECG extraction in which the maternal thoracic ECG was used as a reference signal for MECG cancellation and different filter combinations were tested with LMS, normalized least mean square (NLMS) and RLS algorithms. Similarly, in Widrow et al. 1995 [6], a linear adaptive filter was used. These methods were not the best for clinical practice as they failed to extract FECG when the maternal and fetal signals overlaped each other. Widrow et al., 1975 [7] used the adaptive noise cancellation (ANC) system to cancel periodic interferences in aECG to produce a clear FECG signal. Later Widrow et al., 1976 [8] again used ANC to reduce periodic or stationary random interference in periodic and random signals using LMS adaptive filter. Martens et al., 2004 and 2006 [9,10] proposed an improved adaptive canceller (IAC) for decreasing the fundamental power line interference (PLI). M.Ungureanu et al., 2007 [11] proposed an adaptive subtraction technique to subtract MECG after detecting and removing aECG signal segments with high amplitude variations due to uterine contractions. M. Z. U. Rahman et al., 2011 [12] also developed adaptive filtering techniques for noise elimination with various algorithms for the removal of noise from ECG signals

2. Artificial intelligence (AI)

Some AI techniques mainly based on neural networks have been very useful for real-time applications like FECG signal recording and analysis. Marques et al., 1994 [13] used artificial neural networks (ANN) for FHR baseline determination. Selvan et al., 2000 [14] proposed that the two popular techniques, namely adaptive noise cancellation (ANC) and adaptive signal enhancement were efficient techniques for processing of abdominal FECG by using neural networks. Reaz et al., 2004 [15] and Amin et al., 2011[16] described FECG extraction through an adaptive linear (adaline) neural network filter. The adaline neural network was trained to eliminate the MECG component in the aECG signal. In 1999, Giovanni Magenes et al. [17] proposed neural and fuzzy classifiers to distinguish between normal and pathological fetal states. Azad 2000 [18] developed a fuzzy-based approach to extract the fetal heart rate (FHR) by detecting the QRS complex in the FECG signal. Kezi S.V. et al., 2005 [19] proposed an adaptive neuro fuzzy logic technique for the elicitation of FECG signal by eliminating the MECG signal from the aECG signal. According to G. Camps et al. [20] in 2001, FECG can be extracted using FIR neural network in order to provide highly nonlinear dynamic capabilities. Warrick et al., 2005 [21] described the signal processing tools and neural networks which were used to develop an automated technique to detect the FHR pattern of baseline, acceleration and decelerations.

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. [22,23] Nasiri et al and Assaleh et al 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. In Nasiri et al., 2012 [24] Genetic Algorithm (GA) acts as a tool for training the ANFIS structure, which identifies the non-linear transformation. M. Ahmed et al., 2010 [25] proposed a technique for fECG extraction based on genetic algorithm (GA) working with an adaptive filter. T. M. Nazmy et al., 2009 [26] classified ECG signals using adaptive neuro-fuzzy inference system. A. Sargolzaei et al., 2011 [27] developed an adaptive neuro-fuzzy Interference System (ANFIS) trained with particle swarm optimization (PSO) methodology using four different techniques for the extraction of FECG signal.

The Bayesian filter framework was used by Sameni in 2008 [28] to extract FECG from single channel mixture of MECG and FECG. However, as mentioned in [28], the filter fails to discriminate between the maternal and fetal components when the MECG and FECG overlap in time. V. P. Oikonomou et al., 2005 [29] developed a Bayesian method for FECG signal extraction integrated with PCA technique. R. Sameni et al., 2007 [30] implemented the Bayesian filtering framework for denoising single channel ECG signals. Y. Yin et al., 2010 [31] Extracted FECG signal by using Bayesian inference with Neural Networks. R. Vullings et al., 2011 [32] proposed an adaptive Kalman Filter for enhancing the SNR of ECG Signal.

The kalman filter, a general class of adaptive filter uses only an arbitrary MECG as reference for MECG cancellation and FECG extraction. The drawbacks of Bayesian modelling and Kalman filtering are that it involves mathematical complexity and computational time is not quick.

B Single channel non adaptive processing technique

1. Wavelet transform based method.

The Wavelet transform (WT) is a time scale representation and efficient mathematical tool for analyzing non-stationary and fast transient signals. One of the main properties of WT is that it can be implemented by means of a discrete time filter bank [4]. Wavelet transform based approach proposed in Papadimitriou et al.,1996 [34] efficiently eliminates transient spikes and reduces both Gaussian and coloured noise without affecting or destroying the information content of the signal. The method developed by Echeverria et al., 1996 in [35] used multi-resolution wavelet decomposition for FECG acquisition. The wavelet analysis and pattern matching were used for pre-processing stage to suppress noise and then maternal QRS complexes were cancelled by means of pattern matching and template subtraction. Again in 1998, Echeverria et al., [36] developed a reliable procedure for off-line processing of aECG called Wavelet Analysis and Pattern Matching (WA-PM). Mochimaru et al., 2002 [37] used wavelet based methods to detect the FECG. To remove the large baseline fluctuations in the signal as well as to remove the noise, multiresolution analysis (MRA) was used. Complex Continuous Wavelet Transform (CCWT) based technique was implemented by Karvouniset al., 2004 [38] along with modulus maxima theory to detect fetal QRS complexes from multichannel MECG recordings. Also Karvouniset al., 2006 [39] described a three stage method which was used to extract FHR based on time frequency analysis and complex wavelets and pattern matching techniques. Combination of Wavelet and ICA, called WICA technique was proposed by [40]. Using this WICA method, FHR was detected and the Q, R, and S waves were visible without any signal amplification. An algorithm was proposed by Almagro et al., 2006 [41] to design a new Mother Wavelet (MW) called abdominal ECG Mother Wavelet (AECG MW) for effective extraction of FECG. A way for detecting QRS complex based on dyadic wavelet transform (D WT y) was represented by Kadambe et al., 1999 in [42]. They have designed a Spline wavelet for detecting QRS complex which was the transient part in the ECG signal. Real time FECG feature extraction system was developed by Desai et al., 2012 in [43] based on multi-scale Discrete Wavelet Transform (DWT). Wavelet based peak detection detects QRS complex more accurately for identifying peaks and valleys of noisy FECG signal [33]. Ye Datian et al., 1996 [44] implemented a wavelet analysis method to effectively detect FECG. Khamene et al., 2000 [45] also efficiently developed a wavelet transform based method to extract the FECG from the composite abdominal signal.

2. Correlation, Averaging , subtraction

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 [46] 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. Z. Shi and C. Zhang [47] combined non-Gaussianity and time-correlation of the source signals for FECG extraction. The correlation coefficients of the estimated FECG that were higher than 0.9 was considered to be a good extraction. Averaging method is one of the commonly used method to extract the waveform of the MECG using only the abdominal lead. Due to the large amplitude in the aECG signal, the R-waves of the MECG signal are easily detected by threshold detectors. Hon et al., 1964 [48] proposed the averaging methodology for FECG signal enhancement. The negative aspect of signal averaging is that it removed short term changes in the ECG waveform and moreover, the presence of significant low frequency noise components reduced the effectiveness of averaging [4]. The subtraction method of subtracting the MECG signal from the aECG signal is one of the most primitive methods. The resulting FECG signal with noise is obtained, while the noise isfiltered out. Bergveld et al., 1981 [49] proposed a subtraction method but the major challenge was that the amplitude of the thoracic MECG rarely matched the scale of the MECG present in the aECG signal. As a result correct FECG is hardly ever obtained. C. Levkov et al., 2005 [50] used this subtraction methodology for power line interference elimination from ECG signals without degrading the signal spectrum.

Since FECG is our signal of interest, all other noise including MECG are considered as artefact. The FECG signal are filtered by using various filtering methodologies like linear time domain filters, frequency domain filters, finite impulse response (FIR) filters, infinite and impulse response (IIR) filters and Wiener filters. However linear filters are not suitable when the spectrum of the signal and noise are overlapping. Frequency domain filters can also be used such as, low pass, high pass, band pass and notch filtering features [51]. Kam. A and Cohen. A, 1999 [52] proposed two different techniques. One method used IIR filter with genetic algorithm adaptation. The other method used IIR filter with genetic algorithm without adaptation. The resulted FECG was good compared to methods using genetic algorithm alone. Alcaraz et al., 2007 [53] implemented different filters for filtering baseline wandering, high frequency noise (eliminated by an eight order bidirectional IIR Chebyshev low pass filter) and the power line interference was eliminated by notch filtering. L. Chmelka and J. Kozumpl, 2005 [54] used wiener filtering for ECG denoising. The limitations of the Wiener filter [55] are the requirements of autocorrelation matrix, cross-correlation vector and matrix inversion, which also lead to a time consuming process [4].

C Multichannel non adaptive processing technique

Blind source separation (BSS) and Independent Component Analysis (ICA) has become a promising tool and developing work in recent biomedical signal processing research works. There are different techniques of BSS methodologies, independent component analysis (ICA), principal component analysis (PCA) and signal decomposition techniques. In 2004, Chareonsak et al. [55] proposed a real time BSS method that can be used to separate the FECG from the AECG effectively. Jafari et al., 2005 [56] have addressed the problem of FECG extraction using Blind Source Separation (BSS) in the wavelet domain. Blind Source separation methods can also be combined with wavelet decomposition methods [57] for denoising and extracting FECG from composite abdominal ECG signal. Karvounis et al., 2010 [58] proposed a three stage methodology adopting BSS technique. The extracted FECG was compared with real FECG signal and was found to be correlated with the true FECG.

In 2000, de Lathauwer et al. [59] proposed the technique of ICA, to extract FECG from multilead potential recordings on the mother's abdomen. 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. D. E. Marossero et al., 2003 [60] proposed an efficient method using the mermaid algorithm for ICA method, where the performance of the Mermaid algorithm, based on minimizing Renyi's mutual information, was evaluated. 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 [61]. Najafabadi et al.,2005 [62] also applied the ICA for the separation of FECG and MECG signal from the AECG. It is concluded that ICA works magnificently in order to extract FECG. Y. Ye et al., 2008 [63] proposed a neural network based ICA algorithm, called Fast Adaptive orthogonal group (OgICA) algorithm to separate mixtures of sub Gaussian and super Gaussian source signals. D. Luo in 2012 [64] discussed the nonlinear blind mixed ECG signals separation technology and introduced the model of the ICA algorithm and the implementation methods. Martın-Clemente in 2011 [65] described a fast and simple algorithm that was developed based on ICA but computationally demanding calculations were substituted to make it simpler in FECG extraction. Camargo-Olivares et al., 2011 [66] MICA based approach extraction method was presented which was more appropriate than ICA in FECG extraction. Estimated maternal signals were subtracted from AECG, however this approach fails when FECG is weaker than the residual noise.

A method presented in [67] was based on non-stationary ICA and wavelet de-noising. Due to low amplitude and poor signal to noise ratio (SNR) of the FECG recorded at the abdominal region of a pregnant woman, the proposed algorithm removed the maternal ECG, reduced motion artefact and enhanced FECG signal. Here due to the non-stationary nature of the FECG signal, non-stationary ICA method was used to eliminate maternal complex. In [68,70], ICA based BSS methods were used for extracting FECG, which showed that reconstruction of FECG could be possible by means of higher order statistical tools. Hyvarinen, 1999 [78] proposed the fast and robust fixed point algorithms for ICA ,which can be used efficiently to extract FECG. I.Romero 2010 [69] investigated the performance of principle component analysis (PCA) in denoising ECG signals recorded in ambulatory conditions.

TABLE I
SUMMARY OF EXISTING FECG EXTRACTION TECHNIQUES

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

Spatial filtering techniques such as singular value decomposition (SVD), blind and semi-blind source separation, can be considered as decomposition methods that are driven by data, which creates the required basis functions from the data itself, by maximizing several statistical quantities of signal segregation. Gao et al., 2003 [70], described a method which was employed with the combination of Singular Value Decomposition (SVD) and ICA for FECG signal separation from AECG. This method uses SVD of the spectrogram followed by an iterative application of ICA. Barros et al., 2001 [71] proposed a semi blind source separation algorithm which has been developed and requires prior information about the auto correlation function of the primary sources to extract the FECG signal.

De Lathauwer et al. (2000) [72] have discussed the pros and cons of techniques relying on the ordinary singular value decomposition (SVD), quotient SVD and multilinear SVD for the elicitation of the FECG from multilead cutaneous potential recordings. The multilinear SVD approach has the advantage that the mixing matrix can be estimated in an unsupervised way. In addition, the separation of the measurements into statistically independent source signals is easier to interpret than decomposition in time-orthogonal principal components. On the other hand, the algorithm is computationally more complex. The Table 1 presents several methods proposed in the literature for the extraction of FECG. Due to the fact that there is no benchmark database for this area and therefore, each approach is evaluated and performed using different approaches.

III. Conclusion

Detailed analysis and monitoring of the FECG during labor could provide very important additional information about the fetal distress , fetal health status and hence assist clinicians in reducing incidents of unnecessary medical intervention. As a result, fetal heart rate monitoring is important during the pregnancy and labor. Methods for FECG signal extraction from the composite aECG signal were listed along with their advantages and drawbacks. Therefore, the aim of this paper was to provide concise information and compare the various techniques to efficiently and effectively conduct FHR monitoring.

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