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Acquiring Fetal ECG Signal from Combined ECG Signal Using Fast Independent Component Analysis

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***Abstract*— Combined ECG signal(Maternal ECG+Fetal ECG) is taken as input in jpeg (or) gif image format which is a different approach from earlier days. Blind Source Separation is the technique used for separating these source signals. The FAST ICA a technique of blind source separation, that partitions the FECG from the MECG and other unwanted background interferences. Since the FECG contains minimal amount of noise, it can be eliminated using pre-processing. Finally the FECG signal is extracted and the method is tested with simulation results using MATLAB. The decomposed mixed signal can also be reconstructed using Inverse lifting Transform. Comparison results show that Lifting Wavelet Transformation and FAST ICA algorithm produces the best SNR value of 11.39 for maternal and 10.10 for Fetal Electro Cardio Gram signals.**

***Index terms*—Discrete Wavelet Transform, Fast Fourier Transform, Fetal Electro Cardio Gram, Maternal Electro Cardio Gram, Signal to Noise Ratio.**

I. INTRODUCTION

ECG signal is the record of electrical activity of the heart that results when the heart muscle cells in atria and ventricles contract. ECG is a non stationary signal and composed of atrial depolarization (P wave), ventricular depolarization (QRS complex) and re-polarization of the ventricles (T wave). So far, research and extensive works have been made in this area, developing better algorithms, upgrading existing methodologies, and improving detection techniques to reduce noise and acquire accurate FECG signals.

Wavelet transform is well fitting to non stationary signals like ECG. The combination of wavelet analysis and BSS methods also shows potential attitude for the separation of the maternal and fetal signals from ECG. Blind adaptive-filtering tactic overcomes the theoretical limitations in applying conventional BSS methods based on ICA for FECG signal extraction problem.

In this regard different ECG databases were collected from reputed hospitals and some were also collected from MIT and Physionet websites which were in digital format. These signals were scanned and converted to jpeg format as images, which were then read by MATLAB and converted into a one dimensional format to be used in the algorithm.

A. Characteristics of ECG

ECG signal is the record of electrical activity of the heart that results when the heart muscle cells in the atria and ventricles contract. The signal is recorded by placing electrodes on the body surface and it can be obtained in a printed form as ECG graph. A normal ECG wave is composed of a P wave, QRS complex and a T wave. The P wave represents atrial depolarization and the QRS represents ventricular depolarization. The T wave reflects the phase of rapid re-polarization of the ventricles.

B. Importance of FECG

FECG (Fetal Electrocardiogram) is a biomedical signal that gives electrical representation of FHR (Fetal Heart Rate) to get vital information about the condition of the fetus during pregnancy from the recordings on the mother's body. The characteristics of the fetal electrocardiogram (FECG), such as heart rate, waveform, and dynamic behaviour, are convenient in determining the fetal life, fetal development, fetal maturity, and existence of fetal distress or congenital heart disease. The FHR may change as the fetus responds to conditions in the uterus. An abnormal 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 caesarean delivery is needed. During pregnancy, the motivation for monitoring the fetal is to recognize pathologic conditions, typically asphyxia, with sufficient warning to enable intervention by the clinician. Therefore, FHR carries a significant importance of clinical perspectives.

The FECG signal is a comparatively weak in amplitude (less than 20% of the mother's ECG) and often mixed with noise. The FHR lies in the range from 1.3 to 3.5 Hz and sometimes it is possible for the mother and some of the FECG signals to be closely overlapping. So it is necessary to separate the maternal and fetal cardiac signal in order to diagnose properly during pregnancy time.

The extraction of FECG from the complex signal (mother and fetus) can be reframed in a more efficient manner using blind source separation (BSS) methods such as principal component analysis and independent component analysis (ICA). Wavelet transform is well fitting to non stationary signals like ECG. The combination of wavelet analysis and BSS methods also shows potential attitude for the separation of the maternal and fetal signals from ECG [1]. Blind-adaptive-filtering tactic overcomes the theoretical limitations in applying conventional BSS methods based on ICA for FECG signal extraction problem. So far, research and extensive works have been made in the area, developing better algorithms, upgrading existing methodologies, and improving detection techniques to reduce noise and acquire accurate FECG signals to obtain reliable information about the fetal state thus assuring fetal well-being during pregnancy period.

II. SYSTEM ANALYSIS

A. Blind Source Separation

Blind source separation (BSS) refers to the problem of recovering signals from several observed linear mixtures. The strength of the BSS model is that only mutual statistical independence between the source signals is assumed and not a priori information about e.g., the characteristics of the source signals, the mixing matrix or the arrangement of the sensors is needed. Therefore BSS can be applied to a variety of situations such as, e.g., Separation of simultaneous speakers, analysis of biomedical signals obtained by EEG or in wireless telecommunications to separate several received signals as shown in fig. 1.

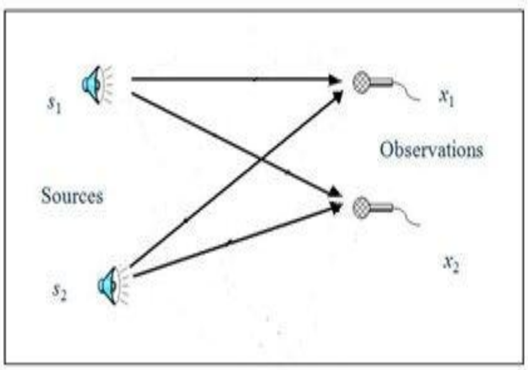

Fig. 1 Block Diagram illustrating Blind Source Separation

Imagine that in a room, two people are speaking simultaneously. There are two microphones, which are held in different locations as shown in the above figure. The microphones give two recorded time signals, which could be denote by x1(t) and x2(t), with x1 and x2 the amplitudes, and t the time index. Each of these recorded signals is a weighted sum of the speech signals emitted by the two speakers, which is denoted by s1(t) and s2(t). This could be expressed as a linear equation:

$$X1(t) = a11s1 + a12s2 \quad (1)$$

$$X2(t) = a21s1 + a22s2 \quad (2)$$

Where a11, a12, a21, and a22 are some parameters that depend on the distances of the microphones from the speakers. It would be very useful if one could now estimate the two original speech signals s1(t) and s2(t), using only the recorded signals x1(t) and x2(t). This is called the cocktail-party problem. For the time being, any time delays or other extra factors are omitted from the simplified mixing model.

Humans cannot select the voice of a particular speaker from an ensemble of different voices corrupted by music and noise in the background. One approach to solve this problem is to record the mixed audio signals with microphone arrays and subsequently apply blind source separation methods. Several simultaneously active signal sources at different spatial locations can then be separated by exploiting mutual independence of the sources. In the field of audio processing BSS is applicable, e.g., Realization of noise robust speech recognition, high-quality hands-free telecommunication systems or speech enhancement in hearing aids. Because temporal redundancies (statistical regularities in the time domain) are "clumped" in this way into the resulting signals, the resulting signals can be more effectively de-convolved than the original signals. Independent Component Analysis (ICA) is one of the methods of blind source separation.

B. Independent Component Analysis

Independent component analysis (ICA) is a signal processing technique that has demonstrated the ability of separating independent sources from mixed recorded signals when specific boundary demonstrated in studies on specific problems dealing with speech recognition systems, telecommunications and medical signal processing. ICA techniques can also be applied to non-conventional problems, because the basic assumption of the ICA problem, i.e. the independence of the variables, is realistic in many situations, hence permitting a completely blind source signals separation, or independent components retrieval, starting from given mixed input signals. ICA belongs to a class of blind source separation method for separating data into underlying components, where such data can take the form of images, sounds, telecommunication channels or stock market prices [3]. It can also be defined as a computational method for separating a multivariate signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals.

The successful applications of ICA in several fields where data analysis, source separation or feature retrieval were required, had encouraged its use also in biological signal processing, which are in general more complex to analyze than non-biological systems [3]. An intriguing application of ICA regards the processing of cardio logical signals. The data we used as input were acquired by means of magneto cardiograph (MCG), a technique that allows the non-invasive detection of the extremely low magnetic field variations associated to the spontaneous electrical activity of the human heart [3]. A particular application of MCG is fetal magneto cardiograph (fMCG), which records the magnetic field variations occurring over the abdomen of a pregnant woman; the data obtained with fMCG contain a combination of signals that are due to the electrical activity of both the fetal and the maternal hearts, since both are included in the same space volume, i.e. the maternal abdomen. The ICA prerequisites for independent sources and for mixed recorded traces are satisfied with fMCG data; in fact, pregnancy is a unique physiological condition in which a healthy human being has two distinct beating hearts, which, from the mathematical point of view, are the independent signal sources.

The ICA problem is, however, rather complex in the case of fMCG data; one reason for this complexity is that fetal and maternal cardiac signals are both quasi-periodic and have a similar waveform, which is the electromagnetic expression of the atrial and ventricular depolarization and re-polarization processes taking place during the cardiac cycle. Notwithstanding their similar shape, the fetal and maternal cardiac signals are characterized by different values of frequency (the fetal heart rate is higher than the maternal one) and intensity (the maternal heart is bigger than the fetal one and therefore produces a stronger signal). As a consequence, some weak fetal beats may be hidden behind the more intense maternal beats. As a further complication, no heart rate is ever perfectly constant; this condition implies that the source signals to be retrieved are not strictly periodic; on the contrary, they are characterized by a variability that, in case of cardiac disease, may also drastically increase.

ICA is a statistical method that searches from multivariate statistical data for underlying factors or components that are statistically independent. The recorded data is a linear superposition of n different sources of the form,

$$X=A*S \quad (3)$$

where A is the mixing matrix and S is the source matrix. The goal of ICA is to find a "separating matrix" W, which is as close to A-1 as possible, based upon a proper statistical criteria, in order to optimally recover the original source signals as

$$y(t)=Wx(t)=WAs(t) = s(t) \quad (4)$$

The matrix A is a time independent constant matrix and the matrix S is time dependant amplitude function. ICA is based on three assumptions they are,

- The independent components are assumed statistically independent.
- The independent components must have non Gaussian distributions.
- For simplicity, assume that the unknown mixing matrix is square.

C. Ambiguities of ICA

The following are some of the ambiguities of the Independent Component Analysis (ICA) model:

We cannot determine the variances (energies) of the independent components. The reason is that, both s and A being unknown, any scalar multiplier in one of the sources could always be cancelled by dividing the corresponding column ai of A by the same scalar; As a consequence, we may quite as well fix the magnitudes of the independent components; as they are random variables, the most natural way to do this is to assume that each has unit variance: E{s2i}= 1. Then the matrix A will be adapted in the ICA solution methods to take into account this restriction. This still leaves the ambiguity of the sign: we could multiply the independent component by −1 without affecting the model. This ambiguity is, fortunately, insignificant in most applications.

We cannot determine the order of the independent components. The reason is that, again both s and A being unknown, we can freely change the order of the terms in the summing, and call any of the independent components the first one. Formally, a permutation matrix P and its inverse can be substituted in the model to give,

$$X=AP – PS \quad (5)$$

III. PROPOSED METHODOLOGY

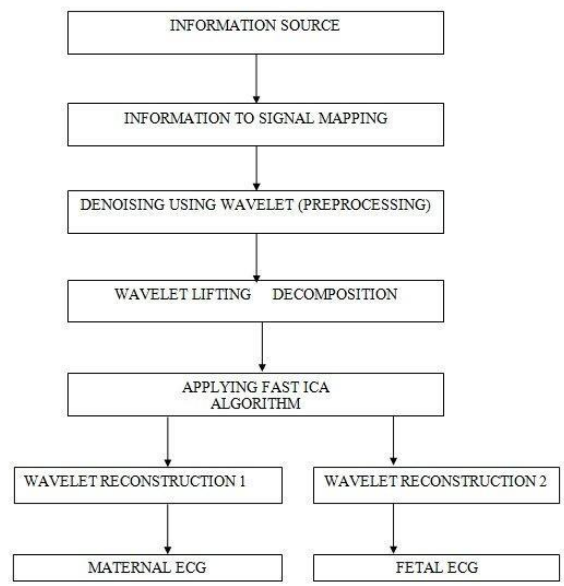

Fig.2 Flow Chart of Proposed Methodology

A. Information Source

Combined ECG signal(MECG+FECG) have to be collected from either a hospital or a laboratory. Or it is collected from databases such as the MIT and Physionet websites. It is scanned and used as input. The graphical image is read and then converted to binary format and

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finally it is scanned and mapped to two dimensional format. This signal is then preprocessed using Wavelet transform to remove noise. It is then decomposed to time frequency domain using Wavelet Lifting Decomposition. The fetal and maternal signals are then separated by applying FAST ICA algorithm to the decomposed signal. The separated signals are finally reconstructed using the inverse Wavelet Lifting Transform.

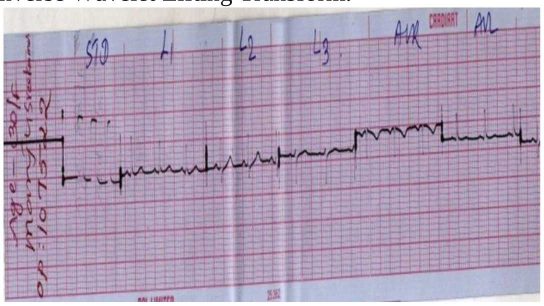

Fig. 3 Scanned Combined ECG signal as input

B. Preprocessing

Noise reduction in ECG signals is one of the main problems, which appear during analysis of electrical activity of the heart. The most troublesome noise sources contain frequency components within ECG spectrum, i.e.: electrical activity of muscles (EMG), and instability of electrode-skin contact. Such noises are difficult to remove using typical filtering procedures. Efficient analytical tool which allows to increase signal to noise ratio is a technique of averaging of cardiac cycles. Effectiveness of this method strictly depends on stable sinus rhythm. That requirement is however not fulfilled in case of arrhythmia, or the presence of many extra systoles. In such signals noise reduction is only possible with using, more advanced signal processing method, as wavelet denoising technique.

The input raw data of ECG signal has to be processed by several stages before getting separated. First, the signal undergoes a denoising stage using wavelet transform, then it is decomposed to time –frequency domain using the wavelet lifting transform. Now, by applying the Fast ICA algorithm to the decomposed signal it can be separated into fetal and maternal ECG. As a last stage the signal is reconstructed back using the inverse wavelet lifting transform.

Denoising: Noise reduction in ECG signals is one of the main problems which appear during analysis of electrical activity of the heart. The signal is transformed to another domain for denoising, a signal transform is used to transform a signal to a different domain, perform some operation on the transformed signal and inverse transform it, back to the original domain. Wavelet transform is a method for denoising images and signals with sharp discontinuities. Wavelet transforms are time-frequency representations of analog signals. These transforms use discrete-time filter banks. These filter banks are called the wavelet and scaling coefficients

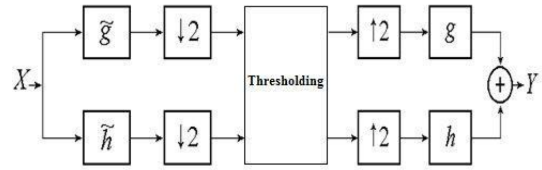

Fig. 4 Wavelet Transform

Fig. 4 shows a one stage wavelet transform using a low pass filter and a high pass filter followed by sub-sampling. The general wavelet denoising procedure [4] is as follows :

- Apply wavelet transform to the noisy signal to produce the noisy wavelet coefficients to the level which we can properly distinguish the PD occurrence.
- Select appropriate threshold limit at each level and threshold method (hard or soft thresholding) to best remove the noises.
- Inverse wavelet transform of the thresholded wavelet coefficients to obtain a denoised signal.

Procedure of noise reduction in signal is based on decreasing of noise content in high frequency components of signal. As the first step Wavelet Thresholding algorithm is applied at every level of decomposition. Next step is modification of values based on the algorithm. Finally the inverse transform is performed by an up-sampling step and then followed by two synthesis filters h (low-pass) and g (high-pass) to reconstruct the signal. Hence this technique is very useful to remove noise from the ECG signal.

The noisy FECG signal is decomposed to five levels of wavelet transform by using the daubechies wavelet (db4) [2]. The daubechies wavelet is orthogonal when the scaling functions have the same number of coefficients as the wavelet functions, or biorthogonal when the number of coefficients is different. In general these wavelets have highest number of vanishing moments for defined support width and it can be put into practice with minimum phase filters.

C. Wavelet Decomposition

For some applications, it may not be able to find a suitable wavelet among the usual ones widely available. In this case, it is necessary to design a new wavelet adapted to the problem to be solved or the task to be processed. For example, inorder to adapt a wavelet for the continuous wavelet transform (CWT) to a given pattern so that the resulting wavelet allows accurate pattern detection Designing new wavelets that are well suited for the discrete wavelet transform (DWT) is more delicate and, until recently, was exclusively a topic for wavelet specialists. The lifting method proposed by Sweldens facilitates this kind of construction. It allows to generate an infinite number of discrete bi-orthogonal wavelets starting from an initial one.

In this project wavelet decomposition is done by using Lifting Wavelet Transform (LWT). Lifting scheme is a technique for performing discrete wavelet transform. The main advantage of lifting scheme is that it is easy to perform the inverse transform and also for long filters the lifting scheme cuts computation complexity in half, compared to the standard iterated FIR filter bank algorithm. This type of wavelet transform has a complexity of N, in other words, much more efficient than the FFT with its complexity of N log (N) and lifting speeds up with another factor of two. In this scheme there is no need for samples other than the output of the previous lifting step and therefore the old stream can be replaced by a new stream. Two main properties of interest are

- The perfect reconstruction property and
- The link with "true" wavelets

These properties are very well satisfied in Lifting Wavelet Transformation (LWT) than in DWT. The principle of lifting is to generate from a given bi-orthogonal quadruplet a new one by applying a finite sequence of primal or dual elementary lifting steps (ELS).

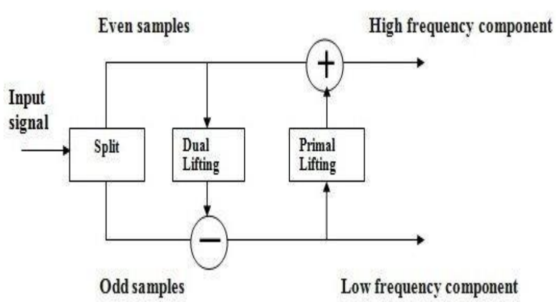

Fig 5 Forward Wavelet Lifting Scheme

From the Fig. 5 it can be inferred that the input is divided into even and odd stream, followed by lifting one of the streams by applying Laurent polynomial to other and adding it to the first. The lifting theorem now states that any other finite filter g^{new} complementary to h is of the form

$$g^{new}(z) = g(z) + h(z)s(z^2) \tag{6}$$

$$g^{new}(z) = h(z) + g(z)t(z^2) \tag{7}$$

D. Fast ICA

The Fast ICA algorithm was introduced in 1997 by Aapo Hyvarinen and Erkki Oja, from the Helsinki University of Technology. The basic concept is to take a neural network learning rule and convert it into a fixed-point iteration. This yields “an algorithm that is very simple, does not depend on any user-defined parameters, and is fast to converge to the most accurate solution allowed by the data.”Two important applications of ICA are blind source separation, and feature extraction. This includes some very focused, interesting applications such as analysis of fMRI data, and fetal heart monitoring. ICA is still in its infancy and its applications are still growing.

This particular algorithm can be used in batch mode (processing all the data at once) or in a semi-adaptive manner, working with subsets of the data at a time. In one experiment comparing it to a neural network algorithm, FastICA required 10% of the floating point operations used by the neural algorithm. The convergence of the FastICA algorithm is proven to be cubic, much faster than other similar algorithms. Another important aspect is that FastICA can be used to only extract desired components, instead of having to extract them all at once(though this requires proper initialization of the un-mixing matrix).

With these desirable features, FastICA is a good candidate for porting to a fixed point implementation. This report will first focus on the original floating-point method, and provide a set of tests/results for it. Then a modified version of the algorithm for fixed-point computation will be tested.

E. Reconstruction

In the inverse transform up-sampling is to be done after which filtering is performed. Up-sampling is nothing more than inserting zeros in between every two samples. The drawback of this is that the filter will perform a lot of multiplications by zero, again a waste of computing time. Since the idea of moving the down sampler in front of the filters worked rather well for the forward wavelet transform, a similar approach is performed for the inverse wavelet transform, i.e. moving the up-sampler behind the filters. In the inverse lifting transform it is possible to undo this lifting step by again applying the same Laurent polynomial to the other stream and then subtract it from the first as shown in Fig.4. Here the low pass sub-band is lifted first with the help of high pass sub-band, called as primal lifting. The high pass sub-band is then lifted with the help of low pass sub-band, called as dual lifting. Finally the reconstructed signal is taken in the output using a switch.

IV. Results

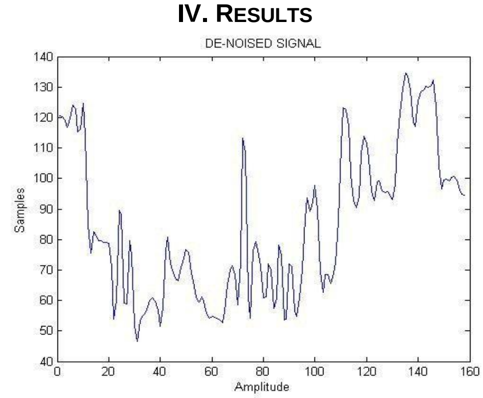

Fig. 6 Denoised Combined(MECG+FECG) Signal

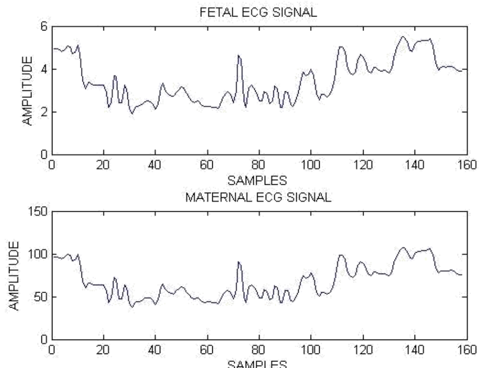

Fig. 7 Separated MECG and FECG signals using FAST ICA

TABLE I
SNR: ICA Vs FAST ICA

Algorithm	*MECG Signal*	*FECG Signal*
ICA	10	1.8
FAST ICA	11.39	10.10

V. CONCLUSIONS

In this paper it is proposed to separate the FECG and MECG signal from the recorded ECG signal so that a correct diagnosis can be given during pregnancy. The algorithm to be used is Fast ICA which is more efficient than current algorithms like ICA, AMBS and Echo.

In the initial part of the project the data is converted to a format acceptable by MATLAB. Then the process of de-noising, decomposition and reconstruction of the signal is done so that the Fast ICA algorithm can be applied. Thus the required FECG signal can be retrieved from Mixed ECG signal and further analysis can be made.

Future Scope: The input ECG signal has been mapped to the format acceptable by Matlab. The denoising of the FECG signal has been completed using Wavelet Transform. The decomposition of the signals and its images are obtained and Fast ICA algorithm is applied for the decomposed signal. Finally the maternal and fetal ECG signals are separated. Analysis can be made with different separation algorithms. The MATLAB code can then be converted to a C code and embedded in a DSP processor. This processor should be given the mixed signal from the maternal body as input and the output obtained after processing can be displayed in screen or taken in graphical format.

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