International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
Vol.4, No.11, November 2015 DOI:10.15693/ijaist/2015.v4i2.491-496

Extraction of Non Invasive Fetal ECG Using Stationary Wavelet Transform and Extended Kalman Filter

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***Abstract* - Fetal Electrocardiogram (FECG) identifies the congenital heart problems at the earlier stage. Non invasive fetal ECG extraction is a method to assess the fetal well-being during both pregnancy and delivery. In this paper, a new method is proposed for non invasive fetal ECG extraction based on stationary wavelet transform(SWT), weighted least square regression (WLSR) and the extended kalman filter (EKF) algorithm from abdominal ECG. The original FECG signal is nevertheless very complex and severely contaminated by external disturbances or noises. Identification of these cases during early pregnancy reduces risks by timely treatment or planned delivery. The noninvasive Fetal ECG (FECG) monitoring by means of abdominal surface electrodes provides information about the cardiac electrical activity of fetus. First, abdominal signals and thoracic signal were processed by stationary wavelet transform(SWT) and the wavelet coefficients at each scale were obtained. For each scale, the detail coefficients were processed by the WLSR algorithm to remove the maternal ECG (MECG). Secondly, a method based on bayseian filtering theory and dynamic ECG model is used to extract FECG from the residual signals. The effectiveness of the proposed method is evaluated using signal to noise ratio and and is implemented using MATLAB.**

***Index Terms* — Stationary Wavelet Transform(SWT), Weighted Least Square Regression (WLSR), Extended Kalman Filter (EKF), Electrocardiography, Fetal Electrocardiography (FECG).**

I. INTRODUCTION

Now and then, it is essential to monitor adult heart condition, it is often necessary to monitor the fetal heart activity during pregnancy and at childbirth[14]. The process of monitoring the heart condition is called electrocardiography(ECG) which demonstrates the electrical activity of the heart. In the case of fetus, it is called fetal electrocardiography. Fetal electrocardiography (FECG) endows information in both fetal heart rate and fetal heart condition.

There are two methods of obtaining fetal ECG. The first one is obtaining FECG non-invasively by placing electrodes on the abdomen surface region of a pregnant woman and the second one is invasive; that is, by placing electrodes inside the uterus of the mother on the scalp of the fetus during labour. Invasive extraction of fetal ECG is more accurate because of the recording electrode placed on the fetus' scalp but it can be done just during delivery. The non-invasive method is a promising one which can be used in all gestation weeks and also during delivery process. But there are some difficulties in this method. Since in non-invasive method the recording electrodes are placed on the abdomen region of the pregnant woman, they record both maternal electrocardiogram (MECG) and the fetal electrocardiogram (FECG), whereas MECG represents the ECG of the mother which is taken from the abdomen of the pregnant woman and FECG represents the ECG of the fetus. In addition to this, it may also contain a relatively large amount of noise.

II. LITERATURE SURVEY

Since the first demonstration of the fetal electrocardiogram(FECG) carried out in 1906 by Cremer[4], various methods for FECG monitoring have been proposed to obtain information about the heart status. Linear or nonlinear decomposition methods[3] are common approaches in which, single or multi-channel recordings are decomposed into different components using suitable basis functions. Linear decomposition methods use either fixed basis functions (e.g., wavelets), or data-driven basis functions (e.g., singular vectors). This limits performance of decomposition in nonlinear or degenerate mixtures of signal and noise . Blind or semi-blind source separation[8], which are categorized as linear decomposition approach, have also been used for FECG extraction. These methods are based on the assumption of independent components (or more generally independent subspaces or partitions for the maternal and fetal signals. In another recent work, a new technique was proposed to fasten traditional Independent Component Analysis (ICA) method. In blind source separation methods it is usually assumed that signals and noises are mixed in a stationary and linear manner. However, FECG and other interferences and noises are not always stationary mixed and linearly separable. Nonlinear transforms have been also used for MECG cancellation and FECG extraction. In these methods, constructed phase space of noisy signal and of its delayed versions is smoothed using conventional or Principal Component Analysis (PCA) smoothers. The samples are then transferred back to the time-domain representation. Although these methods are interesting since they are applicable to as few as one single maternal

abdominal channel, the selection of the required time lags for constructing phase space representation is empirical and the important inter-beat variations of the cardiac signals can be wiped-out during the state-space smoothing. Moreover, they demand higher computational complexity in comparison to linear methods, and the correct embedding dimension can change as the noise statistics change. Adaptive filtering[7] is another common approach for MECG cancellation and FECG extraction. The conventional adaptive filtering is based on training an adaptive filter for either removing the MECG using one or several maternal reference channels or directly training the filter for extracting the fetal QRS wave. However, existing adaptive filtering methods for MECG artifact removal, either require a reference MECG channel that is morphologically similar to the contaminating waveform or require several linearly independent channels to roughly reconstruct any morphologic shape from the references. Both of these approaches are practically inconvenient and with limiting performance, because the morphology of the MECG contaminants highly depends on the electrode locations and it is not always possible to reconstruct the complete MECG morphology from a linear combination of the reference electrodes.

Wavelet transform is a powerful mathematical tool for analysis and synthesis of digital signals. Discrete wavelet transform (DWT) decompose the signal in different levels. Each level has a unique time and frequency resolution thus it gives both time and frequency information. With proper thresholding in each level, coefficients that estimated to be noise, remove from decomposed data and with the remained coefficients, denoised signal can be constructed. In DWT, after down sampling, low frequency coefficients will be decomposed to obtain next level decomposition. In wavelet packet transform (WPT) in addition to low frequency coefficients, high frequency coefficients also will be decomposed to obtained richer resolution. In both DWT and WPT coefficients in each level, after filtering will be down sampled. Due to down sampling, these transforms will suffer from the lack of shift invariance.

III. PROPOSED METHOD

In this paper, a combined application of stationary wavelet transform and extended kalman filter is used to extract the fetal ECG from the abdomincal ECG as shown in the fig.1 Stationary Wavelet Transform is used here for maternal ECG(MECG) cancellation and Extended Kalman filtering framework(EKF), which can be considered as a member of the general class of adaptive filters, is a promising approach for FECG enhancement. In this work, during the extraction of fetal ECG, four steps are included. They are Obtaining the input signal, Stationary Wavelet Transform, Extended Kalman Filter(EKF) Framework and model parameter estimation. During the extraction of fetal ECG, maternal ECG acts as a main source of noise.

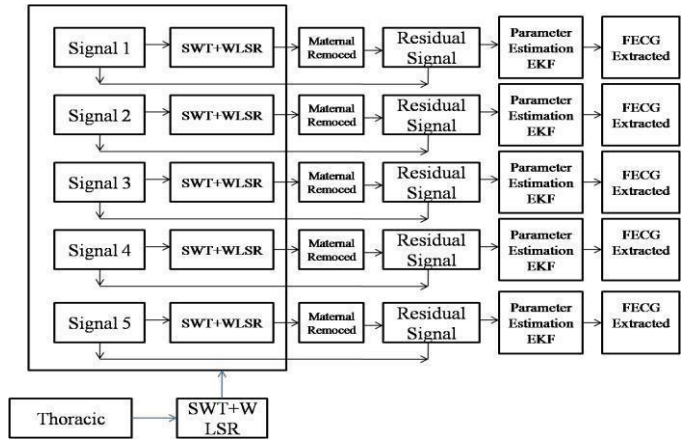

Fig 1 Proposed Method

Stationary Wavelet transform (SWT) eliminates down sampling operators at each level to obtain shift invariance property and so it is used here for the cancellation of maternal ECG (MECG). In this project the proposed method includes Stationary Wavelet Transform to cancel maternal ECG from abdominal signal, bayseian filtering theory and dynamic ECG model[12] based EKF algorithm is used to extract FECG from the residual signals using extended state kalman filter. The parameter analysis for different values of signal to noise ratio (SNR) between fetal and maternal ECG's shows its effectiveness and is implemented using matlab.

IV. METHODOLOGY

A. Input Signal

Input signal can be an actual data. The actual data used here is Daisy Database[2]. It includes 8 signals (5 signal from abdomen and three signals from thoracic region of a pregnant woman). The five signals from the abdomen includes maternal ECG, fetal ECG and noises. The three signals from the thoracic region includes only the maternal ECG. Thus five signals from the abdomen which includes FECG is considered for fetal ECG extraction.

B. Stationary Wavelet Transform

In both DWT and WPT, after filtration the coefficients will down sampled, that prevents redundancy and allow using the same pair of filter in different levels. And so, these transforms will suffer from the lack of shift invariance, which means that small shifts in the input signal can cause major variations in the distribution of energy between coefficients at deferent levels and may causes some error in reconstruction. This problem is carried out by eliminating the down sampling steps after filtration at each level in stationary wavelet transform (SWT). By eliminating down sampling, the number of coefficients at each level is as long as original signal. Fig. 2 shows decomposition of a signal by SWT up two levels. The original signal (S) passes through a pair of low pass ($h(n)$) and high pass ($g(n)$) filters. Then Outputs of low

pass and high pass (*g(n)*) filters are called approximation coefficients (Ca) and detail coefficients (Cd) respectively. Ca represents low frequency and Cd, the high frequency components of the signal. In DWT, For the next level of decomposition, the approximation coefficients will pass through the same low pass and high pass filters to obtain the next level detail and approximation coefficients and so on. Here the MECG is cancelled using SWT by calculating weighted least square regression. Weighted least squares is an efficient method that makes good use of small data sets. It also shares the ability to provide different types of easily interpretable statistical intervals for estimation, prediction, calibration and optimization. The main advantage that weighted least squares enjoys over other methods is the ability to handle regression situations in which the data points are of varying quality. If the standard deviation of the random errors in the data is not constant across all levels of the explanatory variables, using weighted least squares with weights that are inversely proportional to the variance at each level of the explanatory variables yields the most precise parameter estimates possible. In decomposition a signal through a filter bank, if down sampling operators were eliminated, for the next level of decomposition the high and low pass filters must be modified. For this, the low pass and high pass filters at each level will be up sampled by putting zero between each filter's coefficients of previous level that called á trous algorithm [6].

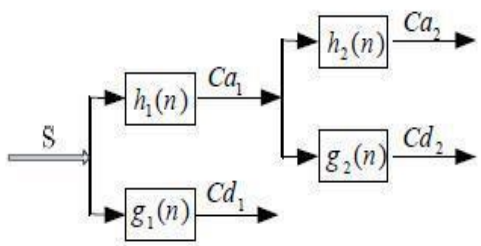

Fig. 2 Filter bank implementation of SWT

C. Extended Kalman Filter(EKF) Framework

1) Kalman Filter - The goal of Kalman Filter (KF) is to estimate the state of a discrete-time controlled process. Consider a state vector x_{k+1} governed by a nonlinear stochastic difference equation with measurement vector y_{k+1} at time instant k + 1:

$$\begin{cases} X_{k+1} = f(X_k, W_k, k+1) \\ Y_{k+1} = f(X_{k+1}, V_{k+1}, k+1) \end{cases} \quad (1)$$

where the random variables w_k and v_k represent the process noise and measurement noise, with associated covariance matrices Q_K = E {w_k W_K^T} and R_K= E { $V_K V_K^T$ }.

2) Extended Kalman Filter - The Extended Kalman Filter (EKF) is an extension of the standard KF to nonlinear systems f(.) and h(.), which linearizes about the current mean and covariance. In order to improve the estimations, EKF can be followed by a backward recursive smoothing stage leading to the Extended Kalman Smoother (EKS). In this work, Daisy database is used to extract fECG from mixture of an mECG, one (or more) fECG(s) and other signals considered as noises. In polar coordinates, one ECG signal can be expressed as the sum of five Gaussian functions defined by their peak amplitude, width and center, denoted α_i, b_i and ψ_i, respectively : (θ)= $\sum_{i\in w} \alpha_i \exp\left(-\frac{(\theta-\varphi_i)^2}{2b_i^2}\right)$. Each Gaussian function thus models one of the five waves as follows, W = {P,Q,R,S,T} of a heart beat. The state vector in equation (1) is defined by the phase θ and the amplitude *z* of the ECG : x_k = [θ_k; z_k]^T .

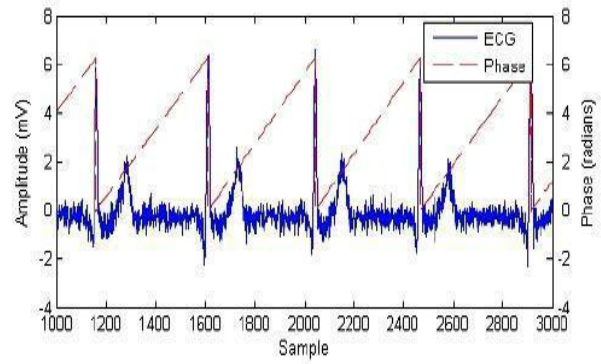

Fig. 3 Illustration of the phase assignment approach on one ECG.

Assuming a small sampling period δ, the state noise η_k, and defining w_k as [0; _k]T , the state process f(.) is

$$\emptyset_{k+1} = (\theta_k + \omega\delta) mod(2\pi) \quad (2)$$

$$z_{k+1} = -\sum_{i\in w} \frac{a_{i\Delta\theta_{i,k}\omega\delta}}{b_i^2} exp\left(-\frac{\Delta\theta_{i,k}^2}{2b_i^2}\right) + z_k + \eta_k \quad (3)$$

where ω is the phase increment, $\nabla\theta_{i,k}$ = (θ_k – ψ_i)mod(2π).From the ECG, one can define the observed phase $\emptyset_k$ by a linear time wrapping of the R-R time intervals into [0,2 π) (Figure 3). The measurement process h (.) is finally defined as y_{k+1} = x_{k+1} + v_{k+1}, where y_{k+1} = [$\emptyset_{k+1}$; s_{k+1}]^T . The ECGs composing the observed mixture can be estimated by applying the described EKF: at each step, one ECG is extracted according to a deflation procedure. In case of a mixture of noises and FECG, as shown in fig.1 the first step extracts, from the raw recording, the noises as a unique Gaussian noise. After subtracting the noises from the residual signal, the second step is the extraction of FECG from the residual signal.

D. Model Parameter Estimation

The Signal to Noise ratio is calculated for the proposed method and the performance is evaluated. It is often written as S/N or SNR, a measure used in science and engineering that compares the level of a desired signal to the level of background noise. A ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise. The ratio is usually measured in decibels (dB). If the incoming signal

strength in microvolts is V_S, and the noise level, also in microvolts, is V_n, then the signal-to-noise ratio, S/N, in decibels is given by the formula

$$S/N = 20 \log_{10}(V_S/V_n) \quad (4)$$

If $V_S = V_n$, then S/N = 0, the signal borders on unreadable, because the noise level severely competes with it. Ideally, V_S is greater than V_n, so S/N is positive. As an example, suppose that V_S = 10.0 microvolts and V_n = 1.00 microvolt. Then

$$S/N = 20 \log_{10}(10.0) = 20.0 \text{ dB}$$

which results in the signal being clearly readable .If V_S is less than V_n, then S/N is negative. In this type of situation, reliable communication is generally not possible unless steps are taken to increase the signal level and/or decrease the noise level at the destination (receiving) computer or terminal. Both signal and noise power must be measured at the same or equivalent points in a system, and within the same system bandwidth.

V. RESULTS AND DISCUSSIONS

Daisy Database have been used to study performance of the proposed method. The Daisy fetal ECG database as shown in fig 4, used here consists of a single dataset of cutaneous potential recording of a pregnant woman. A total of 8 channels (5 abdominal and 3 thoracic) sampled at 250 Hz are used. The heart rate for the maternal ECG ranges between 60 - 80 beats per minute. The heart of a fetus beats noticeably faster than that of its mother, with rates ranging from 120 to 160 beats per minute. The heart rate for the fetal electrocardiogram signal corresponds to 139 beats per minute. The amplitude of the fetal electrocardiogram is also much weaker than that of the maternal electrocardiogram.

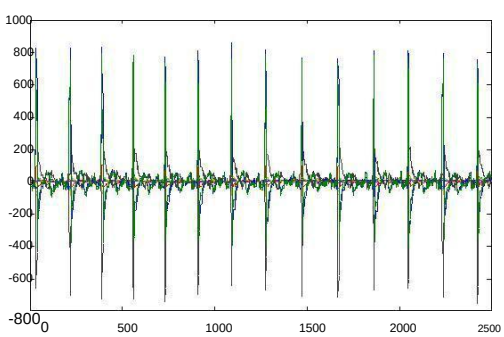

Fig. 4 Abdominal ECG signal

The abdominal ECG signal as shown in fig. 4 measured from the mothers abdomen includes fetal electrocardiogram signal and maternal electrocardiogram signal and noises. It is usually dominated by the maternal heartbeat signal that propagates from the chest cavity to the abdomen. The fig. 5 shown below describes the decomposition of approximation and detailed coefficients in three levels using stationary wavelet transform on actual data. Thus the maternal ECG is cancelled and the output obtained here is residual signal i.e addition of fetal ECG and noises

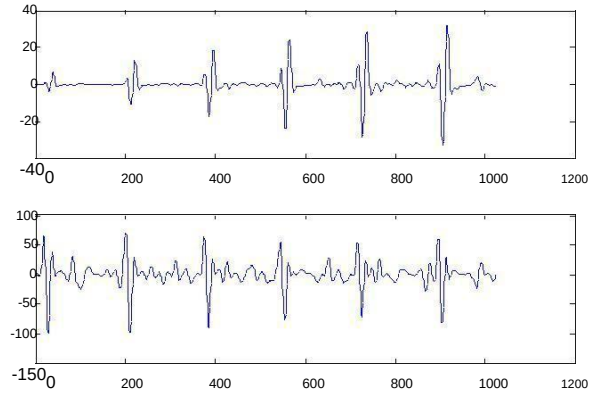

Fig. 5 Third level Decomposition of signal using SWT

By applying EKF for the decomposed signals individually, FECG can be extracted based on bayesian filtering theory from the residual signal. Bayes' theorem current probability to prior probability. It is important in the mathematical manipulation of conditional probabilities. Bayes' rule can be derived from more basic axioms of probability, specifically conditional probability. When applied, the probabilities involved in Bayes' theorem may have any of a number of probability interpretations. In one of these interpretations, the theorem is used directly as part of a particular approach to statistical inference. ln particular, with the Bayesian interpretation of probability, the theorem expresses how a subjective degree of belief should rationally change to account for evidence. The extracted FECG based on proposed algorithm is shown in the fig 6.

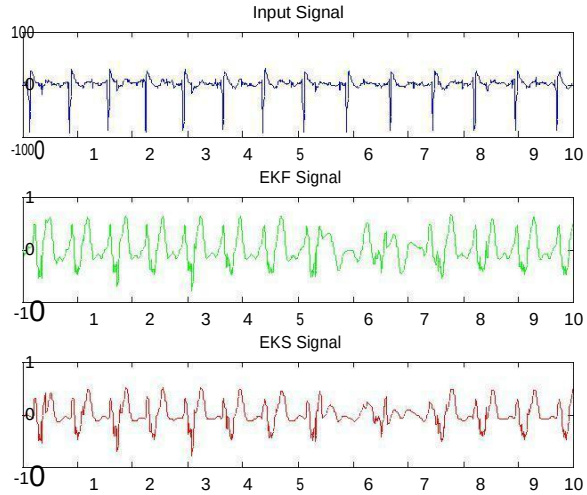

Fig. 6 Extracted FECG Signal

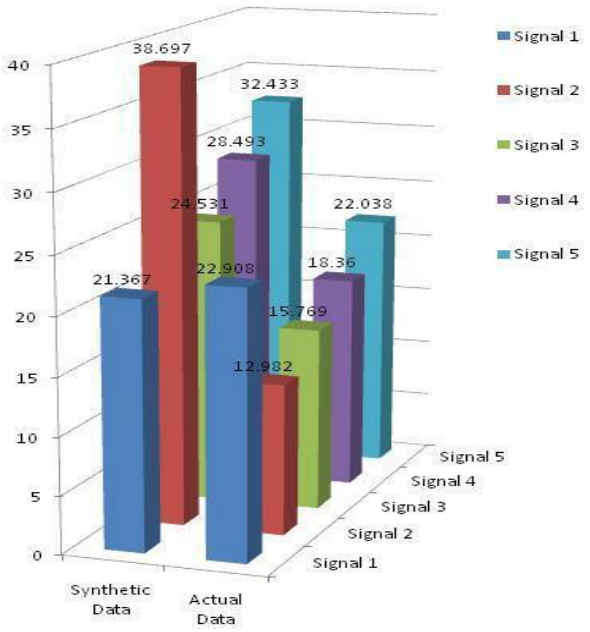

Fig. 7 Parameter Analysis

The proposed method is tested for five input signals taken from the mothers abdomen in both synthetic(simulated signals) and actual data as shown in fig 7. While computing Signal to Noise Ratio for proposed method, the maximum SNR value ranges between 12 - 22 db for synthetic data and 0 - 12 db for actual data. The higher SNR generally indicates that the reconstruction is of higher quality. Thus based on the Signal to Noise Ratio (SNR) it is proved that, the extraction of fetal ECG(FECG) is efficient in the proposed method and has the highest SNR value of 22.908db on actual data and 38.697 db on synthetic data.

VI. CONCLUSION

In this paper, a synthetic dynamic ECG model within a EKF framework has been extended to jointly model several ECGs to extract desired ECGs from a unique mixture of maternal and fetal ECGs and noise. Although the proposed method only uses a single channel to separate different ECGs, since each ECG has a corresponding term in the model, the proposed model can efficiently discriminate ECGs even if desired and undesired ECG waves overlap in time. As proved on synthetic data and illustrated on actual data the main merit of the proposed algorithm relies on its performance in a large class of situations. Performance of the proposed method on extraction of FECG from one mixture of MECG and FECG was examined according to signal to noise ratio (SNR). The results show that the proposed method can be successfully employed in FECG extraction and the maximum signal to noise ratio of 38.697 is obtained.

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