A Modified Approach to FECG Extraction using Sequential and Parallel Kalman Filter

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Abstract - The extraction of Fetal Electrocardiogram (FECG) is very important to know the health of fetus .It is also useful for doctors to get complete well being of fetus and decide to take required decision regarding delivery. The extraction of fetal electrocardiogram (FECG) is from maternal ECG signal obtained from the abdominal lead. The FECG contains activity of electrical depolarization and repolarization of fetal heart. This paper suggests extended Kalman filter (EKF) for the extraction of Fetal ECG (FECG) from Mother's ECG (MECG) and filtering of noisy FECG signals. An extended Kalman filtering is used for extracting electrocardiograms (ECGs) from a single channel as encountered in the fetal and maternal ECG extraction from abdominal sensor is done. The proposed system facilitates the prenatal procedures for monitoring of the cardiac condition of both the mother and the fetus. The database used is taken from physionet.org. i.e. direct fetal electrocardiogram.

Key Words: Abdominal ECG (AECG), Extended Kalman filtering (EKF), Fetal electrocardiogram (FECG) extraction, Mother's ECG (MECG), Parallel EKF (par-EKF), Sequential EKF (seq-EKF), Linear quadratic estimation (LQE).

1. INTRODUCTION

The Fetal ECG (FECG) signal is obtained from the Abdominal ECG (AECG) of a pregnant woman. This FECG is an effective diagnostic tool for determining the general condition of the fetus. The fetal contribution to the AECG is very small, so it is common to record a very degraded signal from which even the fetal heart rate (FHR) can hardly be detected. Hence we have to eliminate MECG and noise signals to extract FECG.

Adaptive filtering is a common approach for removing MECG and extracting FECG. The basic adaptive filtering is based on adaptive filter for either removing the MECG using one or several maternal reference channels or directly using the filter for extracting the fetal QRS waves. 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 their morphology.

The Kalman filter, also known as linear quadratic estimation (LQE) an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. The Kalman filter has numerous applications in technology. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics. he algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. Because of the algorithm's recursive nature, it can run in real time using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required. It is true that premature standardization of technique is not necessarily advantageous.

The Kalman filtering (KF) Algorithm, which can be considered as a member of the general class of adaptive filters, is a promising approach for removing MECG and extracting FECG. The Kalman filter has as objective the minimization of the estimation square error of a non-stationary signal buried in noise. The estimated signal itself is modeled utilizing the state-space formulation describing its dynamical behavior. In and , a set of state-space equations was used to model the temporal dynamics of ECG signals, for designing a Bayesian filter for ECG de-noising. This Bayesian filter framework was used in to extract FECG from single channel mixture of MECG and FECG. However, as mentioned in, the filter fails to discriminate between the maternal and fetal components when the MECG and FECG waves fully overlap in time. The reason is that when MECG is being estimated, FECG and other components are supposed to be Gaussian noises.

However, this assumption is not true, especially when MECG and FECG waves fully overlap in time it is difficult for the filter to follow desired ECG. Clinical monitoring of fetal cardiac activity is usually based on a small number of electrodes located on mother's abdomen, and on a sound sensitive sensor. In such a context, in this study, we wonder what performance can be obtained with only one electrode, by using a refined model of the signal recorded on the unique electrode: the model will explicitly take into account that the signal is the superposition of a few ECG signals. The rest of this paper is organized as follows. In Section II, equations and theory supporting our proposed method including the Bayesian filtering theory and dynamic ECG model are described. In Section III, results of the proposed method applied on different data and discussion about the results are presented. Finally, our conclusion is stated in Section IV.

1.1 METHOD

A. Sequential EKF

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

$$X_{k+1} = f(X_k, W_k, k+1)$$

$$Y_{k+1} = h(X_{k+1}, V_{k+1}, k+1) \qquad (1)$$

where the random variables W_k and V_k represent the process and measurement noises, with associated covariance matrices $Q_k = E\{W_k W_k^T\}$ and $R_k = E\{V_k V_k^T\}$. The extended Kalman filter (EKF) is an extension of the standard KF to nonlinear systems, which linearize about the current mean and covariance. In this study, a synthetic dynamic ECG model 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 αi , bi , and ψi, respectively. From the ECG, one can define the observed phase φk by a linear time wrapping of the R–R time intervals into $[0, 2\pi]$[1].

The ECGs composing the observed mixture can be estimated by applying the described EKF: at each step, one ECG is extracted according to a procedure. In case of a mixture of MECG and one FECG, the first step extracts, from the raw recording, the dominant ECG (often the MECG) considering the concurrent ECG (respectively, FECG) and other noises as a unique Gaussian noise. After subtracting the dominant ECG from the original signal, the second step is the extraction of FECG from the residual signal. This procedure is referred to as *sequential* EKF (seq-EKF). In this extraction, during the first step, the concurrent MECG and additional noise are modeled by Gaussian noises. In fact, although this assumption may be acceptable when there are not strong artifacts interfering with the ECG, it is no longer accurate when other ECG artifacts are considerable (i.e., at the first step) since the noise is no longer normally distributed.

B. Parallel EKF

The extended state Kalman filtering procedure is referred to as *parallel* EKF or EKS (par-EKF). The related extended state vector $\mathbf{x}_k = [\theta^{(1)}k, z^{(1)}k, \ldots, \theta^{(N)}k, z^{(N)}k]^T$ is thus defined by where each $[\theta^{(i)}k, z^{(i)}k]^T$ is related to one of the ECGs. Finally, the measurement process leads to express the measurement vector $\mathbf{y}k{+}1 = [\varphi^{(1)}k{+}1, \ldots, \varphi^{(N)}k{+}1, sk{+}1]^T$ [1]. This par-EKF is more accurate to extract FECG from abdominal sensors than the seq-EKF. Indeed, in the proposed method, all ECGs are jointly modeled by dynamic states so that only the state and measurement noise vectors are assumed to be normally distributed.

Moreover, the extended state par-EKF fully models overlapping waves of several ECGs. Finally, the state and observation noises, ηnk and vnk , respectively, allow the filter to fit some variability of the ECG shapes. Although the model does not fit too large variations inspection of the residue will reveal these abnormal beats.

C. Model Parameters Estimation

The proposed par-EKF lie on several state parameters $\{\alpha^{(n)}i, b^{(n)}i, \psi^{(n)}I\}\ i \in Wn, Vn \in \{1, \ldots, N\}$. The procedure described below is an extension of the single ECG parameter estimation. The parameters estimation procedure first needs the R-peak detection for all ECGs to perform the time wrapping of the R–R intervals. The R-peaks are found from a peak search in windows of length T, where T corresponds to the R-peak period calculated from approximate ECG beat-rate. R-peaks with periods smaller than $T/2$ or larger than T are not detected. Although maternal R-peaks are easily detectable from the mixture, fetal R-peak detection is more complex due to its lower amplitude than MECG. Therefore, a rough estimation of FECG is obtained by using the seq-EKF algorithm, which now allows us to detect easily the fetal R-peaks. Then, for each ECG, each beat (defined by the signals between two consecutive R peaks) is time wrapped into $[0,2\pi]$. The average of the ECG waveform is obtained by the mean of all time-wrapped beats, for all phases between 0 and 2π. Finally, by using a nonlinear least-squares approach, the best estimate of the parameters in the minimum mean square error (MMSE) sense is found.

1.2 RESULTS AND DISCUSSIONS

Synthetic and actual data have been used to study performance of the proposed method. In Subsection III-A, the synthetic mixed ECG is considered and performance of the method has been studied. In Subsection III-B, the effectiveness of the method on actual data has been examined.

A. Experimental Performance on Synthetic Data

In realistic synthetic mixtures of MECG and FECG with white Gaussian noise have been generated for different situations, and the proposed method has been applied on them to extract MECG and FECG. Synthetic MECG and FECG used in this study are based on single dipole vector of the heart, proposed in and inspired by the single-channel ECG dynamic model presented in. Sampling frequency is set to 500 Hz and signals include 1000 samples. The main parameters that can affect the mixtures are input noise power, ratio between amplitudes of FECG and MECG, and ratio between fetal and maternal heart rates. In order to investigate the performance of the proposed method, several trials were carried out under each value of these parameters. In the output, estimated MECG and FECG signals, $\hat{}sm$ and $\hat{}sf$, are assumed to be the sum of MECG, FECG, and noise, such that

$$\hat{}sm = a1sm + a2sf + a3n$$

$$\hat{}sf = b1sm + b2sf + b3n \qquad (2)$$

where coefficients $a1$, $a2$, $a3$, $b1$, $b2$, and b3 have to be estimated and sm, sf , and n denote MECG, FECG, and noise, respectively[1].

Fig 1: Mixture synthesized ECG

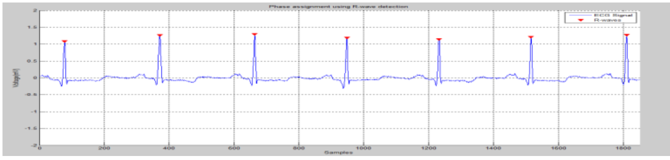

Fig 2: Mixture synthesized ECG R-R peak detection

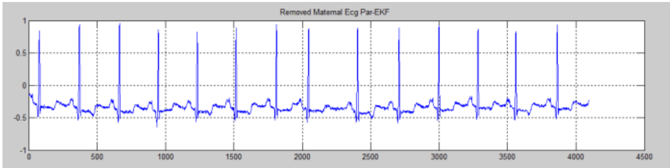

Fig 3: Maternal separation from mixture using par-EKF

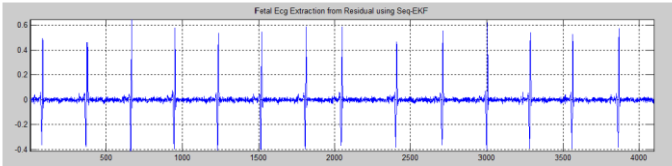

Fig 4: Filtered Fetal-ECG from residual ECG using seq-EKF

B. Fetal ECG Extraction on Actual (Physionet) Data

Abdominal Direct FECG Database: This database consists ofa series of abdominal FECG recordings, taken from a single subject between 21 and 40 weeks of pregnancy.

The recordings include direct abdominal signal. The signals were recorded at 1 kHz. Fig. shows results of Seq-EKS and par-EKS using single channel of the first 10s of namely the r01_direct dataset. To show the effectiveness of the proposed method in extraction of the FECG at different periods of pregnancy, and from channel locations, the first 10s of the mixtures and fetal par-EKS outputs of the datasets r04, r07, r08, r010, are plotted in Figures [7].

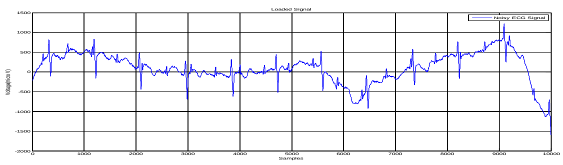

Fig 5: Direct abdominal ECG (r01) from Physionet

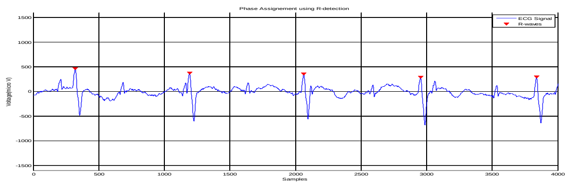

Fig 6: Direct abdominal ECG (r01) from Physionet R-R peak detection

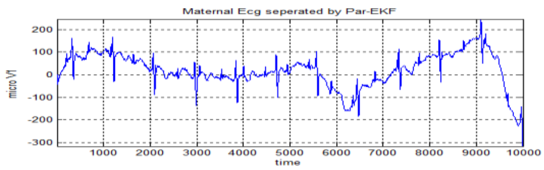

Fig 5: Maternal separation from mixture using par-EKF

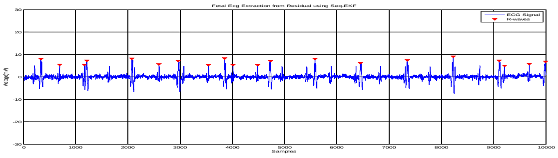

Fig 6: Filtered Fetal-ECG from residual ECG using seq-EKF

C. Analytical Results

Applying Kalman Filter on the 8 data sets, the FECG signals were extracted from 8 of them, and with an average percentage of 90.0 % of FECG R peaks extraction as calculated in Table I. Figures above shows the comparison between abdominal signal and extracted FECG signal. Looking at the figures in earlier points, maternal and extracted fetal ECG two different signals can be seen. Maternal ECG signal was removed followed by fetal ECG. Applying the peak detection algorithm to extracted FECG signals, the number of detected fetal R peaks was calculated. Table I shows the number of peaks of the direct FECG from scalp and the extracted ones in addition to the percentage of extraction for the different 8 sets and the total average percentage after applying the technique[19].

Table -1: THE PERCENTAGE OF THE R PEAKS EXTRACTION OF EACH DATA SET AFTER APPLYING KALMAN FILTER

Data Set NO.	Peak numbers of Direct FECG	Peak numbers of Extracted FECG	% of Extraction
DATA Set 1	20	17	85
DATA Set 2	20	20	100
DATA Set 3	20	17	85
DATA Set 4	20	20	100
DATA Set 5	21	21	100
DATA Set 6	18	17	94.44444444
DATA Set 7	18	20	111.1111111
DATA Set 8	18	12	66.66666667
Average of % Extraction			90

3. CONCLUSIONS

In this paper, a synthetic ECG has been used for Kalman Filter. The same concept is used for actual data taken from Physionet i.e. direct Fetal ECG from abdomen 2. Here the actual data is downloaded and filtered followed by peak detection, i.e. R-R interval. After the peaks are detected then the aligned with phase and Maternal ECG is extracted by using Par-EKF and residual signal remains which consist Fetal ECG. To detect the peaks of Fetal from the residual signal the Seq-EKF is used extract desired FECGs from that mixture. This proposed method only uses a single channel to separate different ECGs, i.e. Maternal and Fetal ECGs. Synthetic data and illustrated on actual data (single channel fetal ECG). The comparison of the extraction is done by counting the number of peaks of Direct FECG captured from the scalp with the signal acquired from the various leads of abdomen of the same pregnant women. Hence the comparison is done by counting the number of peaks as shown in the table.

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