Fetal Electrocardiogram R-peak Detection using Robust Tensor Decomposition and Extended Kalman Filtering

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Abstract

In this paper, we propose an efficient method for R-peak detection in noninvasive fetal electrocardiogram (ECG) signals which are acquired from multiple electrodes on mother's abdomen. The proposed method is performed in two steps: first, we employ a robust tensor decomposition-based method for fetal ECG extraction from mixtures of fetal and maternal ECGs; then a method based on extended Kalman filter (EKF) is used for fetal R-peak detection. In order to obtain a rough estimate of fetal ECG, a weighted tensor decomposition method is utilized to capture weak traces of fetal ECG mixed with maternal ECG and noise. In this method, it is assumed that maternal and fetal heart rate values are different. After fetal ECG extraction, a recently introduced Bayesian framework for ECG fiducial point extraction is used. In this method each ECG wave (P, QRS and T) has a separate state in the EKF formulation. Each parameter of the Gaussian functions used for modeling each ECG wave is considered as a simple autoregressive (AR) model and is estimated via the EKF. The results show that the proposed method is efficiently able to estimate the location of R-peaks of fetal ECG signals. The average score of our proposed method for the PhysioNet Challenge 2013 on set B from entry 1 are 1326.21 and 45.06 for event 4 and 5, respectively, which are better than the average score for sample submission physionet2013.m (available at PhysioNet) on set B which were 3258.56 and 102.75 for event 4 and 5 respectively.

1. Introduction

Electrocardiogram (ECG) records the electrical activity of heart and is a noninvasive, safe and quick tool for cardiac disease diagnosis. During the recent years there have been significant advances in adult clinical electrocardiography but analysis of fetal ECG (fECG) is still in its infancy. Some methods have been proposed for processing the fetal ECG using the direct fetal ECG which is acquired from a fetal scalp electrode during delivery. As acquiring the direct fECG is invasive and can be done only in labor time, extraction of noninvasive fECG can be of great interest. Since the noninvasive fECG is highly contaminated by maternal ECG (mECG) and other artifacts, developing a method that can extract fetal ECG from mixture of mECG, fECG, and other interference sources is underway by biomedical engineering communities.

Among the several methods addressing this problem there are many methods (such as periodic component analysis (πCA) [1] and extended Bayesian filtering framework [2]) that use fetal R-peak positions. Indeed, these methods utilize fetal R-peak positions as prior information for exploiting the quasi-periodic nature of this signal.

In this paper, we propose an efficient method for R-peak detection in noninvasive fetal ECG signals which are acquired from multiple electrodes on mother's abdomen. The proposed method is performed in two steps: first, we employ a robust tensor decomposition-based method to roughly extract fetal ECG from mixtures of fetal and maternal ECGs; then a method based on extended Kalman filter (EKF) is used for fetal R-peak detection.

The ECG Kalman filtering framework is recalled in Section 2. In Section 3, we explain our proposed method for fetal ECG extraction and R-peak detection. In Section 4, we present the results of applying the proposed method on actual noninvasive fetal ECG signals. Finally, our discussion and conclusions are stated in Section 5.

2. ECG Kalman Filtering Background

McSharry et al. [3] have proposed a synthetic ECG generator, which is based on a nonlinear dynamic model. Details of this model can be found in [3]. Sameni et al. [4] transformed these dynamic equations into the polar form to obtain a simpler compact set, with the simplified discrete form shown as:

$$\begin{cases} \varphi_{k+1} = (\varphi_k + \omega\delta) \ \ mod(2\pi) \\ z_{k+1} = -\sum_i \delta \frac{\alpha_i \omega}{b_i^2} \Delta\theta_i \exp(-\frac{\Delta\theta_i^2}{2b_i^2}) + z_k + \eta \end{cases} \quad (1)$$

where $\Delta\theta_i = (\varphi_k - \theta_i) \, mod(2\pi)$, δ is the sampling time, η is a random additive noise that models the inaccuracies

of the dynamic model and the summation over i is taken over the number of Gaussian functions used for modeling the shape of the ECG. The α_i, b_i and θ_i terms in (1) correspond to the amplitude, width and location of the Gaussian functions and ω is the angular velocity that represents the RR interval variability.

3. Proposed Method

The proposed method is performed in two steps: first, we employ a robust tensor decomposition-based method to roughly extract fetal ECG from mixtures of fetal and maternal ECGs; then a method based on extended Kalman filter is used for fetal R-peak detection.

3.1. Fetal ECG Extraction

The deterministic blind separation of sources having different symbol rates, proposed in [5] has been adapted to ECG signal in this study for fECG extraction. This method, assumes that each of the $n = 1, \ldots, N$ sources has periodic symbols. Then, it builds a three-way tensor $\bar{Y}^{(n)} \in \mathbb{C}^{\mathbb{M}\times\mathbb{T}_\kappa\times\mathbb{L}_\kappa}$, where M, T_n, and L_n denote the number of sensors, symbol period and time samples per symbol period of the n-th source, respectively. For each source, the tensor is built by stacking the data for each period of the source into a slice of the tensor. In the ECG context, due to the quasi-periodic nature of the ECG signal, one can firstly detect ECG R-peaks then stack ECG beats centered at the R-peaks to build the tensors $\bar{Y}^{(n)}$. Each of these tensors can then be decomposed into the loading matrices $\mathbf{A}^{(n)} \in \mathbb{C}^{\mathbb{M}\times\mathbb{R}_\kappa}$, $\bar{\mathbf{S}}^{(n)} \in \mathbb{C}^{\mathbb{T}_\kappa\times\mathbb{R}_\kappa}$ and $\bar{\mathbf{H}}^{(n)} \in \mathbb{C}^{\mathbb{L}_\kappa\times\mathbb{R}_\kappa}$, which provide estimates of the mixing matrix, the ECG beat amplitude, and the ECG temporal pattern. In [5], the Canonical Polyadic (CP) has been used for tensor decomposition. However, in order to track the fECG mixed with the strong mECG, a robust tensor decomposition should be used. We employ a weighted CP (WCP) for decomposition of the tensors, which applies a weight on each entry of the tensor to better concentrate on the signal of interest. Therefore, the new criterion is:

$$\min_{\left\{\hat{\mathbf{A}}^{(n)},\hat{\bar{\mathbf{S}}}^{(n)},\hat{\bar{\mathbf{H}}}^{(n)}\right\}} \sum_{i,j,k} \left\| w_{ijk}^{(n)} \left(y_{ijk}^{(n)} - \sum_{r=1}^{R_n} a_{ir}^{(n)} \bar{s}_{jr}^{(n)} \bar{h}_{kr}^{(n)} \right) \right\|_F^2, \tag{2}$$

where

$$w_{ijk}^{(n)} = \exp\left\{ -\frac{(y_{ijk}^{(n)} - \mu_{ik})^2}{\sigma_{ik}^2} \right\}, \quad n = 1, \ldots, N \tag{3}$$

are the elements of a nonnegative weight tensor, which is of the same size as $\bar{Y}^{(n)}$. Here, μ is the mean of $\bar{Y}^{(n)}$ over the j-th dimension and σ is the median absolute deviation (MAD) estimator of $\bar{Y}^{(n)}$ over the j-th dimension.

In order to apply this method to roughly estimate fECG, first maternal R-peaks are easily detected from the mixture and the maternal tensor is built. Decomposition of this tensor yields the maternal leading matrices that are then used to reconstruct mECG. The reconstructed mECG is subtracted from the mixture to provide a noisy estimate of fECG, which can be used to roughly estimate fetal R-peak positions. Having the rough fetal R-peak positions, the fetal tensor can be constructed and decomposed. The fetal loading matrices are finally used to reconstruct the rough fECG estimate.

3.2. R-peak Detection

After extracting the fECG, we use an EKF-based method for R-peak detection [6]. Discrete state and observation equations of our proposed model are defined in (4) and (5), respectively.

$$\begin{cases} \varphi_{k+1} = (\varphi_k + \omega\delta) \ \ mod(2\pi) \\ P_{k+1} = -\sum\limits_{i\in\{P_1,P_2\}} \delta \frac{\alpha_{ik}\omega}{b_{ik}^2} \Delta\theta_{ik} \exp(-\frac{\Delta\theta_{ik}^2}{2b_{ik}^2}) + P_k + \eta_P \\ C_{k+1} = -\sum\limits_{i\in\{Q,R,S\}} \delta \frac{\alpha_{ik}\omega}{b_{ik}^2} \Delta\theta_{ik} \exp(-\frac{\Delta\theta_{ik}^2}{2b_{ik}^2}) + C_k + \eta_C \\ T_{k+1} = -\sum\limits_{i\in\{T_1,T_2\}} \delta \frac{\alpha_{ik}\omega}{b_{ik}^2} \Delta\theta_{ik} \exp(-\frac{\Delta\theta_{ik}^2}{2b_{ik}^2}) + T_k + \eta_T \\ \alpha_{i,k+1} = \alpha_{i,k} + u_{j,k}, j = \{1, \cdots, 7\} \\ b_{i,k+1} = b_{i,k} + u_{j,k}, j = \{8, \cdots, 14\} \\ \theta_{i,k+1} = \theta_{i,k} + u_{j,k}, j = \{15, \cdots, 21\} \\ i \in \{P_1, P_2, Q, R, S, T_1, T_2\} \end{cases} \tag{4}$$

$$\begin{aligned} \Phi_k &= \varphi_k + v_{1k} \\ PP_k &= P_k + v_{2k} \\ CC_k &= C_k + v_{3k} \\ TT_k &= T_k + v_{4k} \end{aligned} \tag{5}$$

In (4), we have 25 states and we call it "EKF25" approach. The first state is the phase of the ECG. The second, third and forth ones are the different waves of ECG which are separately considered as a state. The parameters of the Gaussian functions are considered as hidden-state variables (states 5 to 21) with first order AR dynamics but without corresponding observations.

In (5), we consider four observations for our model. The first one corresponds to the phase observation and the others correspond to the ECG observation in P, C and T intervals, respectively. In fact, we determine three windows for segmenting the original ECG and finding the PP_k, CC_k and TT_k observations. Here we use windows which are the difference of two sigmoid functions and have almost soft rising and falling edges. Figure 1 shows these windows for P, C and T intervals. The begining and end of these windows are defined corresponding to the phase of ECG. Indeed, we assume that P , C and T intervals correspond to ECG phase in the intervals $[-\pi, -\pi/6]$, $[-\pi/6, \pi/6]$ and

$[\pi/6, \pi]$ respectively. It is important to note that this assumption for normal ECG signals is almost valid. These windows are defined in (6) and the shape of the windows is controlled with γ, set here as $\gamma = 30$. Observations PP_k, CC_k and TT_k in (5) are calculated by multiplying the original (observed) ECG signal and windows defined in (6).

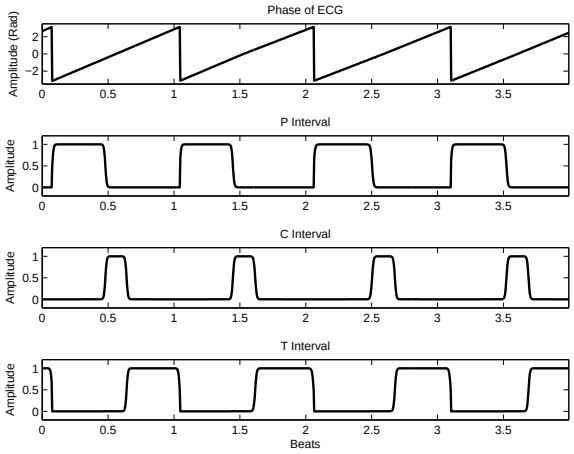

Figure 1. ECG Phase and Windows for ECG Intervals.

$$
\begin{aligned}
(Pw)_k &= \frac{1}{1+\exp^{-\gamma(\Phi_k-(-\pi))}} - \frac{1}{1+\exp^{-\gamma(\Phi_k-(-\pi/6))}} \\
(Cw)_k &= \frac{1}{1+\exp^{-\gamma(\Phi_k-(-\pi/6))}} - \frac{1}{1+\exp^{-\gamma(\Phi_k-(\pi/6))}} \\
(Tw)_k &= \frac{1}{1+\exp^{-\gamma(\Phi_k-(\pi/6))}} - \frac{1}{1+\exp^{-\gamma(\Phi_k-(\pi))}}
\end{aligned}
\tag{6}
$$

Figure 2 shows the block diagram of proposed approach for finding R-peaks of fetal ECG signals. At first, all states of the model are estimated by EKF25. After estimating the Gaussian parameters (states 5 to 21), we construct the P1, P2, Q, R, S, T1 and T2 Gaussian functions ((7)).

$$
i(\theta) = \hat{\alpha}_i \exp(-\frac{(\theta-\hat{\theta}_i)^2}{2\hat{b}_i^2}), i \in \{P_1, P_2, Q, R, S, T_1, T_2\} \tag{7}
$$

The proposed method consists of three steps:

- Using "peak detection" method (finding the maxima) for estimated QRS Complex ($\hat{C}$) and finding its peak which is called P_C.
- Constructing $Q+R+S$ Gaussian function and find the maximum of this function which is called Θ_R. ((8)).
- Using a decision rule like (9) to find the final R-peak points of ECG (R_{peak}), where s_k is the extracted fetal ECG signal.

$$\Theta_R = argmax(Q(\theta) + R(\theta) + S(\theta)) \tag{8}$$

$$R_{peak} = argmax(s_k(\Theta_R), s_k(P_C)) \tag{9}$$

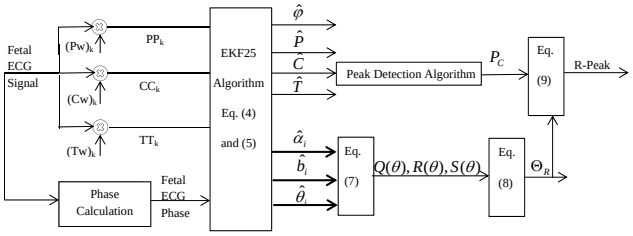

Figure 2. Block diagram for detecting R-peaks.

4. Results

For validation of our method, we use the noninvasive fetal ECG database in the Physionet/Computing in Cardiology Challenge 2013 [7]. This dataset consist of a collection of one-minute fetal ECG recordings. Each recording includes four noninvasive abdominal signals and was sampled at 1 kHz. Details can be found in [7].

Figures 3 and 4 show the first channel of recorded ECG (which is a mixture of maternal ECG, fetal ECG and other noises), estimated maternal and fetal ECGs by the proposed method for data "a08" and "a12" from the database, respectively. In these figures, the reference annotations (the given R-peaks) and the estimated R-peaks by the proposed method are shown with green and red points, respectively. We can see that the proposed method can extract fetal ECG from recorded ECG and also can detect the R-peaks with a high accuracy. Figure 5 shows the estimated fetal ECG, the given R-peaks (green points) and the estimated R-peaks (red points) for data "a03", "a04", "a05" and "a22" of database.

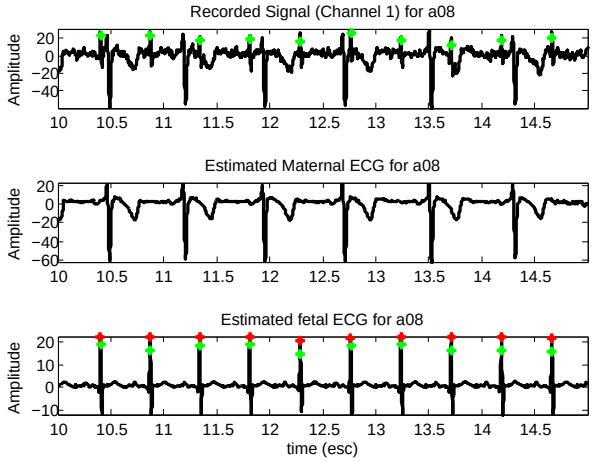

Figure 3. (a). First channel of recorded ECG (data "a08") and given R-peaks (b). Estimated maternal ECG (c). Estimated fetal ECG, given R-peaks (green points) and estimated R-peaks (red points).

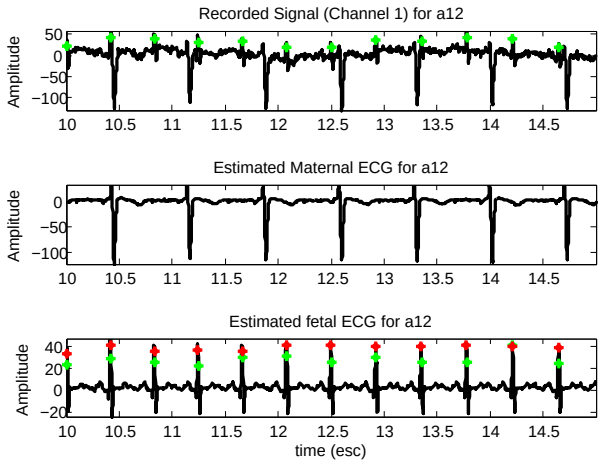

Figure 4. (a). First channel of recorded ECG (data "a12") and given R-peaks (b). Estimated maternal ECG (c). Estimated fetal ECG, given R-peaks (green points) and estimated R-peaks (red points).

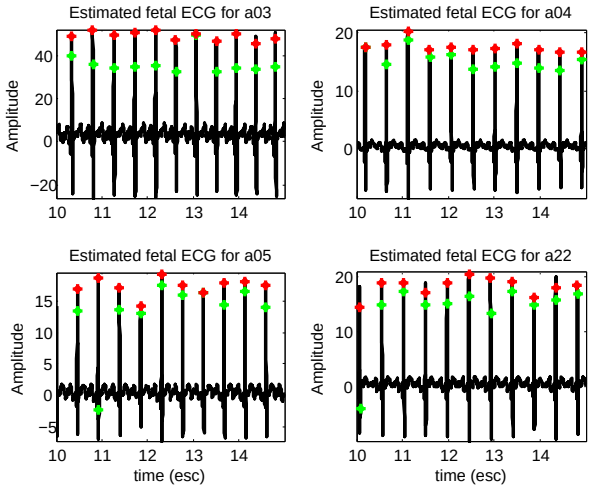

Figure 5. Estimated fetal ECG, Given R-peaks (green points) and estimated R-peaks (red points) for data "a03", "a04", "a05" and "a22".

5. Discussion and Conclusions

In this paper, we proposed a method for accurate fetal R-peak detection from noninvasive maternal and fetal ECG mixtures which are acquired from multiple electrodes on mother's abdomen. For rough fetal ECG extraction, we employed a robust tensor decomposition method and for fetal R-peak detection, we used a method based on EKF. The WCP decomposition used in this study enables us to capture weak traces of the fECG mixed with the strong mECG. In addition, by introducing a simple AR model for each of the 21 dynamic parameters of the Gaussian functions and considering separate states for ECG waves, new EKF structure was constructed.

Quantitative and qualitative results show that proposed approach detects R-peaks of fetal ECG with a high accuracy. The average score of our proposed method for the PhysioNet Challenge 2013 on set B from entry 1 are 1326.21 and 45.06 for event 4 and 5 respectively.

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