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

Mahsa Akhbari[1,2], Mohammad Niknazar[2], Christian Jutten[2],
Mohammad B Shamsollahi[1], Bertrand Rivet[2]

[1] BiSIPL, Sharif university of Technology, Tehran, Iran, [2] GIPSA-Lab, Grenoble, France

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, assuming different heart rates for mother and fetal ECG; then a method based on extended Kalman filter (EKF) in which the ECG beat is modeled by 3 state equations (P, QRS and T), is used for fetal R-peak detection.

The results show that the proposed method is efficiently able to estimate the location of R-peaks of fetal ECG signals. The obtained average scores of event 4 and 5 on the set B of "Physionet Challenge 2013" data are 1326.21 and 45.06, 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.

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. fECG signal contains precise information that can help clinicians and physicians in making important decisions during labor. Fetal heart rate (FHR) monitoring is a routine for obtaining significant information about the fetal condition during pregnancy and labor. The characteristics of the fECG, such as heart rate, waveform, and dynamic behavior, 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 [1].

Analyzing the fECG and finding its R peaks are so important in different applications. In [2], Altuve et al. use the RR interval extracted from the fECG to detect apnea bradycardia episodes. They study three time series (RR interval, R wave amplitude and QRS complex duration) for periods at rest, before, during and after apnea-bradycardia episodes.

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. In [1], various methodologies and developed algorithms on fECG signal detection and analysis for fetal monitoring are illustrated.

Among the several methods addressing fetal extraction, there are many methods (such as periodic component analysis (πCA) [3] and extended Bayesian filtering framework [4]) 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. [5] have proposed a synthetic ECG generator, which is based on a nonlinear dynamic model. Details of this model can be found in [5]. Sameni et al. [6] transformed these dynamic equations into the polar form to obtain a simpler compact set, with the simplified discrete form shown as:

$$
\begin{cases}
\varphi_{k+1} = (\varphi_k + \omega_k \delta) \ mod(2\pi) \\
z_{k+1} = -\sum_i \delta \frac{\alpha_{ik}\omega_k}{b_{ik}^2} \Delta\theta_{ik} \exp(-\frac{\Delta\theta_{ik}^2}{2b_{ik}^2}) + z_k + \eta_k
\end{cases}
\tag{1}
$$

where $\Delta\theta_{ik} = (\varphi_k - \theta_{ik}) \ mod(2\pi)$, δ is the sampling time, η_k is a random additive noise that models the inaccuracies of the dynamic model. In (1), z_k is the state model of ECG, which models the whole PQRST complex as a sum of N Gaussians and the summation over i is taken over the number of Gaussian functions used for modeling the shape of the ECG. The α_{ik}, b_{ik} and θ_{ik} terms correspond to the amplitude, angular spread and location of the Gaussian functions and ω_k is the beat-to-beat angular frequency of the RR interval.

3. Proposed method

3.1. Fetal ECG extraction

In this paper for fECG extraction, the deterministic blind separation of sources having different symbol rates, proposed in [7] has been adapted to ECG signal. This method, assumes that each of the $n = 1, \dots, N$ sources has periodic symbols. Then, it builds a three-way tensor $\bar{Y}^{(n)} \in \mathbb{C}^{M \times \mathbb{T}_\ltimes \times \mathbb{L}_\ltimes}$, 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 $\mathbf{A}^{(n)} \in \mathbb{C}^{M \times \mathbb{R}_\ltimes}$, $\bar{\mathbf{S}}^{(n)} \in \mathbb{C}^{\mathbb{T}_\ltimes \times \mathbb{R}_\ltimes}$ and $\bar{\mathbf{H}}^{(n)} \in \mathbb{C}^{\mathbb{L}_\ltimes \times \mathbb{R}_\ltimes}$, which provide estimates of the mixing matrix, the ECG beat amplitude, and the ECG temporal pattern. In [7], 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

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

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 rough fECG, we use an EKF-based method for R-peak detection [8]. Discrete state and observation equations of our proposed model are defined in (4) and (5), respectively.

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

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

In (4), 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 : $\alpha_{i,k}$, $b_{i,k}$ and $\theta_{i,k}$) with first order AR dynamics but without corresponding observations.

In [9], we used (4) and assumed that the ECG observation can be defined as a summation of P_k, C_k and T_k states ($z_k = P_k + C_k + T_k + v_{2k}$). This assumption was not wrong but estimated ECG waves had rising and falling drifts, compensated in the estimated ECG which is the sum of estimated waves. These drifts may be due to this fact that in that model, we have only one observation (based on 3 states) which corresponds to original ECG. There, we had not used the estimated waves directly and we just used a peak detection method for finding their peaks which, despite the drift of estimated waves, peak of waves can be estimated accurately.

Here we modify the previous model and consider four observations for our model. In (5), 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. 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 $\gamma = 30$ in order to provide quite instantaneous transistions. Observations PP_k, CC_k and TT_k in (5) are calculated by multiplying the original (observed) ECG signal and windows defined in (6).

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

The R-peak detection is based on 3 successive tasks:
• Using "peak detection" method (finding the maxima) for estimated QRS Complex ($\hat{C}$) and finding its peak which is called P_C.
• Constructing $Q(\theta)$, $R(\theta)$ and $S(\theta)$ Gaussian functions (7) and find the maximum of $Q(\theta) + R(\theta) + S(\theta)$ function which is called Θ_R. ((8)).
• Using a decision rule like (9) to find the final R-peak points of fetal ECG (R_{peak}), where s_k is the extracted fetal ECG signal.

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

$$\Theta_R = argmax(Q(\theta) + R(\theta) + S(\theta)) \qquad (8)$$

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

4. Results

For evaluation of our method, we use the noninvasive fetal ECG database in the Physionet/Computing in Cardiology Challenge 2013 [10]. 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 [10].

Figures 1 and 2 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 3 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. The obtained average scores of event 4 and 5 on the set B of "Physionet Challenge 2013" data are 1326.21 and 45.06, respectively
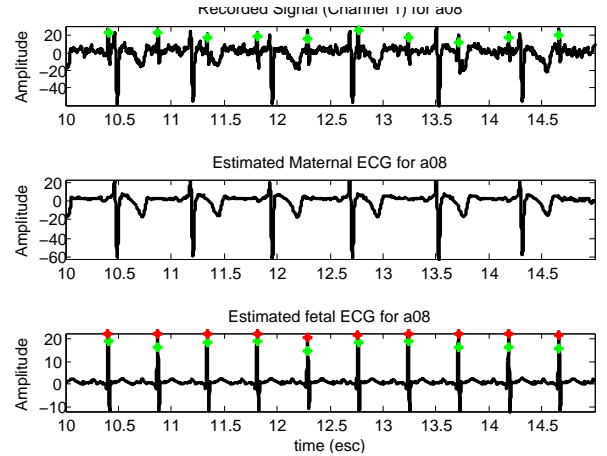

Figure 1. (a). First channel of recorded ECG (data "a08") and given R-peaks (b). Estimated maternal ECG (c). Estimated fetal ECG, given R-peaks (green points) and estimated R-peaks (red points).

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
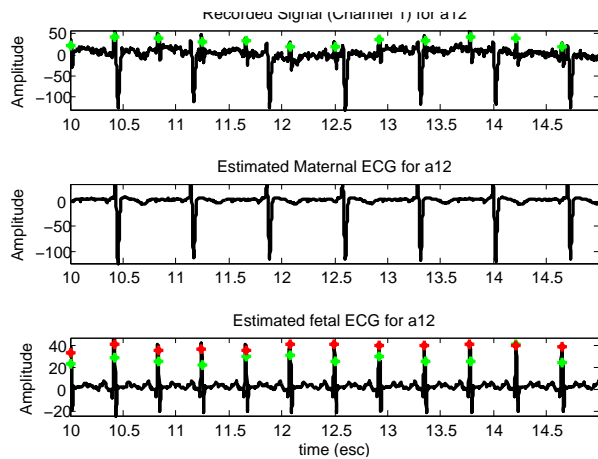
Figure 2. (a). First channel of recorded ECG (data "a12") and given R-peaks (b). Estimated maternal ECG (c). Estimated fetal ECG, given R-peaks (green points) and estimated R-peaks (red points).
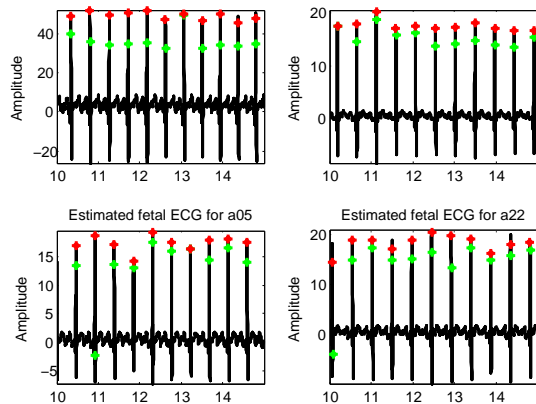

Figure 3. Estimated fetal ECG, Given R-peaks (green points) and estimated R-peaks (red points) for data "a03", "a04", "a05" and "a22".

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.

References

[1] Hasan MA, Reaz MBI, Ibrahimy MI, Hussain MS, Uddin J. Detection and processing techniques of fECG signal for fetal monitoring. Biological Procedures Online 2009;11(1).

[2] Altuve M, Carrault G, Cruz J, Beuche A, Pladys P. Multivariate ECG analysis for apnoeabradycardia detection and characterisation in preterm infants. Int J Biomedical Engineering and Technology 2011;5(2-3):247–265.

[3] Sameni R, Jutten C, Shamsollahi MB. Multichannel electrocardiogram decomposition using periodic component analysis. IEEE Trans Biomed Eng Aug. 2008;55(8):1935–1940.

[4] Niknazar M, Rivet B, Jutten C. Fetal ECG extraction by extended state kalman filtering based on single-channel recordings. IEEE Trans Biomed Eng Dec. 2012; 60(5):1345–1352.

[5] McSharry PE, Clifford GD, Tarassenko L, Smith LA. A dynamic model for generating synthetic electrocardiogram signals. IEEE Trans Biomed Eng Mar. 2003;50(3):289–294.

[6] Sameni R, Shamsollahi MB, Jutten C, Clifford GD. Nonlinear bayesian filtering framework for ECG denoising. IEEE Trans Biomed Eng Dec. 2007;54(12):2172–2185.

[7] Almeida A, Comon P, Luciani X. Deterministic blind separation of sources having different symbol rates using tensor based parallel deflation. In 9th international conference on Latent variable analysis and signal separation (LVA/ICA 2010), Berlin. 2010; 362–369.

[8] Akhbari M, Shamsollahi MB, Jutten C. ECG fiducial points extraction by extended kalman filtering. In 36th International Conference on Telecommunications and Signal Processing (TSP2013), Rome, Italy. July 2013; 628–632.

[9] Akhbari M, Shamsollahi MB, Jutten C. Fiducial points extraction and characteristic waves detection in ECG signal using a model-based bayesian framework. In 38th International Conference on Acoustics, Speech, and Signal Processing (ICASSP2013) ,Vancouver, Canada. May 2013; 1257–1261.

[10] http://www.physionet.org/challenge/2013/.

Address for correspondence:

Mahsa AKHBARI
BiSIPL, School of Electrical Engineering, Sharif University of Technology, Azadi Avenue, Tehran, Iran, P.O. Box. 111554363
mahsa.akhbari@gipsa-lab.grenoble-inp.fr
mahsa_akhbari@ee.sharif.edu