Fetal QRS Complex Detection Based on Three-Way Tensor Decomposition

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Abstract

This study is focused on detection of fetal QRS complexes in multichannel ECG signals recorded from mother's abdomen, containing both fetal and maternal ECGs. Assuming different values for maternal and fetal heart rates, the proposed method relies on a deterministic tensor decomposition method, which aims at deterministic blind separation of sources having different symbol rates. In the ECG context, due to the quasi-periodic nature of ECG signal, maternal ECG R-peaks are firstly detected from the mixture to identify maternal beats as maternal ECG symbols. Then the maternal ECG beats are stacked into a three-dimensional array. Decomposition of this tensor yields three loading matrices that are now used to reconstruct the maternal ECG. The residue of subtraction of the maternal ECG estimate from the original mixture is then used to detect fetal QRS complexes. The obtained average scores of event 4 and 5 on the set B of PhysioNet Challenge 2013 data are 1514.59 and 57.01, respectively.

1. Introduction

Congenital heart disease is the most common type of birth defect [1]. Approximately, one out of 125 babies born each year have some form of congenital heart defects [2]. Since heart defects originate in the early weeks of pregnancy when the heart is forming [2], the regular monitoring of the fetal heart and the early detection of cardiac abnormalities may help obstetrics and pediatric cardiologist to prescribe proper medications in time, or to consider the necessary precautions during delivery. The electrocardiogram (ECG) signal may provide useful information about the fetus' heart condition for detecting the fetus at risk of damage or death in the uterus. However, despite of the rich literature in the field of adult ECG processing, the extraction of fetal ECG (fECG) from mixture of maternal ECG (mECG), fECG, and other interference sources remains a difficult problem for the biomedical engineering community. This is due to much lower amplitude of fECG compared with mECG.

Because of severe weakness of fECG, many attempts have been made to improve the performance of fully blind source separation methods through using a priori information about cardiac signals, such as their quasi-periodic structure that can be realized by R-peak detection. As a result, detection of fetal R-peaks (or QRS complex) is an essential step in the fetal ECG extraction methods in which quasi-periodic nature of ECG signal is exploited (e.g. periodic component analysis (πCA) [3] and extended Kalman filtering (EKF) framework in [4] and [5]).

In these methods, it is assumed that the fetal R-peaks are either already provided using another modality (e.g. using a sound sensor) or directly estimated from ECG mixture. As it has been mentioned in [5], the latter can be done by using a sequential EKF algorithm. In this case, maternal R-peaks are easily detectable from the mixture by an automatic peak search algorithm, while detection of fetal R-peaks is not fully automatic. In this method, because of low amplitude of fetal ECG, maternal ECG is first eliminated from the mixture by the EKF framework, then the residual signal is used for fetal R-peaks detection.

However, efficient elimination of maternal ECG requires careful selection of center of Gaussian functions, which is done manually by visual inspection of maternal ECG mean. The simplest way to automatize mECG elimination might be to reconstruct mECG by concatenating maternal ECG mean at maternal R-peaks. However, in this case all mECG beats are assumed to have exactly same amplitudes. This assumption can significantly impact the performance of maternal ECG elimination.

The proposed method in this paper, which is fully automatic, can be used to recover amplitudes of different beats of mECG to efficiently eliminate mECG. The rest of the paper is organized as follows: In Section 2 the related background of the proposed method is recalled. The proposed method is explained in detail in Section 3. Section 4 is devoted to show the performance of the proposed method on an actual fECG dataset. Finally, our conclusions are stated in Section 5.

2. Methods

2.1. Background

Higher-order tensors have gained increasing importance as they can be used to represent higher order cumulants that are exploited in independent component analysis [6] and have been used successfully in blind source separation (BSS). In addition, they are natural representations of multidimensional (higher than 2) data than matrices in many practical applications (e.g., in chemistry, biomedical engineering, and wireless communications). A fundamental challenge in these applications is to find informative and sparse representations of tensors, i.e., tensor decompositions. Tensor decompositions take into account information about different variables of the data, such as, for example, spatial, temporal and spectral information, and may provide links among the various extracted factors or latent variables with physical or physiological meaning and interpretation [7].

In [8], a parallel deflation procedure based on a deterministic tensor decomposition has been proposed to address the problem of underdetermined (i.e. more sources than sensors) BSS in the cyclostationary context. The basic approach consists in constructing a tensor by synchronizing on the symbol rate of a certain source, and decomposing the tensor using the canonical polyadic (CP) decomposition [9] to extract the characteristics of the source.

The method in [8], assumes that each of the $q = 1, \ldots, Q$ sources of interest has periodic symbols. For each source, it then builds a three-way tensor with dimensions space, symbol period, and temporal pattern from measurement data that is recorded with M sensors over a certain time interval. To this end, for the q-th source, L_q symbol periods composed of T_q time samples are identified from the measurements, yielding a data matrix of size $M \times T_q$ for each symbol period. By stacking these matrices along the second dimension of a three-dimensional array, one obtains the tensor $\boldsymbol{Y}^{(q)} \in \mathbb{C}^{\mathbb{M} \times \mathbb{L}_{\shortparallel} \times \mathbb{T}_{\shortparallel}}$.

The deterministic blind separation of sources having different symbol rates, proposed in [8] has been adopted and customized to ECG signal in this study for estimating mECG amplitude in each beat to better eliminate mECG from mixture.

2.2. Proposed algorithm

In the style of [8], we exploit the quasi-periodic nature of the ECG signal to construct a data tensor with dimensions space, ECG beat, and time from the M-dimensional measurements of mECG and fECG mixtures. To this end, we identify L mECG beats of length T of the measured mixture. This is achieved based on detection of maternal R-peaks to identify and synchronize the signals of different heart beats (each beat corresponds to the recognized pattern of the quasi-periodic source). Please note that the detection of maternal R-peaks is automatic and rather straightforward. The R-peaks are found from a simple 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 $\frac{T}{2}$ or larger than T are not detected. Finally, for the L mECG beats, one can extract an $M \times T$ data matrix from the measurements. These matrices are then stacked along the second dimension of the tensor $\boldsymbol{Y} \in \mathbb{C}^{\mathbb{M} \times \mathbb{L} \times \mathbb{T}}$.

Assuming that an mECG can be described by $R \in \mathbb{N}$ components that are identical for all mECG beats except for changes of amplitude, the elements of the tensor can be written as

$$Y_{ijk} = \sum_{r=1}^{R} a_{ir} s_{jr} h_{kr} + b_{ijk}. \tag{1}$$

The first term in the right-hand side of (1) corresponds to the canonical polyadic (CP) decomposition of a tensor where a_{ir}, s_{jr}, and h_{kr} are the elements of three loading matrices $\mathbf{A} \in \mathbb{R}^{\mathbb{M} \times \mathbb{R}}$, $\mathbf{S} \in \mathbb{R}^{\mathbb{L} \times \mathbb{R}}$, and $\mathbf{H} \in \mathbb{R}^{\mathbb{T} \times \mathbb{R}}$, respectively [9]. The loading matrices correspond to the mixing matrix related to mECG ($\mathbf{A}$), the matrix of mECG beat amplitudes ($\mathbf{S}$), and the matrix containing the temporal pattern of mECG beat ($\mathbf{H}$) that characterize the mixture of the mECG source. The second term contains noise and interference from the desynchronized signals of other sources.

In practice, one can obtain estimates for the mixing matrix, the mECG beat amplitudes, and the patterns of mECG components by decomposing the tensor using the following criterion that optimizes the classical CP cost function:

$$\left\{\hat{\mathbf{A}}, \hat{\mathbf{S}}, \hat{\mathbf{H}}\right\} = \underset{\{\mathbf{A},\mathbf{S},\mathbf{H}\}}{\operatorname{argmin}} \sum_{i,j,k} \left| y_{ijk} - \sum_{r=1}^{R} a_{ir} s_{jr} h_{kr} \right|^2. \tag{2}$$

An important advantage of the CP decomposition in comparison to matrix decompositions, such as principal component analysis (PCA), is that it is essentially unique [10, 11] up to scale and permutation indeterminacies under mild conditions on the tensor rank, without imposing additional constraints such as orthogonality or independence. It has been shown in [8] that if $\mathbf{A}$, $\mathbf{S}$, and $\mathbf{H}$ have full rank and $T \geq R$, $L \geq R$ (i.e., if the number of symbols and the number of time samples per symbol are larger than the number of components R to be extracted), then $M = 2$ sensors are enough to blindly separate R components.

Decomposition of the tensor via the optimization problem in (2) yields three loading matrices $\mathbf{A}$, $\mathbf{S}$, and $\mathbf{H}$. Using these matrices mECG is reconstructed and projected back to the sensor domain to be subtracted from the mixture. The residue of the subtraction, i.e. rough fECG es-

timate, is then used to detect fetal R-peaks using the automatic peak search algorithm that was used for detection of maternal R-peaks.

3. Data

The non-invasive fetal electrocardiogram dataset in the PhysioNet/Computing in Cardiology Challenge 2013 [12] is used in this study to show the performance of the proposed method. This challenge is dedicated to develop accurate fetal R-peak detection methods. Data for the challenge consist of a collection of one-minute fetal ECG recordings. Each recording includes four non-invasive abdominal signals. The data were obtained from multiple sources using a variety of instrumentation with differing frequency response, resolution, and configuration, although in all cases they are presented as 1000 samples per signal per second. In each case, reference annotations marking the locations of each fetal QRS complex were produced, usually with reference to a direct fECG signal, acquired from a fetal scalp electrode. The direct signals are not included in the challenge data sets [12].

4. Results

Figure 1 shows the first ten seconds of the mixed ECG recordings on channels 1 to 4 of the namely a22 dataset and the corresponding stacked mECG beats for one minute from these channels. In order to construct the tensor, the maternal R-peaks are firstly detected then the ECG beats centered at the R-peaks are stacked to build the tensor. The mECG rank for this measurement has been considered to 2 and the tensor is constructed with parameters $M = 4$, $L = 78$, $T = 780$.

Figure 2 illustrates the performance of the proposed method on ten seconds of the first channel of the recording a22. As it is seen, the proposed method is favorably able to detect fetal R-peaks even in coinciding epochs, in which maternal and fetal ECG waves fully overlap in time. This is particularly noticed between t = 5s and t = 6s, where some parts of fECG signal have been corrupted after mECG subtraction.

As it has been mentioned in the previous section, the proposed method is able to extract components of the signal of interest using only two channel recordings. Figure 3 shows the efficiency of the proposed method in detection of fetal R-peaks where only channels 1 and 2 of the recording a12 are utilized to estimate and remove mECG.

The obtained average scores of event 4 and 5 on the set B of PhysioNet Challenge 2013 data, reported by the challenge organizers, are 1514.59 and 57.01, respectively. As a reference, scores from the sample submission physionet2013.m (available at PhysioNet) on set B for event 4 and 5 are 3258.56 and 102.75, respectively, where the lower the scores the better.

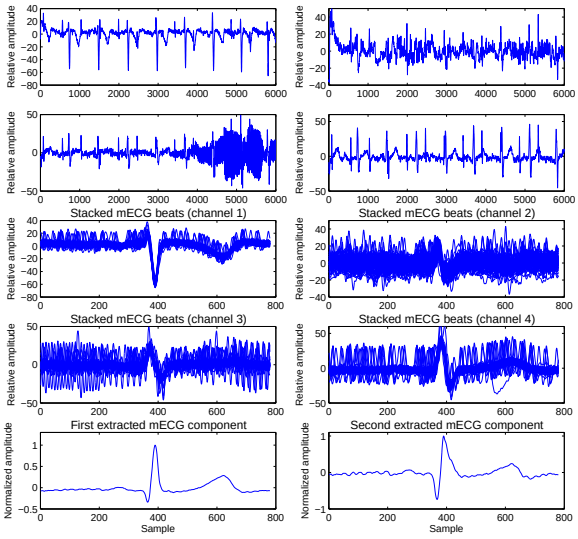

Figure 1. Extraction of mECG components from the namely a22 dataset of the PhysioNet Challenge 2013. Up to down: the first ten seconds of the recorded mixed ECG signals on the channels 1 to 4, stacked mECG beats arranged in the tensor for one minute from the channels 1 to 4, normalized extracted mECG components via classical CP.

5. Conclusions

Most of the promising methods in fetal ECG extraction field need fetal R-peak positions as a key prior information. Using R-peak positions, the quasi-periodic nature of ECG signal can be exploited. Fetal R-peak positions can also be independently used for R-R interval and heart-rate studies. In this paper, a deterministic tensor decomposition method was adopted and customized to ECG signal to efficiently remove mECG signal from mixture of mECG and fECG for detection of fetal R-peaks. The proposed method can be used with only two electrodes, which is a key feature for a monitoring system that can highly affect the systems price, convenience and portability.

Acknowledgement

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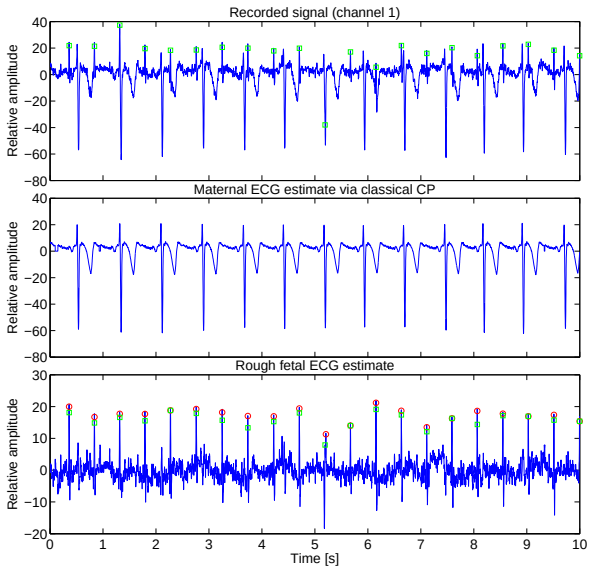

Figure 2. Fetal R-peaks detection via tensor decomposition on the recording a22 of the PhysioNet Challenge 2013 using channels 1 to 4. Up to down: mixed ECGs on channel 1, reconstructed maternal ECG via classical CP, residue of subtraction of reconstructed mECG from the mixture, i.e. rough fECG estimate. Given fetal R-peaks are shown in green squares and estimated fetal R-peaks are shown in red circles.

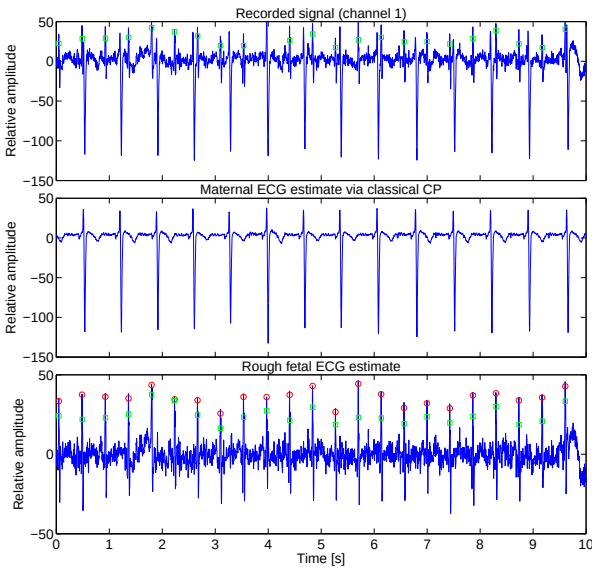

Figure 3. Fetal R-peaks detection via tensor decomposition on the recording a12 of the PhysioNet Challenge 2013 using only channels 1 and 2. Up to down: mixed ECGs on channel 1, reconstructed maternal ECG via classical CP, residue of subtraction of reconstructed mECG from the mixture, i.e. rough fECG estimate. Given fetal R-peaks are shown in green squares and estimated fetal R-peaks are shown in red circles.

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