Fetal ECG Extraction From Abdominal Recordings using Array Signal Processing

Masoumeh Haghpanahi, David A Borkholder

Rochester Institute of Technology, Rochester, NY, USA

Abstract

An algorithm to automatically locate QRS complexes in noninvasive fetal ECG signals is described and was entered in the PhysioNet/CinC 2013 "Noninvasive Fetal ECG" challenge. The algorithm is based on an iterative subspace decomposition and filtering of the maternal ECG components from the recordings of a set of electrodes placed on the mother's abdomen. Once the maternal components are removed, a novel merging technique is applied to merge the recordings and generate a signal with a higher SNR to perform fetal peak detection. The algorithm produces an annotation file for each data set containing the location of the fetal QRS complexes in that set. The final results indicate that the algorithm is able to detect fetal peaks under different scenarios and for variety of devices and signals encountered in clinical practice.

1. Introduction

Congenital heart defects originate in early stages of fetal heart forming and are the leading cause of birth defect-related deaths [1]. Monitoring fetal cardiac activity can provide important information about the fetal well-being and detect cardiac anomalies in early stages of heart forming. However, despite its huge potential applications, noninvasive fetal electrocardiography (fECG) has not lived up to its promises; this is mainly due to the significant amount of noise originating from fetal brain activity, muscle contractions, recording devices, movement artifacts and etc., that is added on top of the maternal ECG (mECG) to the fECG recordings [2].

The aim of this year's PhysioNet/CinC Challenge was to develop accurate algorithms for locating QRS complexes in noninvasive fECG signals obtained by a set of four electrodes placed on the mother's abdomen. In response to this challenge, we developed a fully-automatic algorithm based on the iterative subspace decomposition and filtering technique previously described by Sameni et al [3]. The algorithm is further extended to automatically select reliable initial values for the dynamic model parameters and be applied to general fECG signals without prior information about the shape of the fECG complexes. Once the mECG components are removed from the recordings, a joint polarity detection-merging algorithm is applied to merge the signals and generate a unique signal with a higher SNR value which will then be used to detect fetal QRS complexes.

2. Methods

2.1. Data

Data for the challenge consisted of a collection of one-minute fECG recordings. Each recording included four noninvasive abdominal signals obtained from multiple sources with differing frequency response, resolution, and configuration. In all cases the data was presented as 1000 samples per signal per second. The data was divided into a training set A, which included noninvasive fECG signals as well as the reference annotations for them, and test sets B and C for final scoring. The challenge was to produce a set of annotations that matches the hidden references as nearly as possible, for each record in set B or C.

2.2. Algorithm

The fECG extraction technique is summarized in the block diagram of Fig. 1, with key elements described in detail below.

2.2.1. Signal preprocessing

The source data was checked for missing values corresponding to time points with an invalid ADC output. If existed, these signal values were estimated using an autoregressive interpolation method similar to [4], prior to processing. Next, power line interferences were removed from each channel using a simple second order notch filter. This was followed by a two-step moving window median filter to remove the baseline wander from the recordings [1].

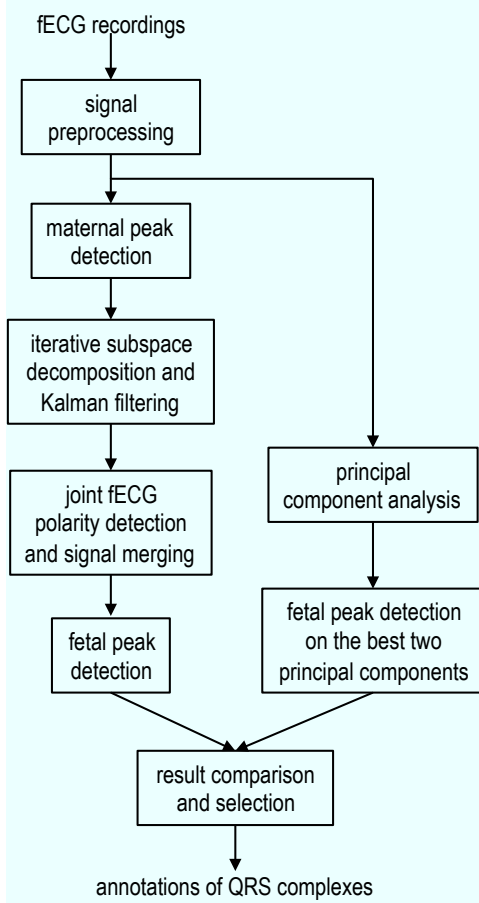[1]We used the preprocessing function available in the Open-Source Electrophysiological Toolbox (OSET) [9] for this step.

Figure 1. Block diagram showing the different steps of the algorithm.

The flow diagram contains:

fECG recordings

→ signal preprocessing

→ maternal peak detection

→ iterative subspace decomposition and Kalman filtering

→ joint fECG polarity detection and signal merging

→ fetal peak detection

(branch from signal preprocessing) → principal component analysis → fetal peak detection on the best two principal components

→ result comparison and selection

→ annotations of QRS complexes

2.2.2. Maternal ECG extraction

mECG artifacts are the dominant source of interference in the fECG signals recorded from the mothers abdomen. In fact, depending on gestational age and electrode locations, the amount of such interference can be in the order of ten times stronger than the fetal signal itself [5].

We used an iterative subspace decomposition and Kalman filtering to remove the mECG components from the recorded signals. Our approach was based on the method previously described in Sameni et al [3].

In short, the method repeatedly applies a sequence of linear decomposition (to separate the maternal and fetal ECG subspaces), denoising (to remove the mECG components), and back-projection to the input data space. This procedure is repeated until maternal components are largely removed from the fECG signals.

The linear source separation method was based on the periodic component analysis (referred to as πCA) which is specifically customized for pseudo-periodic signals [6].

For the denoising step, Kalman filtering was applied at each iteration to the most dominant maternal component of the decomposition step. This is done by modeling ECG waveforms as sum of variable number of Gaussian kernels similar to [7].

One drawback of the existing implementations of the above bayesian filtering approach [7, 8] is that the number of Gaussian kernels is assumed to be known *a priori*. This assumption avoids the automatic set up of the parameters and causes difficulties in handling abnormal rhythms. This is improved in our implementation and Gaussian kernels are selected automatically without imposing *a priori* knowledge about the location of P, Q, R, S, and T waves [2].

2.2.3. fECG polarity detection and signal merging

Once the mECG complexes were removed from the fECG recordings, the filtered fECG signals were sorted based on their overall quality for fetal peak detection. To this end, signals were divided into shorter time frames of 2 seconds and at each time frame, signal kurtosis was used to compare and sort the recordings of the four channels. The signal with the highest kurtosis in the majority of the time intervals was selected to be the first and the rest of the channels were sorted accordingly. Sorting of the fECG signals was a necessary step for the joint polarity detection-merging algorithm described below.

The algorithm also calculates and uses the average ECG beat of a signal (described in [6]) as a measure of accuracy of the R-peaks detected in that signal.

Let X denote the matrix containing the fECG recordings with the ith row $X^{(i)}$ corresponding to the ith best fECG signal, based on the above quality metric. The algorithm starts with initializing the merged signal, denoted by $\mathbf{x_m}$, with $X^{(1)}$ and detecting the polarity of the QRS complexes of $X^{(1)}$. For this purpose, the average ECG beat of $X^{(1)}$ is compared with a known sample fECG beat with positive polarity, and the sign of their inner product determines the sign of the R-peaks of $X^{(1)}$.

For the rest of the channels, the decision of whether or not add $X^{(i)}$ to the merged signal is dependent upon whether adding $X^{(i)}$ would help the peak detection process. To do this assessment, let $l^{(i)}$ and $\mathbf{s^{(i)}}$ denote the number of detected R-peaks and the average ECG beat of $\mathbf{x_m}$ when adding $X^{(i)}$ to the merged signal, correspondingly. Furthermore, let $\rho^{(i)}$ be the correlation coefficient between $\mathbf{s^{(1)}}$ and $\mathbf{s^{(i)}}$. Then, $X^{(i)}$ is added to $\mathbf{x_m}$ if the number of peaks adjusted with the correlation coefficient $(\rho^{(i)} \times l^{(i)})$ is increased when adding $X^{(i)}$ to $\mathbf{x_m}$. The peak adjusting technique is necessary for fetal peak detection as

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[2]The coding of this step was done partly using the related functions in the OSET toolbox [9], as well as the EKF/UKF toolbox [10] for the Kalman filtering.

often times the amplitude of the fetal R-peaks is comparable to the amplitude of noise present in the signal and noise artifacts can be detected as R-peaks.

The peak detection process used at each step of the above merging algorithm is as follows. The process started with a simple R-peak detection using one of the available open source detectors [3]. Then, the unreliable peaks were removed from the results. To this end, the input signal was chopped into segments of 2-second intervals. At each interval, the signal was checked to see if certain time and frequency criteria were met. For the time criteria, the total number of peaks (detected in that interval) and the distance between the consecutive peaks were checked. For the frequency criteria, the FFT of the signal was computed and it was verified that the signal's power in the range of 20 Hz to 40 Hz [4] was a significant amount of its total power and that its high frequency components were negligible. If both time and frequency criteria were met, the detected R-peaks in that interval were kept, and if either condition was violated, the peaks were flagged as unreliable. The unreliable peaks were removed from the annotations and the location of the peaks for those intervals were interpolated based on the preceding and the following peaks in the signal.

2.2.4. Peak detection using PCA

In our observation of training set A and test set B, we came across cases where the fetal peaks could be seen and detected in one of the top four principal components of the original (unfiltered) fECG signals, but that they were lost in noise and undetectable in the filtered fECG signals. Hence, the fetal R-peaks were detected for the best two principal components of the original fECG recordings, and their results were compared with the peaks detected from the merged signal x_m.

To detect fetal peaks from a principal component, a simple peak detection [5] was performed at first to find the location of the maternal peaks. Next, rectangular windowing was used at each peak to remove the maternal components from the signal. Finally, another peak detection was performed to detect the fetal peaks present in the signal.

3. Results and discussion

Fig. 2 shows a 3-second interval of a typical fECG recording before and after the mECG extraction from the

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[3] we used the ad hoc matched filter function available in the OSET toolbox [9].

[4] This is the frequency range where the most dominant fetal components reside.

[5] Because of manipulating the frequency content of the principal components as a result of the windowing procedure, only the time criteria mentioned in Section 2.2.3 were used to check the reliability of the detected peaks.

signal. It can be verified that the Kalman filtering has totally removed the mECG parts of the signal and that the fetal complexes are easily detectable after this extraction.
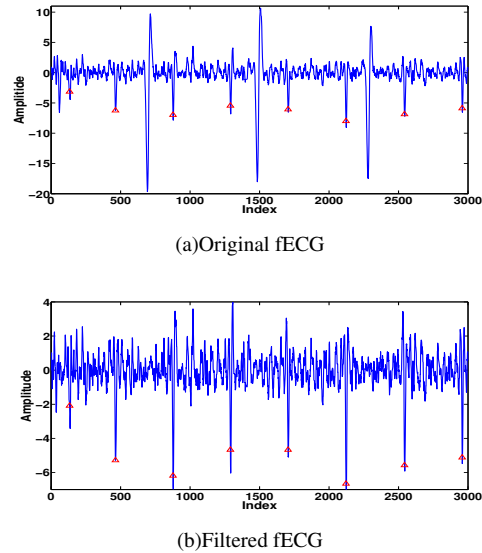

(a)Original fECG

(b)Filtered fECG

Figure 2. (a) Original fECG signal after removal of baseline wander and power line interferences from the recording. (b) Filtered fECG signal after removal of the maternal complexes from the signal. The red triangles point to the location of the fetal R-peaks in both figures. Note the difference in the Y-axis scales of the figures.

Fig. 3 depicts a situation where the fetal complexes cannot be seen in the original fECG signal and that they are not easily detectable from the filtered fECG, due to the considerable amount of noise in the signal. However, both fetal and maternal complexes are detectable from the first principal component of the original fECG recordings.

One important observation that needs more study is related to the scenarios under which the fetal complexes were detectable from the principal components but not from the recordings themselves. Identifying those conditions could increase the accuracy and decrease the running time of the algorithm.

As a final remark, we would like to emphasize the importance of signal preprocessing in the pipeline of Fig. 1. A good preprocessing algorithm can not only remove the baseline wander and power line interferences from the signal, but also dampen other sources of noise (from muscle contraction, recording devices, etc.) which considerably affect the fetal peak detection process. While the signal denoising and baseline wander correction method based on the empirical mode decomposition (EMD) technique described in [11] seems to be a promising approach, the huge computational cost of the EMD technique prevented us from using this method and studying its possible impact

on the overall accuracy of the results.

(a)Original fECG

(b)Filtered fECG
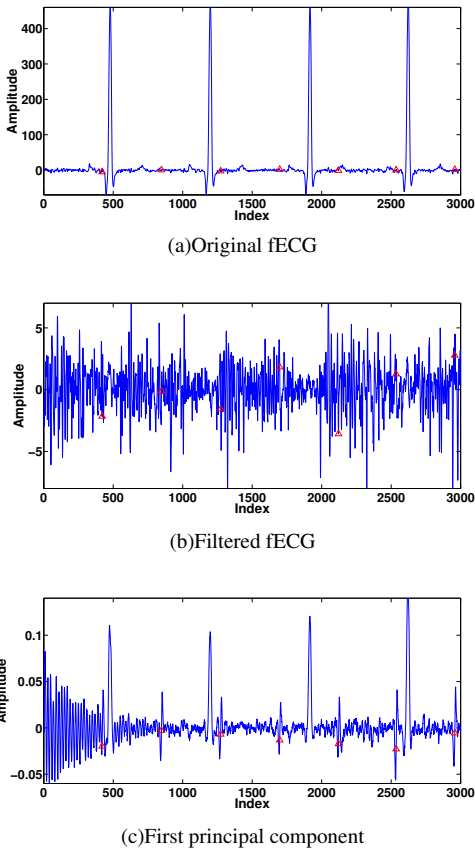

(c)First principal component

Figure 3. (a) Original fECG recording with powerful maternal components present in the signal. (b) Filtered fECG with high amount of noise. (c) First principal component of the original fECG signals with detectable maternal and fetal components. The red triangles point to the actual location of the fetal R-peaks.

Our team gained a score of 50.063 in the *fetal heart rate measurement* contest, which put us in the fourth place, and a score of 9.062 in the *fetal RR interval measurement* contest which put us in the sixth place in the competition.

Our algorithm was able to detect fetal peaks under different scenarios and for variety of devices and signals encountered in clinical practice. Although visual inspection of the results could increase the accuracy of the algorithm, it can be run automatically without human interventions; this is an important feature that makes this algorithm suitable for monitoring applications.

4. Conclusions

An algorithm for automatic detection of fetal peaks from the noninvasive fECG signals was devised and tested in this work. The final results indicated that the algorithm worked well under different scenarios and variety of conditions. Furthermore, the proposed algorithm can be run automatically which makes it suitable for monitoring applications.

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Address for correspondence:

Masoumeh Haghpanahi
Rochester Institute of Technology, James E. Gleason Building, 77 Lomb Memorial Drive, Rochester, NY 14623
mhaghpanahi@gmail.com