

Spatial Filtering and Adaptive Rule Based Fetal Heart Rate Extraction from Abdominal Fetal ECG Recordings

Minnan Xu-Wilson, Eric Carlson, Limei Cheng, Srinivasan Vairavan

Philips Research North America (PRNA), Briarcliff Manor, NY, USA

Abstract

Despite advances in adult electrocardiography (ECG) and signal processing techniques, the analysis of fetal ECGs (fECG) is still in its infancy. The clinical potential of abdominal fECG monitoring by placing electrodes over mother's abdomen in antepartum (prior to labor) has been hampered by difficulties in obtaining a reliable fECG. We propose an algorithm to extract fetal heart rate from abdominal fECG based on spatial filtering and adaptive rule-based fetal QRS detection. The algorithm was trained and validated on 75 and 100 fECG datasets respectively, all obtained as part of PhysioNet Challenge 2013. Two metrics were used by the Challenge to assess the algorithm's performance: (Event4) the mean square error of fetal heart rate (HR) and (Event5) root mean square error of fetal RR interval between the HR obtained via the proposed approach and the HR obtained via the fetal scalp electrode. The proposed algorithm achieved mean scores of 52.49 and 10.61 and (Event 4 and 5 respectively) in the validation dataset. These results suggest the robustness of the proposed algorithm and its potential to advance fECG monitoring in antepartum surveillance.

1. Introduction

Although fECG has been used extensively for fetal heart rate monitoring using a fetal scalp electrode during labor, the actual clinical potential of this approach in antepartum (prior to labor) monitoring by placing electrodes over mother's abdomen has been hampered by difficulties in obtaining a reliable fetal ECG [1]. This could be partly due to the relatively low signal-to-noise ratio of the fetal ECG compared to the maternal ECG and contamination of fECG with fetal brain activity, myographic (muscle) signals (from both the mother and fetus), and movement artifacts [1]. Thus, the fetal monitoring today is based entirely on the fetal heart rate and does not incorporate characteristics of the fetal ECG (fECG) waveform characteristics that are the cornerstone of cardiac evaluation of both children and adults [1].

Several techniques based on adaptive filtering, linear

and nonlinear decomposition have been proposed to extract fECG from abdominal ECG signals [1] and references therein. Although, most of the techniques are capable of extracting fECG, due to the complexity of the problem there are still many open issues that require improved signal processing solutions [2].

This paper presents the results of an improved algorithm for fetal heart rate extraction from abdominal fECG recordings. The proposed algorithm uses spatial filtering (Principal component analysis (PCA) and Orthogonal Projection (OP)) techniques for maternal ECG attenuation and PCA clustering; adaptive rule based fetal QRS detection for the extraction of fetal heart rate.

Abdominal fECG, used to develop/validate the algorithm was obtained as part of PhysioNet/CinC Challenge 2013. The performance of the algorithm was assessed for its accuracy in detecting the fetal heart rate and fetal RR interval with respect to the gold standard based on mean square error of fetal heart rate (Event4) and root mean square error of fetal RR interval (Event 5).

2. Methods

2.1. Fetal ECG data

The training datasets obtained from PhysioNet/CinC Challenge 2013 consist of 75 recordings of abdominal fECG, each of 1-minute duration corresponding to four channels acquired at a sampling rate of 1 kHz. The 75 records are divided into 2 groups: "Set A" (25 records), and "Set A-Ext" (75 records). The reference fetal QRS location is provided for these datasets based on the fetal scalp electrode which serves as the gold standard. In addition, set B, containing 100 fECG datasets, served as a validation cohort [3].

2.2. Proposed algorithm

A general framework of the proposed algorithm is shown in Figure 1. The raw fECG data is first band-pass filtered between 2-50 Hz to remove any baseline-wander and other low-frequency movement artifacts. The filtered

ECG is then subjected to maternal ECG attenuation and fetal QRS (fQRS) detection. The details of maternal ECG attenuation and fQRS detection are described below.

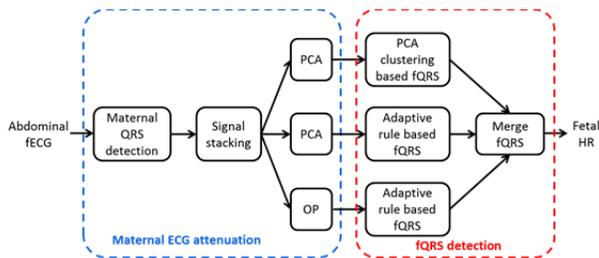


Figure 1. A general framework of the proposed algorithm. Legend: PCA - Principal Component Analysis, OP - Orthogonal Projection, fQRS – fetal QRS

2.3. Maternal ECG attenuation

Maternal ECG attenuation consists of extraction of maternal QRS, signal stacking around the detected maternal QRS and application of spatial filtering techniques to attenuate the maternal ECG.

Maternal QRS detection

Maternal QRS detection consists of four steps, namely, pre-processing, best channel selection, polarity selection and auto-peak detection and auto-correction. The details of the each step are discussed below and diagramed in Figure 2:

Pre-processing: Each channel is split into segments of 0.5 sec duration and has any linear trends removed. The detrended segments are concatenated back together into 1-minute pre-processed fECG data.

Channel selection: The four channels are ranked based on 1) the power spectrum using Fourier transform in descending order with high weight, 2) power using Hilbert transform in descending order with medium weight, and 3) standard deviation in ascending order with low weight.

Polarity selection: If the maximum amplitude of the fECG is smaller than the absolute value of the minimum amplitude of fECG, then this channel is flipped before further processing.

Auto-detection: The simple automated peak detection on each channel is based on one threshold for searching signal indexes at local maximums of ECG amplitude and three thresholds for derivatives of those indexes of local maximums in which the three thresholds partly represents R-R intervals in low, normal and high levels.

Auto-correction: We search for the local maximum in a narrow window around the auto-detected peak.

Optional auto-correction: (see N-loop of Figure 2) First, a channel is selected if it produces a reasonable heart rate (30-132 bpm, calculated from the peaks detected from that channel) and if the heart rate is within 1 bpm of the heart rate detected from other channels. The selected channels are then compared to match the weighted rank in which the highest ranked channel is chosen. If no channel is selected, the 1 minute ECG signal will be segmented into 10 shorter ECGs for each channel and the threshold for peak detection will be the same or reduced for more rounds of ECG auto-detection and auto-correction, until a channel with reasonable peak number is selected. Once the channel and correct peak number is decided, QRS complexes missed are identified by looking for large RR intervals (first derivative of the peak locations). After the correction process, all the maternal R peaks in QRS have been detected.

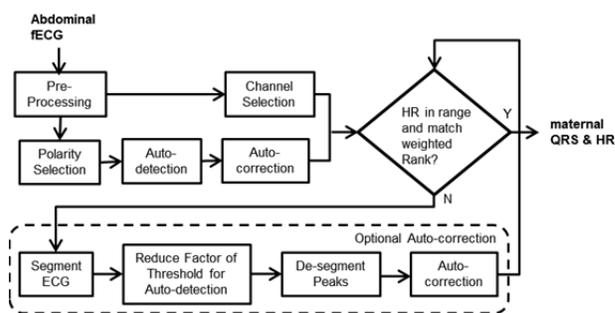


Figure 2. Flow Chart of Maternal QRS Detection

Signal stacking around maternal QRS

For each channel of each record, we apply a fixed n -length window around each of the m maternal QRS complexes. The window size is 110% of the median RR interval for that record, with 35% before the R peak and 75% after the R peak. The resulting $m \times n$ data matrix M , is used for principal component analysis (PCA) and orthogonal projection (OP). This construction actually increases the spatial resolution for a single channel data and would aid the spatial filtering techniques such as PCA and OP to better attenuate maternal QRS.

Principal component analysis (PCA)

PCA has been used to separate ventricular and atrial components of ECG for estimation of atrial fibrillatory wave [4]. Here we extract fetal ECG by applying PCA to the stacked matrix M of maternal beats and subtract maternal contributions. The principal components from PCA can be interpreted in the following way:

- 1) The most significant components are related to the main maternal QRST waveform and the interbeat

variability that exist in maternal QRST waveform.

- 2) The remaining components correspond to fetal ECG and other sources of contamination.

To estimate the fECG, we subtracted from each row of \mathbf{M} the mean of \mathbf{M} and the contributions of the top three principal components to that row. \mathbf{M} with maternal contributions removed is un-stacked to give the fetal ECG. We then apply a low pass filter to remove any discontinuity that may have resulted from windowing.

Orthogonal Projection (OP)

OP has been used in attenuation of maternal and fetal Manganocardiogram (MCG) from fetal Magentoecephalogram (fMEG) [6] and is based on Gram-Schmidt orthogonalization. In our approach, we apply OP to the stacked matrix \mathbf{M} to remove maternal contributions. A data point at which the matrix \mathbf{M} attains the largest amplitude is chosen as the first maternal ECG signal space vector of dimension $m \times 1$, where m is the number of maternal QRS complexes. The choice of the largest amplitude signal space vector can be based on the root mean square (rms) estimate. This vector is projected out from the matrix \mathbf{M} . The procedure is then repeated on the residual, and the next signal space vector is selected and projected out, and so on. The vector selection procedure is stopped when the residual drops below a specified threshold, for example, a multiple of the rms noise estimate [5]. The matrix \mathbf{M} with maternal contributions removed is un-stacked to give the fetal ECG.

2.4. Fetal QRS detection

Two different techniques, namely, adaptive rule based fQRS detection and PCA clustering based fQRS detection are used to extract the fetal QRS. To this end, another technique, namely, merge fQRS uses the information of fetal QRS provided by the three different approaches and combines them optimally to get an accurate fetal QRS location and hence an accurate fetal heart rate.

Adaptive rule based fQRS

The best combination of channels or the polarity of the channel (direction of the R peak) can differ among recordings. Here we apply a basic peak detector [6] to different combinations of channels and polarities. The different combinations were then ranked based on the number of peaks detected and heart rate variability. The combination of channel(s) with the most peaks detected and least heart rate variability is designated the winning combination whose peaks are then output as the fetal QRS locations.

Because fECG is often weak in abdominal recordings, almost all peak detectors will misplace some peaks or miss peaks completely. We apply two rules to make conservative corrections to the detected peaks with minimal alteration of peaks already correctly identified:

- 1) Missing beat(s) is identified when the RR interval is $\geq 1.3 \times medianRR$ interval of the entire record. One or more new beats are then placed equally spread within neighboring peaks.
- 2) A peak is misplaced when a pair of RR intervals (RR_k, RR_{k+1}) shows the pattern of $RR_k \leq 0.9 \times medianRR$ followed by $RR_{k+1} \geq 1.1 \times medianRR$ OR $RR_k \geq 1.1 \times medianRR$ followed by $RR_{k+1} \leq 0.9 \times medianRR$. Misplaced peaks are shifted to midway between neighboring peaks.

PCA clustering based fQRS

The algorithm begins with an optimized thresholding routine that chooses a threshold to minimize the variance of intervals between threshold crossings while constraining the number of threshold crossings to remain in a physiologically plausible range for a fetal heart beat. These crossing points are used to capture 100ms signal snippets, which contains potential fQRS complexes. These f signal snippets are used as rows in an $f \times n$ matrix, to which PCA is applied. This finds the ordered dimensions of maximum variation – there should be a dense cluster representing true fQRS complexes that are similar to each other, and a more distributed set of points representing noise, which will tend to have large variation. This is what we find in practice, and the algorithm proceeds with K-Means clustering to find the cluster that represents the fQRS complexes. The center of this cluster is used to assign confidence to each signal snippet by distance to center – snippets with points closer to the center of this cluster are deemed more likely to be fQRS complexes than points farther away. This list of signal snippet times and confidences (inverse distances) from each channel is then passed to the merging algorithm below to produce a single beat record.

Merge fQRS

Merge fQRS is designed to account for the fact that no single channel or method will be the best in all situations. Given a list of proposed fQRS locations from multiple sources, Merge fQRS implements a modified voting routine to determine likely fQRS complexes, which it then analyzes for likely missed and misplaced complexes. The first step in the algorithm is to create a zero-filled vector of same duration as the ECG recordings. Each input beat list is considered in turn, through a process in which the beat with the maximum certainty is chosen and

its confidence metric is added to the vector. Chosen beats are removed from the channel's list until no beats remain, and the next list is added in the same manner to the vector. Strong fetal complexes should be recorded by multiple channels, and so contributions in corresponding bins should add. To account for timing variations, the signal is filtered by a Gaussian window prior to further analysis. The next step proceeds as the first – the tallest peak in the recording is held as the location of the highest confidence of a complex and is chosen first, its time is added to a list, and the region surrounding it is set to 0. The next highest peak is chosen and similarly added. This process repeats until the maximum peaks are less than 50% of the original maximum. After that point, a filling and shifting process similar to that described in Adaptive Rule Based fQRS is employed to bring the record in line with physiological statistics.

3. Results and discussion

The results of three different algorithms on set A and A-ext are shown in Table 1. A combination of these three algorithms yielded improved scores on the training datasets. Thus we expected merging the three methods would also improve performance on the validation set B, which did indeed yield improved results: 52.49 and 10.61 for Events 4 and 5 respectively.

Table 1. Results of the algorithm on training datasets. Method 1 is PCA-maternal attenuation followed by PCA-clustering based fQRS. Method 2 is PCA-maternal attenuation followed by Adaptive rule based fQRS. Method 3 is OP-maternal attenuation followed by Adaptive rule based fQRS detection.

	Set A		Set A ext	
	Event 4	Event 5	Event 4	Event 5
Method 1	64.35	9.94	248.27	18.68
Method 2	7.02	4.29	165.28	14.11
Method 3	12.70	6.82	243.55	17.91
Merge of 3 methods	5.00	4.05	146.76	14.65

Though the proposed spatial filtering techniques (PCA and OP) attenuate the maternal ECG, there could still be scenarios of maternal cardiac residues. Future work is needed to handle such scenarios. The process of filling and shifting fetal QRS locations is meant to produce heart rate estimates that are physiological. However, this process may not produce true fetal QRS locations.

4. Conclusion

An improved algorithm for fetal heart rate extraction from abdominal fECG recordings has been presented.

The proposed algorithm uses spatial filtering (Principal component analysis and Orthogonal Projection) techniques for maternal ECG attenuation and PCA clustering; adaptive rule based fetal QRS detection for the extraction of fetal heart rate. The results of the proposed algorithm suggest the robustness of the approach and could be used to advance fECG monitoring in antepartum surveillance.

Author contributions

Maternal QRS detection: LC. Signal stacking around maternal QRS, PCA based maternal attenuation, and Adaptive rule-based fQRS detection: MX. Orthogonal projection based maternal attenuation and coordination of the proposed work: SV. PCA based fQRS detection and Merge fQRS: EC.

Acknowledgement

The authors would like to thank Rich Gregg, Saeed Babaeizadeh of Philips Healthcare, and Konstantin Volyanskyy of Philips Research for insightful discussions.

References

- [1] Sameni RCG. A review of fetal ECG signal processing; issues and promising directions. *Open Pacing Electrophysiology & Therapy Journal* 2010; 3: 4-20.
- [2] Sameni R. Extraction of fetal cardiac signals from an array of maternal abdominal recordings (Doctoral dissertation). Institut National Polytechnique de Grenoble-INPG; 2008.
- [3] Physionet Challenge [Online]; 2013. Available from: <http://physionet.org/challenge/2013/>.
- [4] Castells F, Mora C, Rieta J, Moratal-Perez D, Millet J. Estimation of atrial fibrillatory wave from single-lead atrial fibrillation electrocardiograms using principal component analysis concepts. *Medical and biological Engineering and Computing* 2005; 43: 557-560.
- [5] Vrba J, Robinson S, McCubbin J, Murphy P, Eswaran H, Wilson J, et al. Human fetal brain imaging by magnetoencephalography: verification of fetal brain signals by comparison with fetal brain models. *Neuroimage* 2004; 21: 1009-1020.
- [6] Sameni R. Open Source ECG Toolbox (OSET) [Online]; 2006. Available from: <http://ecg.sharif.ir/>.

Address for correspondence.

Srinivasan Vairavan
 Philips Research North America (PRNA)
 345 Scarborough Road, Briarcliff Manor, NY 10501, USA
 Tel/Fax: +19149456006/6580
srinivasan.vairavan@philips.com