An Algorithm for the Analysis of Fetal ECGs from 4-channel Non-invasive Abdominal Recordings

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Abstract

The fetal ECG (fECG) is one of the most valuable tools for monitoring the health of the fetus throughout pregnancy. However, its clinical use has been limited by the difficulty in analysing such non-invasive fECG recordings.

The aim of this study was to develop a robust algorithm for the analysis of 4-channel abdominal fECG recordings and test its performance in the Computing in Cardiology Physionet Challenge 2013.

Signals were pre-processed by a combination of frequency filtering and wavelet de-noising. Adaptive cancellation of the maternal ECG (mECG) was performed using maternal QRS time markers obtained from the principal component containing the largest mECG. Following further wavelet de-noising of the residuals, the fetal QRS time markers were computed with a local peak detection algorithm from the first principal component. The derived fetal HR (event 4) and fetal RR (event 5) time series were compared to the reference values obtained from a scalp electrode signal.

This algorithm scored 223.23 for Challenge event 4 and 19.34 for Challenge event 5, outperforming the sample algorithm.

1. Introduction

The clinical value of fetal monitoring is widely acknowledged [1]. Current state-of-the-art assessment of the fetal heart function is mainly based on the use of an echo probe for monitoring of the fetal heart rate (fHR). This is commonly used in clinical practice along with a second probe, a pressure transducer, (Figure 1) intended for the monitoring of uterine contractions. The combination of these two devices is called a cardiotocograph (CTG) [2]. This technology is expensive, needs an expert nurse for the most appropriate placement of the probe and is extremely sensitive to maternal or fetal movements.

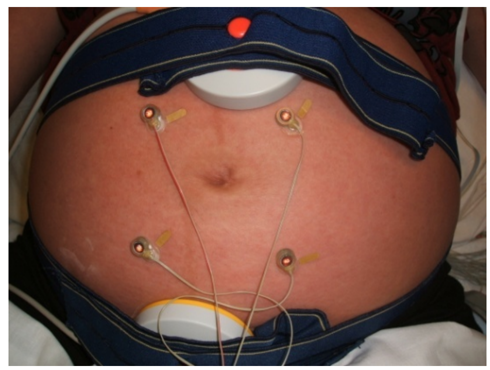

Figure 1. Pressure transducer (upper belt) and echo probe (lower belt) for standard CTG clinical monitoring. In the future this system could be replaced by abdominal electrical recordings, for example using four electrodes placed around the navel as illustrated.

Another approach to monitoring involves using an electrode placed on the scalp of the fetus [3, 4]. This technique provides valuable information as it collects the fetal ECG (fECG) signal from which fHR and other clinical parameters can be derived. However, it can only be used during labour after rupture of the membranes and it is therefore highly invasive.

Motivated by improving diagnostic capabilities and maternal and fetal care, there is growing interest in developing alternative methods of monitoring [5]. Abdominal fECG recordings are non-invasive and facilitate continuous monitoring without excessive discomfort for the mother and fetus. Over and above fHR monitoring provided by current CTG technology, fECG offers the prospect of additional clinical parameters such as fetal QT (fQT) time interval. A recent study demonstrated the reliability of cardiac parameters obtained from abdominal recordings and their excellent agreement with values obtained from a scalp electrode signal [6]. However, the data acquisition and signal processing challenges of abdominal fECG are significant. In particular the signals are contaminated by noise from movement of the mother and fetus, mains power line interference, and other physiological components such as maternal ECG and maternal muscular activity [7].

One of the most commonly used techniques for the extraction of the fECG from maternal abdominal recordings is Independent Component Analysis (ICA) [8]. Different algorithms have been proposed to implement ICA, including JADE and AMUSE. However, ICA by itself has practical limitations due to the significant noise affecting these signals, and the small amplitude of the fECG as compared to other physiological sources. In order to overcome such limitations, ICA has been used in conjunction with wavelet decomposition [9]; or as a component of a 2-stage Blind Adaptive Filtering approach [10].

An alternative approach for separating the different components of these signals is represented by Principal Component Analysis (PCA). PCA is based on obtaining statistically uncorrelated components, which do not necessarily represent independent physiological sources. This method was used, for example, in the algorithm developed by Martens *et al* [11].

The aim of this study was to use state-of-the-art signal processing techniques for the development of a new and robust algorithm for the analysis of 4-channel abdominal fECG recordings, and to test its performance in the Computing in Cardiology Physionet Challenge 2013 [12].

2. Methods

2.1. Dataset

Data for the Challenge consisted of a collection of 1-min 4-channel abdominal recordings (aECG) made available through the Physionet webpage [13]. Gold standard (reference) fECG R-peaks (fR-peaks) time series was expertly annotated from a scalp fetal ECG recorded simultaneously with an aECG.

The algorithm was developed using a training set (Challenge Set-A) of 75 recordings for which the reference fR-peaks were provided. The algorithm was tested on a test set (Challenge Set-B) of 100 recordings for which the reference fR-peaks were hidden.

2.2. Fetal ECG analysis

The proposed algorithm for the detection of the fR-peaks consisted of four steps (as illustrated in Figure 2): step 1, pre-processing of the aECG signals for noise reduction; step 2, detection of the maternal ECG (mECG) R-peaks (mR-peaks); step 3, cancellation of the mECG; step 4, detection of the fR-peaks.

Step 1 consisted of three sub-steps. Step 1.1 applied a 3-100 Hz Butterworth band-pass filter to attenuate low- and high-frequency noise, mainly due to movement

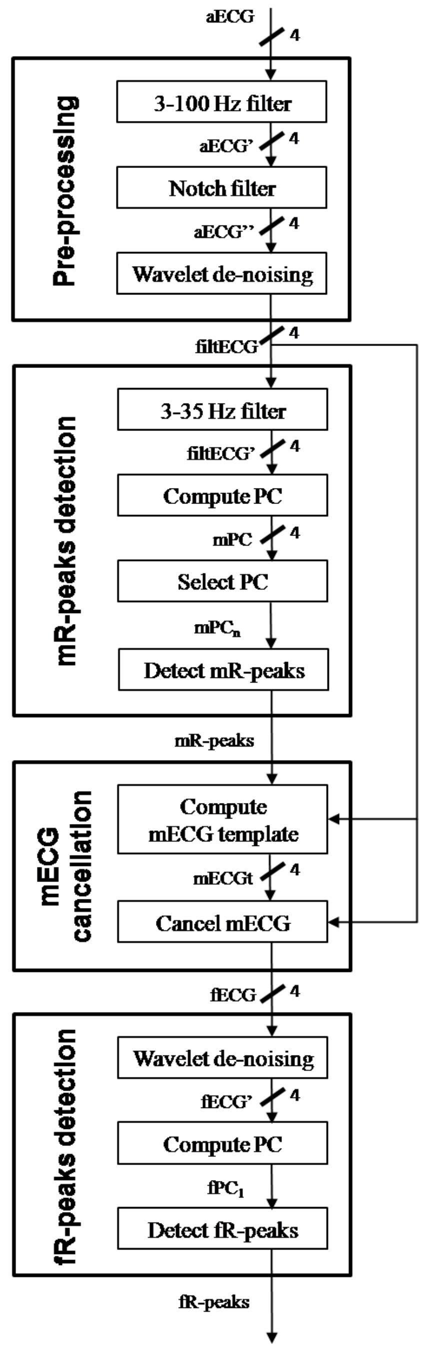

Figure 2. Diagram describing the algorithm.

artefacts, respiration, and electrical noise (aECG'). Step 1.2 applied a notch filter to attenuate the coupling with the mains (aECG''). Step 1.3 used a wavelet analysis based method to cancel large-amplitude noise (filtECG).

Step 2 consisted of 4 sub-steps. Step 2.1 applied a 3-35 Hz band-pass filter to select the main frequency band of the maternal QRS (mQRS) complex (filtECG'). Step 2.2 computed the principal components of filtECG' (mPC) and step 2.3 selected the best one (mPC_n) to use for subsequent mR-peaks detection. mPC_n was chosen as the principal component with the largest mQRS complexes as compared to a baseline level which was defined as the root mean square of the signal. In order to account for baseline noise, this method was applied to a smoothed version of the PC obtained from the correlation between the original PC and a 100-ms triangular wave representing an approximated template of the QRS. Further analysis also corrected for possible spikes resembling a triangular wave which would compromise the correct selection of the optimal PC. Step 2.4 detected the mR-peaks from mPC_n using an algorithm based on enhancing the maternal QRS complexes and applying a threshold based on the root mean square of the signal.

Step 3 consisted of 2 sub-steps. In step 3.1, the mR-peaks time series was used to provide reference time points to calculate an mECG template (mECGt) for each of the 4 channels of filtECG. Each maternal ECG cycle was considered to be contained in a window centred on the mR-peak and including 30% of the previous and of the following RR time interval. Step 3.2 performed an adaptive cancellation of the mECG by aligning the template to each mQRS complex, scaling the template both for width and amplitude, and finally subtracting the template from the signal. This was done separately for each of the 4 channels of filtECG and repeated for windows of 10 heart beats, in order to account for the time variability of the shape of the maternal ECG. The signal obtained after cancellation of the maternal ECG is the actual fetal ECG (fECG) signal.

Step 4 consisted of 3 sub-steps. Step 4.1 performed wavelet de-noising to reduce noise caused by non-optimal mECG cancellation (fECG'). Step 4.2 computed the principal components (fPC) of fECG', and step 4.3 detected the fR-peaks from the first fPC (fPC_1) using a local peak detection algorithm.

2.3. Scoring

The fR-peaks time series was subsequently used in the scoring algorithm (provided by the Challenge organisers) to obtain a fetal RR (fRR) time series. This was also processed further to derive an fHR time series by using an Integral Pulse Frequency Modulation (IPFM)-based method over a 6-second window [14].

The fHR obtained from the reference was compared to the one computed by this algorithm for Challenge event 4. The scoring for this event was based on the mean square error between the two time series.

The reference fRR was compared to the one computed by this algorithm for Challenge event 5. The scoring for this event was done similarly to that specified in AAMI/ANSI 1998 [15].

The scores obtained for both events 4 and 5 were compared to the ones given by a sample algorithm [11] provided by the Challenge organisers.

3. Results

On test Set-B, the algorithm scored 223.23 for event 4 and 19.34 for event 5, performing respectively 15 and 5 times better than the sample algorithm. These results were better than those obtained on training Set-A (Table 1).

Table 1. Performance of the proposed algorithm in comparison to the sample one.

		Sample algorithm	This algorithm
fHR	***Set-A***	2910.90	512.82
	Set-B	3258.56	223.23
fRR	***Set-A***	106.65	27.63
	Set-B	102.75	19.34

4. Discussion

This study has described an algorithm for robust estimation of fECG HR and RR which outperformed the sample algorithm. This method used a combination of frequency filtering and wavelet de-noising for the pre-processing; adaptive cancellation of the mECG; PCA for isolating the best component for maternal and fetal R-peaks detection.

The algorithm performed well with good quality signals and also with noisy signals (Figure 3a and 3b). In the case shown in Figure 3b, the large-amplitude noise probably also corrupted the scalp signal as no reference points were provided for the period during which the noise appeared. However, this algorithm was capable of recovering a significant proportion of this noisy time interval, enhancing what are likely to be fECG R-peaks hidden in the noise.

On the other hand, the algorithm performance was poor in the case of non-optimal maternal ECG cancellation (Figure 3c). There were three main causes:

1) The maternal ECG complex was not fully contained in the ± 30% window. This happened, for example, when the mother had a long PQ and/or QT time interval.
2) Some mR-peaks were not detected.
3) Noise spikes were identified as mR-peaks.

In order to compensate for problem 1, the algorithm could select the time interval for computation of the mECG template adaptively for each subject as the time between the onset of the P-wave and the end of the T-wave. To tackle problems 2 and 3, the algorithm could include adaptive thresholds and methods for the assessment of missed and false mR-peaks.

Future improvements should also include a further step in the pre-processing stage to select only channels with good quality signals for subsequent analysis [16].

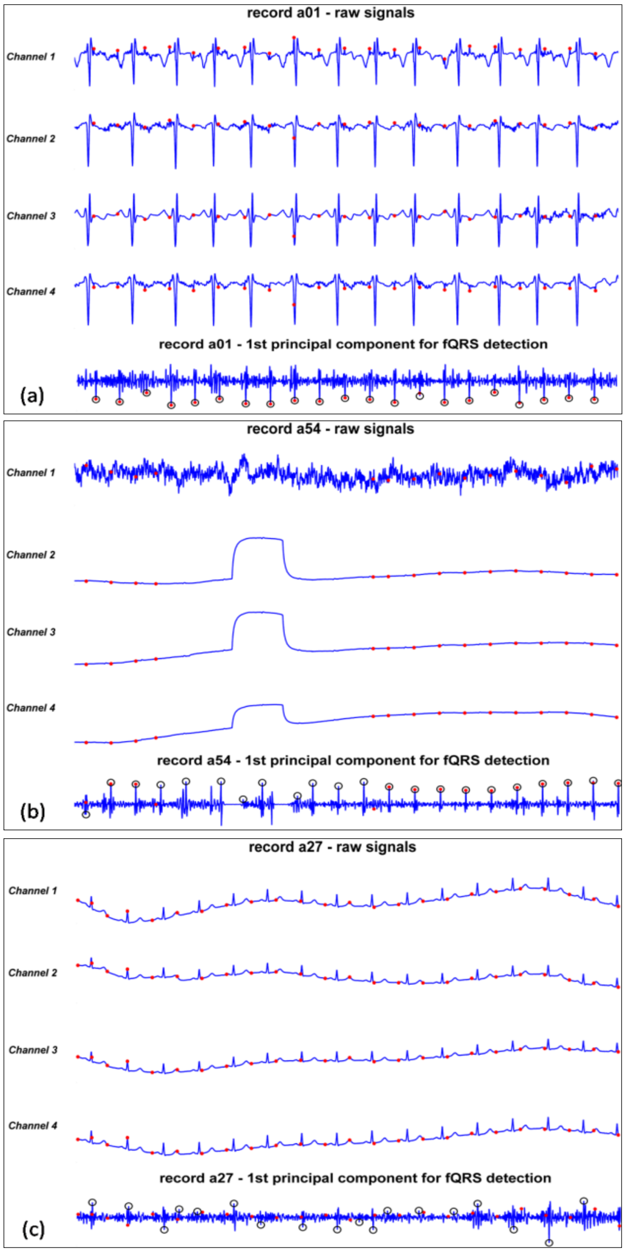

Figure 3. Example of good signal and good algorithm performance (a); noisy signal and good algorithm performance (b); good signal but with poor algorithm performance (c). Red dots are the reference fR-peaks; black circles are the ones computed by this algorithm.

5. Conclusion

This study has presented an algorithm for the analysis of non-invasive fECG recordings which outperformed the sample algorithm. Further improvements are possible to enhance its performance even more.

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