Multichannel Foetal Heartbeat Detection by Combining Source Cancellation with Expectation-weighted Estimation of Fiducial Points

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Abstract

Noninvasive foetal heart rate (fHR) monitoring is important in detecting foetal distress and morbidity. In spite of the improvement achieved in recent years, the accuracy of non-invasive fHR monitors is not satisfactory. In this study a new method is presented with the goal of improving the accuracy of foetal heart beat detection from abdominal recordings of maternal ECG.

A dataset of 75 four-channel abdominal ECG recordings (SetA) provided by Physionet Challenge 2013 was used for training.

Maternal QRSs were detected and subtracted from notch-filtered (50 Hz) and high-pass filtered (4 Hz) abdominal ECGs. The residual ECG signal was further processed (1st derivative squared and low-pass filtered by moving-average). On the resulting signals, local peaks were searched using an expectation-weighted estimate of the "next" fiducial point (foetal QRS (fQRS)) based on a Gaussian distribution $G(\mu,\sigma)$ with μ indicating the most probable time distance of the "next" fiducial point. A grid search was used to determine (μ,σ) minimizing the standard deviation of the resulting estimated fQRS time series for each recording. The fQRS time series were submitted to Physionet Challenge 2013 Events 4 and 5.

In Event 4 (published set of 100 recordings, SetB), a test fHR time series was built by Physionet's Scoring System from fQRS annotations and matched to the reference. Scores were based on test vs. reference mismatches (lower scores indicate better performance). In Event 5 (also using SetB), the RR time series replaced fHR.

According to Phase 1 official scores (14 June 2013) our algorithm scored 135.18 (7.11) in Event 4 (Event 5), corresponding to the 10^{th} (9^{th}) position in the ranking. The reference algorithm provided by Physionet scored 3258.56 (102.75). The proposed method substantially improved the foetal heart beat detection accuracy with respect to the reference algorithm.

1. Introduction

Vigorous uterine contractions such as those occurring during labor may severely reduce the maternal blood flow to the placenta, resulting in an intermittent decrease of oxygen supply to the fetus [1]. In some cases the foetal metabolic reserve is inadequate to compensate for these transient phenomena, resulting in foetal distress.

Noninvasive measurement techniques to detect foetal distress have received great attention since the early studies in the late 19th century [2]. To this end, monitoring foetal heart rate (fHR) has proven crucial, as specific conditions such as bradycardia, rapid fHR acceleration-decelerations, and reduced fHR variability, have been shown to be associated with foetal distress [2, 3].

The most accurate method for measuring fHR is by placing an electrode on the foetal scalp. However, this method is only viable during labor, and its associated risk and cost limit the current use in clinical practice [4].

To overcome these limitations, noninvasive foetal ECG monitoring (fECG) –which only makes use of surface electrodes placed on the mother's abdomen– has been studied extensively in recent years. fECG can be monitored from the maternal abdomen during the second half of gestation (usually not earlier than the 18^{th} week [4]).

However, this method suffers poor signal to noise ratio as fECG has lower amplitude than the mother's, by which it may be obscured. Moreover, fECG is contaminated by foetal brain and muscular electrical activity, as well as motion artifact [4]. All this poses serious challenges to foetal QRS (fQRS) detection algorithms.

Several automatic methods have been proposed for foetal R-wave detection, mainly based on adaptive filtering (either training the filter to remove the maternal ECG or directly extract the foetal R-wave) or signal decomposition (wavelet decomposition, blind source separation), or a combination of the two [4].

Adaptive filtering methods suffer the limitation of needing a reference maternal ECG signal with similar morphology to the contaminating signal. This is difficult to achieve because the morphology of the maternal ECG contaminants is highly dependent on the position of the

electrodes. To this end, blind source separation methods have shown superior ability in fECG extraction compared to adaptive filtering [5].

However, blind source separation methods make the implicit assumption of stationarity and source mixture linearity, which hardly ever holds true due to foetal and maternal motion. [4].

Nonlinear methods have also been proposed, based on a state-space representation of the noisy signal and its delayed version [6]. The state-space trajectory is smoothened by principal component analysis, then re-transformed into the time-domain representation. The choice of the time lag is, however, empirical.

In this study a new method for multi-channel fQRS is presented based on the combination of source cancellation with expectation-weighted estimation of fQRS.

This work was carried out to take part in Physionet Challenge 2013 [7].

2. Methods

2.1. Data

Three datasets of 4-channel abdominal maternal ECG recordings of 1 minute duration were used in the Challenge, namely a training set (SetA) consisting of 75 recordings, a publicly available test set (SetB) of 100 published recordings, and an unpublished test set (SetC) also consisting of 100 recordings. The maternal ECG signals were digitized at F_S = 1000 samples/s. The raw data for each recording were provided along with the time vector (time-stamp series of the ECG samples).

2.2. Physionet Challenge events and scoring criteria

For Events 4 and 5, SetB was used for testing. In Event 4 a test fHR time series was built by Physionet's Scoring System from fQRS annotations and matched to the reference. Scores were based on test vs. reference mismatches, with lower scores indicating better performance. In Event 5 the RR time series replaced fHR. To participate in Events 4 and 5 the annotated fQRS files were required.

2.3. Physionet Challenge sample method

In addition to the raw ECG data, the Organizers disclosed the source code of a sample method (PHYS-SM) for the extraction of fQRS.

2.4. Signal processing

The raw ECG data were preliminarily scanned for missing values using the reference time vector. If any were found, values were imputed by 'prolonging' the last known data-point (zero if first sample).

The signals were then notch filtered (50 Hz) and high-pas filtered (Butterworth 2nd order, 3 dB cut-off F_c = 4 Hz) by zero-phase filtering. Further processing was divided into three sequential stages: *I*) maternal QRS detection, *II*) maternal QRS subtraction, *III*) foetal QRS detection

I) Maternal QRS detection. The maternal QRS complexes were detected by a modified Pan-Tompkins [8] algorithm, considering all the channels. The ECG signals were band-pass filtered (zero-phase, Butterworth 4th order, 3 dB pass-band: 8–25 Hz). The first derivative of the filtered signal was further filtered by moving average (zero-phase, length=33) to obtain the smoothed signal S_k (k=1,…,4). A new signal S was constructed:

$$S = \sqrt{\sum_{k=1}^{4} \left(\frac{S_k}{std(S_k)} \right)^2} \quad (1)$$

where *std* indicates the standard deviation. Dominant peaks of S were identified in a running window (W=2 s) as those with amplitude greater than 50% of the maximum amplitude in W.

The resulting time series of dominant peaks was defined as the maternal QRS series. For each QRS fiducial point, a fixed window W_{QRS} of ±50 ms was defined. The fiducial point's position was fine-tuned within W_{QRS} by cross-correlation of different QRS complexes. This was done for each channel individually.

II) Maternal QRS subtraction. For each QRS complex, the 10 best-matching QRS complexes from the same channel were collected to create a median template (fixed window of ±80 ms surrounding the fiducial point). The template QRS was then subtracted from the abdominal ECG to obtain the foetal signal (residual signal (rECG)).

III) Foetal QRS detection. For each channel individually, the first derivative of rECG was filtered by a moving average filter (zero-phase, length = 49) to obtain a smoothed signal Γ_k (k=1,…,4). If any peaks were found in Γ_k in the first 600 ms, the dominant peak was retained as the first fQRS data-point, otherwise the first peak was considered, regardless of the time of occurrence. It is worth noting, that a learning period of 3 seconds was

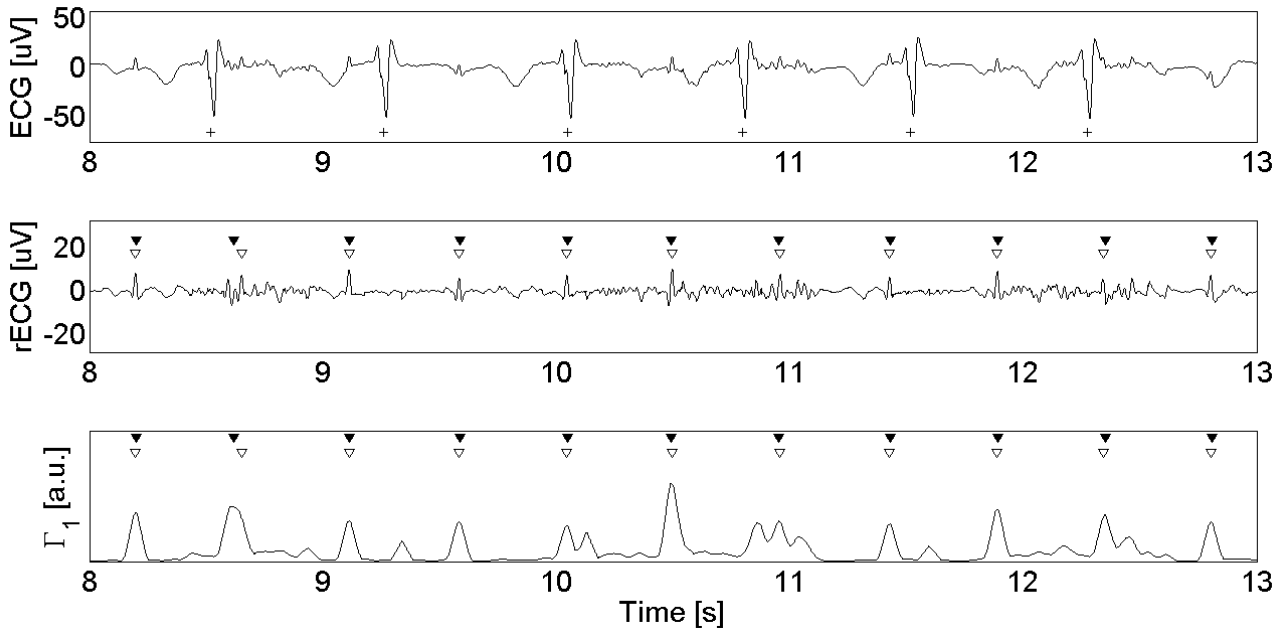

Figure 1. Example of intermediate output of signal processing cascade (data from 1st record of training set, SetA). Abdominal ECG Channel 1 (top panel), residual ECG after maternal QRS subtraction (central panel), and Γ_k (k=1) (bottom panel). An arbitrary window of 5 seconds is shown, with maternal QRS (+), detected fQRS (black triangle) and officially annotated fQRS (white triangles).

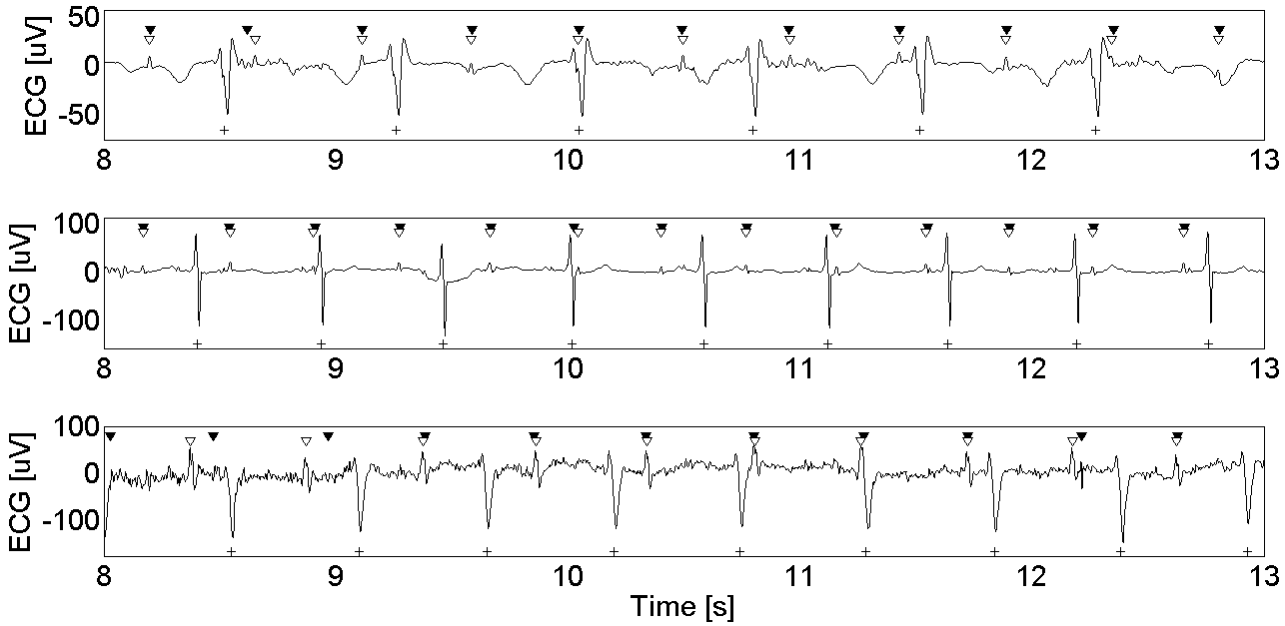

Figure 2. Abdominal ECG Channel 1 for the first three records (top to bottom panels) of the training set (SetA). An arbitrary window of 5 seconds is shown, with maternal QRS (+), detected fQRS (black triangle) and officially annotated fQRS (white triangles).

allowed by the scoring process.

Subsequent fQRS complexes were identified by weighting Γ_k by a Gaussian distribution $G_{\mu,\sigma}(t)$ with expected value μ and standard deviation σ.

Assuming T_j was the fiducial point of the *j*th fQRS complex, T_{j+1} was estimated at the time-stamp of the dominant peak of Γ_k weighted by $G_{\mu,\sigma}(t)$ in the interval $[T_j, T_j + \Delta T]$, with $\Delta T = 2$ s. By construction, the largest weight coefficient was located at a distance μ of T_j. In other words, $G_{\mu,\sigma}(t)$ indicated the weight (probability) of

the 'next' fiducial point occurring at distance t of the current one. Under this perspective, μ represented the most probable distance between consecutive QRS complexes.

The parameters μ and σ were empirically estimated by a grid search (μ: [350 ms, 480 ms] with step 10 ms; σ: [10 ms, 50 ms] with step 5 ms) with the goal of minimizing the standard deviation of RR-intervals of the estimated fQRS time series.

The range for μ was defined taking into account that the fHR after the 20th week of gestation is generally between 120 and 160 beats/minute [4].

The fQRS time series obtained from the channel k (k=1,…,4) with the lowest standard deviation of RR-intervals was retained and used to enter Physionet Challenge Events 4 and 5.

3. Results

Only one entry was submitted, during Phase 1. No entries were submitted to participate in the subsequent phases (2 and 3). For this reason, any changes made by the Organizers to the scoring algorithm during or after phase 2 are not considered in this work. Table 1 summarizes the scores obtained, and those of the reference algorithm (PHY-SM). Lower values of the score indicate better performance.

Based on the official scores released by the Organizers after the closing of Phase 1 (14 June 2013) our method scored 10th in Event 4 and 9th in Event 5.

Table 1. Physionet Challege 2013 Phase 1 official score(†)

Method	Event 4	Event 5
PHYS-SM	3258.56	102.75
This work	135.18	7.11

(†) released 14 June 2013.

Figure 1 illustrates an example of the intermediate output of the signal processing cascade. In Figure 2 the abdominal ECG of the first three records of the training set (SetA) is shown with annotations.

4. Discussion

In this study, a novel method for fQRS detection was presented based on simple template-based maternal QRS cancellation and expectation-weighted estimation of fQRS fiducial points. To improve immunity to noise (such as motion or electromyographic artifacts), information from all the available abdominal signals was exploited.

In its simple logic, this method does not rely on *prior* morphological information (model) of either the maternal or the foetal QRS. It is also worth noting that the expectation weighting parameters μ and σ are estimated based on *a priori* criteria. They are not obtained from maximizing any performance score on the training dataset. On the other hand, a limitation of this method is that it relies on the assumption of a 'fairly' stable foetal heart beat pattern. In particularly severe cases of foetal hypoxic stress, this may not be the case, especially in the presence of large variability of consecutive RR-intervals (i.e. rapid fHR deceleration or acceleration) [2,3]. Replication on a larger dataset –also including different abdominal electrodes placement– is required to further validate the proposed method.

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