A Robust Algorithm for Fetal QRS Detection using Non-invasive Maternal Abdomenal ECGs

Martin Kropf[1], Robert Modre-Osprian[2], Günter Schreier[2], Dieter Hayn[2]

[1] Ludwig Boltzmann Institute for Translational Heart Failure Research, Graz, Austria
[2]AIT Austrian Institute of Technology, Graz, Austria

Abstract

This paper presents an algorithm for automated fetal QRS (fQRS) detection. The algorithm was developed with the Fetal ECG (FECG) Challenge Database from PhysioNet. This database provides noninvasive ECG signals recorded from the mother's abdomen, and expert annotations for fQRS locations.

Our algorithm consisted of four separate steps: 1. Maternal QRS complexes were detected using our QRS detector, featuring adaptive thresholds and automated, ECG-quality-based channel selection. 2. Maternal beat elimination by subtracting averaged maternal beats and by blanking maternal QRS complexes. 3. On the remaining signal QRS complex detection was applied with different parameter sets and detection quality was measured. 4. Finally, the parameter set leading to the highest fQRS detection quality was chosen and the detected fQRS sequences were optimized using statistical methods

We achieved final scores of 82.413 for event 1 (MSE of fetal HR) and 7.354 for event 2 RMS of fetal RR) when participating in CinC Challenge 2013.

1. Introduction

Fetal electrocardiography (FECG) analysis has the potential to be a reliable technology to prevent fetal hypoxia and to detect heart defects, which are the most common birth defect and leading cause for deaths during birth [1]. Currently, this technique is inaccurate and provides a relatively low positive predictive value, it is reliable only when the condition of the fetus is clearly good or clearly bad [2]. Even state-of-the-art noninvasive FECG analysis techniques show only insufficient reliability and, therefore, FECG is currently used in a rather small field of applications.

To develop a fetal QRS (fQRS) detection algorithm – or any other algorithm – several tools are required to help the developer finding the suitable features of the signal, implementing the algorithm, validating the algorithm's results and optimizing parameters in order to achieve a predefined or optimised performance.

The present paper describes a robust algorithm for fQRS detection using non-invasive maternal abdomen ECG. The algorithm was developed using an existing biosignal processing system [3], including several algorithms useful for this task, e.g. a QRS-detection algorithm and an algorithm for removing averaged heart beats, which already were successfully utilised in the CinC Challenges 2004 (1st place) and 2011 (1st place, event 3).

We validated our algorithm by taking part in CinC challenge 2013, which consisted of three events:

Event 1: Fetal heart rate measurement. The goal is to produce a set of N annotations that can be used to construct a test FHR time series that closely matches the reference FHR time series.

Event 2: Fetal RR interval measurement. The goal is to produce a set of N annotations that can be used to construct a test RR interval time series that closely matches the test FHR time series. Matching intervals must begin within 100ms of each other.

Event 3: Fetal QT interval measurement: The goal is to produce an estimate of the median QT interval for each recording in the test set. [4]

Since only Event 1 and Event 2 were eligible for closed-source entries, we decided to only participate in those both events.

2. Methods

For processing biosignals we used MATLAB 8.1 2013a (The MathWorks, Natick, MA, USA) and our ECG Signal Processing Toolbox, which was already described in detail in [3]. Briefly, it consists of a signal viewer, a set of biosignal processing algorithms, several tools for algorithm development, an annotation editor, an optimization toolbox and a single beat viewer.

2.1. Datasets

The algorithm described has been developed using the

FECG Challenge Database from PhysioNet [4].

Data for the challenge consisted of a collection of one-minute FECG recordings. Each recording included four noninvasively recorded 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 were presented with 1000 samples per signal per second.

Challenge data comprised three different sets: learning (training) set-a (75 FECGs, reference annotations for participant's use available), open test set-b (100 FECGs, reference annotations withheld) and hidden test set-c (unpublished records, for evaluation of open source entries). [4]

We found six signals in set-a, which had incorrect reference fQRS annotations (A33, A38, A52, A54, A71, A74). We decided to exclude these signals and train our algorithm with the remaining 69 signals from set-a. We also used these 69 signals to gain unofficial results with the provided scoring software for the CinC Challenge 2013.

fQRS detection comprised of four separate steps:

1. Maternal QRS detection: maternal QRS complexes were detected using our pre-existing QRS detector
2. Subtraction of averaged maternal ECG: maternal ECG components were removed with two different approaches (subtracting average beat with and without additional QRS blanking)
3. fQRS detection: on the resulting signals fQRS detection was applied using an unsupervised filter selection algorithm and detection quality was measured
4. fQRS event series correction: the best detection results were picked out and fQRS event series were optimized using statistical methods to fill gaps and remove outliers

2.2. Maternal QRS detection

We detected the maternal QRS complexes with our QRS detection algorithm, featuring adaptive thresholds and automated, ECG-quality-based channel selection. A detailed description of our QRS detector can be found in [5]. QRS detection was based on an adaptive threshold based algorithm that was applied to the first derivative of one of the four channels of the original signal. Selection of the channel featuring better properties for QRS detection was done automatically.

To assess and optimize maternal QRS detection we first manually created annotations locating maternal QRS complexes with the signal viewer and annotation editor from our toolbox [3].

Using these reference annotations and our optimization toolbox we then calculated the parameter set leading to the best detection result for maternal QRS complexes.

2.3. Subtraction of averaged maternal ECG

To remove the predominant maternal ECG the averaged maternal beat had to be determined first. The averaged beat was then subtracted from the original signal and two new signals (averaged beat subtraction with and without maternal QRS blanking) were created as described in [6].

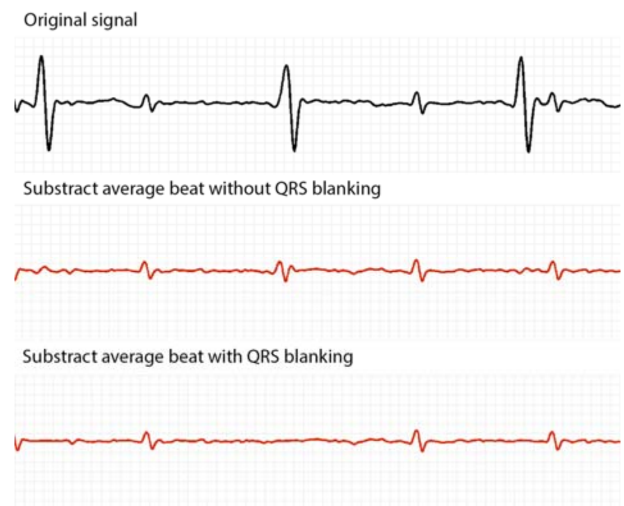

Figure 1. Signal *a23* from the FECG Challenge Database (time resolution: 25mm/s). Top: Original Signal. Middle: signal after maternal QRS subtraction. Bottom: Maternal QRS blanking removes fQRS in case of coincidence.

2.4. fQRS detection

In this step we detected fQRS complexes in the resulting signal from step 2.2 with our QRS detection algorithm, as already described in 2.1, using an adapted set of processing parameters. These adapted parameters were determined using our optimization toolbox and the reference annotations provided for set-a by PhysioNet for all 69 signals in set-a.

2.5. fQRS event series correction

In this final step the fQRS event series was optimized using statistical methods. First we created an average fetal heart beat and removed outliers, which have a low correlation with the average fetal beat.

Thereafter, we identified missing fetal beats by calculating the average fetal RR-interval and identified pauses of two or three times of the fetal RR-interval in the detected fetal event series. These pauses were interpolated with fetal heart beats.

2.6. Quality measure of QRS detection

The reliability of fQRS detection was assessed based on a pre-existing QRS detection quality measure [5]. Briefly, quality assessment was based on several factors: a) signal to noise ratio (amplitude of the lowest QRS complex detected divided by the highest amplitude of none-QRS-signal-portions), b) maximum QRS amplitude and c) regularity of the detected rhythm.

Regularity of the detected rhythm was determined by the portion of events where the beat-to-beat heart rate differed less than 20% from the median heart rate.

In addition the number of fQRS complexes, which coincide with maternal QRS complexes was determined. Coincidence was given, if a maternal QRS occurred 0.01 seconds before or after the fQRS complex. We calculated the ratio between coinciding and non-coinciding beats and used this factor in our quality measure.

Finally these quality factors were multiplied with weight factors, which were previously determined and optimized on the 69 signals from training set-a.

2.7. Quality-based threshold for CinC 2013

With the help of the unofficial scoring tool we found out that we obtained much better results, if we just used the detection results from signals with high quality (quality measure>1). For signals with moderate quality (between 0.9 and 1) we constructed a fetal heart rate series with respect to the number of detected events. For signals with modest quality (quality < 0.9) we used a fetal heart rate series of 140 beats per minute, which seemed to be a good approximation of the average heart rate, at least for signals from learning set-a.

3. Results

PhysioNet's set-a was used for training our fQRS detector, leading to the results shown in Table 1.

Table 1. Results for different FECG detection approaches for set-a

#	Event 4	Event 5
1	352	21.0
2	229	16.3
3	332	21.7
4	192	17.0
5	351	19.1
6	205	14.4
7	167	7.72
8	40.3	3.5

#	Explanation of approaches
1	Subtract average maternal ECG **without** QRS blanking (75 signals)
2	Subtract average maternal ECG **without** QRS blanking (69 signals)
3	Subtract average maternal ECG **with** QRS blanking (75 signals)
4	Subtract average maternal ECG **with** QRS blanking (69 signals)
5	Quality-based automatic selection of best processing method and parameters (75 signals)
6	Quality-based automatic selection of best processing method and parameters (69 signals)
7	Final best (unofficial) result for challenge (75 signals)
8	Final best (unofficial) result for challenge (69 signals)

With our quality-based threshold approach described in 2.8 we were able to score a promising unofficial score of 40.3 for event 4 and 3.53 for event 5 with 69 signals from set-a.

Thereafter, the algorithm was evaluated using set-b by taking part in the CinC Challenge [4]. The results were sent to the challenge organizers, who determined the accuracy of our fetal HR and fetal RR sequences against the reference annotations that were available only to them. We achieved final scores of 82.413 for event 1/4 (MSE of fetal HR) and 7.354 for event 2/5 (RMS of fetal RR).

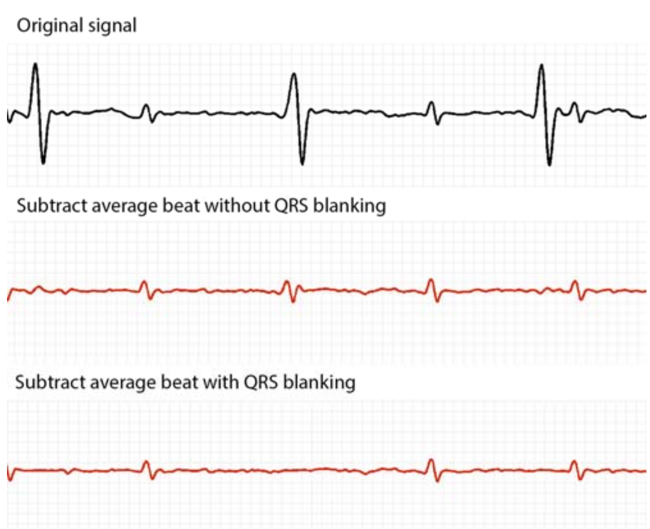

Figure 2. Signal *a06* from the FECG Challenge Database (time resolution: 25mm/s). Top: Original signal. Middle: Residual maternal components are still present after subtraction without blanking. Bottom: maternal components are completely removed after blanking.

4. Discussion and conclusion

When eliminating portions of the ECGs by averaged beat subtraction we already learned in CinC Challenge 2004 [6, 7], subtraction of the averaged beats does not always accurately remove the portions of the signal in the regions of QRS complexes. Especially if the QRS morphologies change a lot from beat to beat (e.g. in case of heart rate variations) the performance of the QRS-subtractor is rather modest (see Figure 2). For handling this issue a blanking procedure, which relies on linear interpolation in a predefined blanking window around the R-peak of the QRS-complex, was introduced. The drawback of the blanking approach was that in case of coincidence of fetal and maternal QRS complexes, it removed the fetal QRS complex as well.

Therefore, an unsupervised method was implemented which chose the best of both approaches – leading to a better fQRS detection quality measure. Assessment of this quality measure based on several different factors seems crucial for unsupervised selection of optimal processing parameters.

Currently our detection algorithm works event-based, because it was initially designed to detect atypical features of ECGs like extra-systoles and arrhythmias. But for the current challenge a sequence-based detection algorithm may probably give better results.

Another alternative approach that we studied for this year's challenge was to improve subtraction of maternal components from the original signal by compressing or stretching the QRS part of the averaged maternal beat in order to obtain a better maternal QRS elimination. Unfortunately this approach did not lead to the expected improvements.

Our results significantly improved when we introduced a threshold value, which was able to differentiate between signals with a high and low quality measure. Signals with high quality measure were used as-is. For signals with a low quality measure we constructed a regular FHR time series with respect to the number of detected fetal heart beats. Although this approach does not seem to be very sophisticated it finally exhibited our best result. Further work should focus on improving this threshold approach.

Acknowledgements

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Address for correspondence.

Martin Kropf
Ludwig Boltzmann Institute for Translational Heart Failure Research
Stiftingtalstraße 24
8010 Graz, Austria
martin.kropf@heart.lbg.ac.at