Noninvasive Fetal QRS Detection using a Linear Combination of Abdomen ECG Signals

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Abstract

The fetal ECG can serve as a tool for fetal distress detection. However, the abdominal ECG of a pregnant woman contains mainly the maternal ECG and a relatively small amplitude fetal ECG signal, contaminated by various noises. As part of the 2013 PhysioNet/CinC Challenge, this study aimed to develop an algorithm for noninvasive fetal QRS detection.

The proposed algorithm is mainly based on fetal ECG source signal enhancement using a modified linear combiner. After initial noise reduction, the maternal QRS complexes are detected. Then, fetal QRS candidates are found. For each candidate, a Gaussian-like synthetic fetal QRS signal is created. This signal is considered an observation signal for a modified linear combiner. The 4 filtered abdomen ECG signals then undergo maternal ECG cancellation and serve as reference signals in this linear combiner; hence by finding the appropriate weight coefficients, their linear combination is forced to converge to a signal that represents the fetal QRS complexes solely.

The method was developed using the entire 75 1-minute-long abdomen ECG training set, and its evaluation on the 100 abdomen ECG test set led to scores of 262.076 for event 4 (fetal heart rate measurement) and 27.848 for event 5 (fetal RR interval measurement).

1. Introduction

Fetal distress is mainly described as a limited maternal-fetal respiratory exchange [1]. When it happens during labor an emergency is declared [2], since low oxygen levels can cause long-term disabilities and possible death [3]. The fetal heart rate value and regularity are considered parameters that can indicate fetal distress [4]. Since fetal distress is a common indication for the necessity of Caesarean delivery [5], it is important to obtain a highly accurate fetal heart rate estimation, which on one hand assists the physician in early diagnosis of dangerous situations and on the other hand prevents false fetal distress detections, which might result in unnecessary operative actions.

The fetal ECG signal contains valuable information for characterizing the fetal heart rate variability and additional evaluation of the cardiac function. A possible means for obtaining the fetal ECG is using a fetal scalp electrode. Although this is a widely used technique, it contains several potential risks [6] and is possible only during labor. A more attractive option is placing electrodes on the maternal abdomen in order to record the fetal ECG. However, the resulting abdomen ECG (AECG) contains mostly a high amplitude maternal ECG (MECG), a relatively small amplitude fetal ECG (FECG), and additional bioelectric undesired noises (generated by the muscles, movement, etc.).

Various studies were conducted in order to develop a method for fetal ECG extraction and analysis [7]. One of these methods is nonlinear decomposition [8], which involves certain assumptions or known properties regarding the fetal QRS (FQRS) characteristics. A different approach involves performing singularities detection using the modulus maxima in the wavelet domain in order to extract the fetal ECG [9]. Another common approach is blind source separation (BSS), which includes methods such as independent component analysis (ICA) [10], principal component analysis (PCA), or their combination [11]. Great effort was also taken in an attempt to perform MECG cancellation or FECG enhancement using adaptive filtering. A common approach [12] uses the least mean square (LMS) algorithm, in which the maternal ECG estimated signal is adaptively reduced from the abdomen ECG signal, by using additional electrodes placed on the maternal chest, in order to constitute a reference for the MECG. Another method [13] performed MECG cancellation using LMS suited for a priori information about the expected location of maternal P and T waves respective to previously detected maternal QRS (MQRS) complexes.

As part of the 2013 PhysioNet/CinC challenge, this work describes a method for FQRS detection, using a

multistage fetal ECG source signal enhancement, primarily achieved using a linear combination of AECG signals.

2. Methods

The core of the proposed algorithm automatically detects a *single* FQRS from the AECG, and uses it as an input to a modified linear combiner so that it will produce an output signal containing peaks in the respective locations of *all* FQRS complexes. The phases of the method can be seen in Figure 1.

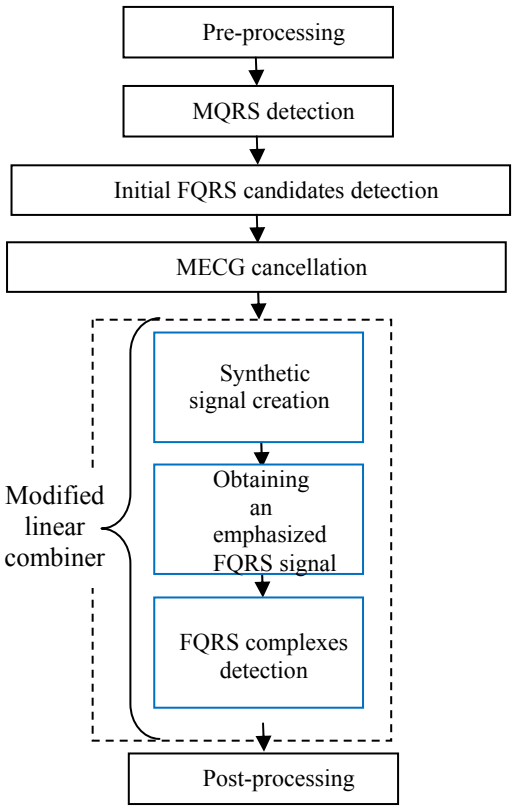

Figure 1. A block diagram of the proposed method. The dotted block is the core algorithm – a modified linear combiner.

2.1. Pre-processing

Initially, the 4 AECG signals undergo 0.5–49.5 Hz band pass filtering in order to avoid various noises.

2.2. MQRS detection

At this stage, the MQRS complexes are detected at each filtered AECG signal, using a well-validated method [14].

2.3. Initial FQRS candidates detection

In order to reduce the maternal T-wave amplitude and obtain initial emphasis of the FQRS complexes, the AECG filtered signals are again filtered, but now with a 10–49.5 pass band filter. Then, a search process is initiated in which the highest amplitude peak, between each two subsequent MQRS complexes, is considered an initial FQRS candidate [Figure 2(B)]. This process is performed for each of the 4 AECG filtered signals separately.

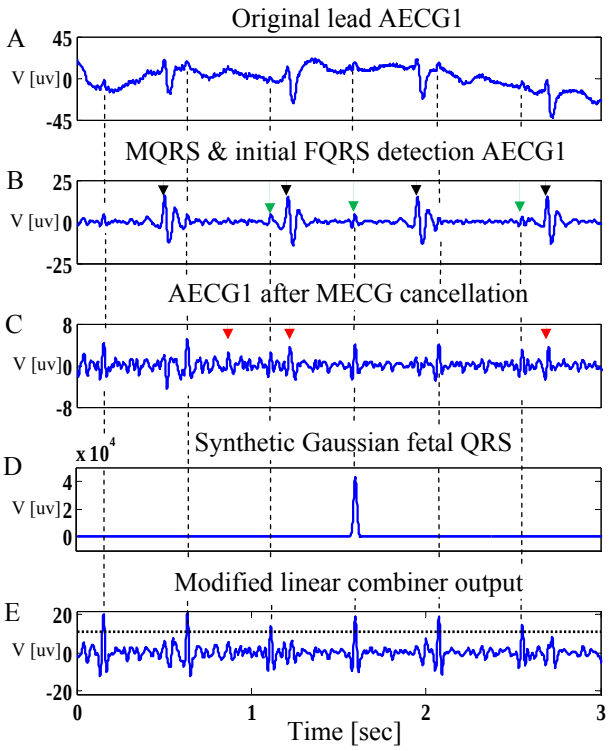

Figure 2. A. Original lead AECG1. B. MQRS and initial FQRS detection. The short (black) arrows mark the detected MQRS, the long (green) arrows mark the initial FQRS candidates detected. C. Lead AECG1 after MECG cancellation. Although the MECG is reduced, there are still significant peaks that could result in false FQRS detection (red arrows). D. The synthetic Gaussian signal. E. The modified linear combiner output. The horizontal dotted line indicates the top 2.5% threshold. The vertical broken lines indicate the actual FQRS locations.

2.4. MECG cancellation

The aim of this step is to provide a certain reduction of the MECG manifestation from the filtered AECG signals. By using the MQRS complexes found at stage 2.2. as input to an existing MECG cancellation method [13], the

MECG P-QRS-T typical pattern is estimated and properly reduced from the AECG. This process is performed for each filtered AECG signal separately, and produces 4 filtered AECG signals with reduced MECG [Figure 2(C)].

2.5. Modified linear combiner

Although the previous step reduced the MECG amplitude, in many cases they weren't entirely removed, and a further process is needed in order to significantly emphasize the FQRS, at least for it to be more prominent than the MECG remnants. Our recently developed modification of the linear combiner allows using a single wave or element from a certain source, in order to reveal the entire original source, when hidden in a two-source linear mixing problem. This approach was found useful in the field of atrial electrical activity detection [15] and cardiac arrhythmia classification [16]. The modified linear combiner includes 3 phases – synthetic signal creation, obtaining an emphasized FQRS signal, and FQRS complexes detection.

2.5.1. Synthetic signal creation

For each FQRS candidate (in each AECG lead separately) a synthetic signal is created [Figure 2(D)]; it contains a Gaussian in the respective location of the candidate and an isoelectric line in all other samples. The Gaussian mean is the center of the FQRS candidate, and its standard deviation is one-quarter of the candidate's length.

2.5.2. Obtaining an emphasized FQRS signal

At this phase, we utilize a modified linear combiner as follows (see Figure 3):

1. The observed signal is the synthetic Gaussian signal created at phase 2.5.1., denoted as $g[k]$.

2. The 4 filtered AECG signals with reduced MECG (obtained after phase 2.4) serve as reference input, and their respective matrix is defined as:

$$\mathbf{a}[k] = [a_1[k]\, a_2[k]\, a_3[k]\, a_4[k]]^T, \quad (1)$$

where $a_1[k] - a_4[k]$ are the 4 filtered AECG signals.

We aim to create a linear combination of the reference signals [17] that will resemble the FQRS signal as much as possible. This is achieved by constraining the mean square error of the two sources to be minimal:

$$MSE = E[(g[k] - \mathbf{w}^T \mathbf{a}[k])^2]. \quad (2)$$

The optimal weight vector $\mathbf{w}_{opt}$ is found using:

$$\mathbf{w}_{opt} = \mathbf{R}_a^{-1} \mathbf{r}_{ga}, \quad (3)$$

where:

$$\mathbf{R}_a[k] = \begin{bmatrix} r_{a_1 a_1} & \mathrm{L} & r_{a_1 a_4} \\ \mathrm{M} & \mathrm{O} & \mathrm{M} \\ r_{a_4 a_1} & \mathrm{L} & r_{a_4 a_4} \end{bmatrix} \quad (4)$$

$$\mathbf{r}_{ga} = \begin{bmatrix} r_{ga_1} r_{ga_2} & r_{ga3} & r_{ga4} \end{bmatrix}^T \quad (5)$$

and the general correlation r_{xy} is calculated using the time average estimator (assuming the signals are correlation ergodic). At the end of this phase we obtain an emphasized FQRS signal:

$$f[k] = \mathbf{w}_{opt}{}^T \mathbf{a}[k], \quad (6)$$

which contains peaks in the locations that correspond to the actual FQRS complexes [Figure 2(E)]. A diagram of the described modified linear combiner can be seen in Figure 3.

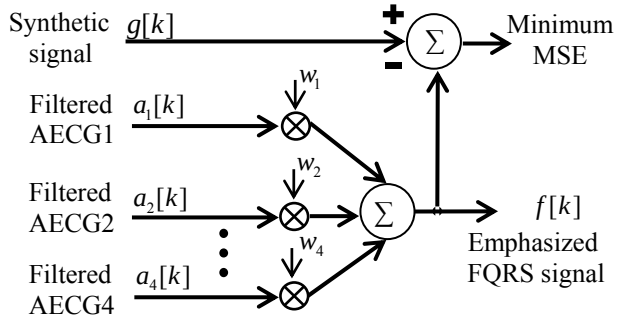

Figure 3. Obtaining an emphasized FQRS signal using a synthetic signal and a linear combination of 4 filtered AECG leads.

2.5.3 FQRS complexes detection

The top 2.5% peaks in $f[k]$ are considered as possible FQRS complexes. An example for performing Steps 2.1–2.5 can be seen in Figure 2.

2.6. Post-processing

By now, we have obtained possible FQRS complexes from each initial FQRS candidate that was found in each AECG lead. The post-processing phase purpose is to fuse the results gathered so far into a single accurate FQRS

locations vector. We start by separately processing the FQRS complexes detected using one of the 4 AECG leads. We calculate the fetal RR (FRR) intervals, and discard FQRS that are related to intervals shorter than 240 milliseconds and are least common. We then estimate the most common FRR-interval and use it to correct fetal RR-intervals that are longer than 1000 milliseconds, by adding uncommon FQRS complexes that were previously discarded or by adding synthetic FQRS detections. The FRR-intervals' regularity is then calculated by dividing their standard deviation by their mean, and the process is repeated for all other AECG leads. At the last step, the FQRS complexes from the AECG lead that resulted in minimal FRR-interval regularity are considered the final FQRS complexes.

3. Experiment setup

The data for the challenge consisted of 4 abdomen ECG signals. The training database (set A) included 75 1-minute long signals with provided FQRS annotations. The test database (set B) consisted of 100 1-minute long signals, without provided annotation to competitors.

4. Results

The test annotations produced using the described method were evaluated by the competition organizers and led to scores of 262.076 for event 4 (fetal heart rate measurement) and 27.848 for event 5 (fetal RR interval measurement). In event 4, the score is calculated as the mean squared error between obtained and reference values and in event 5, the score is calculated as the root mean square error between obtained and reference values.

5. Conclusions

In this paper we presented a method for noninvasive FQRS detection using AECG. The method combines MECG cancellation with FQRS enhancement and takes advantage of the information located in multiple leads. The obtained results significantly outperform the sample submission (3258.56 for event 4 and 102.75 for event 5). A possible improvement could be achieved by using more than 4 AECG leads, so that the linear combination could have more freedom and ability to converge to the actual FQRS signals.

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