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Extraction of Fetal Heart Rate from Maternal Surface ECG with Provisions for Multiple Pregnancies

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***Abstract*— Twin pregnancies carry an inherently higher risk than singleton pregnancies due to the increased chances of uterine growth restriction. It is thus desirable to monitor the wellbeing of the fetuses during gestation to detect potentially harmful conditions. The detection of fetal heart rate from the maternal abdominal ECG represents one possible approach for noninvasive and continuous fetal monitoring. Here, we propose a new algorithm for the extraction of twin fetal heart rate signals from maternal abdominal ECG recordings. The algorithm detects the fetal QRS complexes and converts the QRS onset series into a binary signal that is then recursively scanned to separate the contributions from the two fetuses. The algorithm was tested on synthetic singleton and twin abdominal recordings. It achieved an average sensitivity and accuracy for QRS complex detection of 97.5% and 93.6%, respectively.**

I. Introduction

Fetal wellbeing is of great concern in a number of pathological conditions, such as gestational diabetes and hypertension, fetal hypoxia, placental abruption, and intra-uterine growth restriction (IUGR). Tracking of fetal health is hindered by a lack of monitoring methodologies that could alert caregivers to the development of potentially dangerous conditions. While fetal heart rate monitoring represents the standard of care to diagnose antepartum and intrapartum complications, such as fetal distress [1,2], no such monitoring methodology is currently available outside of the hospital setting.

The standard in-hospital methodology to monitor fetal well-being is cardiotocography (CTG), which is based on the recording of fetal heart rate using Doppler ultrasound, and uterine contractions using strain-gauges [3]. CTG has the advantage to be reliable when used in single pregnancies. The main problem of CTG is the high sensitivity to fetal movement, as the detection of fetal heart rate mainly relies on the correct positioning of the ultrasound probe, which needs to be repositioned in case of fetal movement. The use of CTG to detect fetal heart rates in twin pregnancies is even more challenging [4].

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The main alternatives to CTG are the recording of fetal ECG using electrodes on the maternal abdomen or the recording of magnetocardiographic signals using SQUID sensors. Our research group is currently working on a compact and wearable ECG monitor to record fetal heart rate during pregnancy, in order to detect conditions such as IUGR that put the fetus at risk [5]. The device contains nine electrodes placed on a wearable garment, which allows the acquisition of eight abdominal ECG channels.

Since growth restriction is often encountered with multiple pregnancies, we developed an algorithm to extract fetal heart rate from abdominal ECG recordings for single and multiple pregnancies. Our algorithm is based on the conversion of the detected fetal QRS complexes into a set of binary series, which are then cleaned using a recursive approach in order to separate QRS complexes belonging to different fetuses and to obtain the fetal heart rate series of each fetus. The algorithm showed high sensitivity and accuracy for detecting and separating the fetal QRS complex series, as tested on synthetic singleton and twin ECG recordings simulated using an algorithm of signal generation.

II. Materials and Methods

A. Generation of synthetic ECG signals

To test our ECG extraction procedure, we generated plausible body-surface ECG recordings as superposition of a maternal ECG signal and fetal ECG signals. The algorithm assumes that eight surface electrodes are placed on the mother's abdomen, arranged as the vertices of an octagon [5]. The positions of the fetal hearts are then modeled as one (singleton) or two (twins) point sources that are randomly picked from a set of allowed positions (Fig. 1). The eight electrodes record eight body-surface potentials (time series), $x_1, \ldots, x_8$, that are taken to be weighted sums of the maternal and (y_{mat}) and fetal (y_{fet1} and y_{fet2}) ECGs:

$$X = A \cdot Y$$

where $X = [x_1, \ldots, x_8]^T$ is the (8×*N*) matrix of body-surface ECGs, A is an (8×3) matrix of coefficients (mixing matrix), $Y = [y_{mat}, y_{fet1}, y_{fet2}]^T$ is the (3×*N*) matrix of source signals, and *N* is the number of samples in each ECG signal. In case of a singleton pregnancy, A becomes an (8×2) matrix and $Y = [y_{mat}, y_{fet1}]^T$. The matrix A allows the linear mixture of source signals y and can take into account several factors such as tissue attenuation and distance of the sources from the electrodes.

The first step of the algorithm is the positioning of the fetal heart sources. This is done by randomly selecting a

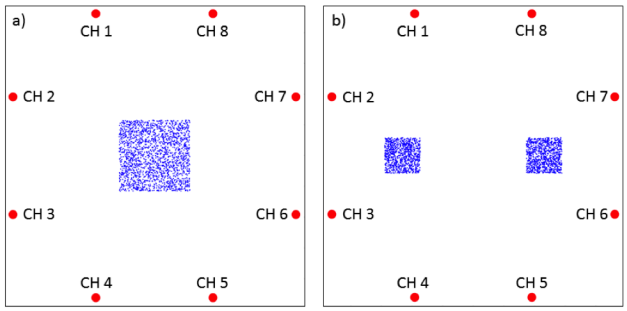

Figure 1. a) Possible positions of the fetal heart source in the generation of singleton abdominal ECG. b) Allowed positions of the two fetal sources in the generation of twins abdominal ECG.

position for each source from among the allowed regions (Fig.1). We then compute the normalized distances between the source locations and the eight sensing electrodes and assume that the attenuation of the fetal ECG amplitudes is proportional to the squared inverse of those distances. In addition to this geometric attenuation, we capture further attenuation of the source signal by multiplying them with constant attenuation factors μ that represent the degree of prematurity, for example. The matrix A is thus given by

$$A = \begin{bmatrix} 1 & \frac{\mu_1}{d_{11}^2} & \frac{\mu_2}{d_{21}^2} \\ 1 & \frac{\mu_1}{d_{12}^2} & \frac{\mu_2}{d_{22}^2} \\ \vdots & \vdots & \vdots \\ 1 & \frac{\mu_1}{d_{18}^2} & \frac{\mu_2}{d_{28}^2} \end{bmatrix}$$

where d_{ij} represents the normalized distance between the fetal heart source i and electrode j, and the μ range between 0 and 1, but typically are chosen between 0.2 and 0.6. In case of a single pregnancy, the matrix A reduces to the first two columns.

To generate the matrix Y, we used signals from the MIT-BIH Normal Sinus Rhythm Database, available from PhysioNet (*www.physionet.org)* [6]. These signals are adult ECG recordings sampled at 128Hz. From each recording, we subtracted the overall mean of the record and normalized the signal by dividing each record by its 2-norm. Two different records were chosen as y_{fet1} and y_{fet2} and directly fed to the matrix A. To generate y_{mat}, a third such signal was chosen and oversampled to 256Hz. We then assume the native sampling frequency of all three signals to be 256Hz, which results in the fetal signals to have twice their original heart rates. (Since different records from the MIT-BIH database are used for the maternal and the two fetal ECGs, the original heart rates are different. The generated fetal heart rates are therefore also different from each other and are not harmonics of the maternal heart rate.) The resultant signals are then multiplied by the matrix A to generate the body-surface ECGs X.

B. Algorithm for fetal ECG extraction

The algorithm we developed for extraction of the fetal ECGs is based on two steps. In the first step, the maternal ECG is detected and removed from the abdominal recordings. The second step consists of an iterative extraction of the fetal heart rate series from the combined beat-onset series.

The first step is described in detail in [5]. The removal of the maternal ECG is mainly based on an averaging and subtracting process. The success of the algorithm presented here is based on the successful detection and removal of maternal QRS. As described in [5], we were able to obtain very good results for this process. After the removal of the maternal ECG, fetal QRS complexes are detected using a template-matching approach. The result of this step is a set of annotations (time points) of the detected (but not yet separated) fetal QRS complexes in all eight channels. Although this first step allows a reliable fetal QRS detection in singleton pregnancies, it is not sufficient in twin pregnancies. Indeed, when two different fetal ECGs are present in the recorded signals, it is necessary to separate the QRS complexes generated by the first fetus from the ones generated by the second.

The second step of the algorithm allows for that separation that, and is based on the assumption that at least one of the eight leads records only one of the two fetal ECGs. This assumption is not unreasonable, for two reasons: (i) usually only the electrodes that are very close to the fetus are able to record the fetal ECG, (ii) twins compete for the space inside the uterus. Thus, it is highly probable that one subset of electrodes will predominantly record the electrical activity of the first fetus, while a second subset will record the activity of the other. Some subset of electrodes may record activity from both fetuses, while another might just register noise.

After the detection of all fetal QRS complexes at the end of the first step of the algorithm [5], we obtain eight series that correspond to the time samples at which fetal QRS complexes were detected. These series are then converted into eight binary series: a time sample is coded as a 1 if a fetal QRS has been detected at that sample, otherwise it is coded as 0. Fig. 2 shows the eight binary series for a sample stretch of data after this conversion.

As shown in the figure, the detected QRS complexes in Channels 6 and 7 are regular and mainly belong to one fetus. In Channels 2 and 3, the detected QRS complexes are also regular and mainly belong to a different fetus. In the remaining channels (Ch1, Ch4 Ch5, Ch8) we see a combination of incorrectly detected QRS complexes and a mixture of correctly detected QRS from both fetuses.

To quantify the quality of detection in the eight channels,

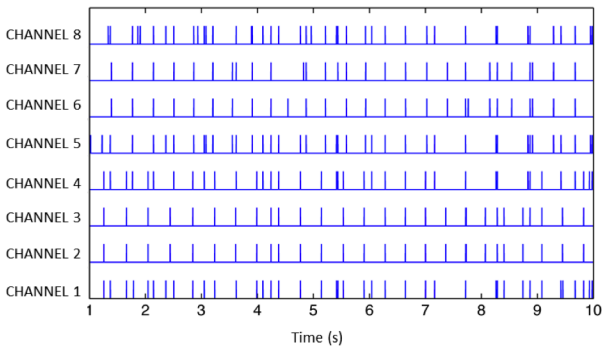

Figure 2. The image shows the fetal QRS detection in the 8 channels after the binary conversion. Each dash corresponds to a QRS detection in that sample.

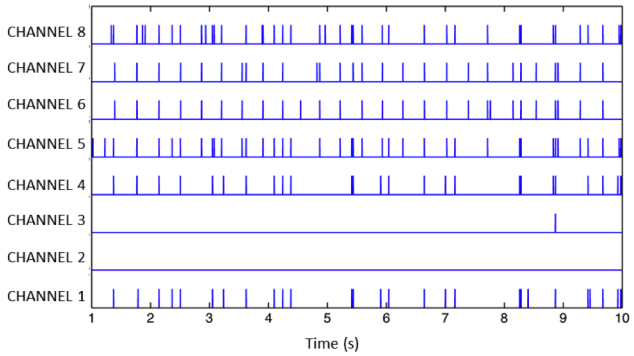

Figure 3. Result obtained after removing the first detected fetal component from all the other channels.

we employed two parameters that are computed for each 10-sec window of the binary signals: the average value of the inter-beat distance (IBAVG) and the number of detections (DN). A small number of detections (and thus a high average inter-beat distance) is usually associated with a channel in which only one fetal component is present and the detection is reliable.

By computing IBAVG and DN, it is possible to identify the channel with the most reliable detection (smallest DN, highest IBAVG), which we take to be the first fetal source (Ch2 in the example above). This is the only step of the algorithm that relies on the assumption that at least one channel records predominantly one fetus. (If none of the eight channels contain predominantly one fetal component the fetal extraction algorithm fails.) After identifying the first fetal source, the samples associated with the QRS of the first fetal source are set to 0 in the remaining channels. Fig. 3 shows the result of this process. To identify the QRS of the second fetus, we compute the number of detections (DN) and the inter-beat standard deviation (IBSTD). The second fetal component is identified as the channel with the minimum IBSTD (highest regularity), and with at least ten detections (to reject channels in which the first fetal component is dominant).

For every new 10-sec window, the two fetal components are extracted. The two components are then associated with the first or second fetus according to the spatial position of the electrode in which the fetal component was dominant.

III. Results

We tested the algorithm on five datasets generated using only one fetal source, and on 14 datasets generated using two fetal sources. Each dataset was six minutes in duration (N=92160). The only parameters under our control during the generation phase of the synthetic ECG signals were the constants μ_1 and μ_2. Thus, we tested different values for these parameters, ranging from 0.1 to 0.7. The position of the fetal heart sources and the PhysioNet signals used to build the *Y* matrix were randomly chosen. For this reason, the results we obtained depend not only on the value of μ_1 and μ_2, but also from the noise levels in the PhysioNet source records and on the assigned fetal source positions within the octagon.

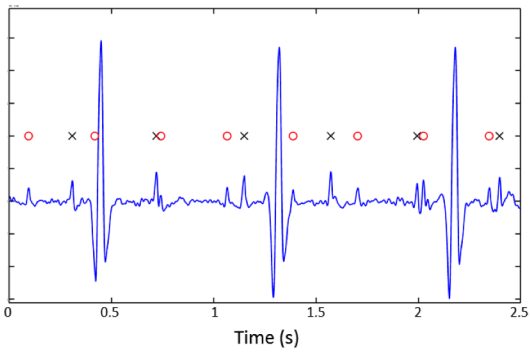

Figure 4. Detection of fetal QRS in twin abdominal recordings. The fetal QRS of the two fetuses are detected and distinguished correctly. Red circles highlights the fetal QRS of the first fetal component, black crosses the fetal QRS generated by the other twin.

The results are shown in Tables I and II. In six cases, the detection failed and the algorithm couldn't correctly detect fetal QRS complexes. This scenario occurred when the value of μ_1 and μ_2 was too small and the amplitude of the fetal QRS complexes was at or below the noise level.

In the other cases, we obtained an overall sensitivity of 98.1% and an accuracy of 95.2% for fetal QRS detection for the singleton case, and a sensitivity of 97.5% and an accuracy of 93.6% for the twin ECG extraction. The algorithm's performance was referenced against manual annotations of all ECG complexes. An example of fetal QRS detection in a twin abdominal ECG is shown in Fig. 4.

IV. Discussions And Conclusions

In this paper, an algorithm for the detection of fetal QRS in singleton and twins abdominal recordings is presented. The

TABLE I. Results obtained in the analysis of singleton datasets.

Run	Sources	μ	Fetus	
			Accuracy	Sensitivity
S1	1	0.1	Detection Failed	
S2	1	0.12	0.79	0.93
S3	1	0.15	0.96	0.98
S4	1	0.18	0.97	0.97
S5	1	0.2	0.95	0.98
S6	1	0.25	0.92	0.97
S7	1	0.3	0.98	0.99
S8	1	0.35	0.99	0.99
S9	1	0.4	0.97	0.98
S10	1	0.45	0.99	0.99
S11	1	0.5	0.99	0.99

TABLE II. Results obtained in the analysis of twins datasets.

Run	Sources	μ_1	μ_2	Fetus 1		Fetus 2	
				Accuracy	Sensitivity	Accuracy	Sensitivity
T1	2	0.2	0.2	Detection Failed		Detection Failed	
T2	2	0.25	0.25	Detection Failed		Detection Failed	
T3	2	0.3	0.3	0.98	0.99	0.99	0.99
T4	2	0.35	0.35	0.93	0.97	0.98	0.99
T5	2	0.4	0.4	0.92	0.97	0.92	0.96
T6	2	0.45	0.45	0.91	0.95	0.95	0.97
T7	2	0.5	0.5	0.90	0.99	0.74	0.86
T8	2	0.55	0.55	0,.96	0.97	0.95	1
T9	2	0.6	0.6	0.98	0.99	0.89	0.98
T10	2	0.65	0.65	0.98	0.99	0.89	0.97
T11	2	0.7	0.7	0.93	0.99	0.98	0.99
T12	2	0.2	0.4	0.99	0.99	Detection Failed	
T13	2	0.4	0.6	0.90	0.92	0.86	0.92
T14	2	0.6	0.8	0.98	0.98	0.90	0.98

algorithm was tested on synthetic data generated using a simple generation model. The algorithm showed high reliability in the detection of fetal QRS both in singleton and twin recordings. However, the algorithm failed when the fetal the QRS complexes were barely visible and their amplitude was at or below the noise level.

The algorithm showed better performance when applied to singleton than to twin datasets. Indeed the number of wrong or missed beats is bigger when two fetal sources are present in the same channel. In these cases, the algorithm can switch from tracking one fetus in one data window to the other fetus in the subsequent data window. Probably, a control on the shape of the QRS would allow us to reduce the misdetection but would thus increase the computational load. The algorithm has been designed to follow fetal movements. Every 10 seconds it detects the 2 electrodes with the strongest fetal component and, in this way, a position change of the fetuses can be easily handled.

This algorithm represents the first attempt to realize an automatic approach to extract fetal QRS complexes from maternal abdominal recordings of twin fetuses without using methods based on blind source separation (BSS) [7]. In the literature there are only few publications regarding the extraction of fetal ECG or fetal MCG in twin pregnancies. For example Comani *et al*. [8] employed fastICA to extract twin fetal EMG from 55-channel recording. Kam and Cohen [9] employed BSS for the same purpose. Burghoff *et al*. [10] also used Independent Component Analysis (ICA) to extract twin fetal EMG from a 37-channel system. The remaining examples available in the literature [11] rely on ICA to extract twin fetal ECG and detect fetal QRS complexes. However, none of those algorithms have been thoroughly tested for sensitivity and accuracy of fetal QRS complex detection. We quantified the performances of our algorithm, getting an average sensitivity and accuracy of 97.5% and 93.6%, respectively.

In order to use BSS-based methods a big number of leads are required to extract a reliable fetal heart rate. According to BSS theory, the number of signals should be at least equal to the number of independent sources (which include maternal ECG, fetal ECGs, and a broad spectrum of different noise sources), while in our approach we only have eight channels. Moreover, it is extremely difficult to understand which of the extracted sources are noisy signals and which are the signals of interest. For those reasons, we decided to abandon the blind approaches, proposing a novel solution for this problem instead.

Our study has some limitations. First of all, we did not test the performances of the algorithm on real twin abdominal recordings. Unluckily, it is really difficult to find in the public domain datasets of maternal abdominal recordings from twin pregnancies, and the low incidence of twin pregnancies (about 1.1%) reduces the possibility to acquire real data. However, testing the algorithm on real data remains one of the next steps of our research. Second, our algorithm for signal generation considers the maternal abdomen as a 2D surface rather than a 3D volume. However, we designed all the steps of the generation process in order to get plausible signals in terms of amplitude, frequency and shape. Finally, the success of the algorithm in the detection of twin QRS relies on the hypothesis that at least one of the eight leads records only one of the two fetal ECGs. However, as explained in Section II.B, this assumption should be close to what will be encountered in reality.

Even if we tested the algorithm only on singleton and twin datasets, we believe that its recursive structure might allow fetal QRS detection in datasets with more than two fetal sources, probably with a progressive decrease in performances. We are currently working on generating multiple abdominal recordings, in order to test the performances of the algorithm on those data by exploiting its recursive structure.

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