Principal Component Analysis (PCA) based single-channel, non-invasive fetal ECG extraction

Radhika Mujumdar[1], Prince Nadar[2], Ameya Bondre[3], Aditya Kulkarni[4], Shantanu Pathak[5]

[1]Biomedical Research Engineer
[2]Embedded Hardware Developer
[3]Head: Clinical Research and Development
[4]Managing Director
[5]Executive Director

CareNX Innovations Pvt. Ltd.

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Abstract

Accurate detection and monitoring of fetal electrocardiography (fECG) and its clinical application is being examined under several studies. Knowledge of fetal cardiac parameters is critical for taking prompt clinical decisions for effective antenatal and neonatal care. This paper presents an approach for extracting fECG from the maternal electrical abdominal signal, non-invasively, using a single electrode. We have implemented the Pan-Tompkins algorithm for detecting R peaks from maternal ECG (mECG), Principal Component Analysis (PCA) for mECG attenuation, and subsequently, an improved Pan-Tompkins algorithm for detecting fetal R peaks. The algorithm was implemented on a database obtained from an online repository, Physionet, and validated using the corresponding scalp fetal ECG, which is the gold standard.

Keywords

Fetal Electrocardiography (fECG), maternal abdominal electrocardiography, fetal heart rate (FHR), Pan Tomkins algorithm, Principal Component Analysis (PCA)

1 Introduction

Monitoring fetal heart rate (FHR) and electrocardiography during pregnancy and labor is critical for tracking fetal well-being. Currently, there are three widely known methods to measure fetal cardiac parameters - Doppler Ultrasound, Invasive fetal ECG and non-invasive fetal ECG (fECG). Doppler Ultrasound is routinely used in hospitals and clinics for FHR monitoring, however, it has certain limitations - it is susceptible to fetal and maternal movements; it uses a probe placed on maternal abdomen which can be uncomfortable; and the probe transmits ultrasound signal in the order of 2 MHz towards the fetus, which could be harmful if used for long periods of time [1]. Invasive fECG involves an electrode inserted through the dilated cervix and the ECG signal is obtained from the fetal scalp. Although scalp ECG is accurate, it can only be measured during labour and it increases the chances of causing infection to both the fetus and the mother [2]. Alternatively, non-invasive detection of fECG (NIfECG) from the maternal abdominal signal is possible from the 20th gestational week and is most suitable for long term monitoring of fetal health [2].

There has been growing research on the detection of NIfECG [2–9]. However, extraction of NIfECG from abdominal ECG (aECG) poses a number of challenges - the abdominal signal is a mixture of signals overlapping temporally as well as in the frequency domain as shown in Figure 1 [2]. In Figure

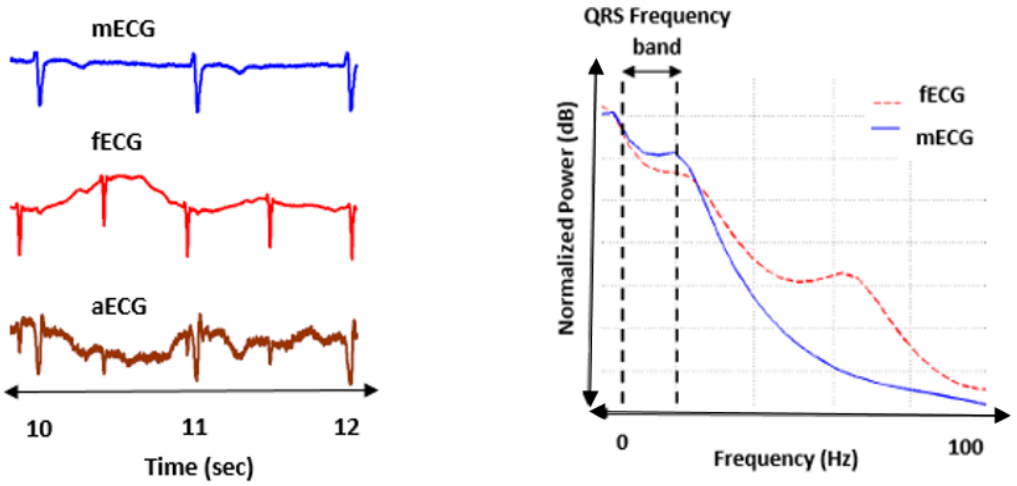

Figure 1: (a) Temporal overlap of mECG and fECG in aECG. (b) Frequency domain overlap of QRS band of mECG and fECG. [2]

1(a), the overlap of mECG and fECG in the time domain is evident in aECG. Figure 1(b) shows the overlap between the two signals in the frequency domain. Moreover, the fECG signal is affected by the fetal and maternal movements, mothers abdominal muscle artefacts, uterine contractions, maternal respiration, electrical noise from the device and power line and the major source of interference is the maternal ECG (mECG) that is predominant in the abdominal signals [2, 3, 10]. The strength of mECG is illustrated by the fact that its amplitude is 2-10 times that of fECG [4], and the frequency of the QRS band of the ECG overlaps for the fetus and the mother [2, 11], making it difficult to separate these signals with simple signal processing techniques.

Numerous methods have been developed to extract fECG. Techniques like template subtraction [6–8], adaptive filtering [9], Independent component analysis (ICA) [12–14], are commonly used to extract fECG from the abdominal signal. However, these methods use multichannel abdominal recordings i.e. the signal is measured simultaneously from an array of electrodes (typically 4 or more) to be placed on the mothers abdomen. This not only increases the hardware complexity but may also be operationally cumbersome for the patient and clinician, particularly in low-income developing country settings that have limited resources, training capacity, large patient numbers, and greatest needs of continual monitoring of fetal wellbeing. Thus, studies should explore techniques that can extract fECG with minimum operational challenges.

Our study explores the possibility of using a single electrode to record aECG. The proposed method works on Principal Component Analysis (PCA) for extracting fECG from aECG.

2 Methods

The algorithm was implemented on two databases from the PhysioNet repository (Goldberger AL et al, 2003) [15]:

- Abdominal and Direct Fetal Electrocardiogram Database
- PhysioNet and Noninvasive Fetal ECG - The PhysioNet Computing in Cardiology Challenge 2013.

The first database contains 5 datasets obtained from 5 different women with gestational ages of 38-41 weeks. Each dataset consists of multichannel abdominal recordings from the 4 electrodes placed in a circular manner around the umbilicus and a reference recording of the fetal ECG registered from the fetal scalp invasively, which acts as the gold standard for comparison of fetal heart rate. The second database also has datasets having simultaneous recordings from 4 electrodes. The direct invasive fECG is not included in this dataset, however, the location (time in milliseconds) of each fetal R peak

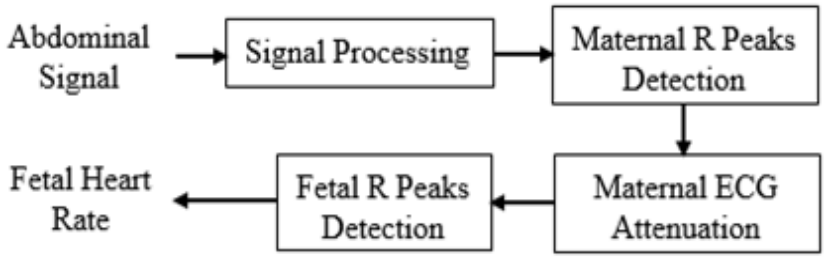

Figure 2: Signal processing steps

is marked to be used as a reference for validation. This reference has been obtained by using the fetal scalp ECG whenever possible. It is also derived by crowd-sourcing from experts and algorithms while maintaining the accuracy of fetal R peaks locations. The sampling rate of signals in both databases is 1KHz. The datasets have multichannel recordings, but the proposed algorithm is capable of extracting fECG from a single abdominal signal.

The algorithm was implemented using MATLAB R2017b for each electrode separately and the signal with the best quality was selected based on the precision of fetal R peak locations, compared to the gold standard. The steps in fetal ECG extraction from the abdominal signal are as per the research conducted by Rahamati et.al. who achieved a sensitivity of 93.103% for detecting fetal R peaks [3]. Figure 2 shows the block diagram explaining the steps.

3 Signal Processing

The abdominal signal is predominantly composed of a strong maternal ECG along with interfering noise from uterine contractions, respiration, artefacts due to maternal and fetal movements, muscle artefacts and electrical noise from the power lines and electrical devices, as discussed before, which need to be removed before implementing the fetal ECG extraction algorithm. To remove the noise, a digital Butterworth filter of order 2 and cut-off frequencies from 3-80Hz was designed to remove the low and high-frequency noises. This was followed by a notch filter to remove the 50/60 Hz noise from electrical sources. The filtered signal was then normalized as shown in the following equation:

$$Sn(i) = \frac{S(i) - mean(S)}{Sd(S)}$$

Where 'i' varies from 1 to the length of the signal; Sn is the normalized signal; S is the filtered signal and Sd stands for Standard deviation. Figure 3 shows the original and the processed abdominal signal respectively.

4 Maternal 'R' peaks detection

For the maternal QRS to be eliminated successfully, the first step is to detect the location of the maternal R peaks accurately. For this, Pan and Tompkins R peak detection algorithm was implemented [3]. This algorithm identifies QRS complexes by analyzing slope, amplitude, and width of the maternal ECG signals, to allow their separation during analysis. Separation of QRS complexes allows application of Principal Component Analysis (PCA) on those in order to attenuate mECG. Pan-Tompkins algorithm has an accuracy of 99.3% in detecting QRS complexes. [16].

5 Maternal ECG Attenuation

The Maternal ECG is attenuated using the Principal Component Analysis (PCA) algorithm. According to research findings, the P-R interval is about 200 ms and the R-T interval is about 300 ms as shown in Figure 4 [3]. Therefore, once the Maternal R peak locations are obtained from the Pan and

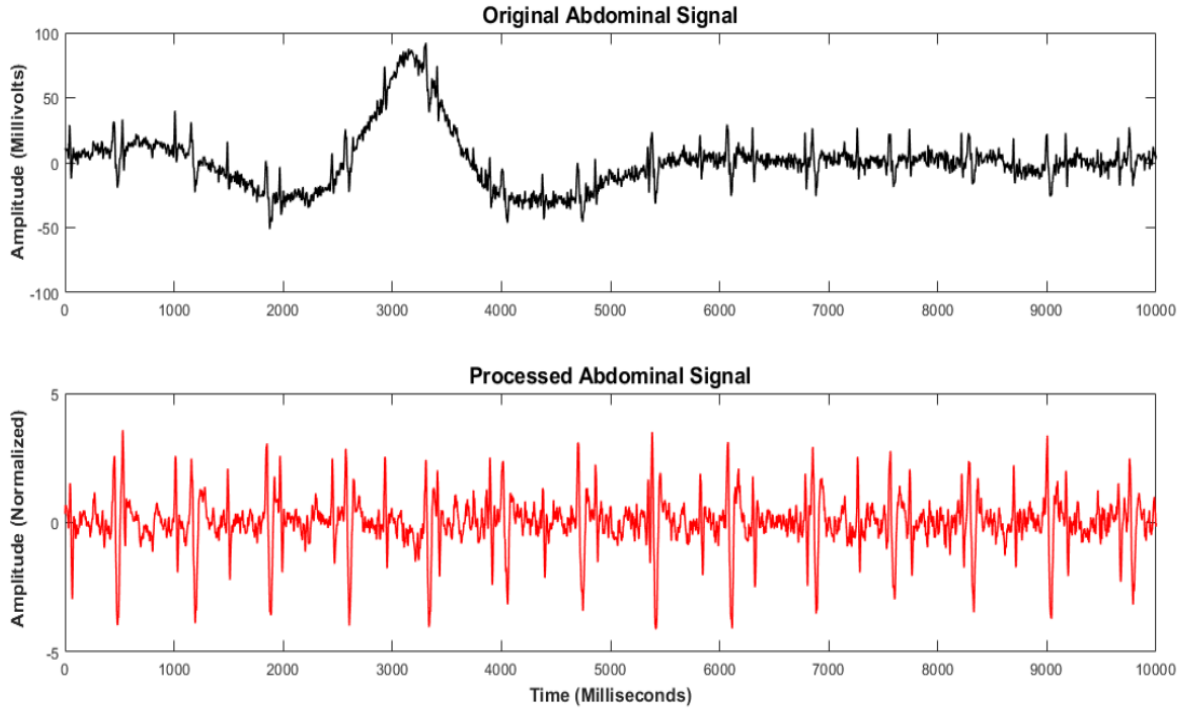

Figure 3: Original and Processed abdominal signals

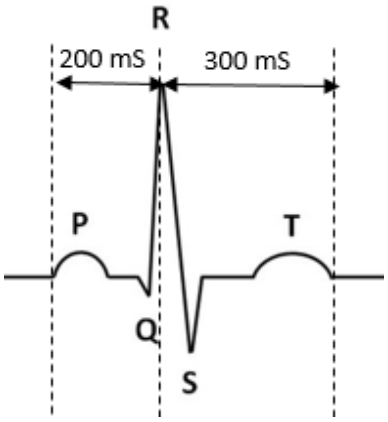

Figure 4: PQRST waveform

Tompkins algorithm, the PQRST (ECG) locations can be obtained by taking 200 ms before and 300 ms after the R peak. The complexes are then stacked one below the other forming a matrix of n rows corresponding to n R peaks and m columns, where m is the length of the PQRST complex [3]. PCA classifies data based on different variances in descending order. Since maternal ECG is the predominant signal (a highly variant signal with respect to the other signal components) in the mixtures, by performing PCA on the matrix, the mECG component gets grouped as the first few principal components followed by fECG and noise depending on their respective variances in the signal. Thus, by eliminating the first few components, we can remove the maternal ECG greatly. And the signal reconstructed after removing the first few components is majorly, the fetal ECG and noise [3].

6 Fetal 'R' peaks detection

An improved Pan-Tompkins algorithm (described in previous research) for R peaks detection in fetal ECG was implemented for achieving the fetal R peaks and thereby the fetal heart rate. The algorithm was evaluated by Agostinelli et.al on the Abdominal and Direct Fetal Electrocardiogram Database

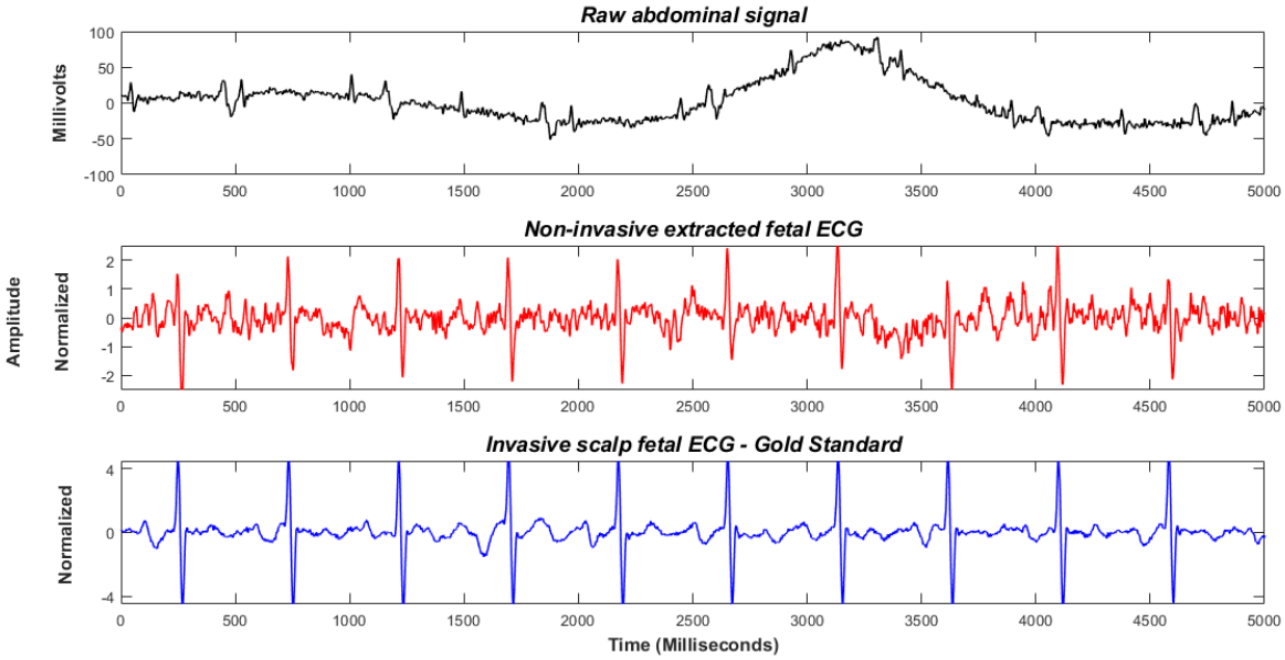

Figure 5: (a) Raw, unprocessed abdominal signal. (b) Extracted fetal ECG in the present study. (c) Scalp fetal ECG (Gold standard)

and showed a positive-predictive value of 94%, sensitivity of 95% on fetal ECG [11].

7 Results

Figure 5 shows the results of one of the channels of dataset r08 from the database 'Abdominal and Direct Fetal Electrocardiogram Database, PhysioNet'. The first graph (black) shows the unprocessed signal from the database. The second plot (red) shows the fetal ECG extracted from the abdominal signal using our algorithm and the last plot (blue) is the reference invasive fetal scalp ECG or the gold standard. It can be seen that the peaks in the second and third plot, which are the fetal R peaks, coincide visually and qualitatively.

8 Discussion

Presently, India carries the burden of 5 million annual high-risk pregnancies and a substantial number of these contribute to newborn mortality. Most newborn deaths occur due to prematurity and complications in the first week of life (e.g. asphyxia) and these can be traced to inadequate monitoring of fetal risks during pregnancy. Regular fetal health monitoring is limited in India and assessment of fetal ECG is extremely scarce, if we look at the majority of rural and semi-urban women who are often dependent on the limited skills of a community health worker who conducts home-based or centre-based visits and given the insufficient numbers of gynecologists (only 60,000 and concentrated in the cities). Fetal ECG can be correlated to critical fetal health parameters, for example, ST segment elevations are known to predict fetal hypoxia, which in turn puts the newborn in danger, close to the due date.

Due to the operational complexity, bulk, cost and training-intensive nature of the current standard i.e. cardiotocography (Toco), a large majority of low-income women have been deprived of cost- and time-effective fetal monitoring. Our approach to extract fECG is a part of a non-invasive passive abdominal sensor called 'UAct,' which is capable of measuring uterine electrical activity using the established principle of electrohysterography. UAct is currently being validated in an urban hospital to check its accuracy relative to Toco viz. assessment of uterine contractions in labour and prediction of

premature labour. UAct's simplicity, affordability, portable nature and smartphone linkage and now with the added component of fECG monitoring can transform maternal and fetal health monitoring during pregnancy for the vast majority of women in India and other developing countries. The simple usage will enable midwives and community health workers to administer the device and flag risks using the mobile application to relay information to a remotely located gynaecologist. The doctor can thereby take decisions early and suggest further treatment or course of action based on the patients severity. Such a triage-based referral linkage system can ensure improved management of fetal (and thereby neonatal) complications and potentially save newborn lives.

9 Potential Research

Our approach extracted the fetal ECG from the raw abdominal signal in a minute. Signal processing studies are being conducted to further reduce this time interval.

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