Ic4FECG: A New Index for Automatic Selection of the Most Relevant Independent Component in Noninvasive Fetal Electrocardiography

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Abstract

Independent Component Analysis is often used to extract fetal ECG (FECG) from maternal abdominal signals, but choosing the correct independent component (IC) has traditionally been empirical and subjective. This study introduces Ic4FECG, a quantitative index for automatically selecting the most relevant IC. The index is based on the assumption, supported by the literature, that the typical Fetal Heart Rate (FHR) is around 140bpm, (RR interval of 428ms), and that deviations reflect noise or maternal contamination. Ic4FECG is defined as Ic4FECG = ||(428ms-μFRR)×σFRR||, where μFRR and σFRR are mean and standard deviation of the fetal RR interval series. Using 36 maternal abdominal recordings from the "NInFEA" database, maternal interference was first reduced with PCA, assuming FECG lies in the lowest 5% variance. ICA then decomposed the residual into 20 ICs. Fetal R-peaks were detected in each IC, and Ic4FECG was computed. The IC with the lowest Ic4FECG was selected, and its FHR (FHR_{IC}) was compared with ultrasound-derived FHR ($FHRD_{US}$). Results showed strong agreement with FHR_{IC} = 140 ± 9 bpm, and FHR_{DUS} = 141 ± 8 bpm, and significant correlation ($\rho = 0.75$, $p < 10^{-8}$). Ic4FECG appears to be a potentially useful tool for automated selection of the most relevant IC in FECG analysis.

1. Introduction

Assessing the fetal well-being throughout the pregnancy is of utmost importance to promptly detect abnormalities in the fetal development and possibly act preventively. Fetal Heart Rate (FHR) can provide valuable insights in this direction [1]. Even if its most traditional application is in intrapartum monitoring (e.g., for detecting fetal hypoxemia), accurate assessment of FHR during pregnancy could aid in identifying alterations in the fetus' growth and cardiac development, and help designing timely medical intervention [2].

Accurate FHR estimation is still an open problem in the current clinical practice. At date, Cardiotocography (CTG) and Ultrasound Doppler analysis are considered the clinical gold standards[3]. Nevertheless, they require a skilled clinical practitioner to perform the test, which opens to other options. Noninvasive Fetal Electrocardiography (FECG) is a technique for monitoring the fetal heart's electrical activity by placing electrodes on the maternal abdomen [4]. It has been widely explored in the literature as an interesting alternative to CTG and Doppler because it could open to domiciliary monitoring along with facilitating monitoring in low-resource scenarios. Nevertheless, FECG still suffers of a range of technical problems, such as maternal-fetal signal overlap, motion artifacts, and sensor misplacement, which can compromise data quality and interpretation [4].

In this work, we focus on the separation of fetal and maternal contributions on FECG. Previous works show that blind source separation methods such as Independent Component Analysis (ICA) can be leveraged to extract the FECG from maternal abdominal recordings [5], [6], [7], [8], [9]. However, selection of the most relevant independent component (IC) is still largely empirical: this makes the selection subjective, and prevents from the use of ICA in fully automated monitoring systems.

In this study, we propose Ic4FECG, a quantitative and objective index to automatically select the best IC in FECG recordings performed on the maternal abdomen, with the scope of accurately estimate the FHR for fetal monitoring during pregnancy.

2. Materials and Methods

Our method grounds on abdominal and thoracic ECG recordings performed on pregnant women. The proposed processing pipeline involves four steps: 1) reduction of maternal interference; 2) separation of FECG, maternal contribution and noise using ICA; 3) selection of the independent component (IC) with the most relevant FECG contribution; 4) estimation of FHR from the selected IC. In the end, we validated the estimated FHR against fetal pulse-wave Doppler (PWD), as a clinical

gold standard. The next paragraphs will present details about each step.

2.1. Dataset

To explore the use of ICA for FECG extraction and define Ic4FECG, we leveraged "NInFEA: Non-Invasive Multimodal Fetal ECG-Doppler Dataset for Antenatal Cardiology Research", published on PhysioNet [10]. The dataset includes 60 recordings from 39 healthy pregnant women between the 21st and 27th weeks of gestation, and it's therefore suitable for the analysis of the early cardiac development during pregnancy. Each recording contains:

- 27 abdominal unipolar ECG leads
- 3 thoracic bipolar ECG leads
- synchronized fetal PWD

ECG signals are sampled at 2048 Hz and captured with 22-bit resolution, PWD is provided with a frame rate of 74 frame/second. All signals were resampled to 1 kHz for consistency.

The last recording was selected from each subject and included in our analysis. Three signals were excluded due to low signal quality following visual inspection. In the end, the sample population for the proposed analysis counts 36 recordings.

2.2. Maternal Interference Reduction

Abdominal ECG recordings can be physiologically modelled as a linear mixture of FECG, maternal ECG (MECG) and noise. Similarly, thoracic recordings can be modelled as a linear mixture of MECG and noise alone. The first processing step is the removal of MECG from abdominal recordings, leveraging thoracic leads. A N-by-27 matrix was created with the 24 abdominal leads and the 3 thoracic leads (N is the number of samples).

Each signal was pre-filtered with a cascade of a bidirectional band-pass Butterworth filter from 0.5 to 100 Hz to reduce baseline wandering and high-frequency noise, and a stop-band FIR filter centered on 50 Hz to reduce power line interference.

Principal Component Analysis (PCA) was carried out. The MECG component is the main contributor to all the leads, both the abdominal and the thoracic ones. Therefore, since MECG is the strongest and most correlated source, it appears in the first principal components. Following the mentioned considerations, we removed MECG under the experimental assumption of FECG being represented in the lowest 5% of the explained variance.

2.3. Independent Component Analysis

PCA proved capable of reducing the effect of MECG on the abdominal recordings but could not be fully removed. Therefore, ICA was carried out as a second processing step. The goal is to separate FECG, MECG and all possible noise contributions as independent components (ICs). For the purpose, we used the FastICA algorithm is a widely used algorithm, particularly known for its computational efficiency and robustness [11]. With FastICA the maximization of the independence among the ICs, estimating using their kurtosis, is achieved through maximum likelihood estimation. The number of components to be separated was set to 20.

2.4. Definition of Ic4FECG

R peaks were identified in each IC using an enhanced version of Pan Tompkins' algorithm [12]. Then, for each IC, the mean and the standard deviation of the RR interval series are estimated and defined as μFRR and σFRR respectively. The latter values were used to estimate the Ic4FECG index. The definition of the index grounds on the knowledge that the typical FHR is higher than the typical adult heart rate, even in pregnant women. In particular, FHR is expected around 140 bpm [1], corresponding to an average RR interval of 428 ms. ICs can reflects three types of signals: FECG, MECG, noise. ICs corresponding to MECG result in a μFRR far from 428 ms (typically much higher). ICs corresponding to noise are expected to result in a high σFRR, since the identified peaks are not real R peaks and thus, they are not periodic. On the contrary, ICs corresponding to FECG are expected to have a μFRR close to 428 ms, and a low σFRR. Therefore, we defined Ic4FECG as:

$$Ic4FECG = \|(428ms - \mu FRR) \times \sigma FRR\| \quad (1)$$

The IC that minimized Ic4FECG was selected as the most relevant IC, and used to estimate the FHR.

2.5. Heart Rate Estimation and Validation Against Ultrasounds

FHR was computed using the R-peaks identified on the best IC selected using the Ic4FECG index (FHR_{IC}). For validation, we estimated FHR also from the synchronized PWD (FHR_{DUS}).

PWD is provided in the dataset as an image, accompanied by Matlab code to extract the upper and lower envelope of the flow-based Otsu 2D thresholding [10]. The envelopes were then upsampled from the original sampling frequency of 284 Hz to 1 kHz and filtered using a 5-sample moving median to reduce the high-frequency noise caused by inaccuracies in the envelope extraction process. The upper envelope is characterized by a positive peak in the diastolic phase (corresponding to the A-E complex), not present in the lower envelope; similarly, the lower envelope is

characterized by a negative peak in the systolic phase (V wave), not present in the upper envelope [13]. The sum of the two envelopes enhances the two peaks. We filtered the sum-envelope using a 180-sample median filter and identified the negative peaks, corresponding to the peak of the systole. We used the difference between consecutive peaks as a proxy for the RR interval and used the latter to estimate FHR_{DUS}. In the end, we statistically compared FHR_{IC} and FHR_{DUS}. For the purpose, we computed Pearson's correlation coefficient (ρ) and we carried out a linear regression analysis. Statistical significance was set at 0.05.

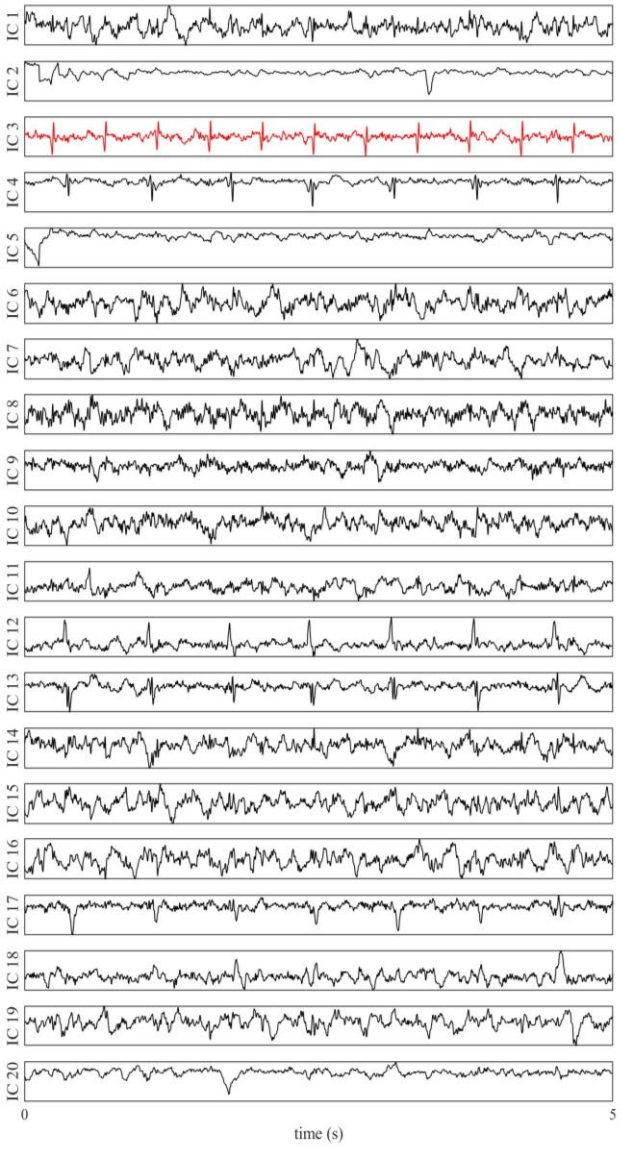

Figure 1. Example of ICs on a sample recording. Each IC is accompanied by the estimated μFRR and σFRR values, and the resulting Ic4FECG value. IC3 (colored in red) minimizes the Ic4FECG and was selected as representative of FECG.

3. Results

In the following paragraphs, the results of our analysis will be presented and discussed. The value of Ic4FECG for IC selection will be shown in detail for a sample recording. Then, aggregated results regarding the validation against PWD will be proposed.

3.1. IC Selection Using Ic4FECG

Figure 1 shows an example of the set of 20 ICs resulting from applying ICA on a recording from the sample population. In this case, IC3 minimized Ic4FECG and was selected as representative of FECG: visual observation confirms that the selection was correct. It can be observed that noisy ICs are characterized by a high value of σFRR. This results in a higher Ic4FECG: for example, IC16 has a μFRR closer to 428 ms than IC3, but its higher σFRR, due to the selected R-peaks not being real R-peaks, increases its Ic4FECG. On the contrary, σFRR is minimized by IC12 Nevertheless, the heart rate of IC12 is compatible with the maternal heartbeat, not the fetal one. Also in this case, Ic4FECG increases.

3.2. Validation Against Ultrasounds

Table 1 shows the statistics of the distributions of FHR_{IC} and FHR_{DUS} over the population under analysis. Moreover, the Pearson's correlation coefficient ρ is reported with its p-value.

Table 1. Statistical analysis of FHR_{IC} and FHR_{DUS}.

Parameter	mean (bpm)	stdev (bpm)	ρ	p-value
FHR_{IC}	140	9	0.75	$<10^{-8}$
FHR_{DUS}	141	8		

The two estimates present a strong correlation, which confirms that the selection of the IC using the proposed Ic4FECG index is effective in identifying the fetal contribution.

In the end, Figure 2 shows a scatter plot of the FHR_{IC} and FHR_{DUS} values for each recording. The blue line represent the regression line resulting from regression analysis. It can be observed that most values lie on the bisector, as expected and confirmed by the correlation and regression analysis.

4. Discussion

This study introduces Ic4FECG, a novel quantitative index for the automated selection of the most relevant independent component in FECG analysis. By leveraging physiological constraints of fetal heart rate, Ic4FECG

provides an objective criterion that minimizes subjectivity in IC selection. In the overall, despite its simplicity, Ic4FECG proved effective to perform a reliable selection of the IC representing the FECG contribution, as shown in the example reported in Figure 1. Validation against Doppler ultrasound demonstrated strong agreement, highlighting the potential of Ic4FECG to improve reliability in FHR estimation. This is true both for FHR values close to 140 bpm, which is the value we used as reference for the fetal beat in the definition of the Ic4FECG index, both for FHR values far from it. We can thus confirm that using a common reference is effective to discriminate the fetal from the maternal contribution but does not negatively affect the estimate even when it's far from the reference, which may happen in pathological cases. Future works will further investigate the outliers visible in the scatter plot in Figure 2, and provide a more extensive validation on larger datasets including pathological cases.

5. Conclusions

We can conclude that our findings suggest that Ic4FECG could be a valuable addition to automated FECG processing pipelines, with promising applications in real-time fetal monitoring and clinical decision support. Future studies will further test Ic4FECG on larger datasets and evaluate its possible integration into real-time fetal monitoring systems.

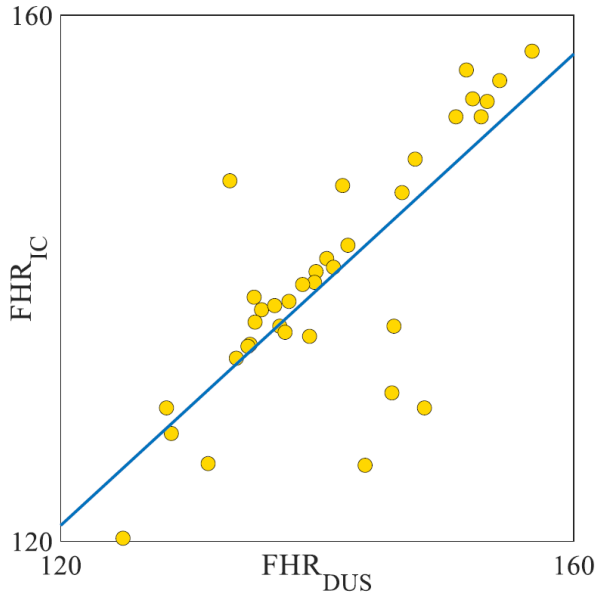

Figure 2. Scatter plot of FHR_{IC} and FHR_{DUS} estimates. The blue line is the regression line.

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