Extraction Algorithm for Morphologically Preserved Non-Invasive Multi-Channel Fetal ECG

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Abstract

Non-invasive fetal ECG (fECG) is a promising technique that could allow low-cost and risk-free diagnosis, and long-term monitoring of fetal cardiac wellbeing. However, the low quality of the fECG extracted from non-invasive abdominal recordings hampers its adoption in clinical practice. In this work, a new algorithm for the recovery of clean and morphologically preserved fECG signals from multi-channel trans-abdominal recordings is presented.

The proposed method exploits optimal shrinkage and nonlocal median algorithms, along with a de-shape short-time Fourier transform-based detection, to recover high-quality fECG traces from a morphological perspective, while ensuring very high performance also in terms of fetal QRS detection. On a small dataset, composed of three real 20 min-long four-channel abdominal ECG recordings, a preliminary performance assessment of the proposed fECG extraction method in terms of fetal QRS detection capabilities revealed a median accuracy of 95.8% and F1 score of 97.9%. The obtained results suggest the possibility of successfully applying this approach for an effective non-invasive fECG extraction, deserving further investigations on larger real and synthetic datasets.

1. Introduction

Non-invasive fetal ECG (fECG) represents a promising tool for continuous, low-cost, and risk-free prenatal cardiac monitoring and diagnostics, by allowing the fetal cardiac electrical activity examination from the maternal abdomen [1]. As such, unlike more conventional ultrasound-based techniques, fECG could support the diagnosis of cardiac pathologies that alter the ECG waveform morphology [2], such as fetal arrhythmias or some congenital heart diseases, in order to trigger therapeutic interventions antenatally or immediately after birth. However, fECG extracted from non-invasive abdominal recordings suffers from low quality, which limits its adoption in common clinical practice mainly to the fetal heart rate (fHR) estimation [3]. This aspect, which has been deeply investigated for more than 50 years, is mainly ascribed to the several electrophysiological interferences due to maternal respiration, uterine contractions and ECG (mECG), which overwhelm the weaker fECG content. Therefore, although a great scientific effort has been put into the development of signal processing and analysis techniques able to recover high-quality fECG signals from non-invasive recordings [4], even in real-time [5], clinically reliable fECG signals are rarely obtained.

In this work, we tried to address this issue by introducing a novel algorithm for fECG extraction from multi-channel non-invasive trans-abdominal recordings, which exploits the nonlocal Euclidean median algorithm, the de-shape short-time Fourier transform (dsSTFT) technique, and optimal shrinkage denoising algorithm.

2. Materials and Methods

By considering several advanced signal processing tools and methodologies for an efficient fECG extraction developed in the literature [6]–[9], a multi-channel fECG extraction method was developed. Therefore, in this section, the multi-channel fECG extraction algorithm is firstly introduced, and then the dataset adopted for its evaluation and the performance metrics are described hereafter.

2.1. fECG extraction algorithm

The main processing steps of the proposed fECG extraction algorithm are graphically summarized in

Figure 1 and deeply described hereafter.

Pre-processing. At first, each abdominal ECG signal was pre-processed in order to remove eventual baseline wandering artifacts. To this aim, the baseline wander was firstly estimated by a moving median filter with a sliding window of 0.5 s and then subtracted, thus resulting in a smooth high-pass filtering stage.

mECG estimation. Then, in order to properly estimate the mECG by optimal shrinkage and nonlocal median algorithms, an accurate maternal R-peak detection was initially performed. Specifically, by exploiting the dsSTFT along with the dynamic programming curve extraction algorithm and the beat tracking technique [6]–[8], the maternal R peaks were identified in each pre-processed abdominal ECG recording. At this stage, a collection of maternal R-peak locations was obtained for each abdominal channel, which however might differ because of the background noise or the different fECG contents. Therefore, to achieve a unique and robust maternal R-peak annotation, the R-peak collection of each channel was compared with that of all the other channels in terms of F1 score, by imposing a 10-ms tolerance window. In this way, each abdominal channel was ranked according to the number of other channels exhibiting a significant detection coherence, by considering a F1 score higher than 0.95. Finally, the maternal R-peak locations belonging to the two collections of abdominal channels showing the highest number of consistent detections were compared, and then only the common R-peak annotations, i.e., those falling into the 10-ms tolerance window, were retained. On this basis, each abdominal signal was segmented by extracting each maternal beat. As such, a window centered on each R peak, with a duration equal to the quantile 0.95 of all the RR intervals, was estimated and extracted from each pre-processed signal, and then denoised by optimal shrinkage [6], in order to attenuate both noise and fECG contents.

Then, in order to remove any uncorrelated residual noise, the nonlocal median algorithm was applied. However, since the nonlocal median has been adopted in single-channel applications only so far [6], [7], in order to deal with a multi-channel set of abdominal recordings, the similarity between each pair of maternal cardiac cycles was evaluated by summing their squared Euclidean distances across all available channels. At this point, the proper median template for each maternal cycle was estimated by considering its 60 most similar neighbors belonging to the same abdominal ECG trace. Finally, the noiseless multi-channel mECG was retrieved by introducing each median template in its proper temporal location.

Optimal fECG recovery. Once the estimate of the mECG has been recovered, a raw multi-channel fECG signal was obtained by subtracting each mECG from its corresponding pre-processed abdominal recording.

However, to perform an optimal multi-channel fECG recovery by nonlocal median post-processing, some other additional steps were involved. Specifically, on the raw

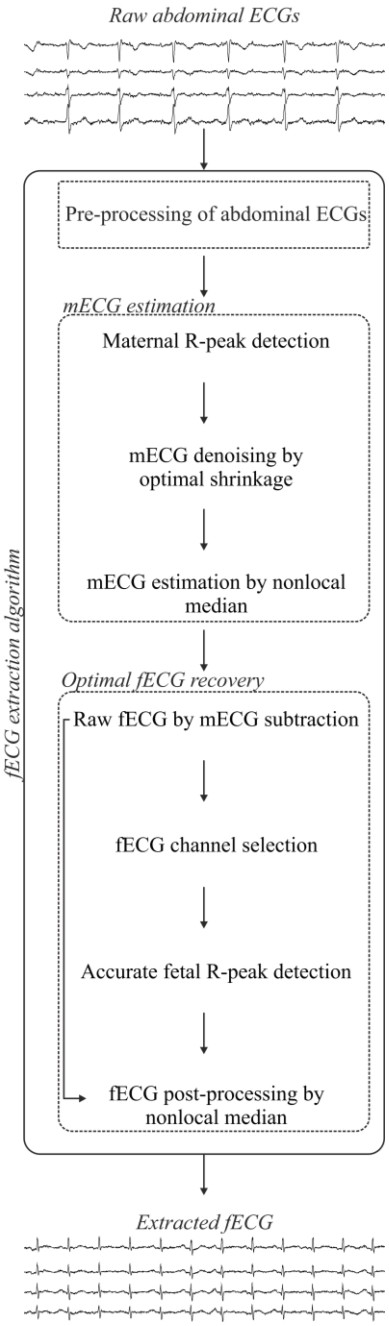

Figure 1. Main processing stages involved in the developed fECG extraction algorithm.

fECG, a channel selection approach was performed in order to identify those channels providing sufficient and useful information in terms of fetal content. In this step, two fetal R-peak detectors of the scientific literature were exploited, i.e., an algorithm based on the Pan-Tompkins' method [10] and the combination of the beat tracking algorithm with the dsSTFT [6]–[8], and then the channel selection was based on the R-peak annotation consistency provided by the two detectors. In this regard, R-peak

detection consistency was assessed in terms of F1 score. Specifically, all R-peak annotations identified by both detectors, within a 20-ms tolerance window, were considered as true positives, whereas the extra beats identified by the dsSTFT-based detector only or by the peak detector based on Pan-Tompkins' approach only were assumed as false negatives and false positives, respectively. Then, all fECG channels exhibiting an F1 score above 0.85 were selected. Finally, to carry out an accurate fetal R-peak detection, the singular value decomposition (SVD) was introduced. Each signal reconstructed from each SVD component was initially filtered by a bidirectional 10th-order IIR Butterworth high-pass filter with a cut-off frequency of 10 Hz, in order to enhance fetal QRS complexes [10]. Then, a signal quality index (SQI) based on pseudo-periodicity [11] was considered. Furthermore, since the lower the pseudo-periodicity SQI value, the higher the fECG content [11], the SVD-based reconstructed signal showing the lowest SQI was selected. As such, its fetal R-peak locations were taken as fetal QRS positions for the nonlocal median post-processing, after an R-peak annotation refinement was performed by looking for a local maximum or minimum in a 10-ms window around each R peak location, according to the signal polarity.

Finally, all fECG channels were post-processed by the nonlocal median approach, in order to attenuate residual noises, by considering the 80 closest beats, according to the multi-channel squared Euclidean distance.

2.2. Adopted dataset

A publicly available real multi-channel dataset [12] providing 20-min long traces with the reference fetal R-peak annotations was chosen for testing. It is composed of ten four-channel abdominal recordings performed on pregnant women between the 32nd and the 42nd week of gestation. Specifically, to challenge the algorithm in a very adverse context, in this preliminary investigation, we selected those three abdominal recordings exhibiting the highest mECG interference with respect to the fECG component (i.e., those affected by the higher WMF index, defined according to [12]). An example of antenatal recording adopted for this evaluation is shown in Figure 2. Furthermore, since all signals were sampled at 500 Hz, an initial resampling at 1 kHz was performed for a more accurate processing implementation and algorithm evaluation.

2.3. Performance evaluation

The performance obtained by our algorithm has been quantitatively assessed in terms of the fetal QRS complex detection accuracy (ACC), the true positive rate (TPR), the positive predictive value (PPV) and the F1 score provided by the dsSTFT-based fetal R-peak detector, as:

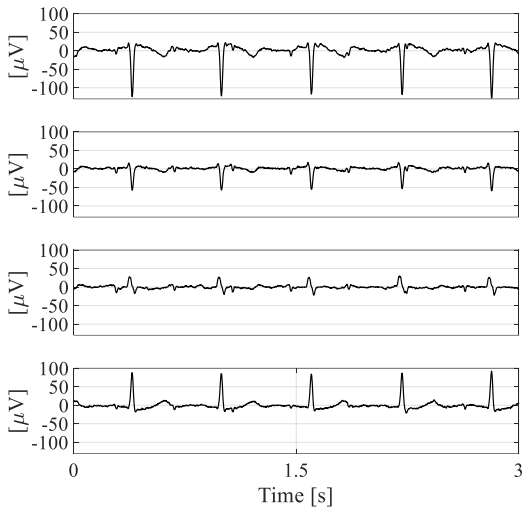

Figure 2. A 3s-long abdominal signal of the adopted dataset.

$$ACC = TP/(TP + FN + FP) \quad (1)$$
$$TPR = TP/(TP + FN) \quad (2)$$
$$PPV = TP/(TP + FP) \quad (3)$$
$$F1 = 2\,(TPR \times PPV)/(TPR + PPV) \quad (4)$$

where the correctly detected fetal beats are named as TP, the undetected fetal R-peaks as FN, and the incorrectly detected ones as FP. For this evaluation, a 20-ms tolerance window was chosen.

All processing stages and evaluations were performed with MATLAB 2022a.

3. Results

As can be seen from Figure 3, the fetal QRSs were accurately detected in the fECG signals provided by our algorithm, with overall median ACC, TPR, and F1 score of 95.8%, 98.1%, and 97.9% respectively, thus leading to very promising results for its possible exploitation in fHR monitoring systems. Furthermore, by looking at the fetal R-peak detection performance on individual recordings, the same findings are confirmed and stable across the different analyzed cases, despite the substantial mECG interferences initially affecting the adopted abdominal signals. Finally, the ability of the proposed algorithm to recover high-quality morphology-preserved fECG signals can be appreciated in Figure 4.

4. Conclusions

In this work, a novel effective algorithm for morphologically preserved non-invasive multi-channel fECG extraction has been presented and evaluated. The proposed algorithm revealed very high performance in

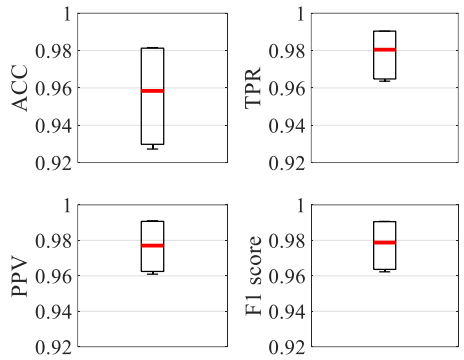

Figure 3. Overall performance results.

Table 1. Results obtained on each examined multi-channel abdominal recording. Mean values are reported along with 95% CI (in squared brackets).

	Case #1	Case #2	Case #3
ACC	98.13	92.86	95.84
[%]	[98.1−98.16]	[92.64−93.09]	[95.84−95.84]
TPR	99.04	96.43	98.05
[%]	[99.04−99.04]	[96.33−96.53]	[98.05−98.05]
PPV	99.08	96.17	97.71
[%]	[99.05−99.10]	[96.03−96.31]	[97.7−97.71]
F1	0.991	0.963	0.979
score	[0.991−0.991]	[0.962−0.964]	[0.979−0.979]

fetal R-peak detection and provided very high-quality fECG traces also in presence of significant mECG and noisy interferences, thus paving the way for its possible exploitability in real fHR monitoring devices. However, further investigations on larger real datasets are needed to test its performance on a wider range of real signals and interferences, but also on synthetic datasets, to perform a quantitative assessment of its morphology-preservation capabilities.

Acknowledgments

This work is supported by the Italian Government—Progetti di Interesse Nazionale (PRIN) under the grant agreement 2017RR5EW3 - ICT4MOMs project.

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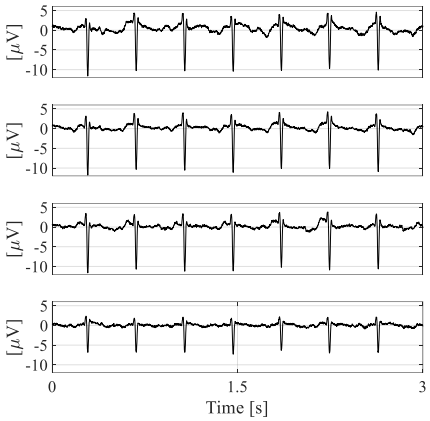

Figure 4. A 3s-long 4-channel fECG extracted by our algorithm from the abdominal recording reported in Figure 2.

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