New Features for the Detection of Fetal QRS Complexes in Non-Invasive Fetal Electrocardiograms

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***Abstract*— Non-invasive fetal electrocardiography (NI-fECG) is a promising technique for continuous fetal heart rate (fHR) monitoring. However, the weak amplitude of the fetal electrocardiogram (fECG), and the presence of the dominant maternal ECG (mECG), makes it highly challenging to detect the fetal QRS (fQRS) complex, which is needed to obtain the fHR. This paper proposes a new method for automated fQRS detection from single-channel NI-fECG signals, without cancelling out the mECG. The proposed method leverages the different spectral behaviour exhibited by mECG and fECG signals. Fetal R-peaks are detected using a hybrid combination of k-means clustering with time and time-frequency features extracted from pre-processed NI-fECG recordings. The performance of our method is evaluated using real and synthetic signals from publicly available datasets, achieving a best of 96.3% sensitivity and 90.4% F1 score. The results obtained demonstrates the effectiveness of the proposed method for the detection of fQRS complexes with high sensitivity and low computational complexity.**

I. Introduction

It is estimated that around 2.65 million stillbirths occur yearly worldwide. Fetal arrhythmias and subsequent hypoxic effects have been implicated in more than 10% of stillbirths [1], [2], with most of them occurring in low-income and middle-income countries. Electronic fetal monitoring aims to improve the outcome of pregnancies by continuously monitoring complications that can occur during pregnancy and help deliver the fetus safely. Non-Invasive fetal electrocardiography (NI-fECG) is one such promising and cost-effective solution.

In NI-fECG, the fetal electrocardiogram (fECG) is acquired from surface electrodes placed on the abdomen of the mother. Since the technique is non-invasive, it is safe and can be performed at any stage of pregnancy. However, detection of the fECG is highly challenging as the amplitude of the fECG signal is very weak at the abdominal surface, and is dominated by the maternal ECG (mECG). The spectrum of the mECG signal largely overlaps with the fECG and constitutes a significant portion of the energy of abdominal recordings. This problem is further complicated as the fECG signal strength depends on several other factors such as gestational week, fetal presentation, and electrode placement, for which no standard lead configuration has been defined [3].

Significant research has been devoted towards fECG extraction using techniques based on adaptive filtering [4], Kalman filtering [5], [6], blind source separation (BSS) [4], [7], [8], machine learning [9] and hybrid methods [10], [11]. The general approach of these techniques is to first cancel out the mECG component to extract the fECG, followed by the detection of fetal QRS (fQRS) complexes to obtain fHR. However, the performance of these techniques is strongly dependent on the quality of estimation of the mECG component. Most of these techniques do not incorporate any prerequisite information about ECG signals which makes them highly dependent on the quality of the recording.

The wavelet transform is another technique that has been sparsely explored for fECG analysis. Wavelets are a powerful tool used to analyse signals with a characteristic time-frequency behaviour, such as the ECG. Though its effectiveness in adult ECG analysis has been well demonstrated, it is mostly used for denoising in NI-fECG signal processing [12].

In this paper, a new method for the detection of fQRS complexes in single-channel NI-fECG recordings is proposed. Time-domain and time-frequency features are extracted from a pre-processed abdominal signal to detect fQRS complexes without cancelling out the mECG. This method leverages the different spectral characteristics exhibited by maternal and fetal QRS complexes to differentiate between them. The effectiveness of the proposed method is assessed using real and synthetic signals obtained from different datasets.

II. Methodology

The abdominal signal is first pre-processed to remove interferences. Each local maximum in the pre-processed abdominal signal is then identified as a candidate fQRS complex. A union of features from the time-domain, and time-frequency domain using wavelet analysis, are extracted and selected to represent each candidate. These features are used to determine whether the candidate is a true fQRS complex. Clustering is used to discriminate candidates as true fQRS complexes. The proposed framework is illustrated in Fig. 1.

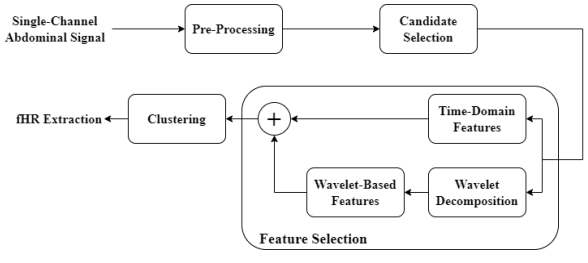

Fig. 1. Framework of the proposed method.

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A. Pre-Processing of the Abdominal Signal

A pre-processing step is used to band limit the abdominal signal and remove power-line interference. A 1000-tap FIR bandpass filter with a passband of 5 Hz - 150 Hz is applied to the abdominal signal. Power-line interference is removed using a 6$^{\text{th}}$ order notch filter centered at 50 Hz, with a quality factor of 20. Zero-phase filtering is done by applying the filters in both the forward and backward directions to preserve phase information. A higher-than-usual low-cutoff frequency of 5 Hz ensures that other noise sources, including maternal P and T waves, are suppressed without affecting the fQRS and mQRS complex (Fig. 2).

B. Feature Selection

Each local maximum in the pre-processed abdominal signal is identified as a potential R-peak candidate. A set of features in the time domain and time-frequency domain are extracted and selected to represent each candidate. These are explained below:

1) Time Domain Features: For good-quality abdominal recordings, the energy signature of the fQRS complex is distinguishable and sufficient to provide a good representation of true fQRS complexes. Since the R-peak of a QRS complex appears as a sharp transition with a large amplitude, the peak-to-peak amplitude, i.e., the magnitude difference between the local maxima and the following local minima, is selected as a feature. Additionally, since the fQRS and mQRS typically have different durations [13], the distance between the local maxima and the local minima is also selected to discriminate between them.

2) Time-Frequency Features: Time-frequency features are extracted using a wavelet analysis. A discrete wavelet transform (DWT) decomposes a signal $x[n]$ by passing it through a scaling filter $h[n]$ followed by decimation to obtain Approximation coefficients A, and through a wavelet filter $g[n]$ followed by decimation to obtain Detail coefficients D at the first level. This process is repeated on the approximation coefficient till the desired level of decomposition is achieved.

$$\begin{aligned} A_1[n] &= \sum_k x[k]h[2n-k] \\ D_1[n] &= \sum_k x[k]g[2n-k] \end{aligned} \tag{1}$$

As there is a decimation operation occurring at each level of decomposition, the DWT is shift-variant. Further, because of decimation, the length of the coefficients after each level of decomposition is halved, making it difficult to relate the wavelet coefficients with the abdominal signal against a common time axis. Hence, the stationary wavelet transform (SWT) is used instead, which is similar to the DWT, except that the down-sampling operation is removed by modifying the filters $h[n]$ and $g[n]$. The new filters $h[n]$ and $g[n]$ are up-sampled versions of the original filters. This modification retains the perfect reconstruction property of the SWT decomposition, producing coefficients of the same length as the signal at each level of decomposition.

The choice of the mother wavelet significantly affects the time-frequency representation. In general, a wavelet basis that is morphologically similar to the desired signal provides a useful representation of the signal in the wavelet domain. For ECG signals, the most widely used wavelet families are Daubechies, Symlets, Quadratic Splines and Biorthogonal wavelets [12]. Symlet wavelet of order 8 (sym8) is used in this paper due to its morphological similarity with the QRS complex.

For time-frequency features, SWT decomposition is performed using the sym8 wavelet up to six levels. The detail coefficients at the 6$^{\text{th}}$ level contains strong wavelet coefficients corresponding to the mQRS only, whereas detail coefficients at the 3$^{\text{rd}}$ and 4$^{\text{th}}$ levels contain strong wavelet coefficients corresponding to the fQRS complex. Hence, these wavelet coefficients are selected as features to identify and discriminate between fQRS and mQRS complexes. However, for the 3$^{\text{rd}}$ and 4$^{\text{th}}$ level detail SWT coefficients, the strongest coefficient is shifted randomly with respect to the location of the candidate, as shown in Fig. 3. This means that a candidate fQRS complex may be misrepresented in the wavelet domain, leading to

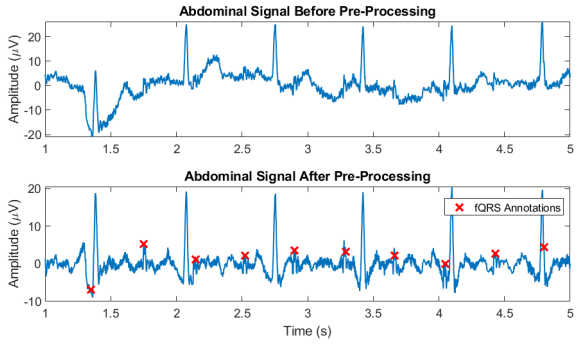

Fig. 2. Pre-processing of an abdominal signal. The abdominal signal is bandlimited between 5 Hz and 150 Hz, and power-line interference is removed using a notch filter centered at 50 Hz. Note in particular the suppression of maternal T-waves. fQRS annotations have been marked for reference.

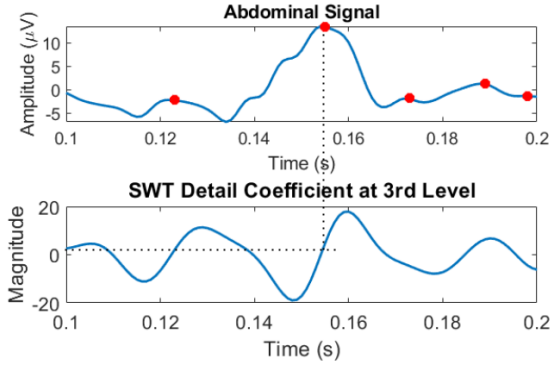

Fig. 3. Misrepresentation of candidate fQRS complexes due to the SWT Detail coefficient peak being shifted with respect to the candidate. In this case, for a true fetal R-peak, the magnitude of the selected wavelet coefficient is close to zero (dashed line), leading to erroneous classification.

erroneous classification. To correct this error, the nearest local maximum in the wavelet coefficients around the candidate is identified, and the corresponding peak-to-peak value is assigned as the corrected feature. The selected features are illustrated in Fig. 4.

This correction is not applied to the 6th level detail coefficients. The wavelet coefficients corresponding to the mQRS at this level are of a much higher magnitude compared to the 3rd and 4th levels. This allows the mQRS to be accurately represented by the 6th level detail coefficients alone, without being influenced by 3rd and 4th level detail coefficients.

C. fQRS Detection

The candidate fQRS complexes can be grouped into three categories based on the selected features as a true fQRS complex, an mQRS complex, or noisy samples. Clustering is used to group candidate fQRS complexes into one of these three categories based on the extracted feature set.

Clustering is an unsupervised learning technique that is used to classify objects into different groups, or clusters, by measuring the similarity between each object. Each object is represented by a set of features that are used to classify it into different clusters. Feature selection is an important step to ensure the quality of clustering. Many different types of clustering methods are available based on hierarchical or partitioning techniques [14]. Partitioning clustering based on the k-means algorithm is used in this work to group the set of candidate fQRS complexes into different non-overlapping clusters.

The relative similarity between objects is measured by using a distance function to compute the distance between them. Various distance measures such as cosine, Chebyshev and Manhattan are available. In our work, squared Euclidean distance is used as the distance measure since the feature set consists of one-dimensional data. The squared Euclidean distance is calculated as $D(x, y) = (x - y)^2$.

The clustering technique classifies each candidate into one of three groups, from which the cluster containing true

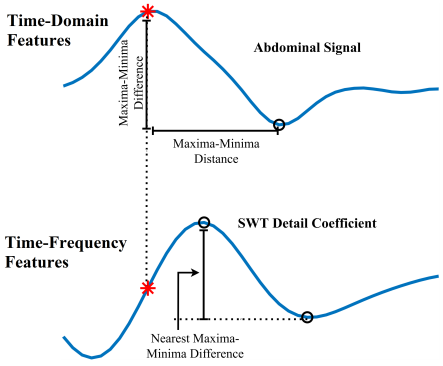

Fig. 4. Visual representation of feature selection. For a candidate fetal R-peak (*), the maxima-minima amplitude difference and distance are chosen as time-domain features. The maxima-minima difference of detail SWT coefficients at levels 3, 4 and 6 are used as time-frequency features. Features at levels 3 and 4 are corrected by selecting the *nearest* maxima-minima difference, as shown in the figure.

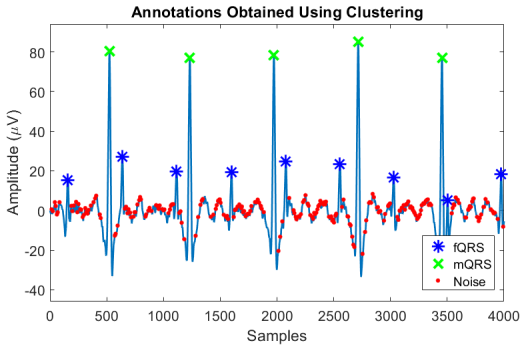

Fig. 5. Output of the classifier after clustering. Clustering is used to group candidate fQRS complexes as a true fQRS complex, mQRS complex or noise. The corresponding cluster for each group is identified based on the centroid value.

fQRS complexes is identified based on its centroid (Fig. 5).

D. Dataset and Validation

Abdominal and Direct Fetal ECG Database (ADFECGDB) [15] and test set-A of the Physionet Challenge 2013 Database (CinC 2013) [16], [17] are used for validation. ADFECGDB consists of 4-channel abdominal recordings sampled at 1KHz with 16-bit resolution. Signals were obtained from five different women in labour and each record is 5 minutes long. fQRS annotations are provided through the use of an invasive scalp electrode, which is considered the gold standard.

The CinC 2013 database consists of a collection of 75 real and synthetic abdominal recordings of one minute in duration. All signals provided in the dataset are re-sampled to 1 KHz as they have been obtained from various sources using different instrumentation. Few records have been noted to be of poor quality, either due to poor signal-to-noise ratio (SNR), or incorrect annotations [7], [18]. These records have been excluded from assessment.

Using reference annotations provided by these datasets, the performance of our method is evaluated on a total of 88-minutes of NI-fECG recordings or 12,090 fetal heartbeats, including 2,221 fQRS complexes that overlap with the mQRS complex. A detected fetal R-peak is considered a true fetal R-peak if it is located within 40 ms from the provided annotation [15], else it is marked as a false positive. The best-performing channel is chosen to represent the results of each record.

III. Results and Discussion

Based on the number of true positives (TP), false negatives (FN) and false positives (FP) obtained, the performance of our method is evaluated by calculating the Sensitivity (Se), Positive Predictive Value (PPV) and F1 score as follows:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{PPV} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{F1 score} = 2\,\frac{PPV \cdot Se}{PPV + Se}$$

TABLE I

PERFORMANCE COMPARISON OF THE PROPOSED METHOD WITH STATE-OF-THE-ART TECHNIQUES IN LITERATURE.

Method	Year	Dataset	Se (%)	PPV (%)	F1 Score (%)
Sequential Total Variation Denoising [7]	2016	CinC 2013	90.5	89.9	89.9
Kalman Filtering [6]	2017	CinC 2013	88.9	91.8	90.3
Clustering [19]	2018	ADFECGDB	92.2	96.0	94.1
Deep Learning [9]	2018	CinC 2013	89.1	92.8	90.9
Non-Negative Matrix Factorization [18]	2019	ADFECGDB CinC2013	95.3 -	94.6 -	94.8 84.0
Ensemble Empirical Mode Decomposition [11]	2021	ADFECGDB CinC2013	95.1 81.8	96.4 87.2	95.7 84.1
Independent Component Analysis [8]	2022	ADFECGDB	84.3	82.9	84.2
Dual Path Source Separation [20]	2022	CinC 2013	94.2	96.5	95.3
Proposed Method	**2022**	**ADFECGDB** **CinC 2013**	**96.3** **91.7**	**85.9** **84.4**	**90.4** **87.6**

The average performance of the proposed method is summarized and compared with the state-of-the-art in Table. I. Our method obtained an average sensitivity, PPV, and F1 score of 96.3%, 85.9%, and 90.4% respectively on ADFECGDB, and 91.7%, 84.4%, and 87.6% respectively on the CinC2013 datasets. The results indicate the ability of our technique to detect fQRS complexes with high sensitivity.

In regions where the SNR of the fECG to noise is poor, our method struggles to distinguish between true fQRS complexes and noise. These noisy segments contain many local maxima, and hence more candidate fQRS complexes. These candidates are misclassified resulting in a larger number of FPs and a lower PPV. However, the obtained F1 score suggests that our method performs well without significantly compromising on the false positivity rate. Implementing a post-processing step that employs signal quality metrics for classification can reduce the number of FPs obtained, improving the PPV.

The use of wavelet-based features in this work exploits the spectral behaviour of fQRS complexes for their detection. The normal duration of an mQRS complex is 80-100 ms, whereas the normal duration of an fQRS complex is 30-60 ms [13]. Since the underlying physiological phenomena producing the QRS complex is the same for both the mother and the fetus, the fQRS complex can be considered as a compressed version of the mQRS in the time domain, or a dilated version of the mQRS in the frequency domain (Fig. 6). Hence, strong wavelet coefficients corresponding to the fQRS are observed at the 3rd and 4th level of decomposition, and the proposed method is able to detect fQRS complexes even in cases where it completely overlaps with the mQRS, allowing us to achieve higher sensitivity.

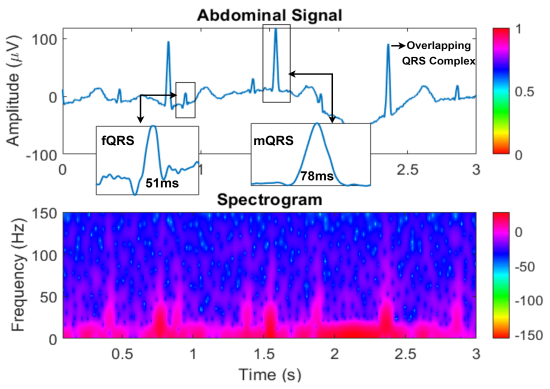

Fig. 6. Abdominal recording (taken from ADFECGDB) and corresponding spectrogram. The fQRS and mQRS durations are 51 ms and 78 ms respectively. Note the higher frequency characteristics of the fQRS, which can also be identified in case of overlapping QRS complexes.

IV. CONCLUSION

A new method for the automated detection of fQRS complexes in single-channel NI-fECG recordings is presented in this paper. The proposed method combines time-domain and time-frequency features to directly identify fQRS complexes without the need for mECG cancellation. The method's performance was validated on real and synthetic abdominal recordings from various datasets. The obtained results demonstrate the ability of our method to reliably detect fQRS complexes, even in cases where it overlaps with the mQRS. This is achieved at a significant reduction in computational complexity when compared to other state-of-the-art techniques in literature, without considerably compromising on the false positivity rate. The use of time-frequency features exploits the spectral characteristics of NI-fECG recordings, which may be extended for the analysis of fetal P-waves and T-waves. Incorporating the spectral behaviour of the characteristic fECG waves into fECG extraction techniques may allow further morphological analysis, which is important for characterizing various types of fetal arrhythmias.

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