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Low-complexity R-peak detection in ECG signals: A preliminary step towards ambulatory fetal monitoring

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Abstract— **Non-invasive fetal health monitoring during pregnancy has become increasingly important. Recent advances in signal processing technology have enabled fetal monitoring during pregnancy, using abdominal ECG recordings. Ubiquitous ambulatory monitoring for continuous fetal health measurement is however still unfeasible due to the computational complexity of noise robust solutions. In this paper an ECG R-peak detection algorithm for ambulatory R-peak detection is proposed, as part of a fetal ECG detection algorithm. The proposed algorithm is optimized to reduce computational complexity, while increasing the R-peak detection quality compared to existing R-peak detection schemes. Validation of the algorithm is performed on two manually annotated datasets, the MIT/BIH Arrhythmia database and an in-house abdominal database. Both R-peak detection quality and computational complexity are compared to state-of-the-art algorithms as described in the literature. With a detection error rate of 0.22% and 0.12% on the MIT/BIH Arrhythmia and in-house databases, respectively, the quality of the proposed algorithm is comparable to the best state-of-the-art algorithms, at a reduced computational complexity.**

I. INTRODUCTION

Fetal heart rate (fHR) monitoring and derivation of the fetal electrocardiogram (fECG) are important means to assess fetal distress during pregnancy and delivery. Currently used methods are however not suited for long term observation throughout pregnancy. The most commonly used methods for fHR monitoring either use Doppler ultrasound, or a fetal scalp electrode as part of a cardiotocogram (CTG), which also includes intrauterine pressure measurements. While allowing for non-invasive measurements, doppler ultrasound measurements introduce energy into the body and need continuous attention of a trained physician, making it unsuitable for long term observation [1]. Furthermore, in many situations the measurements do not provide conclusive information for accurate assessment of fetal health and, therefore, additional information is needed for clinical decision-making [2]. FHR monitoring using an invasive scalp electrode, while giving very accurate ECG readings and an unsmoothed fHR measurement, needs rupturing of the membrane and can therefore only be applied during delivery.

Recently published methods enable monitoring of fHR and fECG non-invasively using abdominal contact electrodes [3], [4], [5]. However, the signal has a reduced SNR compared to the use of a fetal scalp electrode, with the maternal electrocardiogram (mECG) as the predominant interference. The method proposed in [4] removes the mECG to increase the SNR implementing the following steps: 1) preprocessing, 2) maternal R-peak detection, 3) mECG estimation, and 4) mECG substraction. The resulting signal can be used for fetal R-peak detection with results comparable to those obtained using a scalp electrode [4]. Because of the high quality results compared to other methods, e.g. spatial and adaptive filtering, template substraction, and ICA, we used this method as a baseline reference. Continuous monitoring of the fetus in an ambulatory setting using this method is however still unfeasible, due to its computational complexity.

In an effort to reduce the complexity and increase the HR detection quality of [4], we propose an algorithm to replace the formerly used R-peak detection algorithm in [4], which was based on [6]. The preprocessing stage of [6] contains a length transform, composed of consecutive differentiation, absolute value, and integrator stages, to emphasize the features of the QRS complex. Because of the high-pass filtering effect of the differentiation, the method described in [6] is very sensitive to measurement noise and requires pre-filtering, especially on measurements obtained in an ambulatory setting. Therefore, a single FIR filter with a length of 1 s is used in [4], combining a high-pass (HP), low-pass (LP), and notch filter at 2 Hz, 100 Hz and 50 Hz, respectively. The decision stage is based on thresholding, where the height of the threshold is dependent on the absolute local signal amplitude of the preprocessed waveform. The proposed R-peak detection algorithm, which is based on the discrete-time continuous wavelet transform (DT-CWT), reduces the overall computational complexity, while increasing the R-peak detection quality of the maternal ECG. The algorithm is described in Section II after a short introduction of the DT-CWT. Section III discusses the abdominal recordings used for validation as well as details on the methodology of this comparison. The comparison results are shown in Section IV, followed by a discussion and conclusion in Section V.

II. R-PEAK DETECTION ALGORITHM

Algorithm design for detection of the QRS interval in an ECG signal has been a topic of research for the past four decades, and a large number of algorithms exist of which an overview is given in [7]. The most promising group of algorithms is based on the wavelet transform, an approach which has been widely researched, e.g. in recent studies by Li [8], Martinez [9] and Romero Legarreta [10], [11]. These studies show that wavelet based algorithms provide high detection quality at low computational complexity. The DT-

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CWT has proven to be of particular interest to measurements obtained in an ambulatory setting, giving an overall superior performance compared to discrete wavelet transform based methods [11].

Based on the DT-CWT as described in Section II-A, a new R-peak detection algorithm was designed using a Mexican hat wavelet, as proposed in [10]. The algorithm can be divided in a number of successive steps, grouped in preprocessing and R-peak detection stages, as shown in the block-diagram in Fig. 1.

A. Discrete-Time Continuous Wavelet Transform

A wavelet function $\varphi[n]$ can be any localized waveform which has finite energy and a zero mean [12]. We can then define the DT-CWT of a signal $x[n]$ with respect to a wavelet function $\varphi[n]$ as:

$$CWT[\tau] = \frac{1}{\sqrt{s}} \sum_{n=-\infty}^{\infty} x[n] \cdot \varphi\left[\frac{n-\tau}{s}\right], \tag{1}$$

where the 'translation' parameter τ gives the location in time and the 'dilation' parameter s is a scaling factor, changing the characteristic frequency of the wavelet at location τ.

The DT-CWT has a band-pass filtering effect, which allows signal components within a finite range of frequencies, characterized by the energy spectrum of the wavelet function $\varphi[n]$, to pass. In the proposed algorithm, the second derivative of the Gauss function, also referred to as Mexican hat function, is used as wavelet function $\varphi[n]$. The Mexican hat function is defined as:

$$\varphi[n] = (1-n^2)e^{-\frac{n^2}{2}}, \tag{2}$$

where n is in the range $\Delta n = [-4,\ 4]$ samples. This range results in minimal computational complexity while retaining the required accuracy at the edges. The peak frequency of the wavelet's band-pass filtering effect depends on the wavelet scale s and the signal sampling frequency f_s as follows:

$$f_p = \frac{s_{f_c} \cdot f_s}{s}, \tag{3}$$

where s_{f_c} is the relative center frequency of a specific wavelet. For the Mexican hat wavelet $s_{f_c} = \frac{\sqrt{2}}{2\pi} = 0.225$ [12].

B. Preprocessing

The preprocessing stage consists of a DT-CWT of the ECG signal with the Mexican hat wavelet. To reduce the computational complexity of the algorithm, only a single scale s is used in the wavelet analysis. The peak frequency f_p of the wavelet is chosen at 17 Hz, centered in the $10-25$ Hz frequency band, which contains most of the QRS energy of the mECG [7]. This reduces the DT-CWT to a convolution with a single wavelet, which has a support width $\Delta_s = \Delta n \cdot s_{f_c}/f_p = 53$ ms.

Subsequently the absolute value of the wavelet analysis output is taken, resulting in the output signal S. This allows for the use of a single threshold in the following R-peak detection stage, independent of the orientation of the cardiac vector with respect to the electrode position.

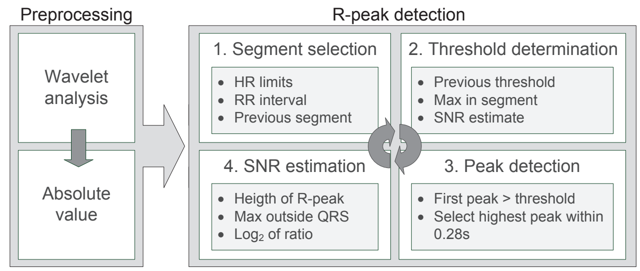


Fig. 1. Block-diagram of the proposed R-peak detection algorithm.

C. R-Peak detection

The R-peak detection part of the algorithm consists of four consecutive stages, which are executed in a iterative process, as shown in the right part of Fig. 1. These stages are, in order, 1) segment selection, 2) threshold determination, 3) peak detection and 4) SNR estimation.

1) Segment selection: To increase the quality of the subsequent threshold determination, the boundaries of the signal segment are chosen, based on previously found R-peak positions, such that the segment is expected to contain exactly one R-peak. Different from [13], where segment selection is used to reduce the computational complexity, this is done to increase the quality of the subsequent R-peak detection. The minimum and maximum segmentation sizes are defined by the allowed HR, which the algorithm assumes to be in the range of 36 - 210 beats per minute.

2) Threshold determination: For each segment a threshold value T is calculated based on the previous threshold value T_{prev} and a new threshold estimate $\widehat{T}$, using the following auto regressive (AR(1)) process:

$$T = \alpha \cdot \widehat{T} + (1-\alpha) \cdot T_{prev}, \tag{4}$$

where $\alpha = 1/3$, which was found experimentally, indicates the dynamic behavior of the threshold. Here $\widehat{T} = N \cdot S_{max}$, where S_{max} is the maximum value in the current preprocessed signal segment and N is the estimated local noise level as defined in Section II-C.4.

3) Peak detection: Within the selected signal segment, a peak position candidate $\widehat{p}$ at time t is selected as the first preprocessed sample crossing the threshold T. The search segment is now reduced to an interval starting at $\widehat{p}$, defined by $\mathrm{HR}_{\mathrm{max}}$, which is 0.28 s for the mECG. Within this interval, a new sample $\widehat{p}+1$ is selected as the new $\widehat{p}$ if $S[\widehat{p}+1] \geq S[\widehat{p}]$.

It is possible that no R-peak $\widehat{p}$ is selected in the current segment. In this case, a new search at the current segment location is performed up to three times, where with each try, the end of the search segment is extended and the threshold value T is reduced by half.

4) SNR estimation: Once an R-peak has been detected, an estimate of the signal-to-noise ratio ($\widehat{\mathrm{SNR}}$) after preprocessing, around the last R-peak position, is calculated according to:

$$\widehat{\mathrm{SNR}} = \log_2(S[\widehat{p}]) - \log_2(I_{max}), \tag{5}$$

where I_{max} is the maximum in S in the two intervals $\widehat{p} \pm [50, 250]$ ms. This is the maximal fixed-length segment without QRS-complex, taking $\mathrm{HR}_{\max}$ into account, and assuming correct detection of $\widehat{p}$. To reduce computational complexity in integer based implementations, $\log_2$ is used in (5). A noise level N indicative of the local SNR is deduced by:

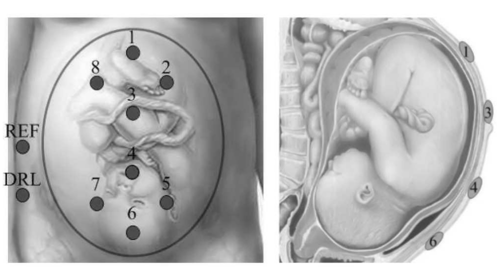
$$N = \frac{N_{prev} + \text{median}\left[\frac{1}{3}, \frac{\left(5-\widehat{\mathrm{SNR}}\right)}{6}, 1\right]}{2}, \tag{6}$$

where N_{prev} is the noise level around the previous R-peak. The noise level is in the range of $N = \left[\frac{1}{3}, 1\right]$, where a low value of N indicates minimal noise level, while $N \geq 5/6$ indicates an $\widehat{\mathrm{SNR}}$ below 0 dB.

III. VALIDATION

Validation of the algorithm was done by comparing the algorithm results with manually annotated R-peak locations on two sets of recordings, measured on the chest and abdomen, respectively. The first set consists of the whole MIT/BIH Arrhythmia database (MITDB) [14], containing 48 thoraxial measurements of 30 min each, sampled at 360 Hz. This dataset was used for comparison with state-of-the-art algorithms as described in literature. The whole MITDB was used for validation, with the exception of some segments in record 207, which are annotated to contain ventricular flutter episodes [13]. The second set consists of an in-house database (IHDB) with a total length of 9.5 hours, comprising 21 abdominal measurements from women during labor at various ages of gestation. These data were collected at the Máxima Medical Centre in Veldhoven (The Netherlands) as described in [15], after which all maternal R-peaks were annotated manually. Each measurement in the IHDB was recorded using the electrode configuration shown in Fig. 2, with eight channels, each sampled at 1000 Hz. For each file in both datasets a single lead was selected for algorithm comparison. For the MITDB lead II was used, while the first principle component was used in the IHDB.

For both the MITDB and IHDB datasets, a comparison was made in R-peak detection quality as well as computational complexity. The detection error rate (D_e) is used to quantify the detection quality of the algorithm and to allow for a comparison with other algorithms from literature. D_e is defined as:



(a) (b)

Fig. 2. Electrode configuration: (a) front view and (b) side view. (Modified from [15])

$$D_e = \frac{FP + FN}{TP + FN}, \tag{7}$$

where TP is the number of correctly detected peaks (true positive), FN is the number of missed peaks (false negative), and FP is the number of falsely detected peaks (false positive). In line with previous studies, a peak is considered to be correctly detected if it is located within a ± 100 ms interval around the annotated peak position [13], [16]. Additionally, the positive predictivity $+P = TP/\left(TP + FP\right)$ and sensitivity $Se = TP/\left(TP + FN\right)$ are used as comparitive quality measures.

The average number of multiplications per sample (MPS) is used as a measure of computational complexity. All operations with a complexity higher than a multiplication (m), e.g. a division or square root, are represented by multiple multiplications. Both operations have a complexity in the order of $m \cdot O\left[n\right]$, where n is the accuracy of a value in number of bits. Assuming an accuracy of 16 bits for both numerator and denominator, a division and square root are substituted by 9 and 17 multiplications, respectively [17]. All simple operations, e.g. addition, substraction or bit-shift, are left out of consideration.

IV. RESULTS

Fig. 3 shows an example of an ECG signal segment as well as the corresponding output of the preprocessing stage.

Table I shows an overview of recent state-of-the-art R-peak detection algorithms on both quality and computational complexity for the MITDB. The quality comparison is based on the results presented in literature by the various authors, while the computational complexity for each of the algorithms is estimated based on the algorithm description or available MATLAB code.

Table II shows a comparison in both quality and computational complexity between Vullings [4], Romero [11] and the presented algorithm for the IHDB, all of which are based on a best effort implementation of each of the algorithms.

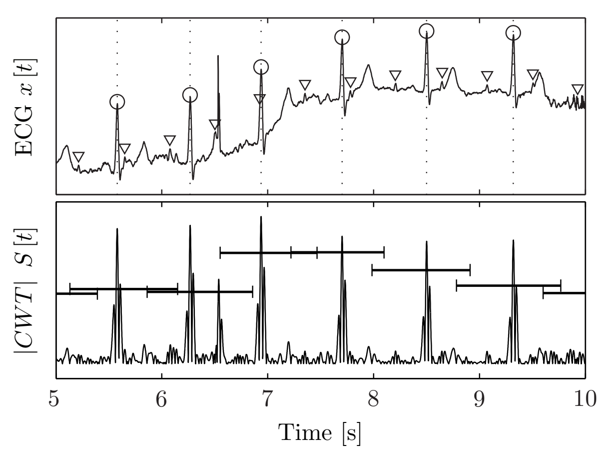


Fig. 3. Example of an ECG signal segment (top), where $\odot$ and ∇ indicate the maternal and fetal R-peaks respectively, The dotted lines indicate the detected maternal R-peaks. The horizontal bars in the prepocessing output (bottom) indicate the threshold level for each of the used segments.

TABLE I

COMPARISON OF THE PRESENTED R-PEAK DETECTION ALGORITHM WITH ALGORITHMS FROM LITERATURE ON THE MITDB

	$Se\,(\%)$	$+P\,(\%)$	$D_e\,(\%)$	MPS
Li et al. [8] [ac]	99.89	99.94	0.17	140
This work	**99.90**	**99.88**	**0.22**	**65**
Martinez et al. [18] [c]	99.80	99.86	0.34	110
Romero Legarreta [11] [b]	99.65	99.79	0.56	103
Vullings et al. [4]	99.62	99.82	0.56	439
Pan-Tompkins [19] [ac]	99.75	99.54	0.71	72
Madeiro et al. [13] [c]	98.47	98.96	2.56	40

[a] Se, $+P$ and D_e recomputed due to discrepancy in presented results
[b] Subset of MITDB used.
[c] Complexity estimates based on description in literature.

TABLE II

COMPARISON OF THE PRESENTED R-PEAK DETECTION ALGORITHM AND BEST-EFFORT IMPLEMENTATIONS OF [4], [11] ON THE IHDB

	$Se\,(\%)$	$+P\,(\%)$	$D_e\,(\%)$	MPS
This work	**99.93**	**99.95**	**0.12**	**135**
Romero Legarreta [11]	99,89	99,94	0.16	260
Vullings et al. [4]	99.89	99.83	0.28	1130

V. DISCUSSION

A high-quality computation-efficient R-peak detection algorithm was developed based on the DT-CWT, combining high quality R-peak detection with a low computational complexity. The algorithm quality, defined by the detection error rate D_e, is quantified by measuring correct and false heartbeat detections on both thoraxial and abdominal measurements from the MITDB and IHDB, respectively.

Tables I and II show that the presented algorithm has an R-peak detection quality comparable to or better than other state-of-the-art algorithms in literature, at a reduced computational complexity. Compared to the R-peak detection algorithm in [4] a decrease in D_e over 50% and an 85% reduction in computational complexity on both thoraxial and abdominal measurement data is obtained. A reduction in both D_e and complexity can also be observed compared to other recent DT-CWT based R-peak detection algorithms. The increase in detection quality is due to the use of dynamic segmentation as well as SNR dependent thresholding. Despite these additions, the overall computational complexity of the algorithm is low because of the application of the DT-CWT, using a Mexican hat wavelet at a single scale. Only the algorithm by Li [8] achieves a slightly higher detection quality than the presented algorithm on the MITDB. However, because of the use of the discrete wavelet transform (DWT) with a quadratic-spline wavelet at multiple scales, as well as significant post processing, the complexity is higher than that of the presented algorithm. Furthermore, DT-CWT R-peak detection methods are claimed to be more robust to noise than the DWT as used by Li, making the proposed algorithm more suitable for use in an ambulatory setting [11].

We have presented a low-complexity algorithm with high quality R-peak detection results, which is suitable for continuous ambulatory monitoring. Although good results have been shown on both thoraxial and abdominal measurements for detection of the maternal R-peak, these signals were recorded while the patient was stationary. In an ambulatory setting motion artifacts will become more predominant and significant work is necessary before ambulatory ECG detection is feasible. Our future work will therefore focus on extending the algorithm for fECG detection while optimizing it for high detection quality in noisy recordings at a low complexity. This will in part be achieved by refining the wavelet analysis method, evaluating other wavelet shapes including a dynamicly changing wavelet shape. Eventually the algorithm will be extended to include detection and analysis of uterine activity using abdominal measurements, in order to get a better estimate of the fetal health.

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