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Fetal Heart Rate Detection Using First Derivative of ECG Waveform and Multiple Weighting Functions

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***Abstract*— Fetal heart rate monitoring using the abdominal electrocardiograph (ECG) is an important topic for the diagnosis of heart defects. Many studies on fetal heart rate detection have been presented, however, their accuracy is still unsatisfactory. That is because the fetal ECG waveform is contaminated by maternal ECG interference, muscle contractions, and motion artifacts. One of the conventional methods is to detect the R-peaks from the integrated power of the frequency corresponding to the fetal heartbeats. However, the detection accuracy of the R-peaks is not enough. In this paper, we propose a method to generate the candidates of R-peaks using the first derivative of the signal and to pick up the estimated heartbeats by a multiple weighting function. The proposed multiple weighting function is designed by the Gaussian distribution, of which parameters are set from a grid search with the goal of minimizing the standard deviation of RR intervals (neighboring R-peaks intervals). The validation for the proposed framework has been evaluated on real-world data, which got the better accuracy than the conventional method that detects R-peaks from the integrated power and uses the weighting function produced by a fixed parameter of Gaussian distribution [12]. The averaged absolute error (AAE) which compares the estimated fetal heart rate and the reference fetal heart rate has been decreased by 17.528 bpm.**

***Index Terms*— Non-invasive ECG recordings, fetal electrocardiogram, fetal heart rate, weighting function,**

I. INTRODUCTION

Fetal heart rate is an important indicator for evaluating the health status of the fetus [1]. Fetal heart rate can be used to identify possible abnormalities, during the early stages of pregnancy and delivery, such as distress and congenital heart disease [2] [3]. Therefore, improving the accuracy of fetal heart rate detection is of great significance for diagnosis purposes.

To collect data, there are usually two methods, where the invasive method is a reliable way to collect electrocardiogram (ECG) recordings from the scalp. However, this method can only be used when the fetal membranes have ruptured. Moreover, it may cause discomfort to the mother and injury to the fetus [5]. For non-invasive methods, so far, the most standard technology to collect the recording is based on the Doppler ultrasound (US) by a US transducer fixed on the maternal abdomen. This is widely used to monitor fetal heart rate (FHR) as an economic and user-friendly tool [4]. However, the system will not record any samples when the fetus or mother is moving [6], which will cause the accuracy of the fetal heart rate detection to decrease [7]. Moreover, the ultrasound may have negative effects and it is unfavorable for long-term monitoring [8]. One of the other non-invasive methods for monitoring fetal heart rate is to use abdominal ECG. However, since the abdominal ECG is contaminated by maternal ECG signal, muscle contraction, fetal brain activity, and other noise, abdominal ECGs require advanced signal processing to overcome the problem of low signal-to-noise ratio (SNR). Therefore, it is not easy to accurately estimate the position of the fetal R-peaks and fetal heart rates. Another major problem is that when the fetal R wave overlaps with the maternal R wave, it can be lost because the maternal R wave is extremely large.

Various related works on fetal heart rate extraction are proposed. To develope accurate methods for FHR detection, the PhysioNet/CinC Challenge 2013 was held [9]. In other examples, the methods using blind source separation (BSS) for separating mixture signals are discussed in the literature [10], [11]. The single-set BSS methods include independent component analysis (ICA). However, the noise is usually independent among each electrode, and the nonlinearity of the mixed observation signals increases. Thus, the extraction of the mixed observation would be incomplete and it is difficult to extract the fetal signal. In another example, the weighting mask for enhancing the hidden fetal R-peaks is introduced in [12]. The R peaks are selected by detecting the integrated power in the frequency corresponding to the candidate heartbeat. The R peaks are enhanced by the weighting mask according to the distribution of the neighboring temporal intervals between each pair of peaks. In addition, the parameters of the weighting mask function are determined by the prior information of the position and the interval of each candidate. To improve the effectiveness of weight, an adaptive weighting will be used for the estimation of parameters.

In this paper, we propose a method using the first derivative of the ECG signal and the multiple weighting function to improve the accuracy of fetal heart rate detection. The approach allows us to generate the candidate R-peaks using the first derivative of the signal and pick up the estimated heartbeats by a weighting function. The proposed multiple weighting function is designed by the Gaussian distribution, of which parameters are adaptively set from a grid search with the goal of minimizing the standard deviation of RR interval. The experiment was designed in four scenarios, which considered a combination of two methods for generating candidate peaks and two weighting functions. Two methods

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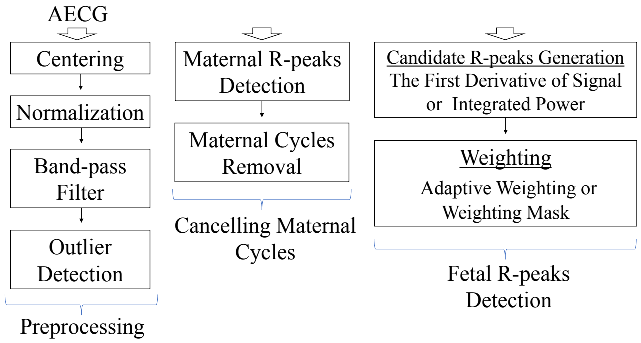

Fig. 1. A block diagram of the proposed framework.

of generating the candidate peaks are the method of using the first derivative of the signal and the integrated power. As for the weighting functions, one of them is the multiple weighting function designed by the Gaussian distribution, and its parameters are adaptively set from a grid search. Another method is to use the weighting mask, which is introduced in [12] in combination with the integrated power method to generate candidate R peaks. It is shown that the method using the first derivative of the ECG signal and the multiple weighting function significantly improves the accuracy of the fetal heart rate detection.

The organization of this paper is as follows. The proposed method is introduced in Section II, and Section III shows the experimental setup and the corresponding results. Finally, the conclusions are given in Section IV.

II. PROPOSED METHODS

The architecture of the proposed framework is illustrated in Fig. 1. The details of each step will be introduced below.

A. Preprocessing

In the first step, since the output of the A/D converter is contaminated, the preprocessing is performed to remove saturated data and invalid data from the raw abdominal ECG. In this process, the centering operation is performed by subtracting the mean of the signal, and normalization is performed to set the amplitude between -1 and 1. We implement the band-pass filter between 2 and 46 Hz to remove the noise interference using a linear-phase Kaiser window. Spike values are removed using the algorithm presented in [13], because the outliers affect the fetal heart rate detection.

B. Maternal cycle removal

An algorithm presented in [14] is considered for removing the maternal cycle. The approach first extracts the maternal R-peaks from the preprocessed AECG. After the locations of maternal R-peaks are detected, the maternal cycles are removed from the AECG by a template. The template is built centered on the maternal R-peak with a duration.

Because the AECG is non-stationay, the template is updated by integrateing cycles while removing the contribution of the oldest QRS complex. To deal with mis-detections, incoming cycles that do not match with the template are rejected. The correlation coefficient denoted as C between the template cycle and an incoming cycle is calculated. This is fomulated as

$$C = \frac{\sum_{j=1}^{n}(t_j-\bar{t})(m_j-\bar{m})}{\sqrt{\sum_{j=1}^{n}(t_j-\bar{t})^2(m_j-\bar{m})^2}}, \tag{1}$$

where t is the template cycle and m is incoming MECG cycle. $\bar{t}$ and $\bar{m}$ are their mean value, and n is the number of the maternal peaks. An incoming cycle of which C is less than 0.8 will be not used to update the template cycle t. After removing the maternal cycles, we call it the residual signal.

C. Fetal R-peaks detection

As we can see from the schematic diagram of the proposed framework in Fig. 1, to detect fetal heart rate, we first generate the candidates of the R-peak. Next, by designing a weighting function, we can detect the fetal R-peaks from the candidates. In this section, we introduce two methods to generate candidate peaks, which are the way using the first derivative of the signal and the integrated power. In addition, two weighting functions called multiple weighting and the weighting mask are designed. The weighting mask algorithm has been presented in [12].

1) Generating the candidates of R-peaks: (1-1) Using the first derivative of the residual signal : One of the methods to generate the candidate peaks is to calculate the first derivative of the signal, which is denoted as S. The fetal R-peak candidates calculated according to the residual signal are given by

$$S = \frac{f'(t)}{\mathrm{std}(f'(t))}, \tag{2}$$

where $f'(t)$ is the first derivative of the residual signal, and $\mathrm{std}(f'(t))$ is the standard deviation of $f'(t)$.
(1-2) Using the integrated power : Another way of detecting the candidates is to select the peaks of the integrated power in the frequency domain corresponding to the candidate heartbeat. The short-time Fourier Transform (STFT) is applied to obtain the time-frequency spectrogram of the residual signal in the form of

$$F(\omega,t) = \int_{\infty}^{\infty} f(\tau)w_1(\tau-t)e^{-j\omega\tau}d\tau, \tag{3}$$

where $f(t)$ is the residual signal and $w_1(\tau)$ indicates the Hanning window. We calculate the integrated power in the selected frequency from 20 to 50 Hz.

$$g(t) = \int_{20}^{50}\int_{\infty}^{\infty} f(\tau)w_1(\tau-t)e^{-j\omega\tau}d\tau df. \tag{4}$$

2) The multiple weighting method and the weighting mask: Based on the assumption that the RR interval follows a Gaussian distribution, the amplitudes of the peaks are weighted. The peak with the maximum amplitude value within the window length is selected as the estimated R-peak. The window is slid from this location as the base point, of which length is 2 seconds. The weighted amplitude of each candidate peak denoted as $Weightedpeak(\tau)$ is expressed as

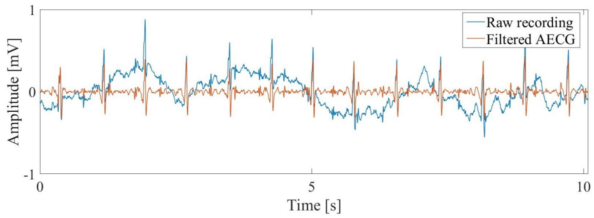

Fig. 2. The raw recording and filtered AECG.

$$Weighted peak(\tau) = w_2(\tau - \iota) \cdot r(\tau), \tag{5}$$

where the Gaussian distribution is represented as a function $w_2(t)$. τ is the location of candidate peaks. ι is the previously estimated location. The amplitude of the candidate is denoted as $r(\tau)$. We adaptively select the parameters of the Gaussian distribution by changing the value of the mean μ and the standard deviation σ. μ is taken in 10 steps from 350 to 480, and σ is taken in 5 steps from 0 to 50. The range of μ is taken from the possible fetal heart rate. As a result, the number of pairs of μ and σ is 154, and we get 154 sets of the estimated R-peaks. For all of these sets of the estimated R-peaks, we calculate the standard deviation of RR intervals. Finally, we select the set of estimated R-peaks of which the standard deviation of RR intervals gives the minimum value.

The second method of weighting, the weighting mask is generated according to the distribution of the neighboring temporal intervals between each pair of peaks [12]. The weighting is formulated as

$$h_{mask,i}(t-\tau_i) = h_i(|t-\tau_i|) + \frac{1}{2}h_i\left(\frac{|t-\tau_i-t_i|}{2}\right) + \frac{1}{3}h_i\left(\frac{|t-\tau_i-2t_i|}{3}\right), \tag{6}$$

where τ_i is the location of the candidate peaks and t_i is the length of the interval between the neighboring candidate peaks. The function $h(t)$ is the Gaussian function, of which the mean is 0 and the standard deviation is 1 according to the conventional method [12]. $h_{mask,i}$ is the base of the weighting function generated from each candidate peak. The masking weighting function is represented as

$$Mask(t) = \frac{\sum_{i=1}^{N} h_{mask,i}(t-\tau_i) - e_l}{e_u - e_l}, \tag{7}$$

where N is the number of the bases of the weighting function, e_u is the upper envelope and e_l is the lower envelope of the sum of the bases of weighting function. $Mask(t)$ is built by summing all the bases of the weighting function expressed as Eq. (7).

III. Experiment

A. Data Description and measurement

We used the abdominal ECG signals of ten subjects, which were recorded by the non-invasive sensor placed on the expectant mother's abdomen. The recording of duration is 60 s, and the sampling frequency is 1kHz. The data and

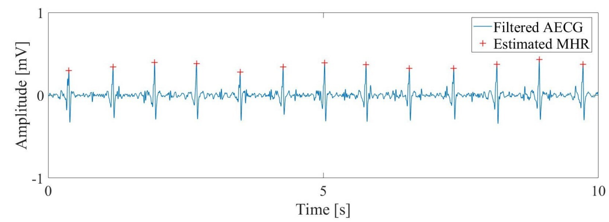

Fig. 3. The filtered signal and the locations of estimated maternal R-peaks.

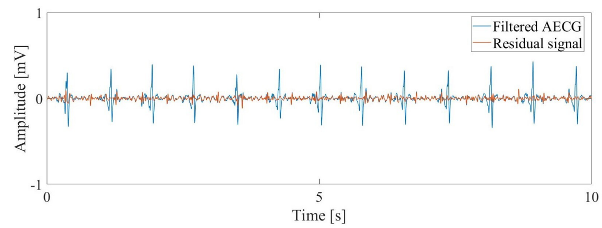

Fig. 4. The filtered signal and the residual signal.

the reference annotation were obtained from Atom Medical Corporation and associated medical experts, in terms of the fetal heart rate and the fetal RR interval. We used these annotations to evaluate the performance of the proposed framework for fetal HR detection.

We consider the averaged absolute error (AAE) which compares the estimated fetal heart rate and the reference fetal heart rate given by

$$\mathrm{AAE}(\mathrm{FHR}, \widehat{\mathrm{FHR}}) = \frac{1}{L}\sum_{i=1}^{L}\left|\left|\frac{60 \cdot f_s}{\mathrm{FRRI}_i} - \frac{60 \cdot f_s}{\widehat{\mathrm{FRRI}}_i}\right|\right|, \tag{8}$$

where $\widehat{\mathrm{FHR}}$ is the estimated fetal heart rate and FHR is the corresponding reference FHR. L is the number of fetal heart rates. The estimated fetal RR interval is denoted as $\widehat{\mathrm{FRRI}}$, and FRRI is the corresponding reference.

B. The experimental setup

We introduce the figure of the signal for each step of the framework as shown in Fig. 1. Fig. 2 shows the raw recording and the filtered AECG after preprocessing. Fig. 3 shows the filtered signal and the location of the estimated maternal R peaks, and Fig. 4 shows the filtered signal and the residual signal after maternal cycle removal. We show the residual signal and the figure of S with the location of the estimated fetal R-peaks and the reference annotations of fetal R-peaks in Fig. 5 and Fig. 6. Some of the reference annotations cannot match the peaks found in the residual signal and S. In contrast, we can see that the reference annotations match the estimated fetal R-peaks.

The experiment was designed in four scenarios, which considered a combination of two methods for generating candidate peaks and two weighting functions. Two methods for generating the candidate peaks consist of the method using S and the integrated power. As for the methods for weighting, one of the two methods is the multiple weighting function designed by the Gaussian distribution of which parameters are adaptively set from a grid search. The other method is the way to use the weighting mask. The details are listed below.

TABLE I
AAE [BPM] BETWEEN THE ESTIMATED FHR AND THE REFERENCE FHR.

Subject		A	B	C	D	E	F	G	H	I	J
AAE [bpm]	(1)	**2.4428**	**3.8199**	**3.1244**	**3.8198**	**1.8117**	2.4006	1.4616	**3.8203**	**4.7094**	1.6335
	(2)	5.5411	13.0182	4.4551	5.6386	1.8705	**1.0382**	**1.4291**	5.0900	6.2455	**1.4882**
	(3)	11.560	10.980	9.8638	7.5354	8.6740	9.1705	10.570	17.455	11.075	14.976
	(4)	19.107	16.365	18.287	13.240	14.271	14.688	16.906	17.351	22.237	13.981

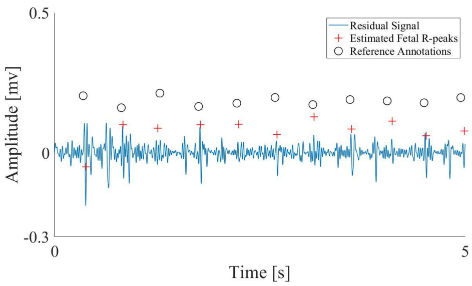

Fig. 5. The residual signal with the location of the estimated R-peaks and the reference annotations of fetal R-peaks.

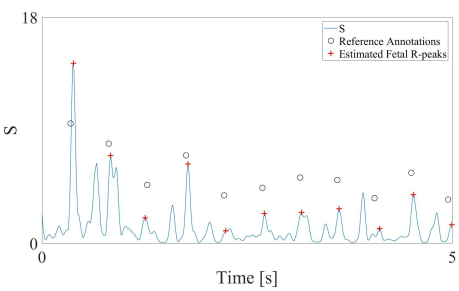

Fig. 6. S and the reference annotations of fetal R-peaks.

(1) The first item introduces the scheme in which the derivative function S is considered to generate candidate R-peaks, and the multiple weighting function designed by the Gaussian distribution is associated.
(2) The second item introduces the scheme, which is also composed of a derivative function S to generate candidate R-peaks, but the weighting uses the weighting mask function defined in Eq. (7).
(3) The third item uses the integrated power in the frequency domain to generate the candidate R-peaks and is associated with multiple weighting functions designed by the Gaussian distribution.
(4) The last item uses the integrated power in the frequency domain to generate the candidate R-peaks, but the weighting is associated with the weighting mask function defined in Eq. (7).

C. Results

According to the results in TABLE I, our proposed method introduced in the first item (1) got the better accuracy to detect fetal heart rates than the other three methods except for the subjects F, G, and J. The results of (1) and (3) show that the method using multiple weighting functions gives better detection accuracy. The possible reason is that the method can adaptively set the parameters from a grid search with the goal of minimizing the standard deviation of the RR interval. In contrast, the weighting mask deals with the parameters as a fixed value that are derived from the detected R-peaks. The major flaw of the weighting mask used in (2) and (4) is that the wrong R-peak detection cannot be avoided, which leads to inaccurate candidates. In addition, the derivative function of the signal used in (1) and (2) can enhance the slope of the peak position.

IV. Conclusion

In the paper, we propose a method using the first derivative of the ECG signal and the multiple weighting function to improve the accuracy of fetal heart rate detection. The approach allows us to generate the candidate R-peaks using the first derivative of the residual signal and pick up the estimated heartbeats by a weighting function. The proposed multiple weighting function is designed by the Gaussian distribution, of which parameters are adaptively set from a grid search with the goal of minimizing the standard deviation of RR interval. To show the effectiveness of the proposed method, the experiments were designed in four scenarios, which considered a combination of two methods for generating candidate peaks and two weighting functions. In general, the method using multiple weighting functions gives better detection accuracy. The possible reason is that the method can adaptively set the parameters from a grid search with the goal of minimizing the standard deviation of RR internal.

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