A Complete Adaptive Method for Fetal ECG Extraction Based on Single Channel

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Abstract. Based on empirical mode decomposition (EMD) and coherent averaging method, a completely adaptive single channel fetal ECG (FECG) extraction method is proposed. EMD is used to decompose single-lead abdominal ECG (AECG) signals, so that the noise, FECG and MECG components main energy in AECG are distributed in different inherent mode functions (IMF), and R wave detection of MECG is performed by means of IMF, where MECG energy is dominant. MECG was extracted from AECG by means of coherent averaging based on R wave detection results. The remaining signal was named as noisy FECG. Usually, when MECG residue in noisy FECG is large, it needs to be further eliminated. To this end, the same method as above was used again to extract FECG from noisy FECG, and threshold method was used to eliminate MECG residue after extraction of FECG, and then superimposed onto FECG again, in order to recover the non-stationary feature lost in the coherent average process. The effectiveness of the proposed method is verified by the experiments of synthetic mixed signals and real database recorded signals.

1. Introduction

Electrocardiogram (ECG) is a record of physiological electrical signals in human heart. The variation of ECG implies the pathological changes of the heart. ECG is irreplaceable by other methods such as Doppler echocardiography and magneto-cardiogram. The acquisition of Foetal ECG (FECG) is classified into invasive and non-invasive. Invasive measurement is sampling FECG directly by attaching electrodes to the scalp while the cervix dilates during delivery. Clear FECG can be provided but long-term monitoring at all stages of maternal pregnancy is impossible. In contrast, non-invasive measurements are made by placing one or multiple electrodes on the abdomen and the chest of a pregnant woman, which can monitor the foetus not just at childbirth. However, these measurements are followed by a variety of noises, such as movement artefacts caused by respiration, electromyogram noise caused by mother's muscle activity, electrode contact noise caused by poor electrode contact with skin, etc. The main noise in abdominal mixed signal is maternal electrocardiogram (MECG) which is the main important issue for extracting FECG from the abdominal mixed signal. According to the number of electrodes placed on the skin, FECG extraction can be divided into single-channel and multi-channel methods. The multi-channel extraction methods can take advantage of the information redundancy in every sampling channels of the signal and "correct" the inaccurate signal collected by individual leads, so as to extract FECG more accurately. However, due to the large number of electrodes, it is suitable for in-hospital monitoring, which is inconvenient for the use of family portable equipment and increases the complexity and power consumption of the equipment. In contrast, single-channel extraction requires only one measuring electrode, which is good for low-cost portable
monitoring equipment. Nevertheless, without other information for "corroboration" or correction, single-channel extraction is vulnerable to inference. It is often necessary to analyse characteristics of MECG and FECG to obtain corresponding prior or posterior information, so as to establish a basic function model to extract FECG. At present, single-channel methods include template subtraction (TS) method [1, 2], adaptive filtering [3, 4], wavelet transform, Wigner-Ville distribution [5], S-transform [6], sequential total variation [7], adaptive neuro-fuzzy reasoning system, extended Kalman Filtering [8], etc. Besides, FECG can also be extracted by multi-channel method after transforming the single-channel signals to multi-channel ones, such as pseudo-phase space reconstruction combined with SVD, PCA [9] and ICA extraction methods [10].

This paper focused on the extraction of FECG from single-channel non-invasive abdominal mixed signal. We proposed an adaptive FECG extraction method based on empirical mode decomposition (EMD) and the principle of coherent average denoising. Firstly, the single-channel abdominal ECG (AECG) was pre-processed to remove baseline wandering. EMD was carried out on the pre-processed signal, and the intrinsic mode function (IMF) with significant feature of MECG was selected for R peak detection. MECG was extracted by means of simplified coherent average processing according to the position of the R peaks. Then an FECG mixed signal containing residual MECG and other noises was obtained by subtracting the MECG from AECG. Secondly, EMD decomposition, R peak detection and simplified coherent average processing were performed on the FECG mixed signal to extract a pure FECG. The pure FECG obtained through coherent averaging was subtracted from the FECG mixed signal. Appropriate threshold value was set for the remaining signal, and the signal larger than the threshold value was regarded as the MECG residual and gross error and eliminated. Finally, the pure FECG obtained by coherent averaging and the signal with the local non-stationary characteristics are added to restore the original local non-stationary characteristics. The remaining high-frequency noise can be removed by other existing denoising methods. In this paper, the effectiveness of the proposed method was verified by the experiments on synthetic signals and the real signals from DaiSy database and ADFECGDB database.

2. Method

2.1. Simplified Coherent Averaging Method

Coherent averaging is an effective denoising method for periodic or quasi-periodic signals. ECG is a typical quasi-periodic signal based on cardiac beats. There is a strong correlation between cardiac beats in ECG signals, and the PQRST wave groups of different cardiac beats are very similar. Most of the noise signals are random and close to white noise. The noise at different times is statistically independent. Therefore, the noise can be eliminated by means of coherent averaging, so as to extract PQRST wave groups effectively and construct clean ECG signals.

Assumptions: a) The PQRST waveform of ECG was correlated within a short time. In other words, the PQRST of adjacent beats has good similarity. b) The variability of PQRST does not vary with the expansion and contraction of beat length, and that is, it is approximately stationary within a short time.

The simplified coherent average method proposed in this paper is as follows:

1) Determine the R peak position of MECG (FECG) and the corresponding RR interval in the AECG signal.

2) Take the position of R peak as the midpoint, and the maximum RR interval as the length to intercept the data. For the first and last R peak of the signal, the data of the left and the right insufficient length are filled with zero.

3) The truncated data segments are used as row vectors to form a matrix, and the column mean value was calculated to establish the mean cardiac beat.

4) Replace each original cardiac beat with the mean cardiac beat obtained above according to the original R peak position, and discard redundant overlapping data. Obtain the coherent averaging MECG (FECG).
2.2. R Peak Detection Based on EMD

Because of the difference in heart rates between MECG and FECG, their QRS fundamental frequencies are different. After AECG is decomposed by ECM, the main energy of FQRS, MQRS and the noise in AECG are distributed into different IMFs. It has been proved that when the variance (or the energy) of an IMF reaches the maximum, the energy of MQRS dominates, and that of FQRS and noise almost disappear. This allows EMD to be used as a tool for R peak detection. The R peak detection method based on EMD is as follows:

1) Determine R peak discrimination threshold and R peak series

Decompose AECG into IMFs by EMD. Calculate the standard deviation of each IMF and the maximum value of the standard deviation $\sigma_{\text{max}}$. Denote the order of the corresponding IMF with $\sigma_{\text{max}}$ as $I$.

The $I$-th order of IMF is denoted by $\text{IMF}_I$. Calculate all extremums of $\text{IMF}_I$, denoted as sequence $A(k)$, and calculate the mean and standard deviation of the absolute value of $A(k)$. The R peak discrimination threshold is denoted as $R_{\text{th}}$:

$$R_{\text{th}} = \text{mean}(|A(k)|) + \text{stdev}(|A(k)|)$$

(1)

where the functions $\text{mean}(\cdot)$ and $\text{stdev}(\cdot)$ represent calculating the mean value and the standard deviation.

The maximum value in $A(k)$ greater than the threshold $R_{\text{th}}$ is denoted as $P_{\text{up}}$, and the minimum value less than $-R_{\text{th}}$ is denoted as $P_{\text{low}}$. Calculate the average value of $P_{\text{up}}$ and $P_{\text{low}}$, respectively. The R peak series are denoted as $R_{\text{peak}}(k)$ by selecting the larger absolute value of the average values.

$$R_{\text{peak}} = \begin{cases} P_{\text{up}} & \text{if mean}(|P_{\text{up}}|) > \text{mean}(|P_{\text{low}}|) \\ P_{\text{low}} & \text{if mean}(|P_{\text{up}}|) < \text{mean}(|P_{\text{low}}|) \end{cases}$$

(2)

2) Eliminate wrong R peaks

Calculate RR interval $T_{\text{RR}}(k)$ and average RR interval $\overline{T_{\text{RR}}}$ from $R_{\text{peak}}(k)$.

$$T_{\text{RR}}(k) = T_{\text{RR}}(k+1) - T_{\text{RR}}(k), \quad \overline{T_{\text{RR}}} = \frac{1}{K-1} \sum_{k=1}^{K-1} T_{\text{RR}}(k)$$

(3)

where $T_{\text{RR}}(k)$ is the time corresponding to $R_{\text{peak}}(k)$, and $k$ is the number of data in $R_{\text{peak}}(k)$.

If $T_{\text{RR}}(k)$ is less than $0.5\overline{T_{\text{RR}}}$, there is a wrong R peak.

When $T_{\text{RR}}(k) < 0.2\overline{T_{\text{RR}}}$, eliminate $R_{\text{peak}}(k)$ or $R_{\text{peak}}(k+1)$ with smaller absolute value.

When $T_{\text{RR}}(k) = (0.2 - 0.5)\overline{T_{\text{RR}}}$, $R_{\text{peak}}(k+1)$ is eliminated if $T_{\text{RR}}(k-1) > \overline{T_{\text{RR}}}$, $R_{\text{peak}}(k)$ is eliminated if $T_{\text{RR}}(k-1) + T_{\text{RR}}(k) < \overline{T_{\text{RR}}}$. For the others situation, eliminate $R_{\text{peak}}(k)$ or $R_{\text{peak}}(k+1)$ with smaller absolute value. After eliminating the wrong R peak, repeat the above steps until there is no wrong R peak.

2.3. Extract FECG Mixed Signal

EMD decomposition is performed on AECG. R peaks of MECG is detected by the method in section 2.2, and then MECG is extracted by the coherent averaging in section 2.1. The FECG with noise residue is obtained by subtracting the MECG from AECG.

2.4. Eliminate the Residue of MECG

The FECG mixed signal contains residual MECG and other noises which affects the shape of FECG and the clarity of FQRS (See figure 1a). We extract the pure FECG from the FECG mixed signal by the same method of MECG extraction. The standard deviation is used as the threshold. The values larger than the threshold are regarded as MECG residue to eliminate. Then add it and the pure FECG.
This will restore the non-stationary properties which is lost in the coherent averaging process. The finally obtained FECG has the advantages of clear QRS wave, complete non-stationary feature and reasonable trend of local waveform. See figure 1b.

![Figure 1](image1.png)

**Figure 1.** The extracted result of abdominal signals in DaISy database.

### 3. Results and Discussion

In order to verify the performance of the proposed method, synthetic data and real data are used in the experiments. In section 3.1, the influence of the main parameters of mixed ECG on the performance of this method is quantitatively studied by simulation method. These studies give the validity conditions of the proposed method. In section 3.2, the validity of the method in this paper for real data is further verified.

#### 3.1. Experimental Performance Analysis on Synthetic Data

Since there is no clean source signal in real data, it is necessary to verify the performance of the method by quantitative analysis from simulation method. In this paper, the real database ADFECGDB, NIFECGDB, DaISy and MITDB are selected. The direct scalp FECG and thorax MECG are filtered and corrected to obtain clean ECG signals without loss of true ECG characteristics. The linear combination of these signals is used to construct synthetic mixed AECG. Figure 2 shows the comparison between five FECG processed results and the original signal.

![Figure 2](image2.png)

**Figure 2.** Effects of noise removal and baseline correction for ADFECGDB scalp FECG.
In this paper, signal to noise ratio (SNR) and correlation coefficient ($C_R$) are used as the evaluation performance of the method. $s_f$, $s_m$ and $n$ represent FECG, MECG and noise source signals, respectively. The estimated FECG extracted through the proposed method is denoted by $\hat{s}_f$. The synthesized abdominal mixed signal is represented by $s$.

$$s = s_m + s_f + n$$ (4)

The SNR of the mixed signal $s$ (input SNR), the SNR of the estimated FECG (output SNR) and the improved SNR are defined as follows:

$$SNR_{in} = 10 \log_{10} \left( \frac{P_s}{P_{(s_m+n)}} \right)$$, $P_s = \frac{1}{N} \sum_{n=1}^{N} s_f^2$, $P_{(s_m+n)} = \frac{1}{N} \sum_{n=1}^{N} (s_m + n)^2$ (5)

$$SNR_{out} = 10 \log_{10} \left( \frac{P_{\hat{s}_f}}{P_{(\hat{s}_f-s_f)}} \right)$$, $P_{(\hat{s}_f-s_f)} = \frac{1}{N} \sum_{n=1}^{N} (\hat{s}_f - s_f)^2$ (6)

$$SNR_{improve} = SNR_{out} - SNR_{in}$$ (7)

Correlation coefficient $C_R$ is used to evaluate the similarity between the extracted FECG signal $\hat{s}_f$ and the original FECG signal $s_f$, which are defined as:

$$C_R = \frac{\sum_{n=1}^{N} \hat{s}_f(n)s_f(n)}{\sqrt{\sum_{n=1}^{N} (\hat{s}_f)^2 \sum_{n=1}^{N} (s_f)^2}}$$ (8)

(1) SNR analysis

Figure 3a displays SNR improvement and correlation coefficient of the extracted FECG when the noise varying. 105 synthetic signals are used in the following experiment. The energy of FECGs are maintained at 1 (0 dB) for all synthetic signals. The standard deviation ratio of FECG and MECG is 0.3. The heart rate ratio was randomly distributed by the combined signals. We define the FECG energy to (mixed) noise ratio (FNR) is $FNR = 10 \log_{10}(P_s / P_n)$, where $P_s$ and $P_n$ represent the energy of FECG and noise, respectively. In the experiment, the magnitude of $FNR$ represents the energy of the mixed noise. In figure 3a, the blue line denotes the maximum value while the red line denotes the minimum value. The thick black line denotes the average value. As displayed in figure 3a, SNR improvement increases as $FNR$ increase when $FNR$ is from -8 dB to 10 dB. When $FNR$ is equal to 10 dB, the minimum of SNR improvement is 14.8 dB. When $FNR$ is equal to -8 dB, the corresponding noise energy is 6.25 times of the FECG energy, and the SNR improvement is greater than 13.4 dB. Since the method in this paper does not eliminate random noise, the increase of SNR means that MECG energy is eliminated. Within the experimental range, the mean value of SNR improvement is from 15 dB to 17 dB, with a small range of variation. This indicates that in the case of FECG identifiable ($FNR$ is equal to -8 dB), random noise has little influence when MECG is extracted by the proposed method. The graph of correlation coefficient in figure 3a shows that $C_R$ increases with the increase of $FNR$. The average is between 0.75 and 0.89 with the minimum 0.61 and the maximum 0.92. This indicates that FECG is extracted successfully by our method and has good similarity with the original FECG.

(2) Amplitude ratio analysis
The basic problem with FECG monitoring is to extract FECG from mixed signals. Therefore, it is very important to study the impact of FECG to MECG amplitude ratio (FMAR) on the performance of the method. In the experiment, FECG energy of mixed signals is maintained at 1 (0 dB) and FNR is 10dB. The experimental results are shown in figure 3b. With the increase of FMAR, the energy ratio of FECG and MECG increases. Therefore, as the input SNR increases, the relative energy of MECG is reduced, and the SNR improvement is also reduced. The increasing of correlation coefficient $C_R$ indicates that the quality of the extracted FECG is improved. When FMAR is small, MECG residue increases relatively, which will affect FECG identification. When FMAR is less than 0.1, FECG identification becomes difficult. Conversely, when FMAR increases, the amplitude of FECG and MECG tends to be close, affecting the recognition of MECG. When FMAR is greater than 0.7, the R peaks of FECG interferes with MECG recognition, resulting in MECG extraction error.

![Figure 3. SNR improvement and correlation coefficient for synthetic data.](image)

(a) Experimental results of FNR variation  
(b) Experimental results of FMAR variation

(3) Heart Rate Ratio Analysis

According to the statistics of experimental results in (1) and (2), the heart rate ratio range of 105 mixed signals is from 1.2 to 2.8. The statistical results are shown in figure 4. The results show that heart rate ratio has no significant effect on the performance of our method.

![Figure 4. SNR improvement as the heart rate ratio changing when FNR is fixed.](image)

(a) Experimental results of FNR variation  
(b) Experimental results of FMAR variation

3.2. Experimental Performance Analysis on Real Data

In section 3.1, the synthetic signals by combining 105 FECG and MECG were used to study the effectiveness of the proposed method in FECG extraction and the effect of parameters. This section presents the results of the proposed method to real data.

(1) Results on DaISy Database

DaISy database was provided by Belgian scholar Lathauwer, which only contains a single data set of skin potential records of a pregnant woman. There are eight-channel signals, of which the first five channels were collected at the abdominal wall electrodes and the last three channels were collected at chest electrodes. The sampling frequency is 250Hz, and the sampling time is 10s. Figure 5 shows the experimental results of the proposed method on five abdomen mixed signals in DaISy database. It can be seen from the results that the method in this paper has a good performance on extracting DaISy data.
FECG can be extracted even in ill-conditioned mixed signals, such as channel 4 and Channel 5. In addition, it can be seen that FECG extraction not only has clear QRS waveform, but also retains the local change trend of P and T waves, which is of great significance for FECG extraction. Since the proposed method is completely adaptive, the recognition of R peak is an important factor affecting the extraction effect. For signals in ill-conditioned environment, an individual misjudgement may result in the dislocation of R peak in the extraction results, such as between 2nd second and 3rd second of channel 4 and channel 5. In general, an individual misjudgement of R peak does not affect FECG analysis or heart rate calculation.

![Figure 5](image)

**Figure 5.** FECG extraction results from abdominal signals of No. 1 - No. 5 channels in DaISy database.

(2) Results on Abdominal and Direct FECG Database

ADFECGDB database has five data sets, namely r01, r04, r07, r08 and r10. Each data set contains one direct scalp FECG signal and four abdomen measurement signals. Sampling frequency is 1000Hz and sampling duration is 5min. FECG extraction experiment is conducted with length 10s in this paper. FECG information is not observed in channel 1 of R04, channel 1 of R07 and channel 3 of R10, and FECG is not extracted. All the other channels show good extraction effect. FECG is successfully extracted even when heart rate ratio in r10 recorded is only 1.11. From the extracted FECG waveform, the FECG successfully extracted by the proposed method has a complete QRS waveform, and a clear and accurate R peak. In addition, the trends of P waves and T waves are clear and similar to those in the directly measured scalp FECG. Figures 6 and 7 show the extraction results of r01 and r10. The scalp FECG after denoising and baseline eliminating is used as the source signal to calculate the correlation coefficient of FECG extracted successfully. The results are listed in table 1.

|              | Channel 1 | Channel 2 | Channel 3 | Channel 4 |
|--------------|-----------|-----------|-----------|-----------|
| r01          | 0.778     | 0.827     | 0.816     | 0.843     |
| r04          | x         | 0.839     | 0.822     | 0.818     |
| r07          | x         | 0.827     | 0.769     | 0.800     |
| r08          | 0.726     | 0.509     | 0.732     | 0.704     |
| r10          | 0.771     | 0.725     | x         | 0.609     |

**Table 1.** Correlation coefficient between successfully extracted FECG and FECG from clean scalp.
Figure 6. FECG extraction results from r01 signals in ADFECGDB database.

Figure 7. FECG extraction results from r10 signals in ADFECGDB database.

4. Conclusion
A single-channel FECG extraction method based on EMD and coherent average method is proposed. The validity is verified by experiments of synthetic data and real data. Experimental results showed that FECG has no significant effect on MECG extraction when the energy ratio of FECG and random noise is greater than -8dB. The method is effective if the amplitude ratio of FECG and MECG is within the range of 0.1 to 0.7, which meets the range of true abdominal ECG signals. After the heart rate ratio of FECG and MECG is greater than 1.1, there is no effect on the proposed method in this paper. The SNR improvement, correlation coefficient and the FECG waveform of the experimental results all show that the FECG extracted by our method has a high quality. QRS waves are clear. P and T wave trends are reasonably visible. Waveform amplitude and interphase are not significantly distorted. And it can fully retain the nonlinear and non-stationary characteristics of ECG signals.

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