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A Novel Cluster-Based Method for Single-channel Fetal Electrocardiogram Detection

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Abstract— Fetal electrocardiography (FECG) is a promising technology for non-invasive fetal monitoring. However, due to the low amplitude and non-stationary characteristics of the FECG signal, it is difficult to extract it from maternal abdominal signals. Moreover, most FECG extraction methods are based on multiple channels, which make it difficult to achieve fetal monitoring outside the clinic. This paper proposes an efficient cluster-based method for accurate FECG extraction and fetal QRS detection only using one channel signal. We designed min-max-min group as the basis for feature extraction. The extracted features are used to distinguish the different components of the abdominal signal, and finally extract the FECG signal. To verify the effectiveness of our algorithm, we conducted experiments on a public dataset and a dataset record from the Tongji Hospital. Experimental results show that our method can achieve an accuracy rate of more than 96% which is better than other algorithms.

I. Introduction

Fetal monitoring is essential for the early screening of certain diseases in the womb and reduces the risk of fetal death. Compared to ultrasonic fetal cardiotocography [1], non-invasive fetal electrocardiography (FECG) can provide additional clinical information without any safety risk. FECG signals are derived from the measured signals from the maternal abdomen, i.e., abdominal electrocardiography (AECG) signals. However, in addition to the FECG signals, AECG signals also accompany maternal electrocardiography (MECG) signals and additional noises, which poses a great challenge for FECG signal extraction. A typical AECG signal is shown in Fig. 1. It can be observed that the FECG signal is hard to identify as it is mixed into the noisy AECG signal. To use FECG signals to analyze fetal health, we must obtain relatively pure FECG signals which retain most of the morphological information.

Existing FECG signal extraction algorithms can be divided into two categories: (1) Combined source (CS) methods, which require reference signals of chest electrodes, such as least mean squares method [2] and artificial neural network[3]. (2) Abdominal electrode-sourced (AES) methods, which are straight-forward ways to extract FECG without using the chest reference signals include independent component analysis [4] and periodic component analysis [5]. However, the above mentioned methods require multiple abdominal or chest channels to ensure accuracy. To reduce the maternal burden and facilitate the production of portable devices, this study explores a solution for extracting fetal information based on single-channel AECG.

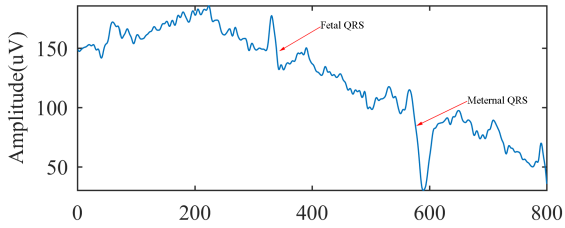

Fig. 1. A short period of AECG signal, which is comprised of FECG, MECG, and extraneous noises.

Template subtraction (TS) methods, as an effective single-channel algorithm [6], have been developed in the context of ECG subtraction. However, the effectiveness of the TS method depends on the accuracy of QRS complex detection from AECG signals [7]. To this end, Zhang et al. [8] proposed a TS method based on the k-means clustering algorithm [9] to distinguish the maternal QRS complex, fetal QRS complex, and others. They proposed a max-min pair selection technique to help locate QRS complexes. However, this technique will fail when the maternal QRS and fetal QRS morphology are inconsistent. As an example, when maternal QRS complex is QR complex but fetal QRS complex is RS complex, it is difficult to separate the features provided by the max-min pairs.

In this paper, we propose a novel efficient cluster-based QRS detection method followed by a relevant single-channel fetal ECG signal extraction algorithm. In our method, FECG signal extraction is divided into three steps: pre-processing, maternal QRS detection and MECG components canceling, and fetal QRS detection and FECG enhancement. The contributions of our work are as follows: 1) A systematical single-channel FECG extraction framework is developed, which can be embedded into a portable medical device for non-invasive fetal monitoring; 2) We designed a min-max-min group technique to precisely locate the maternal QRS complex and fetal QRS complex, and then calculate the corresponding features for k-means clustering; 3) The proposed algorithm is validated on a public dataset and another self collected dataset constructed from patients at Tongji Hospital, China. Experiments prove that our algorithm has achieved higher F1-score, sensitivity, and

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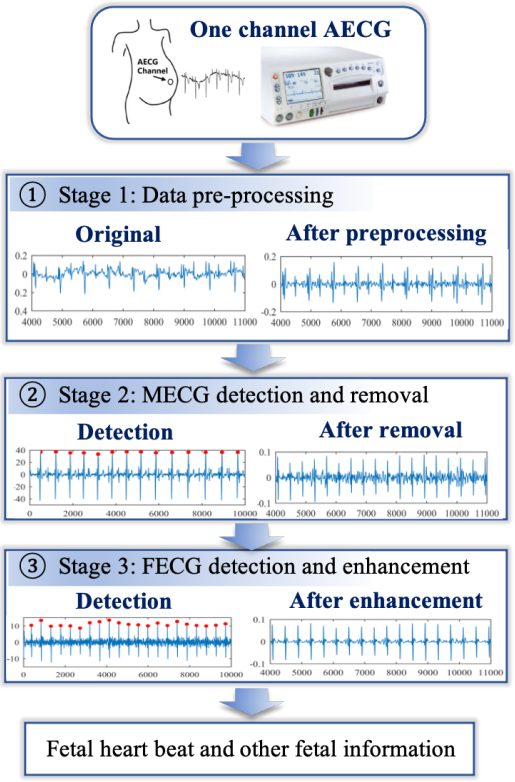

Fig. 2. Overall framework for single-channel FECG extration of this paper.

positive predictive values.

II. METHOD

The overall framework for the FECG signal extraction is shown in Fig. 2, fetal information and heartbeat can be obtained from the original AECG by three stages: data-preprocessing (Section II-A), MECG detection and removal (Section II-B), and FECG detection and enhancement (Section II-C) respectively.

A. Data pre-processing

Given the raw single-channel AECG signal $\mathrm{x} = \{x(k)|k = 1, 2, \ldots, N\}$ acquired from the maternal abdomen, with the time index k and the number of time samples N. A signal filter, W_f, which is a cascade of two filters (i.e., a Butterworth high pass filter W_h and a Butterworth low pass filter W_l), designed for noise reduction [8]. The filtered signal $\bar{\mathrm{x}}$ can be obtained by:

$$\bar{\mathrm{x}} = W_f \cdot \mathrm{x} = W_l \cdot W_h \cdot \mathrm{x}, \tag{1}$$

where the transfer functions of second order Butterworth filter mentioned are:

$$W_l = \frac{1}{s^2 + 1.4142s + 1}, \tag{2}$$

$$W_h = \frac{s^2}{s^2 + 1.4142s + 1}, \tag{3}$$

and the cut-off frequencies of these filters are empirically defined.

B. Maternal ECG detection and removal

After data pre-processing, we attempt to capture the min-max-min group (see red and grey sections in Fig. 3 as examples) to precisely locate the QRS pairs, which are periods of filtered AECG signal $\bar{\mathrm{x}}$ with two local minimums and one local maximum. Let $P = \{p_j|j = 1, 2, \ldots, M\}$ represent the captured min-max-min groups, where M is the number of groups. Then, one can calculate the features $F = \{f_j|j = 1, 2, \ldots, M\}$ of each group, in which $f_j = \{f_j^1, f_j^2, \ldots\}$ include several signal features: y-axis direction distance (DY) (see Fig. 3), Short Term Energy $E_{\hat{n}}$, Mean Amplitude X_{ma} and their arithmetic combination. The formulas of $E_{\hat{n}}$, X_{ma} are:

$$E_{\hat{n}} = \frac{1}{n_s - n_e} \sum_{k=n_s}^{n_e} \bar{\mathrm{x}}^2, \tag{4}$$

$$X_{ma} = \frac{1}{n_s - n_e} \sum_{k=n_s}^{n_e} |\bar{\mathrm{x}}|, \tag{5}$$

where n_s and n_e indicates the start and end points of each min-max-min pair.

The maternal ECG QRS peaks can be distinguished by using k-means clustering methods [9] based on features F. First, initialize the two cluster centroids u_1, u_2 for two sets $S = \{s_1, s_2\}$. Assign each feature f_j to the cluster with the nearest mean according to Euclidean distance:

$$s_m = \{f_j : \left\|(f_j - u_m)\right\|^2 \leq \left\|(f_j - u_l)\right\|^2, \forall l, 1 \leq l \leq 2\}. \tag{6}$$

Then, update centroids for f_j assigned to each cluster:

$$u_m = \frac{\sum_{f_j \in s_m} f_j}{\sum_{f_j \in s_m} 1}. \tag{7}$$

Based on the results of clustering sets S, we can locate MECG QRS complexes $C = \{c_i|i = 1, 2, \ldots, O\}$ which O represents the number of MECG QRS complexes. We define the MECG QRS complex templates as $T = \{t_n|n = 1, 2, \ldots K\}$ that K indicates the number of templates. For every MECG QRS complex c_i in filtered signals $\bar{\mathrm{x}}$:

$$c_i = \sum_{n=1}^{K} \lambda_n t_n, \tag{8}$$

where λ_n is weight parameters that depend on the shape of the MECG complex and the specific type of TS methods. Hence, MECG complexes can be subtracted and removed from $\bar{\mathrm{x}}$.

C. Fetal ECG detection and enhancement

We repeat Eqs. (4) to (7) to detect FECG QRS complexes based on the signal after the removal of MECG in the above subsection. Relying on the results of FECG QRS detection, the enhanced FECG signal can be obtained by using the method described in [10].

III. Experiment

The study design was evaluated and exempted from full review by the Huazhong University of Science and Technology Institutional Review Board.

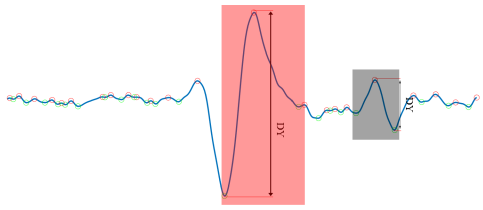

Fig. 3. min-max-min groups

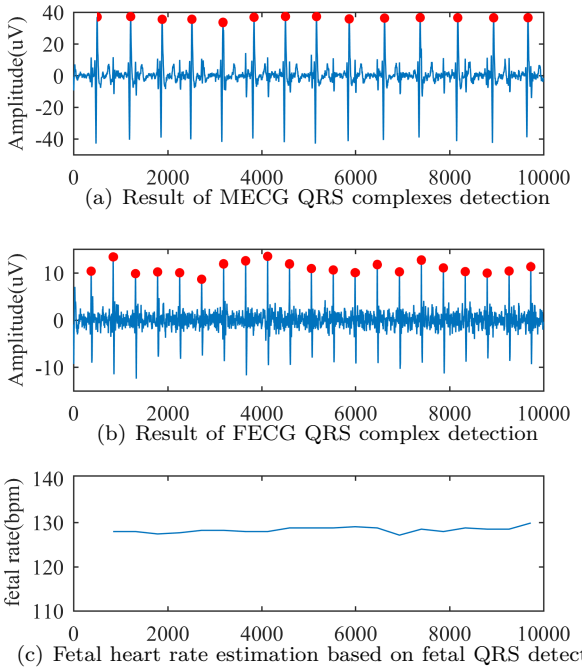

Fig. 4. QRS complex detection

A. Dataset discription

To verify the effectiveness of the proposed FECG detection framework, we conducted out two experiments on a benchmark dataset PhysioNet in a Cardiology Challenge 2013 Set A (Challenge Set A) [11], and another self collected dataset from the Tongji Hospital, Huazhong University of Science and Technology, Wuhan, China. Following are descriptions of the dataset.

- 75 of 447 records in Challenge Set A, where fetal QRS complex location annotations are publicly available concerning a direct FECG signal from a fetal scalp electrode, were used for validation. Each record was sampled by 1kHz with a duration of 1 minute and 4 AECG channels.
- Tongji dataset record abdominal signals of 14 pregnant women at a sampling frequency of 1kHz, each with a duration of 1 minute.

B. Evaluation protocol

We employ the F1 score as the evaluation metric. The F1-score is the harmonic mean of positive predictive value (PPV) and the sensitivity (Se):

$$\text{F1-score} = 2 \cdot \frac{\text{PPV} \cdot \text{Se}}{\text{PPV} + \text{Se}}, \tag{9}$$

where

$$\text{Se} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad \text{and} \quad \text{PPV} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{10}$$

Among them, true positive TP stands for correctly identified, false positive FP stands for incorrectly detected, and false negative FN means missed QRS complexes.

C. Maternal and fetal QRS complex detection of Challenge Set A

To detect the MECG QRS complexes, DY * DY and X_{ma} of the AECG are computed as features for k-means clustering. Taking a record in Challenge Set A as an example, Fig. 4 (a) shows the results of the maternal QRS complex detection. It shows that our min-max-min based algorithm locates the QRS complex (red dots) precisely.

After canceling MECG by TS methods, Fetal QRS complex detection is achieved by k-mean clustering by using DY * DY and $E_{\hat{n}}$ as features. Like Fig. 4 (a), Fig. 4 (b) proves that the proposed algorithm can also achieve precise fetal QRS complex detection. According to the fetal QRS detected, fetal heart rate can be calculated (see result in Fig. 4 (c)).

To further demonstrate the effectiveness of the fetal QRS complex detection, we tested our algorithm in Challenge Set A and compared the result with methods in [8] and IFPTA [7]. Table 1 shows the results of fetal QRS detection and performance metrics from the data of IFPTA and the clustering method based on max-min pairs [8]. According to the experimental results, the clustering method based on min-max-min group in this study obtained the largest scores for more than 90% AECG recordings in Challenge Set A. The average score of each of three metrics is all higher than the other two comparison methods.

D. Maternal and fetal QRS complex detection of Tongji Hospital

To evaluate the generalizability of the fetal ECG extraction framework, 14 AECG records were acquired from Tongji Hospital, China. One test result is shown in Fig. 5. It is worth noticing that the records from Tongji Hospital are nosier and more challenging to detect than the benchmark Challenge Set A, because the records from Tongji Hospital were collected during the actual inspection process, which was not an ideal environment. Fig. 5(a) shows that FECG signal was mixed in the abdominal signal and no valuable fetal information can be seen. After pre-processing, noises including Power Line Interference and baseline wandering were removed and the time series plot after noise removal is depicted in Fig. 5(b). Figs. 5(c) and (d) present the fetal QRS detection and FECG enhancement results respectively. We find that the enhanced FECG signal has obvious morphological characteristics that can be used for clinical practice.

IV. Conclusion

In this paper, a new cluster-based single-channel FECG extraction method is proposed. Compared with

TABLE I

Comparison of FQRS detection on Challenge Set A. Note that not all the results of four channels of each source are presented, because comparison methods [7] and [8] only listed these results in their papers.

		F1(%)			PPV(%)			Se(%)		
source	channel	IFPTA [7]	max-min [8]	Ours	IFPTA [7]	max-min [8]	Ours	IFPTA [7]	max-min [8]	Ours
a03	1	86.5	95.68	**95.75**	88.89	**96.06**	94.66	84.23	95.31	**96.88**
a04	1	90.81	96.52	**97.66**	90.21	96.15	**98.43**	91.42	96.9	**96.9**
a05	1	93.90	**95.72**	94.62	93.49	**96.09**	93.89	94.31	95.35	**95.35**
	4	86.31	93.84	**98.82**	83.97	93.13	**100**	88.78	94.54	**97.67**
a08	1	98.59	**100**	98.41	98.41	100	**100**	98.78	**100**	96.88
a12	1	85.54	94.20	**98.21**	78.86	94.20	**97.16**	93.45	94.20	**99.28**
	2	79.04	94.16	**97.14**	77.79	94.85	**95.77**	80.34	93.48	**98.55**
a15	1	96.89	98.14	**98.89**	96.12	97.78	**97.81**	97.67	98.51	**100**
	2	94.37	**97.06**	89.96	95.51	**95.65**	89.63	93.25	**98.51**	90.30
	2	80.15	94.44	**96.33**	78.89	95.20	**100**	81.46	**93.70**	92.91
a19	3	77.82	93.75	**97.17**	75.48	93.02	**100**	80.32	94.49	**94.49**
	4	75.37	94.53	**96.53**	74.24	93.80	**94.70**	76.54	95.28	**98.43**
a20	2	89.81	95.02	**96.50**	87.51	95.30	**98.41**	92.23	94.66	**94.66**
a23	2	91.48	96.03	**98.39**	90.52	96.03	**100**	92.46	96.03	**96.83**
	3	89.30	94.86	**95.47**	87.53	94.49	**99.75**	91.15	**95.24**	92.06
a24	2	91.22	94.26	**97.10**	90.12	95.04	**99.15**	92.34	93.5	**95.12**
	3	86.99	96.32	**96.64**	84.46	96.72	**100**	87.78	**95.93**	93.50
	4	83.22	94.78	**97.94**	82.25	93.65	**99.17**	94.21	95.93	**96.75**
	1	83.35	95.83	**98.80**	82.57	95.38	**100**	84.14	95.83	**97.62**
a36	2	86.14	94.12	**98.80**	85.86	93.02	**100**	86.42	95.24	**97.62**
	3	91.60	94.96	**98.80**	90.42	94.71	**100**	92.81	95.21	**97.62**
a44	4	93.78	96.63	**99.07**	93.23	96.34	**100**	94.34	96.93	**98.16**
a65	4	87.85	97.95	**98.25**	86.98	96.62	**99.29**	88.74	**99.31**	97.22
a72	3	81.61	96.14	**98.80**	79.24	95.29	**98.80**	84.13	97.01	**98.80**
Average		87.82	95.57	**97.29**	86.62	95.34	**98.22**	89.45	95.78	**96.44**

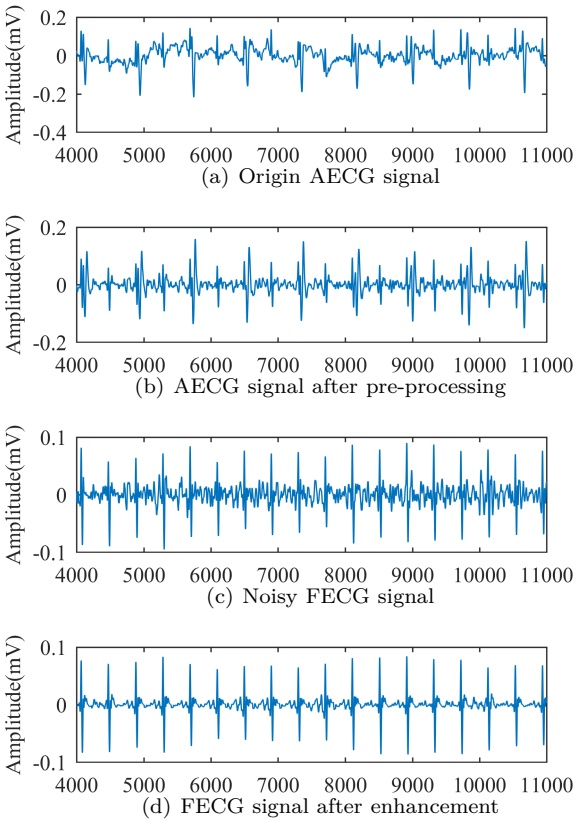

Fig. 5. FECG signal extraction

other existing methods, this paper introduces min-max-min group to increase the accuracy of QRS dectection. Related experiments prove that our method has achieved higher F1 scores in FECG QRS detection for most of the ECG recordings in a benchmark dataset, and our algorithm can extract excellent quality FECG signals from AECG signal obtained by Tongji hospital. Future work includes combining this knowledge with hardware to develop a FECG monitoring device to be used daily during maternity and doing more morphological analysis based on the obtained FECG signals.

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