Australasian Physical & Engineering Sciences in Medicine (2019) 42:1081–1089
https://doi.org/10.1007/s13246-019-00805-x

SCIENTIFIC PAPER

Fetal electrocardiography extraction with residual convolutional encoder–decoder networks

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Received: 22 January 2019 / Accepted: 30 September 2019 / Published online: 15 October 2019

Abstract

In the context of fetal monitoring, non-invasive fetal electrocardiography is an alternative approach to the traditional Doppler ultrasound technique. However, separating the fetal electrocardiography (FECG) component from the abdominal electrocardiography (AECG) remains a challenging task. This is mainly due to the interference from maternal electrocardiography, which has larger amplitude and overlaps with the FECG in both temporal and frequency domains. The main objective is to present a novel approach to FECG extraction by using a deep learning strategy from single-channel AECG recording. A residual convolutional encoder–decoder network (RCED-Net) is developed for this task of FECG extraction. The single-channel AECG recording is the input to the RCED-Net. And the RCED-Net extracts the feature of AECG and directly outputs the estimate of FECG component in the AECG recording. The AECG recordings from two different databases are collected to illustrate the efficiency of the proposed method. And the achieved results show that the proposed technique exhibits the best performance when compared to the existing methods in the literature. This work is a proof of concept that the proposed method could effectively extract the FECG component from AECG recordings. The focus on single-channel FECG extraction technique contributes to the commercial applications for long-term fetal monitoring.

Keywords Fetal monitoring · Non-invasive fetal electrocardiography · FECG extraction · Convolutional encoder–decoder networks

Introduction

Worldwide, an estimated 2.65 million stillbirths occur yearly. And the heart defects are the leading cause of birth defect-related death [1, 5, 8]. Therefore, there is a need for effective monitoring techniques that can provide reliable information on the fetal well-being during the pregnancy.

Doppler ultrasound is the most widespread technique to fetal monitoring in clinical practice [19, 31]. However, the Doppler ultrasound only provides the fetal heart rate (FHR). It cannot offer the waveform morphology of fetal electrocardiography (FECG) for accurate fetal health monitoring. What is more, due to the sensitivity of maternal and fetal motion, the Doppler ultrasound does not allow for long-term monitoring. Unlike the Doppler ultrasound, the FECG can provide both the FHR and FECG waveform morphology for safe, accurate, and long-term screening on the pathological condition of the fetal heart. Therefore, the FECG is suggested as an alternative approach to the traditional Doppler ultrasound technique.

To date, there are two methods to obtain the FECG, namely invasive FECG monitoring method and non-invasive FECG (NI-FECG) monitoring method. The invasive FECG monitoring method, also called scalp ECG (SECG), records the FECG signals with the aid of electrodes placed on the fetal scalp directly while the cervix is dilated. Considering the risk of infection, the SECG method can only be performed during delivery [16]. Unlike the SECG method, the NI-FECG method could be employed at almost any point in the third trimester. NI-FECG method collects the FECG and MECG simultaneously through electrodes attached to the maternal abdomen. Thus the abdominal electrocardiography (AECG) collected from the maternal abdomen contains the

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maternal electrocardiography (MECG), FECG, and noise. In this regard, the research in extracting FECG from AECG has recently been attracting considerable attention [12, 13].

A considerable amount of literature has been published on FECG extraction [5, 7, 8, 20]. Most of the studies could be classified into three categories, namely the blind source separation (BSS) methods, the adaptive noise cancelling (ANC) methods and template subtraction (TS) methods.

The BSS methods aim to separate the MECG component and FECG component from the AECG. The BSS methods include the principal component analysis (PCA) [12], independent component analysis (ICA) [21] and periodic component analysis [23]. The MECG, FECG, and noise are considered as underlying statistically independent sources in the BSS methods. The BSS methods require higher number of available abdominal recordings to obtain reasonable FECG extraction (usually between 8 and 16) [3, 6]. It should be noted that the placement of several electrodes on the abdomen is uncomfortable for the pregnant woman. Consequently, these drawbacks limit the clinical use of the BSS methods.

The ANC methods require single channel AECG as processed signal and one thoracic MECG as reference signal. The ANC methods include the least mean square (LMS), the recursive least square (RLS) and the echo state neural networks (ESN) [6, 28]. The projection of reference signal (thoracic MECG) on AECG recordings could be eliminated by training an adaptive filter in the ANC methods. However, to achieve reasonable MECG removal, the reference signal should be morphologically similar to the AECG waveform [30]. Therefore, the performance of ANC methods is reduced, since a strict similarity between the processed signal and the reference signal is not always the case.

In the context of FECG extraction, the TS methods could be termed as single-channel algorithm which only requires single-channel AECG recording [10, 17, 27, 29]. An estimation of MECG is generated as a template and subtracted from the AECG. However, the TS methods require the accurate locations of maternal QRS for signal alignment. Without these prior knowledge, the misalignment problems could affect the performance of the TS methods in removing the MECG.

In this study, we propose a novel approach for single-channel FECG extraction by using a deep learning model. And the contributions of this work are summarized as follows:

- To address the challenge of FECG extraction, we build a deep learning model for this task by using residual convolutional encoder–decoder networks (RCED-Net).
- Unlike the previous studies based on the elimination or separation of MECG, we propose a novel approach to directly extract the FECG component from single-channel AECG recording for the first time (to the best of our knowledge). It avoids the problems related to MECG elimination such as the signal misalignment.
- Instead of using multiple channel recordings as done in the BSS methods, the focus on single-channel FECG extraction technique contributes to the commercial applications for long-term healthcare at home.

In this work, we extend the contributions by enlarging the experimental part with new datasets and evaluation setups. The evaluation allows a comparison of the proposed methodology against many previously proposed methodologies.

Methods

Problem formulation

Numerous deep learning approaches have been proposed to effective solution to various problems, such as arrhythmia recognition [4, 11, 14, 24, 26]. In this work, a novel model based on the residual convolutional encoder–decoder networks (RCED-Net) is developed for FECG extraction.

Generally, the abdominal signal mixture mainly contains three components, namely the MECG component, FECG component and noise [5, 18], such that

$$W = X + Y + V \tag{1}$$

where $W = [w_1, w_2, \ldots, w_n] \in \mathbf{R}^{1\times n}$ corresponds to the abdominal signal mixture. $X = [x_1, x_2, \ldots, x_n] \in \mathbf{R}^{1\times n}$ to the MECG component, $Y = [y_1, y_2, \ldots, y_n] \in \mathbf{R}^{1\times n}$ to the FECG component and $V = [v_1, v_2, \ldots, v_n] \in \mathbf{R}^{1\times n}$ to the noise.

The RCED-Net can be considered as a function approximator to approximate the transformation function $F(\cdot)$, which operates on the abdominal signal mixture W and yields the estimate of the FECG component in the AECG, such that

$$\hat{Y} = F(W) \tag{2}$$

where $\hat{Y} = [\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n] \in \mathbf{R}^{1\times n}$ is the estimate of the FECG component. $\hat{Y}$ contains the real FECG signal Y and some noise.

In this sequence-to-sequence task, the AECG signal (W) is the input to the RCED-Net, and the network outputs the estimate of the FECG component ($\hat{Y}$) in the abdominal signal mixture. In specific, the averaged mean squared error between the estimated FECG ($\hat{Y}$) and the real FECG component (Y) is employed as the loss function,

$$\ell(\Theta) = \frac{1}{M}\sum_{i=1}^{M} \left\| F(W_i;\Theta) - Y_i \right\|_F^2 \tag{3}$$

where Θ is the parameter needed to be trained in the RCED-Net, and $\{(W_i, Y_i)\}_{i=1}^{M}$ is a set of M AECG-FECG training sample pairs.

In addition, the Tanh activation function (that can be utilized for nonlinearity in the network) is defined as

$$f_t(c) = \frac{exp(c) - exp(-c)}{exp(c) + exp(-c)} \tag{4}$$

here c corresponds to the input of the Tanh activation function.

ECG databases

The data collected from the fetal ECG synthetic database (FECGSYNDB) [2] is used to train the model. And the real AECG collected from two public databases is used to test the performance of the proposed method. These two databases include the Set A of 2013 PhysioNet/Computing in cardiology challenge database (PCDB) [25] and the abdominal and direct fetal electrocardiogram database (ADFECGDB) [15]. The details of the three databases are summarized as follows:

- The FECGSYNDB database consists of 145.8 h of data and 1.1 million fetal peaks. Each realistic simulation of abdominal mixture contains 34 channels (32 abdominal and 2 MECG channels). The separate waveform of each signal source is provided in the database.
- The PCDB database includes 75 one-minute abdominal records. Each record has four channels of recordings. The sampling frequency is $f_s = 1$ kHz and the FQRS reference is available. To date, the PCDB database is the largest publicly available database.
- The ADFECGDB database includes five 5-channel records (4 abdominal channels and the SECG) from five subjects in labour. Each recording lasts 5 min. The data are sampled at $f_s = 1$ kHz. And the reference annotations of fetal QRS (derived from the SECG) are available.

As suggested in [7, 9], some recordings are discarded because of inaccurate reference annotations or severe noise. Specifically, the r04 Ab-1, r07 Ab-1 and r10 Ab-3 are excluded from ADFECGDB. In the PCDB, 80 recordings selected by a specialist are used in this study. After data collection, all the ECG recordings are resampled with $f_s = 250$ Hz for further analysis.

Overall framework

The main framework of the proposed deep learning method consisted of two stages. The first stage is dataset preparation. And the second stage is training and evaluation. More details of each stage in the framework are described hereafter.

Dataset preparation

Figure 1 shows the procedure of dataset preparation. First of all, the high frequency noise and baseline wander are cancelled by a band-pass Butterworth filter in the *Denoising* operation. The filter is cascaded by a 100 Hz low-pass filter and a 3 Hz high-pass filter. Secondly, a *Segmentation and Normalization* operation is employed to the filtered ECGs. In the *Segmentation and Normalization* operation, the single-channel ECG is segmented with frame size $1 * L$ and normalized to $[-1, 1]$. For illustration purposes, an example of the simulated ECG signal is showed in the Fig. 2.

In practice, to learn a complete feature of AECG, the frame size is set at $1 * 1000$ (sample points). Finally, 60, 000 training sample pairs are selected to form the training set. And the test set contains 2475 test samples.

Training and evaluation

Figure 3 represents the procedure of Training and Evaluation for the FECG extraction task. The offline training and

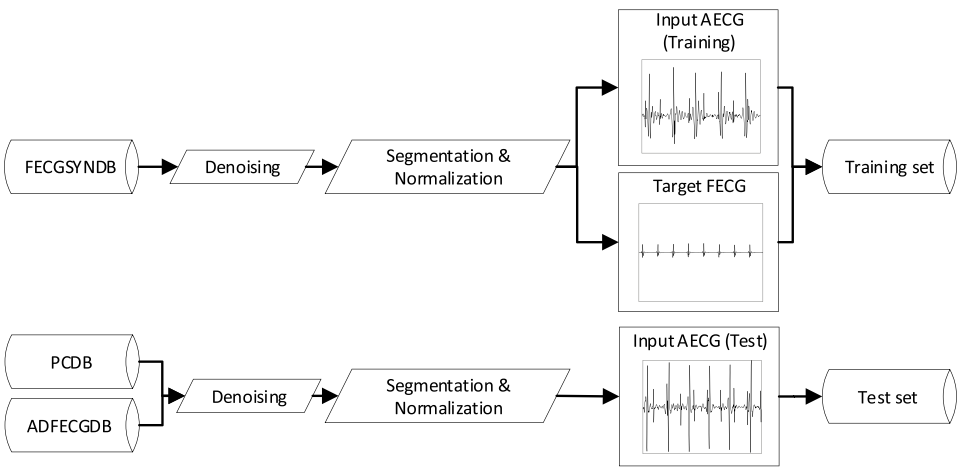

Fig. 1 The procedure of dataset preparation. The training set and test set are generated in this stage

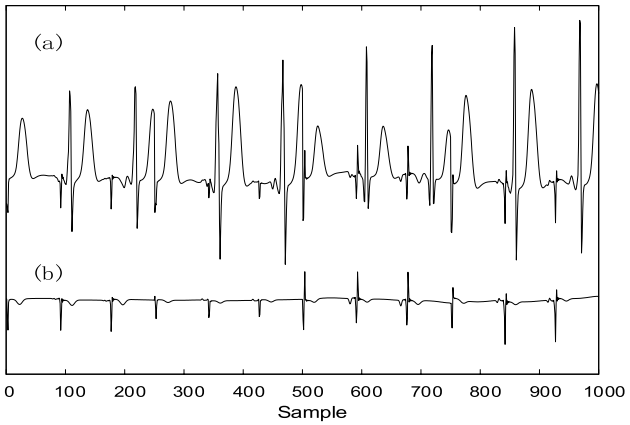

Fig. 2 Simulated data. An example of simulated AECG (a) and the corresponding FECG component (b)

online testing are traditional procedure for neural networks. After the network is trained, the AECG features in the test set are input to the trained deep learning model, and then the model outputs the predicted FECG for the corresponding AECG features.

The beat-to-beat comparisons between the reference FQRS annotations and the detected beats are usually adopted to illustrate the performances of FECG extraction. After the FECG is extracted from the AECG, the high-accuracy approach in [22] is employed on the extracted FECG for QRS detection. Three metrics are used for algorithm evaluation, namely the sensitivity (*SE*), positive predictive value (*PPV*) and F_1 measure [2]. These metrics are defined by

$$SE = \frac{TP}{TP + FN} \tag{5}$$

$$PPV = \frac{TP}{TP + FP} \tag{6}$$

$$F_1 = 2 \times \frac{SE \times PPV}{SE + PPV} = \frac{2 \times TP}{2 \times TP + FN + FP} \tag{7}$$

Here TP, FP and FN are the number of true positives (correctly detected fetal QRS), false positives (wrongly detected fetal QRS) and false negatives (missed detected fetal QRS), respectively. A detected fetal QRS is classically considered a true positive if it is within 50 ms of the reference annotation [2].

RCED-Net architecture

The architecture of the proposed RCED-Net is shown in Fig. 4. The network architecture has five Conv–Deconv blocks and one fully connected layer. Each Conv–Deconv block includes a convolutional layer and a deconvolutional layer. All the convolutional layers and deconvolutional layers are followed by a Tanh activation function layer. In addition, the shortcut connections are employed between the adjacent Conv–Deconv blocks. Therefore, the details of feature map could be passed from the top layers to bottom layers directly.

Specifically, all the convolutional layers and the first four deconvolutional layers have 64 feature filters of size $1 * 3$. The last deconvolutional layer has one feature filter. Each filter can generate one feature map. For example, in the first convolutional layer, the input AECG feature of size $1 * 1000$ is convoluted with each one of 64 feature filters, thus generate 64 feature maps of size $1 * 1000$. The zero padding is employed to ensure the output feature maps have the same size with input AECG feature. More details of the network are summarized in Table 1.

The Conv–Deconv block receives the outputs of the previous block as inputs and then outputs feature maps to the next Conv–Deconv block. Finally, the neurons of the fully

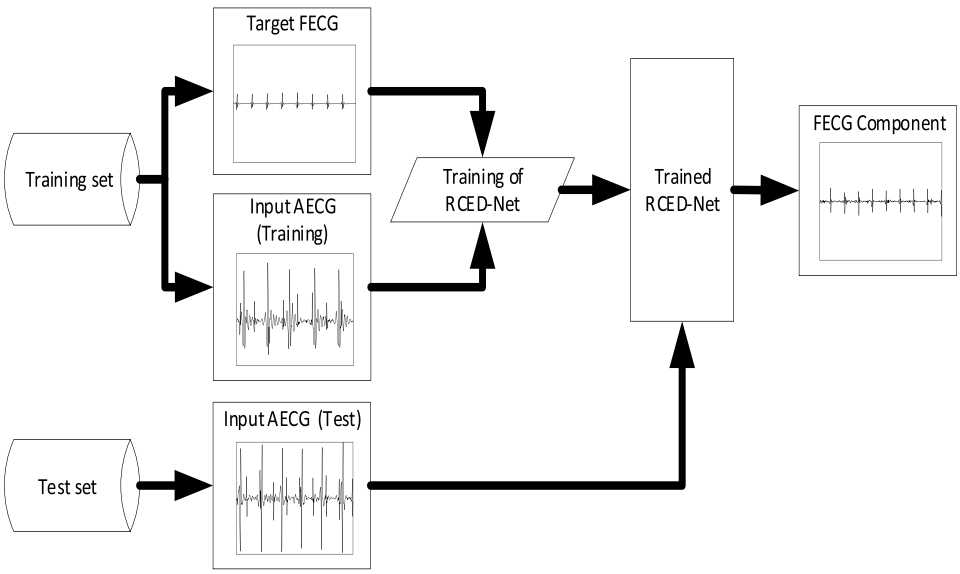

Fig. 3 Experimental procedure. Training and evaluation process of the deep learning model for FECG extraction

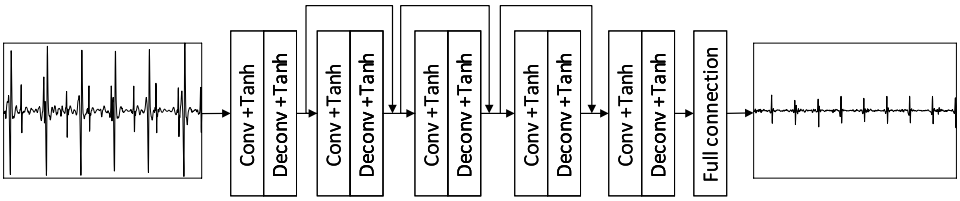

Fig. 4 The architecture of the proposed RCED-Net

connected layer output the predicted FECG of size $1 * 1000$. We use the Adam optimizer with learning rate 10^{-4} to train the model in this study. In practice, we find that using five Conv–Deconv blocks achieves satisfactory results, and we have not found significant performance improvement when using a deeper architecture.

Results

The efficiency of the model is evaluated on the real AECG recordings from the ADFECGDB and PCDB. And the results on ADFECGDB and PCDB are shown in Tables 2 and 3, respectively. The proposed method is compared with other methods in Fig. 5.

As shown in Tables 2 and 3, the values of *SE*, *PPV* and F_1 of the proposed method on ADFECGDB are 96.06%, 92.25% and 94.10%, respectively, and those on PCDB are 92.60%, 94.68% and 93.62%, respectively. It can be concluded that the proposed method is effective in extracting the FECG from the AECG.

As shown in Fig. 5, the proposed method is compared with the existing methods, including the Cerutti method (Cerutti), the Suzanna method (Suzanna), the Vullings method (Vullings), the TS_{PCA} and the EKF [10, 17, 27, 29]. The comparison results on PCDB are shown in Fig. 5a, and those on ADFECGDB are shown in Fig. 5b. It can be seen that the proposed method achieves the best performance on both datasets and behaves the high robustness in FECG extraction as well.

Discussion

In this study, we propose a new framework of single-channel FECG extraction via a deep learning model, which can be utilized for intrapartum and antepartum monitoring. Note that only single-channel AECG signal is required in the proposed method. Compared with the methods which require high number of channels, it is a considerable advantage from the standpoint of pregnant women. And the statistical results on 2.75 h of data show that reliable fetal heartbeat extraction

Table 1 Model hyper parameters

Hyper parameter	Considered values	Hyper parameter	Considered values
Activation function	Tanh	1st–4th deconvolution	
Optimizer	Adam	No. of filters	64
Learning rate	0.0001	Window size	1*3
Loss function	Mean squared error	Stride size	1
Input size	1*1000	Padding	Zero padding
Output size	1*1000	5th deconvolution	
Full connection		No. of filters	1
No. of neuron	1000	Window size	1*3
1st–5th convolution		Stride size	1
No. of filters	64	Padding	Zero padding
Window size	1*3		
Stride size	1		
Padding	Zero padding		

Table 2 Evaluation results on the ADFECGDB

Recordings	*SE* (%)	*PPV* (%)	F_1 (%)	Recordings	*SE* (%)	*PPV* (%)	F_1 (%)
r01 Ab-1	97.92	95.03	96.45	r07 Ab-4	98.83	94.26	96.49
r01 Ab-2	93.50	89.29	91.34	r08 Ab-1	97.77	94.16	95.93
r01 Ab-3	97.88	93.17	95.47	r08 Ab-2	91.26	86.64	88.89
r01 Ab-4	99.67	95.19	97.38	r08 Ab-3	95.96	91.24	93.54
r04 Ab-2	98.14	91.77	94.85	r08 Ab-4	98.22	93.24	95.67
r04 Ab-3	92.88	86.71	89.69	r10 Ab-1	94.04	94.79	94.41
r04 Ab-4	97.92	89.56	93.55	r10 Ab-2	93.00	94.47	93.73
r07 Ab-2	98.99	93.94	96.40	r10 Ab-4	88.75	91.00	89.86
r07 Ab-3	98.33	93.78	96.00				
		Mean *SE* (%)		Mean *PPV* (%)		Mean F_1 (%)	
Total		96.06		92.25		94.10	

Table 3 Evaluation results on the PCDB

Recordings	*SE*(%)	*PPV*(%)	F_1 (%)	Recordings	*SE*(%)	*PPV*(%)	F_1 (%)
a01 Ab-4	92.41	93.06	92.73	a28 Ab-2	96.41	99.38	97.87
a03 Ab-1	89.06	95.80	92.31	a28 Ab-3	97.60	97.60	97.60
a03 Ab-2	91.41	93.60	92.49	a31 Ab-2	91.24	91.91	91.58
a03 Ab-4	89.06	93.44	91.20	a35 Ab-1	95.09	97.48	96.27
a04 Ab-1	94.57	97.60	96.06	a35 Ab-2	93.87	97.45	95.63
a04 Ab-2	94.57	93.13	93.85	a35 Ab-3	95.71	97.50	96.60
a04 Ab-3	97.67	99.21	98.44	a35 Ab-4	93.87	96.84	95.33
a04 Ab-4	95.35	98.40	96.85	a36 Ab-1	91.07	97.45	94.15
a05 Ab-1	91.47	89.39	90.42	a36 Ab-2	89.88	96.79	93.21
a05 Ab-2	96.12	96.12	96.12	a36 Ab-3	89.88	96.79	93.21
a05 Ab-3	96.12	96.12	96.12	a36 Ab-4	88.69	95.51	91.98
a05 Ab-4	93.80	96.80	95.28	a41 Ab-1	85.29	87.22	86.25
a08 Ab-2	92.19	91.47	91.83	a44 Ab-1	95.09	99.36	97.18
a08 Ab-3	98.44	99.21	98.82	a44 Ab-2	94.48	99.35	96.86
a08 Ab-4	97.66	100	98.81	a44 Ab-3	95.71	99.36	97.50
a12 Ab-1	96.38	98.52	97.44	a44 Ab-4	96.32	98.13	97.21
a12 Ab-2	94.20	96.30	95.24	a48 Ab-2	81.20	79.41	80.30
a12 Ab-4	92.75	92.75	92.75	a49 Ab-1	96.62	97.95	97.28
a13 Ab-2	93.65	95.16	94.40	a49 Ab-2	96.62	98.62	97.61
a13 Ab-3	93.65	92.19	92.91	a49 Ab-3	95.27	97.92	96.58
a13 Ab-4	97.62	97.62	97.62	a49 Ab-4	91.22	91.22	91.22
a14 Ab-1	88.62	87.20	87.90	a55 Ab-2	88.81	90.07	89.44
a15 Ab-1	93.28	96.15	94.70	a55 Ab-3	88.11	90.65	89.36
a15 Ab-2	93.28	93.28	93.28	a58 Ab-2	80.29	80.29	80.29
a15 Ab-3	92.54	96.88	94.66	a61 Ab-2	92.86	92.86	92.86
a15 Ab-4	95.52	97.71	96.60	a61 Ab-4	92.86	92.86	92.86
a17 Ab-2	90.91	91.60	91.25	a62 Ab-2	83.33	85.71	84.51
a20 Ab-2	93.13	94.57	93.85	a62 Ab-3	85.42	87.86	86.62
a20 Ab-3	84.73	86.05	85.38	a62 Ab-4	84.03	87.05	85.51
a22 Ab-1	94.44	94.44	94.44	a65 Ab-2	90.97	93.57	92.25
a22 Ab-2	89.68	87.60	88.63	a65 Ab-4	90.97	94.93	92.91

Table 3 (continued)

Recordings	*SE*(%)	*PPV*(%)	F_1 (%)	Recordings	*SE*(%)	*PPV*(%)	F_1 (%)
a22 Ab-4	96.03	99.18	97.58	a66 Ab-3	83.85	81.95	82.89
a23 Ab-2	94.44	95.97	95.20	a67 Ab-4	91.56	93.38	92.46
a23 Ab-3	95.24	94.49	94.86	a69 Ab-1	90.60	95.07	92.78
a23 Ab-4	97.62	97.62	97.62	a70 Ab-1	94.33	96.38	95.34
a24 Ab-2	95.93	97.52	96.72	a70 Ab-2	90.78	92.75	91.76
a24 Ab-3	91.87	94.17	93.00	a72 Ab-1	94.61	100	97.23
a24 Ab-4	96.75	99.17	97.94	a72 Ab-2	94.01	100	96.91
a25 Ab-2	92.00	99.14	95.44	a72 Ab-3	95.81	99.38	97.56
a28 Ab-1	95.21	99.38	97.25	a72 Ab-4	94.01	98.74	96.32
		Mean *SE* (%)		Mean *PPV* (%)		Mean F_1 (%)	
Total		92.60		94.68		n93.62	

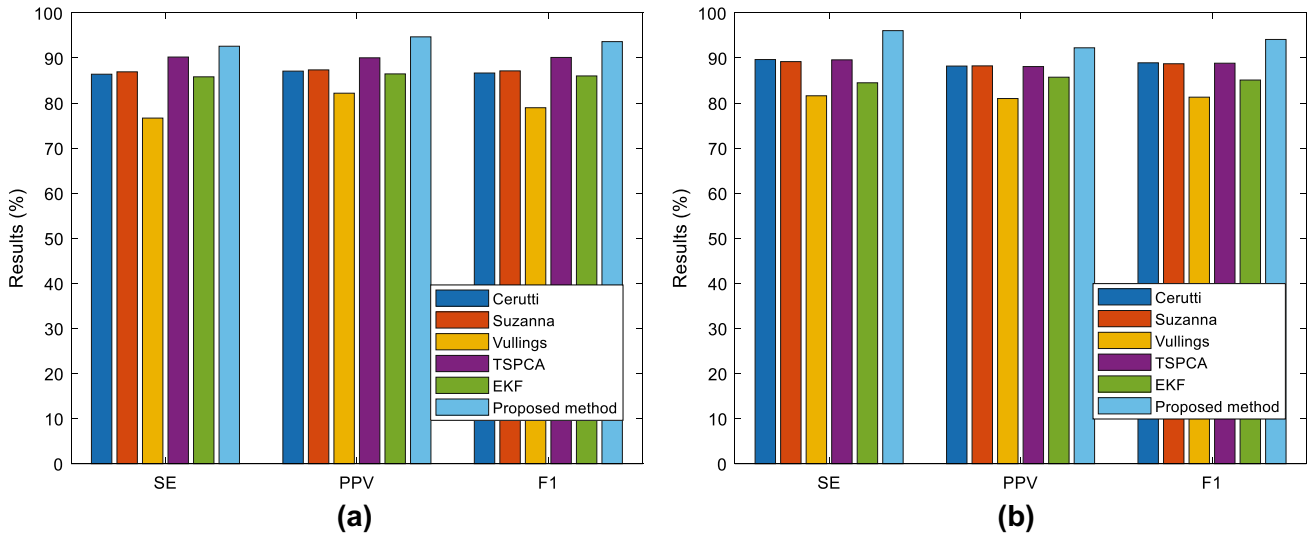

Fig. 5 Comparison results of different methods on PCDB (**a**) and ADFECGDB (**b**). The results from the Tables 2 and 3 are used

can also be obtained by the proposed method using a single abdominal recording.

Using the preceding MECG cycle, the TS methods could construct an adaptive MECG template. Then the FECG could be obtained by subtracting the constructed MECG template from AECG. However, to obtain a reliable MECG template for MECG elimination, some information of the MECG such as the accurate location of the maternal QRS is required for signal slicing and alignment. It should be kept in mind that the accurate location of the maternal QRS is not available in some case. For instance, when the FECG and MECG amplitudes are comparable (see Fig. 6), the location of the maternal QRS is relatively difficult to be accessed. Consequently, the abdominal MECG waveform cannot be completely removed, and the performance in fetal heartbeat extraction of these temporal methods is reduced. Moreover, the residual signal, after removing the MECG, is still noisy. This makes it difficult to confirm the FECG when SNR (signal to noise ratio of the FECG relative to noise) is low.

In the presented study, the proposed method extracts the FECG directly from the AECG without cancelling the MECG waveform. Thus, the problems related to MECG-elimination (e.g., MQRS slicing and alignment) could be avoided. And a high performance is achieved. Overall, the proposed deep learning approach outperforms the five other techniques. The exceeding performance demonstrates the higher robustness of the proposed method in extracting the FECG component from the AECG.

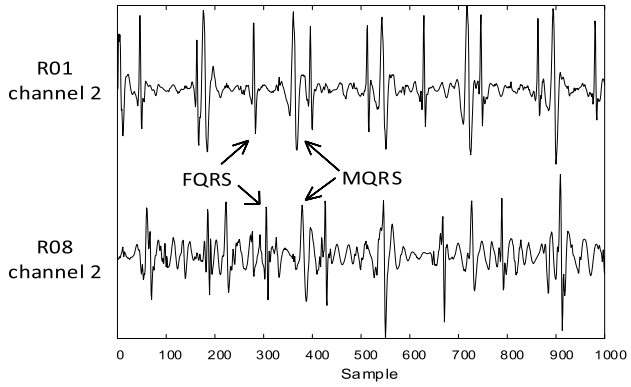

Fig. 6 The examples of comparable amplitudes between the FECG and MECG. These AECG signals are collected from the R01 channel 2 and R08 channel 2 of ADFECGDB

Conclusion

In this study, a novel framework based on residual convolutional encoder–decoder networks that uses single-channel AECG for FECG extraction is presented. The proposed method could extract FECG directly from the AECG without cancelling the MECG waveform. The real AECG recordings from two different databases are used to assess the performance of the proposed system. Compared with the existing methods, the proposed method achieves the best performance. Also, the statistical results show the high robustness of the proposed method in extracting the FECG from the AECG.

Acknowledgements This work was supported in part by the Key Program of the National Social Science Fund of China with Grant No. 18ZDA308 and in part by the National Natural Science Foundation of China under Grant Nos. 61772574, 61375080, and U1811462.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants and animals performed by any of the authors.

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