ARTICLE IN PRESS
BIOCYBERNETICS AND BIOMEDICAL ENGINEERING XXX (2018) XXX–XXX

Available online at www.sciencedirect.com

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Original Research Article

# Automatic identifying of maternal ECG source when applying ICA in fetal ECG extraction

Q1 *Yu Qiong, Yan Huawen, Song Lin, Guo Wenya, Liu Hongxing* *, *Si Junfeng, Zhao Ying*

*School of Electronic Science and Engineering, Nanjing University, Xianlin Campus, Nanjing 210023, China*

ARTICLE INFO

*Article history:*
Received 11 October 2017
Received in revised form
9 March 2018
Accepted 13 March 2018
Available online xxx

*Keywords:*
Fetal ECG extraction
Independent component analysis (ICA)
Automatic identification
ECG features

ABSTRACT

Independent component analysis (ICA) is usually used as a preliminary step for maternal electrocardiogram (ECG) QRS detection in fetal ECG extraction. When applying ICA to do this, a troublesome problem arises from how to automatically identify the separated maternal ECG component. In this paper we proposed a method called PRCH (short for Peak to peak entropy, R-R interval entropy, Correlation coefficient and Heart rate) for the automatic identifying. In the method, we defined four kinds of features, including amplitude, instantaneous heart rate, morphology and average heart rate, to characterize a signal, and determined some decision parameters through machine learning. Experiments and comparison with other three existed methods were given. Through taking metric F1 for evaluation, it showed that the proposed PRCH method has the highest identifying accuracy and generalization capability.
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## 1. Introduction

Fetal ECG (fECG) extraction from abdominal ECG (aECG) has been a hot and difficult problem in biomedical engineering [1,2] for a long time. Classic methods always follow the steps below to solve this dilemma. Firstly, estimate the maternal ECG (mECG) component from aECG, which always takes a main proportion in aECG, then the primary estimation of fECG is obtained after subtracting the estimated mECG. Lots of methods for mECG estimation rely on the precise maternal QRS detection, such as periodic component analysis [3], template subtraction [4–6], comb filter [7,8], singular value decomposition (SVD) [9] and so on. Ahead of maternal QRS detection, pre-processing steps always must be done because of the various interferences and noises contained in aECG. Independent component analysis (ICA) [10–18] is one of the methods for pre-processing. After using ICA, a clear separated mECG component is obtained, and its QRS peaks can be easily detected. Taking the detected QRS peaks as a reference, the accurate maternal QRS position in each original aECG channel can be annotated easily. However, as we all know, the order of the separated independent components (ICs) derived from ICA is uncertain. Therefore, how to automatically identify the mECG IC after ICA leads to a research topic.

Acharyya et al. [16] and Agarwal et al. [17] proposed a method called template matching method (TM) for automatic identifying of the ECG IC while applying ICA to routine multi-channel ECGs. The Symlet wavelet (no specific wavelet is mentioned in the

* *Corresponding author at:* School of Electronic Science and Engineering, Nanjing University, Xianlin Campus, Nanjing 210023, China.
E-mail address: njhxliu@nju.edu.cn (L. Hongxing).
https://doi.org/10.1016/j.bbe.2018.03.003
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paper) is used as the ECG template. The separated IC which has the highest correlation coefficient with the template is chosen as the interesting ECG signal. Although the method is not designed for aECG, since the template is similar to mECG, it can be used as a method to solve the problem we aforementioned. Maria et al. [20] used a similar method but the template was set to be a 100 ms triangular wave.

Behar et al. [14] also designed a method based on a smoothing indicator (SMI). The mECG IC is selected based on an index reflecting the stability of instantaneous heart rate. The index is defined as the number of beats whose instantaneous heart rate variability (defines as the difference between two successive instantaneous heart rates) is more than 29 beat per minute (bpm). The smaller the value, the more stable the instantaneous heart rate. The separated IC with the smallest index value is chosen as mECG. This method implies mECG has a comparatively stable heart rate.

Varanini et al. [15] designed a method by taking into account a priori knowledge of the QRS derivative, width and pseudo-periodicity. This method is called DWP. In the method, DWP index is computed according to this procedure: (1) do derivative filtering on each separated signal, (2) set DWP = mD2/(mD02 + mD8). In (2), mD2 means the average of a series of maximum derivatives, calculating one maximum derivative for each consecutive windowed signal (2 s window), and mECG and fECG component will have larger values for this indicator. At the same time, mD02 means the average of maximum derivatives with windows of 0.2 s, and the fECG component will have a greater value for this indicator; mD8 means the average of maximum derivatives with windows of 8 s, and abrupt impulse components may have a larger value of mD8. The separated IC with the largest DWP is identified as the mECG IC in the method.

Concerning the above mentioned methods, just one feature is used for identifying (that is morphology for TM method, instantaneous heart rate for SMI and amplitude for DWP). Their identification criterions seem too simple. In practice, they cannot always identify the mECG IC accurately. In this manuscript we propose a new automatic identifying method called PRCH (short for Peak to peak entropy, R-R interval entropy, Correlation coefficient and Heart rate), based on four kinds of features – amplitude, instantaneous heart rate, morphology and average heart rate of the signal, and a multi-stage selection process. Machine learning is used for parameter decision.

The arrangement of the manuscript is as follows. In Section 2, three databases we used are described, and the backgrounds of ICA and peak detection are reviewed. In core Section 3, the details of the proposed PRCH method are given. Section 4 is the experiments for testing the accuracy and generalization capability of the proposed method, and comparing with other three methods. Discussion and conclusion can be found in Sections 5 and 6 respectively.

## 2. Material

### 2.1. Databases

Parameter learning for the proposed PRCH and tests in Section 4 are based on a huge number of records. Here we give a brief introduction to the databases we used.

*Database A*. Real records collected by a fECG monitor (Type: GY-EXPL, made in China). Every record has one thoracic channel and three abdominal channels. The sampling frequency is 1 kHz. The duration for each record may be different. However, since the monitor was just used as a fECG recorder in hospitals, generally, when the operator saw a fECG segment whose available length was bigger than 10 s, they would finish the recording. In total, there are 1781 records. The database is used for parameter training.

*Database B*. Real records collected by Nihon Kohden 1350P ECG monitor. Every record has eight abdominal channels, and the sampling frequency is 500 Hz. The duration for each record is 24 s. Detailed collection method can be found in [19]. There are 428 records in the database. Only the first 10-s segment are used for tests in Section 4.

*Database C*. Open databases set-A and set-B for the PhysioNet/Computing in Cardiology Challenge 2013 [14]. Every record has four abdominal channels with 1 kHz sampling frequency, and the duration is 60 s. There are 175 records for set-A and set-B originally, and four of them are discarded because no clear mECG obtained after using ICA (a54, a61, b71 and b73). So only 171 records are used for tests in Section 4, specifically taking the second 10-s segment for each record in the test.

### 2.2. Review of the independent component analysis

The aim of Blind Source Separation (BSS) is to recover the original signal sources from several observation signals. Set $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_M)^T$ to represent the observation data, $\mathbf{S} = (\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N)^T$ is the original signal. The relationship between $\mathbf{X}$ and $\mathbf{S}$ is $\mathbf{X} = \mathbf{AS} = \sum a_i \times \mathbf{s}_i$, here $\mathbf{A} = (\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_N)$ is a $M \times N$ matrix called mixing matrix. Independent component analysis (ICA) is one method for BSS, based on the statistic independency of original signal sources. The goal of ICA is to find an unmixed matrix $\mathbf{W}$, satisfying $\mathbf{Y} = \mathbf{WX}$, $\mathbf{Y} = (\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_N)^T$, and every row in $\mathbf{Y}$ represents an estimated independent signal source, called IC. Classic ICA methods include joint approximate diagonalization of eigen matrices (JADE) [21] and FastICA [22], here we used FastICA.

### 2.3. Method for peak detection

The QRS detection we used in the manuscript is similar to the one in a previous manuscript of Pan and Tompkins [23]. It is used in the later "Feature Generation" section.

## 3. The proposed method

Suppose we have obtained $N$ ICs after ICA, the proposed PRCH method can be described as follows.

Step 1: Generate four features for every IC, include peak-to-peak entropy $x1_i$, R-R interval entropy $x2_i$, correlation coefficient $x3_i$ and average heart rate $hr_i$, $i = 1,2,\ldots,N$.

Step 2: Dimension reduction. Let $y_i = ax1_i + bx2_i + cx3_i$, then the three features $x1_i$, $x2_i$ and $x3_i$ are linearly combined into one feature $y_i$.

Step 3: First selection for reducing the candidate channels number. The channels whose $y_i$ values satisfy $y_i \geq Y_{th}$

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