Fetal ECG Extraction by Combining Single-Channel SVD and Cyclostationarity-Based Blind Source Separation

XiaoPing Zeng[1], ShaoHua Li[1,*], GuoJun Li[1,2], Yu Zhou[1] and DaiHui Mo[3]

[1]*College of Communication Engineering, Chongqing University, Chongqing, 400044, China*
[2]*Chongqing Communication Institute, Chongqing, 400035, China*
[3]*Institute of Chinese electronic equipment system Engineering Corporation, Beijing, 100050, China*
[*]*lishao1988621@126.com*

Abstract

Fetal Electrocardiogram (FECG) can provide important clinical information for the assessment of fetal well-being. However, the extraction of FECG from the maternal abdominal wall remains an open problem due to various kinds of interferences and noises, where the maternal Electrocardiogram (MECG) is the dominant source of interference. In this study, a novel FECG extraction framework by combining single-channel singular value decomposition (S-SVD) and cyclostationarity-based blind source separation (C-BSS) is proposed. First, the MECG signal as the principal quasi periodic component is extracted with S-SVD algorithm from a single channel recording. Then, the FECG signal is preliminarily acquired by subtracting the MECG from the corresponding abdominal MECG (AMECG) recording. Finally, the FECG is further extracted by C-BSS, where a new cost function is constructed with high order cumulant and second order cyclic frequency. Results show the proposed method improves the accuracy of extracted FECG in comparison with the traditional BSS algorithm like independent component analysis (ICA).

Keywords: *FECG,MECG, S-SVD, C-BSS, cyclostationary, quasi- periodic*

1. Introduction

Fetal electrocardiogram (FECG) provides significant clinical information about the healthy condition of the fetus, and it is going to be an important tool in modern fetal monitoring system. However, due to the overlap in time domain and frequency domain of the maternal electrocardiogram (MECG) and FECG, relatively low signal-to-noise ratio (SNR) of the FECG compared to the MECG [1], extraction of FECG from abdominal composite MECG (AMECG) is difficult and has been a classical problem in biomedical signal processing for more than fifty years [2]. In previous researches, varied methods ranging from subspace decomposition to signal modeling were proposed. In terms of subspace decomposition method, [3] decomposes the composite MECG into appropriate orthogonal subspaces and different subspace correspond to different signal source; [4] decomposes the AMECG into wavelet domain thus FECG can be extracted. [5] considers the non-gaussian of the signal and separates the MECG and FECG through spatial filter. Though these methods are simple and easy to carry out, they have a common limitation that they will fail in some special source separation, for they are numerous analysis approaches, it means they do the separation blindly without any priori information used; In terms of modeling method, the key idea is to model the MECG in AMECG and remove it to reserve the FECG. [6] proposes a 3-D dynamical model for generating synthetic ECG Signals, [7] proposes the non-linear Bayes filter framework and suppress the MECG successfully. The shortcoming of modeling method is that they may eliminate some FECG while remove the MECG, also, they must acquire some priori information about MECG in advance.

In this study, a novel method specifically customized for FECG extraction is proposed. The method is separated into three steps. First step is signal preprocessing, aiming to remove the baseline wander (BW), power line inference (PLI), and some other high frequency (HF) noise. Second step is a single-channel method, using single-channel singular value decomposition (S-SVD) to eliminate most of the MECG signal and raise the SNR of FECG signal. Third step is a multi-channel method, using the BSS method and priori information of FECG's cyclostationary property, a cost function constructed by fourth-order cumulant and second-order cyclic frequencies is applied to extract FECG, where the cyclic frequencies are estimated after second step. At last, to get clear FECG signal, we may choose the S-SVD to reprocess the extracted FECG.

The rest of the paper is organized as follows. In Section 2, the theory of SVD and cyclostationary stochastic process are reviewed, then the proposed FECG extraction method is presented in Section 3 and Section 4 presents the performance of the proposed method in comparison with kurtosis-based fast independent component analysis (ICA), Finally, a conclusion on this method is given in Section 5.

2. Theoretical Background

2.1. Theory of SVD

For $m\times n$ matrix A, problem of SVD is finding the matrices U,Λ,V, it can be shown as :

$$A_{m\times n}=U_{m\times m}\Lambda_{m\times n}V_{n\times n}^{T} \tag{1}$$

Where U,V are unitary matrices, $U\in R^{m\times m}$ is the left singular matrix of A and $V\in R^{n\times n}$ is the right singular matrix of A, they form a basis for the column-space and the row-space of A, respectively. $\Lambda=[diag\{\lambda_1,...,\lambda_k\}:0]$ is a diagonal matrix and its diagonal values $\lambda_1,...,\lambda_k$ are singular values of A, singular values are generally arranged $\lambda_1\geq\lambda_2\geq...\geq\lambda_k$ and k is the minimum in set $\{m,n\}$. If $\lambda_1^2/\lambda_2^2>>1$, principal component of the signal will be concentrated in subspace $U_1\lambda_1V_1^T$,where U_1,V_1 is the first singular vector of U,V, respectively. And the concept of extract principal component plays an important role in present work.

2.2. Theory of Cyclostationarity

Considering $x(\mathrm{n})$ is a non-stationary stochastic process, if its one-order and second-order statistical characteristics varied periodically with time, $x(n)$ is called cyclostationary process or periodically correlated process [8]. For $x(n)$, time-varied autocorrelation function denotes $R_{xx}(n)$, assuming period of $R_{xx}(n)$ is T, time delay is m, it can be expressed as:

$$\begin{aligned}R_{xx}(n+m/2,n-m/2)&=R_{xx}(n+m/2+T,n-m/2+T)\\&=\sum_{\alpha}R_{xx}^{\alpha}(\tau)e^{j2\pi\alpha n}\end{aligned} \tag{2}$$

Where α is cyclic frequency corresponding to $x(n)$, $\alpha=\mathrm{n}/T,n\in Z$ is n times of fundamental frequency $1/T$. $R_{xx}^{\alpha}(m)$ is Fourier coefficient of time-varied autocorrelation function $R_{xx}(n)$, or call it cyclic autocorrelation function. It can be expressed as:

$$R_{xx}^{\alpha}(m)=\lim_{N\to+\infty}\frac{1}{2N+1}\sum_{n=-N}^{N}R_{xx}(n)e^{-j2\pi\alpha n} \tag{3}$$

Cyclostationary process $x(n)$ with cyclic frequency α has the following properties [9]:

$$R_{x_ix_j}^{\alpha_i}(m)=\left\langle \mathrm{x_i(n)x}_j^*(\mathrm{n+m})\mathrm{e}^{-j2\pi\alpha_i n}\right\rangle_n=0,\ \text{if}\ \ i\neq j \tag{4}$$

$$R_{x_i x_i}^{\alpha_j}(m)=\left\langle x_i(t)x_i^*(n+m)e^{-j2\pi\alpha_j n}\right\rangle_n = 0,\ \text{if}\ \alpha_i \neq \alpha_j \tag{5}$$

$$R_{x_i x_i}^{\alpha_i}(m)=\left\langle x_i(n)x_i^*(n+m)e^{-j2\pi\alpha_i n}\right\rangle_n \neq 0,\ \forall i \tag{6}$$

Where $\langle\cdot\rangle_n$ is a time average operator and the properties will be used in present work.

3. Methods

3.1. Principles of S-SVD

For a single-channel discrete signal $X(n)=\{x(1),x(2),...,x(n)\}$, where n is sample number. If the signal is periodic or quasi-periodic, assuming the number of period is m and maximal period length is L, then resample the length of each quasi-periodic intervals to L and a periodic matrix A for S-SVD can be configured with m row and each row is a period of the signal $X(n)$. A can be described as:

$$A=\begin{bmatrix} x(1) & x(2) & \cdots & x(L) \\ x(L+1) & x(L+2) & \cdots & x(2L) \\ \vdots & \vdots & \vdots & \vdots \\ x((m-1)L+1) & (m-1)L+2 & \cdots & x(mL) \end{bmatrix} \tag{7}$$

Note: in real life environment, a strict periodic signal can hardly be found. So consider the case of the signal is quasi-periodic and the first or last period is not complete, the following edge processing may be needed.

1) For a simple method, the characteristic points of each period are detected firstly and signal is truncated to abandon the first and last un-complete period, then each complete period is resampled to the length of L and periodic matrix A is configured with each row including a complete period of the signal. This method can be simply carried out but will lose the information of the first and last period of the original signal.

2) For an improved method, which processes all the signal periods including the un-complete ones; using the aforementioned simple method to configure the periodic matrix A, and then the first and last un-complete period are resampled in proportion to the nearby complete periods. For example, assuming the first un-complete period length is L_1 and its nearby complete period length is L_2, so the length of the resampled first un-complete period is $\frac{L_1}{L_2}L$. Then configuring another two periodic matrices A_f, A_l with L points in each row to extract the principal component of the preliminary and terminative un-complete periods, respectively. The starting point in the first row of A_f and A_l is the first sample point and the last sample point of the resampled original signal, respectively. The residual points fail to configure a row of A_f or A_l are abandoned.

After periodic matrices are configured, SVD is used to extract the principal component in each periodic interval of the resampled signal. The most dominant component will be concentrated in subspace $U_1\lambda_1V_1^T$, and residual component can be given by $\left(A\text{-}U_1\lambda_1V_1^T\right)$. Principal periodic component X' can be obtained through numerical operator $U_{1i}\lambda_1V_1^T$ and the additional information mixed with noise will in $\left(X-X'\right)$, where U_{1i} is the i^{th} element of U_1 and λ_1 is the first singular value. Considering synchronization with original signal, X' should be resampled to the original sample rate before $(X - X')$ and the resampling process should be do periodically by periodically.

3.2. Principles of C-BSS

The problem of BSS has been widely studied for its ability of recovering latent sources solely from knowledge of observation signals [10]. The linear mixture model, which describes the instantaneous mixing process, will be used in present work can be written as:

$$X(n) = AS(n) + N(n) \tag{8}$$

Where n is the number of samples, $X(n) = [x_1(n), x_2(n), ..., x_m(n)]^T$ is observed signal and $S(n) = [s_1(n), s_2(n), ..., s_{m'}(n)]^T$ is latent sources; $N(n)$ is additive noise, statistically independent with source signals. $A \in R^{m \times m'}$ is a full-rank matrix modeling the transfers from sources to sensors, m and m' denote sensor number and source number, respectively. All signals here are assumed of finite power and zero-mean. The present purpose is to estimate S and A. Under assumption of mutually independent of $s_i(n)$ and $m' \le m$, the linear mixture model can be solved by high order statistical methods, known as ICA [11].

In ICA context, estimation of an individual source denotes $y(n) = w^T X(n)$, where $y(n)$ and w is the estimator of $s(n)$ and the corresponding un-mixing vector, respectively. The cost function can be constructed from kurtosis of $y(n)$:

$$kurt(y) = E(y^4) - 3(E(y^2))^2 \tag{9}$$

If the source signals are non-gaussian and independent distributed sequence, un-mixing vector w corresponding to the source $y(n)$ can be estimated by maximizing the cost function [12]:

$$J = |kurt(y)| \tag{10}$$

But in this paper, the source signal is cyclostationary rather than stationary. Estimating $kurt(y)$ consistently from a finite number of X is difficult if the cyclic frequencies of the second order statistics of the observations are unknown, especially in case of short samples. For statistical characteristic of X is time-variant and time average and cannot replace statistical average. Under mild technical assumption, $E(y^4)$ can be consistently estimated by $\frac{1}{n}\sum_{i=1}^{i=n} y^4$ [13], but $E(y^2)$ can't be consistently estimated without any priori information of the cyclic frequencies corresponding to $X(n)$.

Using Parseval identity $E(y^2)$ can be written as:

$$(E(y^2))^2 = |R_{yy}^0(0)|^2 + 2\sum_{\alpha \in U^+} |R_{yy}^{\alpha}(0)|^2 \tag{11}$$

Where the right side of the equation from $R_{yy}^0(0)$ is a constant, here $R_{yy}^0(0)$ is normalized to 1, and $2\sum_{\alpha \in U^+} |R_{yy}^{\alpha}(0)|^2$ comes from equation $R_{yy}^{\alpha}(0) = \overline{R_{yy}^{-\alpha}(0)}$, and U^+ stands for the positive cyclic frequencies. After substitution $E(y^2)$ of Eq.6 into Eq.8, J can be written as:

$$J = \left| E(y^4) \text{-} 6\sum_{\alpha \in U^+} |R_{yy}^{\alpha}(0)|^2 \text{-} 3 \right| \tag{12}$$

In practice, all the cyclic frequencies should be estimated in advance and this is a price to pay in present work.

The overall C-BSS algorithm can be expressed as follows:

1) Find the cyclic frequencies $\alpha \in U^{+}$ of the observed signal.

2). Repeat, while $k \in [1,...,n]$

3). Calculate the k^{th} un-mixing vector $w_k = [\mathrm{w}_k(1), \mathrm{w}_k(2), ..., \mathrm{w}_k(\mathrm{m})]^T$ through maximizing the cost function J , where m is row number of $X^k(t)$ and the k^{th} source signal is $y_k(t) = w_k^T X^k(t)$.

4). Subtract contribution of the source extracted at the k^{th}, so $X^{(\mathrm{k}+1)}(t)$ can be expressed as: $X^{(k+1)}(t) = X^{(k)}(t) - w_k \cdot y_k(t)$.

5). $c \leftarrow F(x^{(k+1)}(t))$

6). Until $c \le th\_value$

In this algorithm, $F(\cdot)$ is a function used as the stopping criterion, stopping criterion of the k^{th} output can be defined as:

$$F(x^{(k)}(t)) = \frac{\sum_i \sum_j (x^{(k)}(t))^2}{\sum_i \sum_j (x^{(1)}(t))^2} . \tag{13}$$

th_value is predefined as a stopping threshold, and it approximates to zero generally.

4. Application in FECG Extraction

In noninvasive FECG extraction, the FECG is contained in composite AMECG signal recorded from maternal abdominal lead. The signal is a mixture of MECG component, FECG component and some common high-amplitude noises that can't be removed by simple in-band filtering, such as baseline wander (BW), muscle artifact (MA), electrode movement (EM) and so on. Due to physiological reasons, MECG and FECG components are mutually asynchronous and overlapping in both time domain and frequency domain. Satisfactory results cannot be achieved by directly using the tradition BSS methods.

In the following, the proposed method is used for FECG extraction. Algorithm framework is presented in Figure1. It consists of a signal preprocessing step that applies a notch filter to remove PLI and a low-pass filter to remove the BW. The S-SVD is then applied to eliminate most of the MECG signalfor MECG is the largest interference in composite AMECG and its R wave can be easily detected. The output of this step is a multichannel signal which is a mixture of FECG, little MECG and noise. , FECG is further extracted by C-BSS in the last step which is the kernel of this algorithm framework, where a new cost function is constructed with four-order cumulant and second-order cyclic frequency.

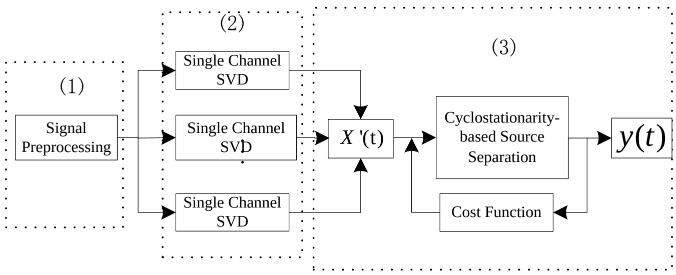

Figure 1. Fetal ECG Extraction Algorithm Framework

4.1. The Data

The latest abdominal and direct fetal electrocardiogram dataset recorded in the Department of Obstetrics at the Medical University of Silesia is used for illustration [14]. These recordings are obtained from 5 different women in labor, between 38 and 41 weeks of gestation. Each recording comprises four differential signals acquired from maternal abdomen leads and the reference direct FECG recorded from the fetal head with a sampling rate of 1000Hz. All the records in dataset have a low FECG SNR and many existing linear source separation methods, such as SVD, ICA can't extract FECG directly. But on the contrary, it has an advantage of its reference direct FECG which can be used as a golden criterion in source separation.

For this real ECG data, it is impossible to evaluate SNR of the extracted FECG; in order to have a quantitative evaluation, similarity of mean FECG heartbeat comes from extracted FECG is used. Definition of mean ECG heartbeat is introduced in [15].

As an illustration, 10 seconds of data in record 04 is used as test data and it requires additional digital filtering for removal of PLI (50Hz) and BW first[14]. In Figure 2 (a), test data is depicted and after signal preprocessing, it is depicted in Figure 2 (b), where the first channel is direct FECG and the others are AMECG, as we can see in Figure 2 (b) the BW is removed and result of PLI cancellation can be seen in its frequency spectrum.

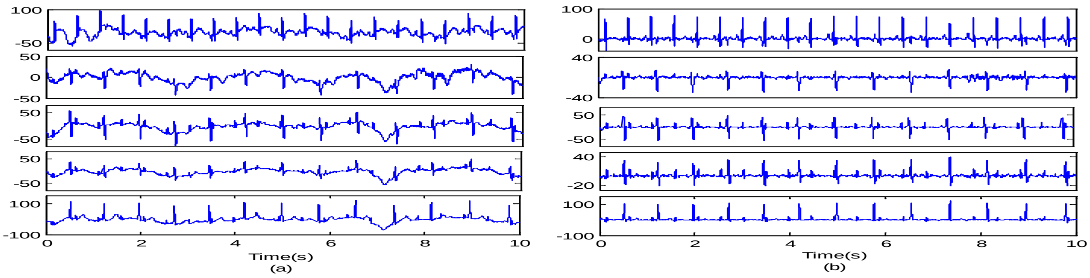

Figure 2. (a). Test Data with One Direct FECG and Four AMECG. (b) Test Data after Signal Preprocessing

4.2. MECG Suppression Using S-SVD

MECG signal has a quasi-periodic structure that is repeated in every cycle of the maternity ECG heartbeat and amplitude up to 20 times stronger than the FECG signal [16, 17]. For a single-channel AMECG signal, the priori information (MECG's quasi-periodicity) is used to form the periodic matrix with each row is a heartbeat of the MECG, and then the SVD is used to extract the principal component of each beat, then matrix reconstruct makes it possible to obtain the principal periodic component of the AMECG signal. As an illustration, , most of the MECG is extracted with scarcely noise and FECG when using S-SVD to process each abdominal channel of test data. Extracted MECG are depicted in Figure 3 (a), and then eliminating the MECG, the noisy FECG are depicted in Figure 3 (b), in red dash line markers, we can see a few MECG are remained. As most of the MECG is suppressed, R wave of FECG can be seen, but due to R wave of MECG and impulse noise, detection of R wave of FECG cannot be realized easily.

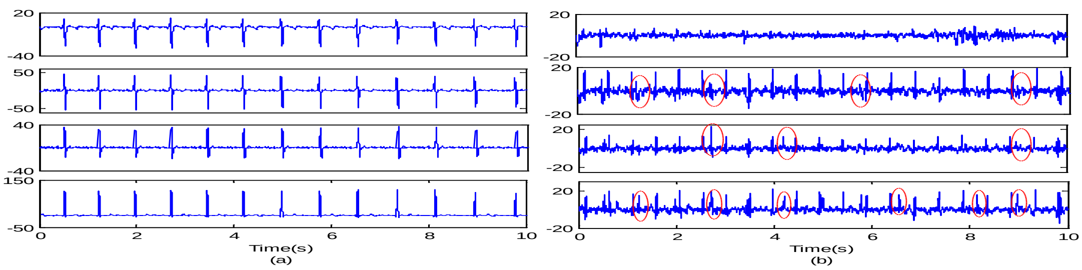

Figure 3. (a) Extracted MECG from Test Data Using S-SVD. (b) Remained Noisy (include FECG, MECG and noise) FECG from Test Data after S-SVD

4.3. FECG Extraction

ECG signals originating from the hearts of the mother and the fetus are independent of each other [18] and FECG is a cyclostationary signal in statistical domain and cyclic frequencies often appear as high peaks in its power spectral density (PSD) [19]. So the proposed method can be used to extract FECG from noisy FECG, and then kurtosis-based ICA is used as the benchmark method. Compared with periodicity estimation in time domain, estimation of cyclic frequency can be in low SNR case and different cyclic frequency corresponds to different cyclostationary signal while impulse noise doesn't have cyclic frequency. Figure 4 depicts a zoom on part of PSD of the noisy FECG, red markers correspond to the part of the cyclic frequencies of FECG (FCY), and here cyclic frequencies are normalized to set $U \in [-1/2, 1/2]$. It can be seen that the spectrum is discrete, so the statistical characteristic of FECG is quasi-periodic, and it also means FECG is a cyclostationary signal.

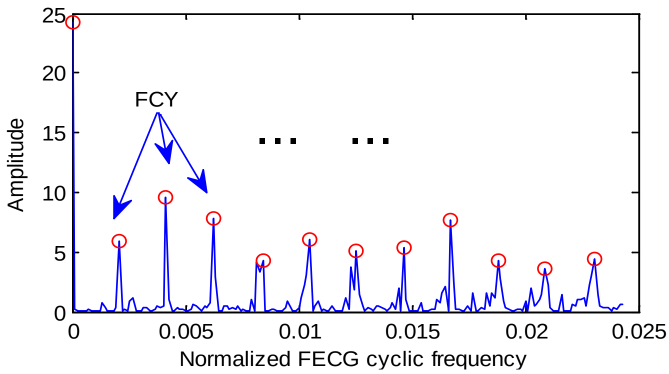

Figure 4. PSD of Noisy FECG from Record 04, Normalized Cyclic Frequencies are [0.0021,0.0042,0.0062,0.0084,0.0105,0.0126,0.0146,0.0167,0.0188,0.0209,0.0231]

Then combining the estimated cyclic frequencies, FECG is extracted by C-BSS. Figure 5 (a.1-a.3) shows the direct FECG of test data, results of extraction using C-BSS and kurtosis-based ICA, respectively. Figure 5 (b) shows a zoom on part of Figure 5 (a.1-a.3). In Figure 5 (b), we can see that the extracted FECG is clear.

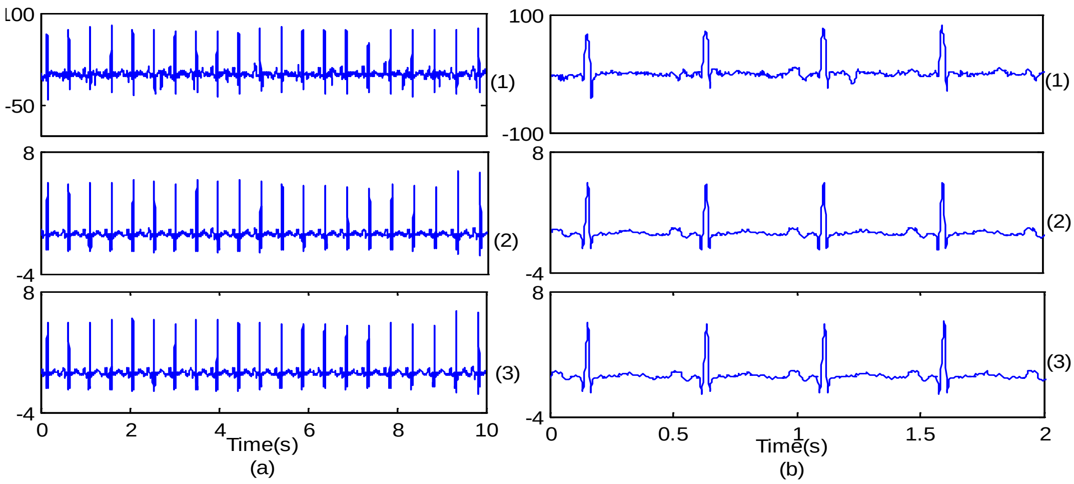

Figure 5. (a.1-a.3) Reference Directs FECG of Test Data, Result of Extraction using C-BSS and Kurtosis-based ICA. (b) A Zoom on Part of (a.1-a.3)

Numerical results on the performance of the proposed method are carried out under different length of test data. Using the aforementioned quantitative evaluation method, mean FECG heartbeat comes from direct FECG (D-FECG), FECG extracted by C-BSS (C-FECG) and kurtosis-based ICA (I-FECG) are depicted in Figure 6, time above the pictures are the length of test data. Similarities of mean FECG heartbeat between D-FECG and C-FECG and similarities of mean FECG heartbeat between D-FECG and I-FECG are presented in Table 1. Results show that the proposed method improves the accuracy of the extracted FECG in short data cases in comparison with ICA and the two methods tend to perform similarly as the length of test data increases.

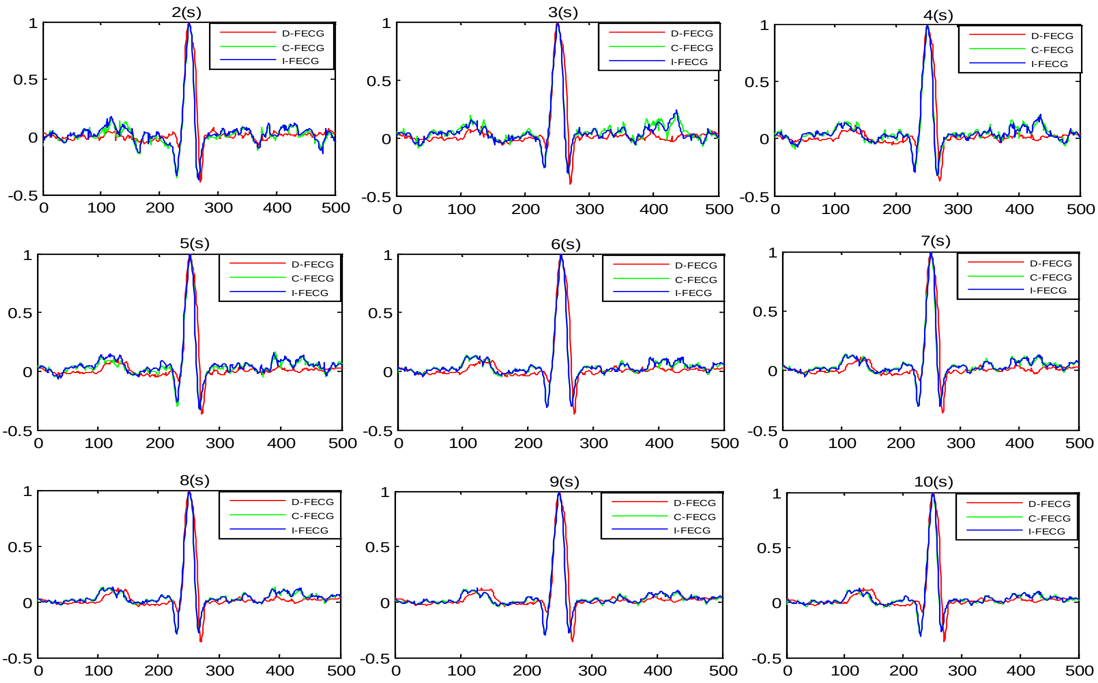

Figure 6. Mean FECG Heartbeat of D-FECG, C-FECG, and I-FECG. Time above the Pictures are the Length of Test Data

Table 1. Similarities of Mean FECG Heartbeat between D-FECG and C-FECG. Vs. Similarities of Mean FECG Heartbeat between D-FECG and I-FECG

Time(s)	C-BSS	kurtosis-based ICA
2	84.85%	84.56%
3	85.11%	84.86%
4	85.95%	84.92%
5	88.33%	87.56%
6	88.98%	88.79%
7	89.18%	89.11%
8	90.34%	90.38%
9	89.21%	88.76%
10	87.91%	88.09%

5. Conclusion

In this paper, a new FECG extraction framework is proposed. The method is based on S-SVD and C-BSS. It has been discussed that the S-SVD method can suppress most of the MECG, so cyclic frequency of FECG in noisy scenario can be estimated accurately, which is a priori information can be used in C-BSS to extract FECG. Results have shown that the proposed FECG extraction method improves the accuracy of the extracted FECG in short data cases in comparison with traditional BSS method.

In future works, the idea of using cyclostationary property to extract FECG can be studied in high order cyclic frequency and semi-blind extraction of interest signal.

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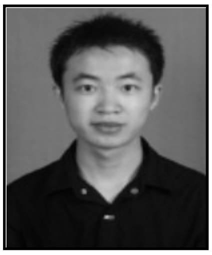
Authors

XiaoPing Zeng received his BS, MS and PhD from Chongqing University in 1982, 1987 and 1996, respectively. He is currently a Professor of College of Communication Engineering at Chongqing University. His research interest covers neural network theory and its applications, information and signal processing, Broadband wireless communications.
E-mail: zxp@ccee.cqu.edu.cn



ShaoHua Li is a graduate student at the College of Communication Engineering, Chongqing University. His research interest covers biomedical signal processing, and big data analysis.
E-mail: lishao1988621@126.com