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FECG Extraction Based on Least Square Support Vector Machine Combined with FastICA*

XIU-JUAN PU, LIANG HAN, QIAN LIU AND AN-YAN JIANG
College of Communication Engineering
Chongqing University
Chongqing, 400044 P.R. China
E-mail: {puxj; hanliangaa}@cqu.edu.cn; {274977693; 1140895871}@qq.com

A new method based on least square support vector machine (LSSVM) combined with FastICA is proposed to extract the fetal electrocardiogram (FECG) from the abdominal signals of a pregnant woman. Firstly, the LSSVM is applied to estimate the maternal electrocardiogram (MECG) component in the multiplex abdominal signals. Then the optimal estimation of multiplex noise-added FECG is obtained by removing the estimated MECG component from the multiplex abdominal signals. Finally, the FastICA is applied to extract the FECG from the multiplex noise-added FECG. The proposed method is validated by the experiments on real electrocardiogram (ECG). The visual results, signal-to-noise ratio (SNR) and training time are used to evaluate the performance of the FECG extraction methods. The experimental results indicate that the FECG is effectively extracted from the abdominal signals utilizing proposed method.

Keywords: FECG extraction, LSSVM, FastICA, MECG component, optimal estimation

1. INTRODUCTION

The fetal electrocardiogram (FECG) is a physiological signal and provides important information about the health condition of the fetus. Many diseases are diagnosed from the FECG during the perinatal period such as anoxia, arrhythmia and increments in the intra-uterine pressure. The early diagnosis of any cardiac defects before delivery increases the effectiveness of appropriate treatments [1-4].

The FECG is obtained directly by placing an electrode on the fetal scalp. However, this is an invasive technique that only is applied during labor when the fetal membranes have ruptured. The other way is to obtain FECG indirectly, that is, put several electrodes on the abdominal area of a pregnant woman to get the abdominal signals, then the FECG is extracted from the abdominal signals. This is a noninvasive method and it is repeatable during the perinatal period. Though it is a promising way, it is not used in the clinic yet mainly because the abdominal signals contain a lot of interferences, such as maternal electrocardiogram (MECG) component, 50 Hz power line interference, baseline wader and electronic random noise. The maternal electrocardiogram (MECG) component is the main interference source among these interferences due to its amplitude is usually 10 times larger than that of FECG [3].

FECG extraction methods based on nonlinear estimation and FECG extraction methods based on blind source separation are widely used to extract FECG from the abdominal signals. FECG extraction methods based on nonlinear estimation only use sev-

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eral collected signals, not taking full information of the collected signals. The methods mainly include adaptive filtering [5-7], artificial neural network (ANN) [3, 4, 8], support vector machine (SVM) [9-12] *etc.* Traditional adaptive filtering cannot adequately remove the MECG component in the abdominal signals. ANN, using empirical risk minimization (ERM) as its rule, has some problem with generalization, structure design and local extremum. SVM, using structural risk minimization (SRM) as its rule, is good at dealing with nonlinear, high dimension and local minimum problem [9, 13]. The typical SVM is based on a ε-insensitive cost function introduced by Vapnik [9]. Though traditional SVM has many advantages in dealing with high-dimensional input space, it also has a quadratic convex optimization problem [14]. Suykens introduced a quadratic cost function into SVM and constructed the least squares support vector machine (LSSVM) [15]. With the quadratic cost function, the optimization problem of LSSVM reduces to finding the solution of a set of linear equations.

FECG extraction methods based on blind source separation are usually based on linear instantaneous mixture model, ignoring the nonlinear mixed characteristics of MECG and FECG signals [16, 17]. Traditional blind source separation (BSS) methods only deal with steady non-Gaussian signals and under noise environment they show bad robustness [17]. Independent component analysis (ICA) is a new BSS technique that shows great convergence and robustness, and has been widely used in speech recognition [18, 19], signal and image processing [20], biomedical signal processing [21] *etc.* FastICA algorithm [22, 23] proposed by Hyvärinen is the most widely used linear ICA methods. It is based on approximate negentropy and Newton iteration that reduce the computation. It has promising properties of easy implementation and fast convergence.

This paper researches a linear instantaneous model combined with nonlinear transformation. Based on the model, a FECG extraction method based on LSSVM combined with FastICA is proposed. The optimal estimation of MECG component in multiplex abdominal signals is obtained utilizing LSSVM. Then the MECG component in multiplex abdominal signals is suppressed to obtain the multiplex optimal estimation of the noise-added FECG. Finally, FastICA is used to extract the FECG from the multiplex estimated noise-added FECG.

2. FECG EXTRACTION MODEL

We placed q electrodes on the thoracic and abdominal area of a pregnant woman to obtain composite signals $X_i(t)(i = 1, \ldots, q)$ consisting of the mixture of MECG component, FECG component and noise [3, 17]. The MECG component is the nonlinear transformation of the MECG signal via maternal chest, skin and other organs and the FECG component is the nonlinear transformation of the FECG signal via amniotic fluid, maternal abdominal cavity *etc.*

FECG Extraction methods based on nonlinear estimation simply choose one signal obtained from the thoracic area as the MECG signal and one signal obtained from the abdominal area as the mixture of the MECG component, FECG signal and noise [3], *i.e.*

$$X(t) = f(S_M(t)) + S_F(t) + N(t) \tag{1}$$

where $X(t)$ is the abdominal signals, $S_M(t)$ is MECG signal, $S_F(t)$ is FECG signal, $N(t)$ is noise and $f(\cdot)$ denotes the nonlinear transformation between the MECG signal and the MECG component. The nonlinear estimation method was used to estimate $f(\cdot)$ and obtain the optimal estimation of MECG component. Then the FECG signal is extracted from the abdominal signals. FECG extraction methods based on nonlinear estimation only use two collected signals, not taking full information of the completely collected signals.

FECG extraction methods based on blind source separation usually assume FECG signal, MECG signal and other noise are independent components, using the linear instantaneous mixture model to model the collected composite signal [23], *i.e.*

$$X_i(t) = H_{iM} \cdot S_M(t) + H_{iF} \cdot S_F(t) + N_i(t) \qquad i = 1, 2, \ldots, q \tag{2}$$

where $X_i(t)$ is the composite signal collected by the ith electrode, $S_M(t)$ is MECG signal, H_{iM} denotes the transmission factor of MECG signal transmitting to the ith electrode, $S_F(t)$ is FECG signal, H_{iF} denotes the transmission factor of FECG signal transmitting to the ith electrode and $N_i(t)$ is the noise. Current research shows that MECG component in the composite signal is a nonlinear transformed version of the MECG signal [3], the linear instantaneous mixture model cannot reflect the nonlinear transformation of the MECG signal and the FECG signal. Besides, traditional blind source separation methods have poor robustness in noisy circumstances and have not brought in priori knowledge [17].

In order to overcome the shortcoming of FECG extraction methods based on nonlinear estimation and based on BSS, a linear instantaneous mixture model combined with nonlinear transformation is proposed to extract FECG, as shown in Fig. 1.

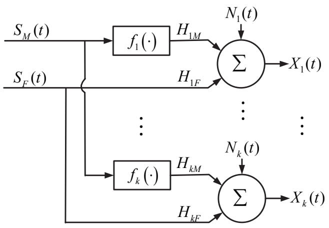

Fig. 1. The linear instantaneous mixture model combined with nonlinear transformation.

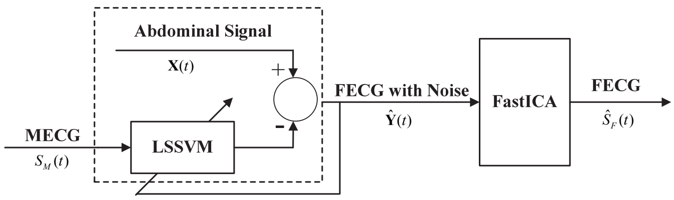

Fig. 2. The proposed method based on LSSVM combined with FastICA.

In the model, one signal obtained from the thoracic area is chosen as the MECG signal $S_M(t)$, and one signal obtained from the abdominal area is

$$X_i(t) = H_{iM} \cdot f(S_M(t)) + H_{iF} \cdot S_F(t) + N(t) \qquad i = 1, 2, \ldots, k \tag{3}$$

where $X_i(t)$ is the ith abdominal signal, k is the number of electrodes placed on the abdominal area of a pregnant woman. $S_M(t)$ is the MECG signal, $f_i(\cdot)$ denotes the nonlinear transformation when the MECG signal transmitting to the abdominal area, H_{iM} is the transmission factor of MECG signal transmitting to the ith electrode and $H_{iM} \cdot f_i(S_M(t))$ denotes MECG component in the ith abdominal signal. $S_F(t)$ is FECG signal, H_{iF} denotes the transmission factor of FECG signal transmitting to the ith electrode and $H_{If} \cdot S_F(t)$ denotes FECG component in the ith abdominal signal. $N_i(t)$ is noise.

There are two key problems need to be solved when utilizing the model to extract

FECG. One is to estimate the nonlinear transformation $f_i(\cdot)$ that MECG signal transmitting to the ith electrode. The other is to estimate the linear instantaneous mixture model coefficient H_{iM} and H_{iF}. Therefore, a new method based on LSSVM combined with FastICA is proposed in the paper, as shown in Fig. 2. In the method, LSSVM is firstly utilized to estimate the multiplex nonlinear transformation $f_i(\cdot)$. Then we obtain the optimal estimation of MECG component $\hat{f}_i(S_M(t))$ (i = 1, …, k) in the multiplex abdominal signals $\mathbf{X}(t) = \{X_1(t), X_2(t), \ldots, X_k(t)\}$. Next, the multiplex optimal estimation of the noise-added FECG $\hat{\mathbf{Y}}(t) = \{\hat{y}_1(t), \hat{y}_2(t), \ldots, \hat{y}_k(t)\}$ is obtained by suppressing the estimated MECG component in the multiplex abdominal signals. Finally, FastICA is used to extract the FECG $\hat{S}_F(t)$ from the multiplex noise-added FECG $\hat{\mathbf{Y}}(t)$.

The advantages of the proposed method are as follows: (1) The estimated noise-added FECG after suppressing the MECG component in the multiplex abdominal signals has much higher SNR than the FECG signal in the multiplex abdominal signals, which is an effective way to improve the performance of the BSS method. Therefore, the proposed method is better than traditional FECG extraction methods based on blind source separation; (2) The signals obtained by suppressing the estimated MECG component in multiplex abdominal signals are the mixture of the FECG signal and noise, which is further processed by the BSS method in the proposed method. However, traditional FECG extraction methods based on nonlinear estimation roughly considers the signal as the extracted FECG. Therefore, the proposed method is better than traditional FECG extraction methods based on nonlinear estimation.

3. LSSVM AND FASTICA

3.1 Least Square Support Vector Machine (LSSVM)

Given a set of training data ($\mathbf{x}_i$, y_i), i = 1, 2, …, l, $\mathbf{x}\in R^n$, $y\in R$, where $\mathbf{x}_i$ is the input vector and y_i is the corresponding target output. The input data $\mathbf{x}$ is mapped into a high dimensional feature space by factor $\Phi(\cdot)$, and then linear regression is used in feature space and optimal studying machine is constructed as

$$f(\mathbf{x}) = \mathbf{w}^T\Phi(\mathbf{x}) + b \tag{4}$$

where $\mathbf{w}$ and b are unknown variables which are estimated by regularization and SRM principle. Based on SRM principle, the regression problem is given as

$$\min\frac{1}{2}\|\mathbf{w}\|^2+\frac{1}{2}C\sum_{i=1}^{l}\xi_i^2; \quad s.t. \quad y_i=\mathbf{w}\cdot\Phi(\mathbf{x}_i)+b+\xi, i=1,2,\cdots,l \tag{5}$$

where $C \geq 0$ and it is a regularization parameter used to decide a trade-off between the training error and margin. Using the Lagrange multiplier method, the regression problem shown in Eq. (3) is formulated as follows

$$L(\mathbf{w},\xi,a,b)=\frac{1}{2}\|\mathbf{w}\|^2+\frac{1}{2}\sum_{i=1}^{l}C\xi_i^2-\sum_{i=1}^{l}\alpha_i(\mathbf{w}\Phi(\mathbf{x}_i)+b+\xi_i-y_i) \tag{6}$$

where α_i (i = 1, 2, …, l) are Lagrange multipliers. By optimality condition, the formula is

$$\begin{cases} \dfrac{\partial L}{\partial \mathbf{w}} = 0 \Rightarrow \mathbf{w} = \sum_{i=1}^{l} \alpha_i \Phi(\mathbf{x}_i) \\ \dfrac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{l} \alpha_i = 0 \\ \dfrac{\partial L}{\partial \xi_i} = 0 \Rightarrow \alpha_i = C\xi_i \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \Rightarrow \mathbf{w}\Phi(\mathbf{x}_i) + b + \xi_i - y_i = 0 \end{cases} \tag{7}$$

Based on Eq. (7), the linear equations are shown as follows

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(\mathbf{x}_1,\mathbf{x}_1)+1/C & \cdots & K(\mathbf{x}_1,\mathbf{x}_l) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(\mathbf{x}_l,\mathbf{x}_1) & \cdots & K(\mathbf{x}_l,\mathbf{x}_l)+1/C \end{bmatrix} \begin{bmatrix} b \\ \alpha_1 \\ \vdots \\ \alpha_l \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_l \end{bmatrix} \tag{8}$$

where $K(\mathbf{x}_i, \mathbf{x}_j) = \Phi(\mathbf{x}_i)\cdot\Phi(\mathbf{x}_j)$ is defined as kernel function. Any function that satisfies Mercer's condition [24] is used as the kernel function. The most commonly used kernel functions are listed as follows

Linear kernel: $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$;
Polynomial kernel: $K(\mathbf{x}_i, \mathbf{x}_j) = (\Upsilon \mathbf{x}_i^T \mathbf{x}_j; + r)^d$;
Sigmoid kernel: $K(\mathbf{x}_i, \mathbf{x}_j) = tanh(\Upsilon \mathbf{x}_i^T \mathbf{x}_j + r)$;
RBF kernel: $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-|\mathbf{x}_i - \mathbf{x}_j|^2/\sigma^2)$.

During experiments, it is better to select RBF kernel in the proposed FECG extraction method. From Eq. (8), the LSSVM regression function is constructed as follows

$$f(\mathbf{x}) = \sum_{i=1}^{l} \alpha_i K(\mathbf{x}_i, \mathbf{x}) + b \tag{9}$$

3.2 FastICA

The aim of ICA is to transform the mixed random signals $\mathbf{x}$ into independent components. One of the most used ICA algorithms for the linear mixing model is FastICA proposed by Hyvärinen and Oja [22, 23]. It is based on the optimization of a nonlinear contrast function measuring the non-Gaussianity of the source. The advantages of FastICA over traditional ICA algorithms are simplicity and flexibility to choose the nonlinearity function. A BSS system is defined as

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{10}$$

where $\mathbf{A}$ is an n by n mixing matrix, $\mathbf{x}$ is the matrix of n observing mixed signal vectors, and $\mathbf{s}$ is the matrix of n blind source signal vectors. The goal of ICA is to recover the source signal $\mathbf{s}$. Observing $\mathbf{x}$, the weight matrix $\mathbf{W}^T$ is found by ICA. Then the blind source signal $\mathbf{s}$ is obtained by

$$\mathbf{s} = \mathbf{W}^T\mathbf{x} \tag{11}$$

where $\mathbf{W}^T$ is equal to the inverse matrix of $\mathbf{A}$. The FastICA algorithm consists of two steps, preprocessing and fixed-point algorithm.

Step 1: Preprocessing

This step includes two parts, centering and whitening. That means the mixed signals with zero mean and unit variance is obtained through this preprocessing. The centering part is expressed as

$$\bar{\boldsymbol{x}}(i) = \boldsymbol{x}_m(i) - E\{\boldsymbol{x}_m\} \tag{12}$$

where $\bar{\boldsymbol{x}}_m(i)$ is the mixed signal with zero mean and $E\{\boldsymbol{x}_m\}$ is the mean value of the random variable $\boldsymbol{x}_m$. After subtracting the mean value, $\bar{\boldsymbol{x}}_m$ is a zero-mean vector. The centering matrix is expressed as below

$$\bar{\mathbf{x}} = \begin{bmatrix} \bar{\boldsymbol{x}}_1^T \\ \bar{\boldsymbol{x}}_2^T \\ \vdots \\ \bar{\boldsymbol{x}}_n^T \end{bmatrix} = \begin{bmatrix} \bar{x}_1^T(1) & \bar{x}_1^T(2) & \cdots & \bar{x}_1^T(n) \\ \bar{x}_2^T(1) & \bar{x}_2^T(2) & \cdots & \bar{x}_2^T(n) \\ \vdots & \vdots & \ddots & \vdots \\ \bar{x}_n^T(1) & \bar{x}_n^T(2) & \cdots & \bar{x}_n^T(n) \end{bmatrix} \tag{13}$$

The eigenvalue decomposition is used to decompose the covariance matrix of $\bar{\boldsymbol{x}}$ and the corresponding operation is expressed as below

$$\mathbf{C}_{\mathbf{X}} = \boldsymbol{E}\{\bar{\mathbf{x}}\bar{\mathbf{x}}^T\} = \mathbf{EDE}^T \tag{14}$$

where $\mathbf{E}$ denotes the orthogonal matrix of $\mathbf{C}_{\mathbf{x}}$ and $\mathbf{D}$ represents the diagonal matrix of $\mathbf{C}_{\mathbf{x}}$.

The whitening process of $\bar{\boldsymbol{x}}$ is expressed below

$$\mathbf{Z} = \mathbf{D}^{-1/2}\mathbf{E}^T\bar{\mathbf{x}} = \mathbf{P}\bar{\mathbf{x}} \tag{15}$$

where $\mathbf{P}$ denotes the whitening matrix of $\bar{\boldsymbol{x}}$.

Step 2: fixed-point algorithm

The meaning of “fixed-point” is an iteration scheme to find the local extreme value of the kurtosis for efficiently estimating the non-Gaussian independent components [25]. The basic method of the FastICA algorithm is as follows

(1) Take a random initial vector and divide it by its norm. Let $k = 1$.
(2) Let $\mathbf{w}(k) = E\{\mathbf{Z}[\mathbf{Z}^T\mathbf{w}(k-1)]^3\} - 3\mathbf{w}(k-1)$.
(3) Divide $\mathbf{w}(k)$ by its norm.
(4) If $|\mathbf{w}^T(k)\mathbf{w}(k-1)|$ is not close enough to 1, let $k = k+1$, and go back to step 2. Otherwise, the algorithm is convergent and outputs $\mathbf{w}(k)$.

$\mathbf{w}$ is the separating vector used to calculate the estimated independent component $\mathbf{s}_{\text{est}}$. k is the iteration index.

If there are independent components to be separated, each converging result of the FastICA algorithm $\mathbf{w}$ is one of the columns in demixing matrix $\mathbf{B}$. Assuming $\mathbf{w}$ is a column of $\mathbf{B}$, the estimated independent component $\mathbf{s}_{est}$ is expressed as

$$\mathbf{s}_{est} = \mathbf{w}^T\mathbf{Z}. \tag{16}$$

To ensure that each estimation is a different independent component, the FastICA algorithm adds the following simple and orthogonal projection:

$$\mathbf{w} = \mathbf{w} - \bar{\mathbf{B}}\bar{\mathbf{B}}^T\mathbf{w},\ \mathbf{w} = \mathbf{w}/\|\mathbf{w}\| \tag{17, 18}$$

where $\bar{\mathbf{B}}$ is a matrix whose columns are the previously determined columns of $\mathbf{B}$.

4. FECG EXTRACTION METHOD

The FECG extraction method based on LSSVM combined with FastICA takes the steps as follows

Step 1: Nonlinear estimation based on LSSVM

One of the key problems of FECG extraction is to estimate the nonlinear transformation the MECG undergoing while transmitting to the abdominal area. LSSVM is used to estimate the nonlinear transformation. The input data of LSSVM is the MECG signal $S_M(t)(t = 1, 2, \ldots, n)$ and its J time-derivations, the target value is multiplex abdominal signals $X_1(t), X_2(t), \ldots, X_k(t)(t = 1, 2, \ldots, n)$. The target signal and the input signal are denoted by $\boldsymbol{X}$ and $\boldsymbol{S}_M$, which are shown as

$$\mathbf{X}=\begin{bmatrix} \boldsymbol{X}_1(t) \\ \boldsymbol{X}_2(t) \\ \vdots \\ \boldsymbol{X}_k(t) \end{bmatrix} = \begin{bmatrix} X_1(1) & X_1(2) & \cdots & X_1(n) \\ X_2(1) & X_2(2) & \cdots & X_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ X_k(1) & X_k(2) & \cdots & X_k(n) \end{bmatrix}, \tag{19}$$

$$\mathbf{S}_M = \begin{bmatrix} \boldsymbol{S}_M(1) & \boldsymbol{S}_M(2) & \ldots & \boldsymbol{S}_M(n) \end{bmatrix}^T = \begin{bmatrix} S_M(1) & \dot{S}_M(1) & \cdots & S_M^{(J)}(1) \\ S_M(2) & \dot{S}_M(2) & \cdots & S_M^{(J)}(2) \\ \vdots & \vdots & \ddots & \vdots \\ S_M(n) & \dot{S}_M(n) & \cdots & S_M^{(J)}(n) \end{bmatrix}. \tag{20}$$

Put $\mathbf{X}$ and $\mathbf{S}_M$ into LSSVM, the output of LSSVM is the nonlinear transformed MECG component in ultiplex maternal abdominal signals $\hat{\boldsymbol{S}}_M(\hat{S}_M = \boldsymbol{H}_M \cdot \hat{f}(\boldsymbol{S}_M))$. The difference of the target signal and the output signal of LSSVM is the error signal $\mathbf{e}$

$$\mathbf{e} = \mathbf{X} - \hat{\mathbf{S}}_M \tag{21}$$

Considering the SRM principle, the minimum function complexity and fitting error $E(\mathbf{e}^T\mathbf{e})$, the optimal estimation $\hat{f}(\cdot)$ of the nonlinear transformation $f(\cdot)$ is obtained.

Step 2: Extract noise-added FECG component

Input MECG and its J time-derivations $\boldsymbol{S}_M(t)$ to trained LSSVM and obtain the optimal estimation of MECG component in multiplex abdominal signals

$$\hat{\boldsymbol{S}}_M(t) = \boldsymbol{H}_M \cdot \hat{f}(\boldsymbol{S}_M(t)) \tag{22}$$

let $\boldsymbol{Y}(t) = \boldsymbol{H}_F \cdot S_F(t) + \boldsymbol{N}(t)$ (23)

the optimal estimation of noise-added FECG component is $\hat{\boldsymbol{Y}}(t) = \boldsymbol{X}(t) - \hat{\boldsymbol{S}}_M(t)$ (24)

Step 3: Extract FECG

Using FastICA to extract FECG from the optimal estimation of FECG $\hat{\boldsymbol{Y}}(t)$

$$\hat{\boldsymbol{Y}}(t) = \boldsymbol{H}_M \cdot \left(f\left(\boldsymbol{S}_M(t)\right) - \hat{f}\left(\boldsymbol{S}_M(t)\right) \right) + \boldsymbol{H}_F \cdot S_F(t) + \boldsymbol{N}(t) \tag{25}$$

choose one of the output signals as the optimal estimation of the FECG $\hat{S}_F(t)$.

Step 4: Quality assessments

In this paper, the eigenvalue analysis and cross correlation are used to estimate the SNR of the extracted FECG [26]. The extracted FECG is firstly segmented into L pulses. These pulses are noted as $r(i)(i = 1, 2, \ldots, L)$, where L is the number of pulses in the extracted FECG, and arranged as columns of a matrix $\mathbf{U}_{K\times L}$.

(1) Estimating the SNR using eigenvalue analysis

$$SNR_{eig} = \sqrt{\frac{\lambda_1^2}{\sum_{i=2}^{L} \lambda_i^2}} \tag{26}$$

where λ_i is the eigenvalue of the matrix $\mathbf{U}^T\mathbf{U}$.

(2) Estimating the SNR using cross correlation

$$SNR_{RMS} = \sqrt{\frac{\eta}{1-\eta}}. \tag{27}$$

The parameter $\eta = \frac{2}{L(L-1)} \sum_{i=0}^{L-2} \sum_{j=i+1}^{L-1} \boldsymbol{r}(i)^T \boldsymbol{r}(j)$ is the mean estimated signal power.

5. RESULTS

5.1 Analysis of the Proposed Method

To evaluate the performance of the proposed method, the real ECG signals contributed by Lathauwer [27] are used in this paper. ECG data is shown in Fig. 3. Abscissa represents sample number and vertical ordinate represents relative amplitude.

The data represent 10s recordings from eight different skin electrodes located on different points of a pregnant woman's body sampled by frequency 250Hz. The upper five recordings are collected from the maternal abdominal area while the other three are collected from the maternal thoracic area. Because of the long distance between the fetal heart and thoracic electrodes, it is assumed that there is no FECG component in the thoracic signals. According to the steps in section 4, LSSVM toolbox is used to estimate the nonlinear transformation. The inputs of LSSVM $\boldsymbol{S}_M(t)$ is the third maternal thoracic signal (Thr3) and its J time-derivations, the target output are multiplex abdominal signals $\mathbf{X}(t) = (X_1(t), X_2(t), \ldots, X_5(t))$. According to the experiments, when $J = 4$, the performance is the best. Also through the experiments, the parameter of LSSVM toolbox is chosen as gam = 1.40 and sig2 = 0.65. The optimal estimation of noise-added FECG component in multiplex abdominal signals are shown in Fig. 4.

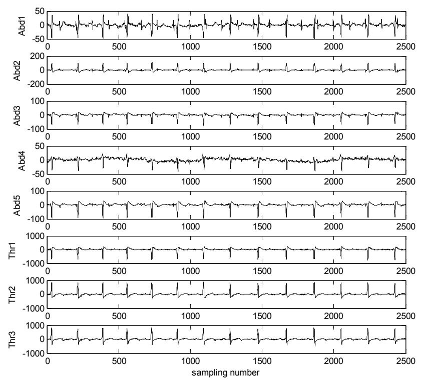

Fig. 3. The original ECG signals collected from a pregnant woman.

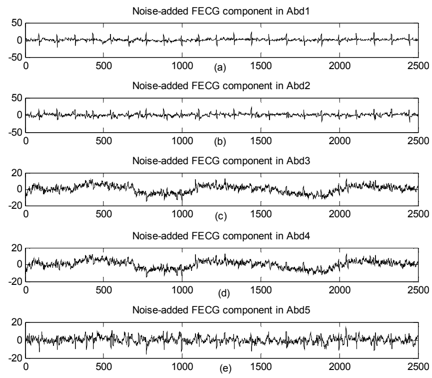

Fig. 4. Five channels noise-added FECG with Thr3 as MECG signal.

Using the signals shown in Fig. 4 as the input signals of FastICA, and the results are shown in Fig. 5. It is seen from the Fig. 5, the signal (Fig. 5 (a)) is the extracted FECG signal. Repeating the FECG extraction experiments with the first and the second lead of thoracic signal as the MECG respectively, the results are shown in Fig. 6. It is seen from Fig. 6 that the proposed method is able to extract clear FECG with different input MECG.

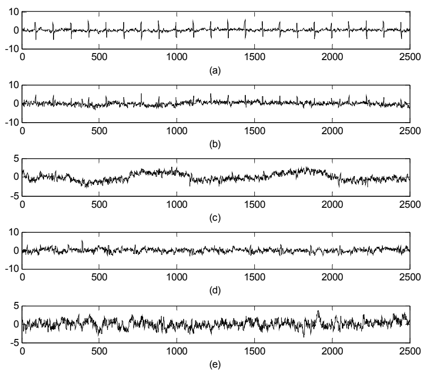

Fig. 5. The results of FastICA with Thr3 as MECG signal.

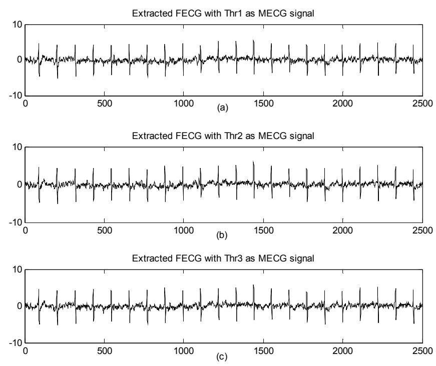

Fig. 6. The extracted FECG with different MECG signal.

5.2 Comparison with LSSVM and FastICA Method

In order to illustrate the performance of the proposed method, LSSVM and FastICA are respectively used to extract FECG. The LSSVM method only needs two signals to extract FECG from the abdominal signal. The input data of LSSVM is the MECG signal Thr3 and its $J = 4$ time-derivations, the target value is abdominal signal Abd1. The parameters of LSSVM toolbox is chosen as gam = 1.4 and sig2 = 0.65. The extracted FECG is shown in Fig. 7 (c). The FastICA method indirectly put all the 8 leads data Abd1 ~ Abd5 and Thr1~Thr3 into FastICA. According to the results of experiment, choose one of FastICA outputs (shown in Fig. 7 (d)) as the extracted FECG signal.

It is seen from the Fig. 7 that three extraction methods all suppress the MECG component in the abdominal signals. Nevertheless, the FECG extracted by the proposed method is much clearer than other. We zoom in the two boxes to illustrate the performance of the three methods. Figs. 8-9 show that the visible remnant of the MECG component in the extracted FECG (boxes) by the LSSVM method and the FastICA method. Using the quality assessment methods introduced in step 4 of Section 4, the SNRs of the extracted FECG are shown in Table 1. The training time is also shown in Table 1 (MATLAB R2013a, CPU is i5-3337u and RAM is 4.00GB).

Table 1. Comparison of SNRs and Training time using the proposed method, LSSVM method and FastICA method.

Methods	SNR_{eig}(dB)	SNR_{RMS}(dB)	Training
LSSVM combined with FastICA	14.7158	14.0922	6.4947
LSSVM	8.8292	7.9214	1.5336
FastICA	11.9743	11.3012	0.7673

Table 1 shows that the FECG extracted by proposed method has higher SNR than others. Therefore, the proposed method based on LSSVM combined with FastICA is better than the LSSVM method and the FastICA method.

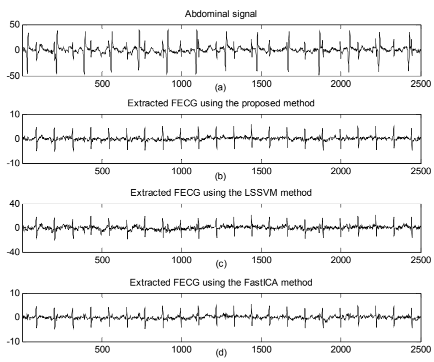

Fig. 7. The experimental results contrast figure with the proposed method, the LSSVM method and the FastICA method.

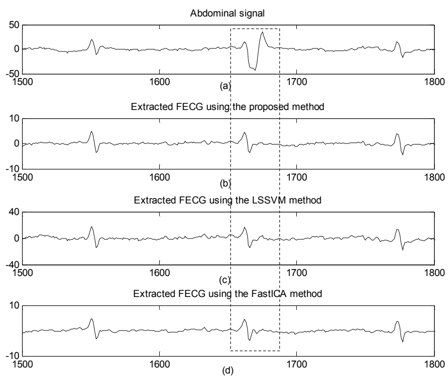

Fig. 8. The experimental results contrast figure with the proposed method, the LSSVM method and the FastICA method (1500-1800).

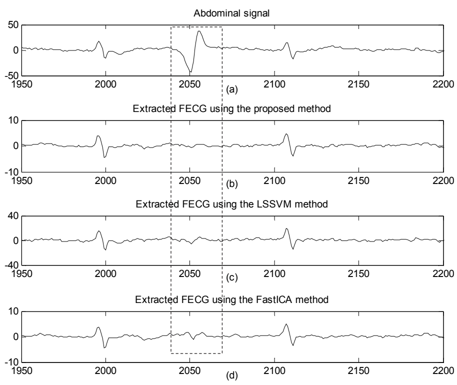

Fig. 9. The experimental results contrast figure with the proposed method, the LSSVM method and the FastICA method (1950-2200).

5.3 Comparison with Some Other Methods

The visual results from the same real ECG signals are used to compare the performance of the proposed method, the ANFIS method [3] and the RLS method [6] in FECG extraction. The results are shown in Fig. 10.

Fig. 10 shows that the FECG extracted by the proposed method is clearer than the two other methods. We zoom in the box to illustrate the performance of the three methods. Fig. 11 shows that the visible remnant of the MECG component in the extracted FECG (boxes) by the ANFIS method and the RLS method. The SNR and training time of these three methods are shown in Table 2 (MATLAB R2013a, CPU is i5-3337u and RAM is 4.00GB).

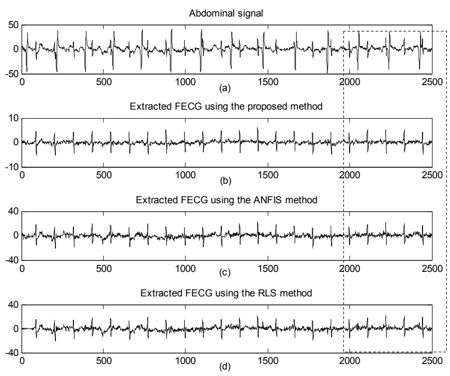

Fig. 10. The experimental results contrast figure with the proposed method, the ANFIS method and the RLS method.

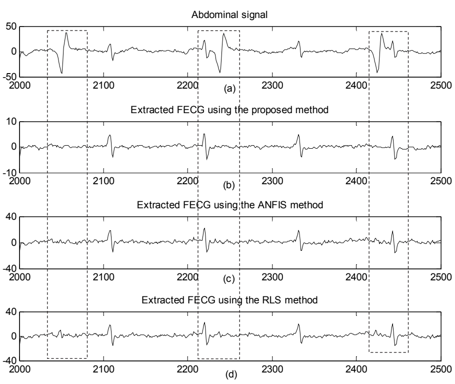

Fig. 11. The experimental results contrast figure with the proposed method, the ANFIS method and the RLS method (2000-2500).

It is seen from Table 2 that the FECG extracted by proposed method has higher SNR than using the ANFIS method and the RLS method. Therefore, the proposed method based on LSSVM combined with FastICA is better than the ANFIS method and the RLS method.

Table 2. Comparison of SNRs and Training time using the proposed method, ANFIS method and RLS method.

Methods	SNR_{eig}(dB)	SNR_{RMS}(dB)	Training time(s)
LSSVM combined with FastICA	14.7158	14.0922	6.4947
ANFIS	8.4719	7.5675	3.3261
RLS	7.3531	6.4117	0.3325

In summary, comparison of visual results and SNR demonstrate that the proposed method of FECG extraction combined with LSSVM and FastICA is the best one among the LSSVM method, the FastICA method, the ANFIS method, the RLS method and the proposed method. The training time of the proposed method is higher than other methods. However, the time of data processing is less than that of data acquisition. Therefore the proposed method have clinical application prospect.

The proposed method has ability to extract the QRS wave effectively. However, it is not enough to extract the whole FECG (including QRS wave, P and T waves). P and T waves have great meaning in diagnosing fetal atrial hypertrophy, anoxia and cord entanglement. It is a restriction of FECG lacking P and T waves for clinical use. Keep exploring how to extract whole FECG is the next research direction. Besides, there is still some noise in the extracted FECG using the proposed method. It is to be further research how to remove noise by using de-noising techniques. Recently, granular computing is an emerging computing paradigm of information processing and provides an ability to create innovative representations of objects. In terms of granular computing, a cluster can be interpreted as an information granule that presents its objects on a coarser and more granular level [28-30]. It is worth of future research to apply granular clustering techniques for FECG extraction.

6. CONCLUSION

In this paper, a new FECG extraction method combined with LSSVM and FastICA was proposed. The proposed method firstly utilized LSSVM to obtain the optimal estimation of MECG components in multiplex abdominal signals. Then we suppressed the MECG components and obtained the optimal estimation of noise-added FECG in multiplex abdominal signals. Finally, FastICA was used to extract the FECG from noise-added FECG.

The clinical ECG data provided by Lathauwer is used in the paper. SNR based on eigenvalue analysis technique and the cross correlation technique is used to evaluate the performance of the FECG estimation methods. Experimental results show that the proposed method is effective in FECG extraction. Either the visual result or SNR shows the proposed method is better than the LSSVM method, the FastICA method, the ANFIS method and the RLS method.

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Xiu-Juan Pu (蒲秀娟) received her B.Sc. degree, M.Sc. degree and Ph.D. degree from Chongqing University in 2001, 2005, 2008, now she is a Lecture in Chongqing University. Her main research interests is biomedical signal processing.

Liang Han (韩亮) received his B.Sc. degree, M.Sc. degree and Ph.D. degree from Chongqing University in 1997, 2004, 2008, now he is an Associate Professor in Chongqing University. His main research interests are signal processing and image processing.

Qian Liu (刘茜) received her B.Sc. degree in 2013 from Chongqing University, now she is a graduate student of Chongqing University. Her main research interests include signal and information processing.

An-Yan Jiang (蒋安炎) received her B.Sc. degree in 2016 from Dhonghua University. Now she is a master student in Chongqing University. Her main research interests include signal and information processing.