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Semi-blind source extraction algorithm for fetal electrocardiogram based on generalized autocorrelations and reference signals

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Abstract

Blind source extraction (BSE) has become one of the promising methods in the field of signal processing and analysis, which only desires to extract "interesting" source signals with specific stochastic property or features so as to save lots of computing time and resources. This paper addresses BSE problem, in which desired source signals have some available reference signals. Based on this prior information, we develop an objective function for extraction of temporally correlated sources. Maximizing this objective function, a semi-blind source extraction fixed-point algorithm is proposed. Simulations on artificial electrocardiograph (ECG) signals and the real-world ECG data demonstrate the better performance of the new algorithm. Moreover, comparisons with existing algorithms further indicate the validity of our new algorithm, and also show its robustness to the estimated error of time delay.

Keywords: Independent component analysis; Semi-blind source extraction; Constrained optimization; Generalized autocorrelation; Fixed-point algorithm

1. Introduction

Over the past decades the problem of blind source separation (BSS) [8,9,11,18] has received much research attention because of its potential applicability to a wide range of problems, such as communications signals and biomedical signals analysis and processing, geophysical data processing, data mining, speech analysis, image recognition, texture modelling and so on [1,2,4,5,7,12,15,16]. In BSS problems, the multidimensional observations must be processed to recover the original sources without the benefit of any a priori knowledge about the mixing operation or the sources themselves. Generally, classical BSS methods consider the simultaneous recovery of all the independent components from their linear mixtures. However, in practice, extracting all the source signals from a large number of observed sensor signals, for example, a magnetoencephalographic (MEG) measurement which may output hundreds of recordings, could take a long time and in these signals only a very few are desired with given characteristics. In this case it is more practical to recover a subset of the source only. This is known as blind source extraction (BSE). When combined with a deflation procedure, BSE algorithms can be viewed as the methods

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of sequential extraction of all the independent sources [10]. BSE may have several advantages over simultaneous BSS [8]. For example, only "interesting" source signals need to be extracted; signals can be extracted in a specific order according to some features of source signals; lots of computing time and resources can be saved. Therefore, it has become a promising method in various fields such as biomedical signal processing and analysis, data mining, speech and image processing, and so on [3,8,11,18].

Nowadays, many source extraction algorithms have been developed through optimization of different cost functions, generally based on high-order statistics [1,6,8,13,18] to extract a source signal. And these methods have been used successfully in many fields. However, it is computationally expensive to exploit high-order statistics. Thus the trend is to develop second-order statistics based extraction algorithms using the priori knowledge about source signals, such as sparseness [29], high-order statistics [27], smoothness or linear predictability [3,8], or time structure [3,7,14,26]. Recently, Lu et al. [20–22] proposed a good candidate, that is ICA with reference (ICA-R), for extracting several source signals from a large number of observed signals. It was formed by minimizing the less-complete ICA objective function and makes the best of the traces of the interesting sources referred to reference signals which carry some prior information to distinguish the desired components but are not identical to the corresponding sources. This method has become an efficient approach utilizing prior information and it has been successfully used for fMRI data analysis etc.

Moreover, in many applications, such as ECG extraction, the desired source signal is periodic or quasi-periodic. So the period property can be used as prior information to extract the desired source signal. Barros and Cichocki [3] provided a simple batch learning algorithm (simplified "BCBSE algorithm") for semi-blind extraction of the desired source signal, which can extract the desired source as long as they are decorrelated and show a temporal structure. However, this method is only carried out the constrained minimization of the mean squared error, which can not accurately describe the probability distribution of the innovation of the signals. It is a possible reason why this algorithm is very sensitive to the estimation error of the time delay and cannot reliably cancel noise contamination in the recovered signals [24]. Recently, Shi and Zhang [24] developed a semi-blind source extraction method (simplified "SemiBSE algorithm"), which based on the non-Gaussianity and the autocorrelations of the desired source signal. This method has been successfully used for fetal electrocardiogram (FECG) extraction, and its advantage in its tolerance to large estimate errors of the period has been pointed in [24]. However, its performance was not entirely satisfactory because the recovered signals often included noise contamination. In [25], authors addressed the semi-blind source extraction problem when the desired source signals have linear or nonlinear autocorrelations. Based on the generalized autocorrelations of the primary sources, a BSE algorithm (called "GABSE algorithm") was proposed. It has been shown that the GABSE algorithm has good stability and convergence, moreover it possesses a higher accuracy of extraction. However, this algorithm is not very robust to the estimation error of the time delay. The width of estimate errors of the period is limited to only about ten time delays, which is smaller than that of SemiBSE algorithm in [24].

In order to improve extraction performance and the tolerance to the estimated error of the time delay, we develop an objective function for extraction of temporally correlated source in this paper, which based on generalized autocorrelations and reference information of desired signals. Maximizing this objective function, we propose a semi-blind source extraction fixed-point algorithm. This algorithm incorporates more priori information of the desired signal, which can be viewed as a refined substitution of the GABSE algorithm. It is able to extract decorrelated periodic source, which is the closest one, in some sense, to the reference signal when the closeness measure is properly chosen. The following simulation experiments show that our new algorithm outperforms many existing algorithms, such as the BCBSE algorithm, SemiBSE algorithm and GABSE algorithm.

This manuscript is organized as follows. In Section 2, we provide a new cost function which is based on the generalized autocorrelations and reference signals of the desired sources, after which we derive the semi-blind source extraction fixed-point algorithm. Section 3 demonstrates the present technique with experiments using artificial ECG signals and real-world ECG data. Conclusions are drawn in the final section.

2. Proposed algorithms

2.1. Objective function

Denote the observed sensor signals $\mathbf{x}(t) = (x_1(t), \ldots, x_n(t))^{\mathrm{T}}$ described by matrix equation

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t), \tag{1}$$

where $\mathbf{A}$ is an $n \times n$ unknown mixing matrix, and $\mathbf{s}(t) = (s_1(t), \ldots, s_n(t))^{\mathrm{T}}$ is a vector of unknown temporally correlated sources (zero-mean and unit-variance). We assume that the desired source signal s_i (in case of the FECG extraction, s_i is the desired FECG) has specific temporal structures—linear or nonlinear autocorrelations. Because we want to extract only a desired source signal, for this purpose we design a single neural processing unit described as

$$\begin{aligned} &y(t) = \mathbf{w}^{\mathrm{T}}\mathbf{x}(t), \\ &y(t-\tau) = \mathbf{w}^{\mathrm{T}}\mathbf{x}(t-\tau), \end{aligned} \tag{2}$$

where $y(t)$ and $y(t-\tau)$ are the recovered source signal at time t and $(t-\tau)$ respectively, $\mathbf{w} = (w_1, \ldots, w_n)^{\mathrm{T}}$ is the weight vector.

Provided that the measured sensor signals $\mathbf{x}$ have already been followed by an $n \times n$ whitening filter $\mathbf{V}$ such that the components of $\tilde{\mathbf{x}}(t) = \mathbf{V}\mathbf{x}(t)$ are unit variance and uncorrelated. Shi et al. [25] present the following constrained maximization problem

$$\begin{cases} \max & \Psi(\mathbf{w}) = E\{G(\tilde{y}(t))G(\tilde{y}(t-\tau))\} \\ \text{s.t.} & \mathbf{w}^{\mathrm{T}}\mathbf{w} = 1, \end{cases} \tag{3}$$

where $\tilde{y}(t) = \mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t)$, $\tilde{y}(t-\tau) = \mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t-\tau)$ and G is a differentiable function, which measures the autocorrelation degree of the desired signal. Example of choices are $G(u) = u$, $G(u) = u^2$, $G(u) = u^3$, or $G(u) = \log\cosh(u)$. In Section 3, we will show the characteristics of different functions G.

In many applications, like biomedical applications, some reference signal is explicitly available which corresponds to stimulus. In such cases, it is usually desired to extract a source signal which is as close as possible to the reference signal $r(t)$. For this purpose, we can add to the cost function discussed above an auxiliary penalty term $\varepsilon(\tilde{y}(t), r(t))$. For example, we can use the following constrained optimization problem for extraction of temporally correlated sources, which is based on the above mentioned generalized autocorrelations and an auxiliary term, i.e.

$$\begin{cases} \max & \Phi(\mathbf{w}, \mu) = E\{G(\tilde{y}(t))G(\tilde{y}(t-\tau))\} + \dfrac{\mu}{2}\varepsilon(\tilde{y}(t), r(t)) \\ \text{s.t.} & \mathbf{w}^{\mathrm{T}}\mathbf{w} = 1, \end{cases} \tag{4}$$

where μ is a penalty parameter, G is the same as above. Notice that $\varepsilon(\tilde{y}(t), r(t))$ is applied to measure the closeness between the recovered signal $\tilde{y}$ and r. Examples of choices are $\varepsilon(\tilde{y}(t), r(t)) = -E\{(\tilde{y}(t) - r(t))^2\}$ or $\varepsilon(\tilde{y}(t), r(t)) = (E\{\tilde{y}(t)r(t)\})^2$ [17].

2.2. Learning algorithms

According to the gradient ascent learning rule, we can maximize the objective function in (4) and derive a gradient method. However, in order to derive a more efficient fixed-point iteration, we note that at a stable point of the gradient algorithm, the gradient must point in the direction of $\mathbf{w}$, that is, the gradient must be equal to $\mathbf{w}$ multiplied by some scalar constant. Only in such a case, adding the gradient to $\mathbf{w}$ does not change its direction, and we have convergence, which means that after normalization to unit norm, the value of $\mathbf{w}$ is not changed except perhaps by changing its sign.

The gradient of $\Phi(\mathbf{w}, \mu)$ with respect to $\mathbf{w}$ can be computed as

$$\begin{aligned} \frac{\partial \Phi(\mathbf{w}, \mu)}{\partial \mathbf{w}} = {} & E\{g(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t))G(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t-\tau))\tilde{\mathbf{x}}(t) + G(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t))g(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t-\tau))\tilde{\mathbf{x}}(t-\tau)\} \\ & + \frac{\mu}{2}\varepsilon'(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t), r(t)). \end{aligned} \tag{5}$$

Using the gradient of $\Phi(\mathbf{w}, \mu)$ in (5) with $\mathbf{w}$, this means that we should have

$$\mathbf{w} \propto E\{g(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t))G(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t-\tau))\tilde{\mathbf{x}}(t) + G(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t))g(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t-\tau))\tilde{\mathbf{x}}(t-\tau)\} + \frac{\mu}{2}\varepsilon'(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t), r(t)). \tag{6}$$

This equation immediately suggests a fixed-point algorithm and gives the right-hand side as the new value for $\mathbf{w}$, i.e.

$$\mathbf{w} \leftarrow E\{g(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t))G(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t-\tau))\tilde{\mathbf{x}}(t) + G(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t))g(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t-\tau))\tilde{\mathbf{x}}(t-\tau)\} + \frac{\mu}{2}\varepsilon'(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t), r(t)), \tag{7}$$

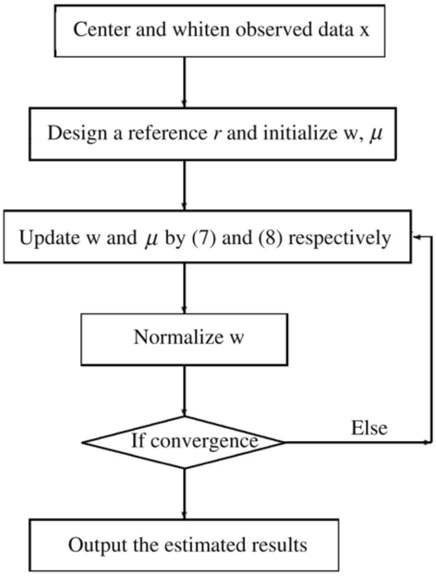

Fig. 1. The flowchart of the proposed algorithm.

where the function g and ε' are the derivatives of G and ε respectively. Note that $\varepsilon' = -2E\{(\tilde{y}(t) - r(t))\tilde{\mathbf{x}}(t)\}$ when $\varepsilon = -E\{(\tilde{y}(t) - r(t))^2\}$ (denoted as "New algorithm1"). Correspondingly, when ε equals $(E\{\tilde{y}(t)r(t)\})^2$, ε' equals $2E\{\tilde{y}(t)r(t)\}E\{r(t)\tilde{\mathbf{x}}(t)\}$ (denoted as "New algorithm2").

Note that the parameter μ is learnt by the gradient $\Phi(\mathbf{w}, \mu)$ with respect to μ, i.e.

$$\mu \leftarrow \frac{\partial \Phi(\mathbf{w}, \mu)}{\partial \mu} = \frac{1}{2}\varepsilon(\mathbf{w}^{\mathrm{T}}\tilde{\mathbf{x}}(t), r(t)). \tag{8}$$

Specifically, our algorithms can be described as follows and their flowcharts are shown in Fig. 1.

Step 1. Center the observed signals $\mathbf{x}$ and whiten them to $\tilde{\mathbf{x}}$.
Step 2. Design a suitable reference signal r and initialize $\mathbf{w}$ and μ.
Step 3. Update $\mathbf{w}$ and μ according to (7) and (8) respectively.
Step 4. Normalize $\mathbf{w}$ by $\mathbf{w}/\|\mathbf{w}\|$.
Step 5. If not converged, go back to **Step 3**.

3. Simulation results

To verify the validity of our algorithms, extensive computer simulations are carried out. The performance of algorithms to estimate the desired signal is measured by performance index (PI), which is defined as follows

$$\mathrm{PI} = \sum_{j=1}^{n} \frac{|p_j|}{\max\limits_{k} |p_k|} - 1, \quad k = 1, \ldots, n, \tag{9}$$

where p_j denotes the j element of the global vector $\mathbf{p} = \mathbf{w}^{\mathrm{T}}\mathbf{VA}$. PI is zero when the desired signals are perfectly extracted. Besides, the accuracy of the recovered source signals compared to the sources is expressed using the signal-to-noise ratio (SNR) in dB given by

$$\mathrm{SNR} = 10\log_{10}(s^2/\mathrm{MSE}), \tag{10}$$

where s^2 denotes the variance of the source signal, MSE denotes the mean square error between the original signal and the recovered signal. The higher SNR is, the better performance is.

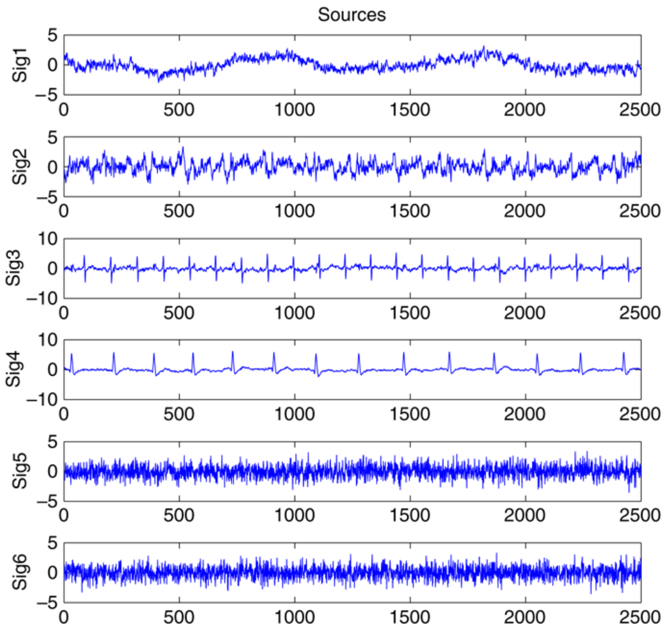

Fig. 2. Six artificial ECG signals used in the simulations. (Sig1) Breathing artifact. (Sig2) Electrode artifact. (Sig3) FECG. (Sig4) MECG. (Sig5-Sig6) Two i.i.d. Gaussian signals.

Table 1
The average PIs of the desired signals using New algorithm1 and New algorithm2 to different $G(u)$ when $\tau = 112$ for artificial ECG signals

$G(u)$	u	u^2	u^3	$\log\cosh(u)$
New algorithm1	0.2587	0.1454	0.1845	0.1547
New algorithm2	0.3218	0.1937	0.1865	0.1229

3.1. Experiments on artificial ECG data

The extraction of FECG using non-invasive technique is an important challenge in biomedical signal processing and analysis. The FECG contains important information about health and condition of the fetus. However, there are some problems, for example, FECG is always corrupted by various kinds of noise, such as the maternal ECG (MECG) with extreme high amplitude, respiration and stomach activity, thermal noise, etc. Therefore, how to extract a clear FECG as the first extracted signal has become a vital issue. In the following, we made many experiments on artificial ECG data and real-world ECG data [23] in order to extract a clearer FECG signal, furthermore, to verify the efficiency of our algorithms. We adopted six zero-mean and unit-variance source signals (2500 samples), shown in Fig. 2. From the top to down, they were, a breathing artifact, electrode artifact, an FECG whose sampling period is 112 (i.e. $\tau = 112$), an MECG and two i.i.d. Gaussian signals [24,25]. The observed signals were generated by a 6×6 random mixing matrix. Note that in the experiment the time delay τ was all chosen to be 112. In order to choose G of New algorithm1 and New algorithm2 suitably, we firstly ran these two algorithms to different G respectively. This experiment was independently repeated 100 times in which $\mathbf{w}$ was initialized randomly. Figs. 3 and 4 shows comparison results of the average PI values of 100 independent trials by two algorithms. New algorithm1 performs better when $G(u) = u^2$, and New algorithm2 performs better when $G(u) = \log\cosh(u)$. Therefore, in the following experiments, we choose $G(u) = u^2$ for New algorithm1 and $G(u) = \log\cosh(u)$ for New algorithm2. The average PIs are shown in Table 1, from which we can also see that the performance of New algorithm2 (when $G(u) = \log\cosh(u)$) is superior to New algorithm1 (when $G(u) = u^2$).

We ran the BCBSE algorithm, SemiBSE algorithm, GABSE algorithm and our two algorithms—New algorithm1 (choosing $G(u) = u^2$) and New algorithm2 (choosing $G(u) = \log\cosh(u)$) for extraction of the FECG simultaneously. In these algorithms, the time delay τ was chosen to be 112. The parameter μ was initialized as

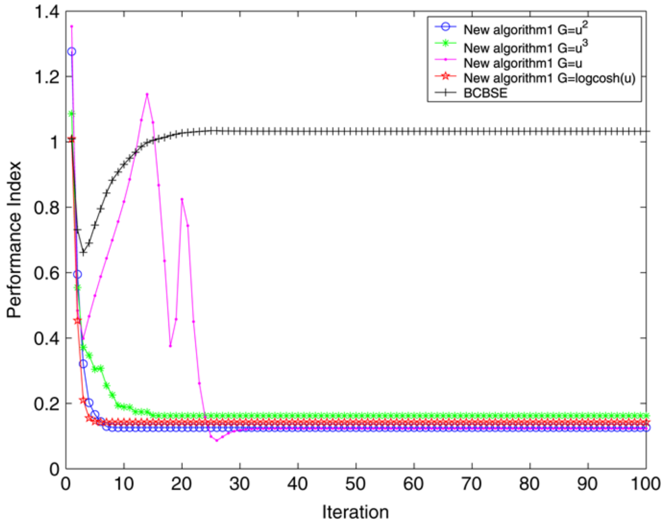

Fig. 3. Average PIs over 100 independent runs to New algorithm1 at $\tau = 112$.

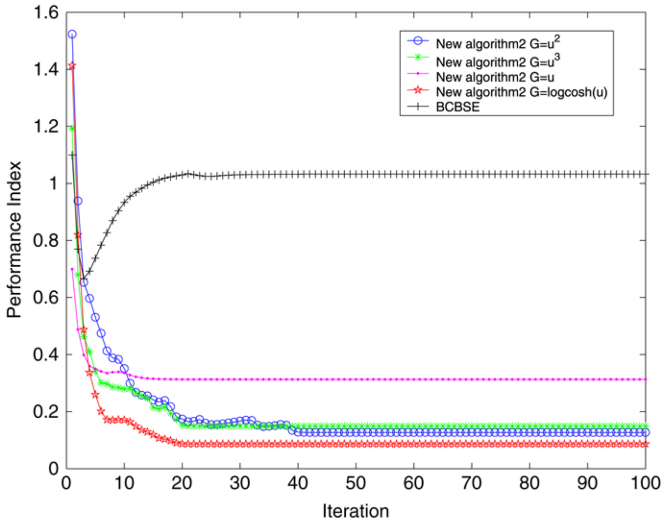

Fig. 4. Average PIs over 100 independent runs to New algorithm2 at $\tau = 112$.

$\mu = 1$ and $\mathbf{w}$ was set randomly. It should be noticed that the selection of the reference signal r is crucial for the performance of our algorithms. In this simulation, we employed the most simple reference signal which was identical to the corresponding source (i.e. Sig3). The accuracy of extraction was measured by the accuracy index (10). The SNRs of the extracted FECGs are 3.397 dB (BCBSE algorithm), 11.067 dB (SemiBSE algorithm), 21.347 dB (GABSE algorithm), 22.595 dB (New algorithm1) and 25.588 dB (New algorithm2) respectively. Fig. 5 presents the FECGs extracted by five algorithms. Compared with other algorithms, New algorithm1 and New algorithm2 obtained more clearer FECG signals. In order to further illustrate the effectiveness of our algorithms, we did this extraction experiment 100 times independently and gave here the mean SNR values of these trials. The mean SNR values are 3.395 dB (BCBSE algorithm), 10.039 dB (SemiBSE algorithm), 21.347 dB (GABSE algorithm), 22.903 dB (New algorithm1) and 25.588 dB (New algorithm2) respectively. The superiority of our algorithms at $\tau = 112$ is straightforward, especially New algorithm2.

It should be mentioned that our algorithms have the property of perfect robustness. Even if the range of the estimated errors was changed largely, our algorithms also worked well, which is important in practice. In the simulations, the SNRs over 100 independent trials were computed when τ was changed from 100 to 145. Note that

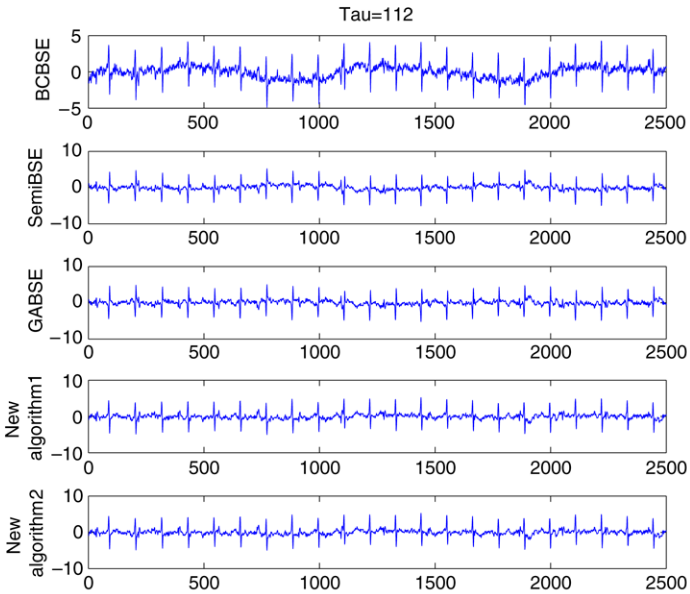

Fig. 5. Extraction results for artificial ECG signals at $\tau = 112$. From top to bottom, the extracted FECGs by BCBSE algorithm, SemiBSE algorithm, GABSE algorithm, New algorithm1 and New algorithm2 respectively.

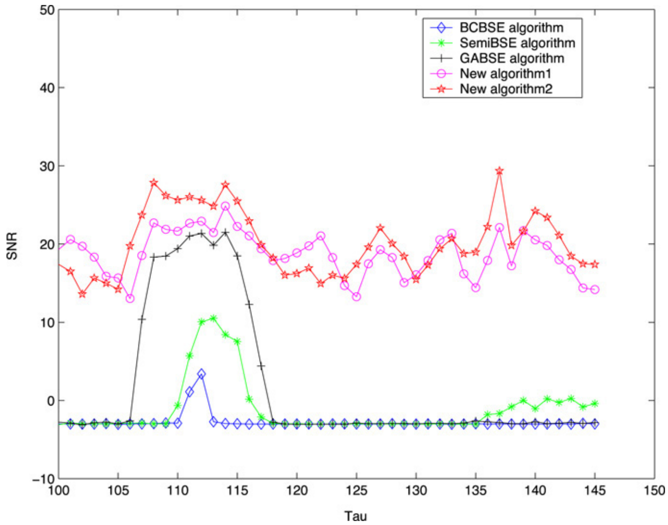

Fig. 6. Comparison of SNRs of five algorithms at different time delay τ for artificial ECG signals.

to each of experiments, the mixing matrix **A** and the weight vectors **w** were generated randomly, and the reference signals using in our algorithms was still Sig3 in Fig. 2. Fig. 6 shows the comparison results of the average SNRs. Even if the time delay has a large estimated errors, our algorithms improve the performance considerably over existing algorithms.

Moreover, it must be noted that the selection of the reference signal is an important issue for the proposed algorithms. Therefore, we will demonstrate this problem with some experiments, which are based on above artificial ECG data and New algorithm2. Three signals r_1, r_2 and r_3 were used as references respectively, which are shown in Fig. 7. Note that r_1 corresponds to the MECG signal, r_2 has the same period as desired FECG but includes lots of respiration noise and r_3 corresponds to Sig3 in Fig. 2, which is the best one among three signals.

Fig. 8 provides the SNR comparison results when the three above-mentioned reference signals were utilized. It can be clearly seen that the best r_3 gives the best performance. On the contrary, r_2 shows the worst one, which contains

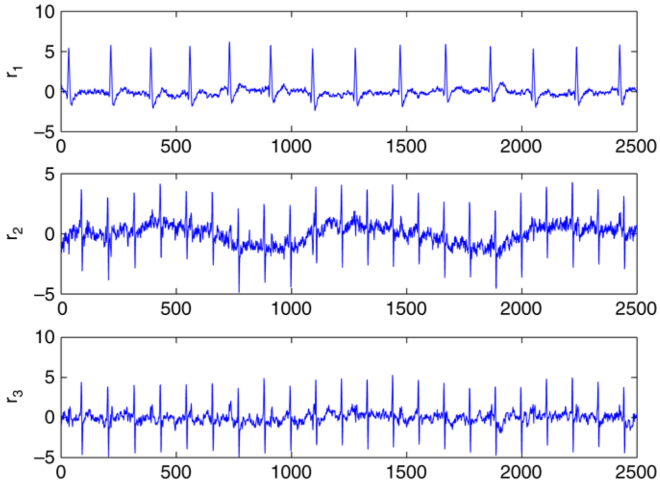

Fig. 7. Three reference signals r_1, r_2 and r_3.

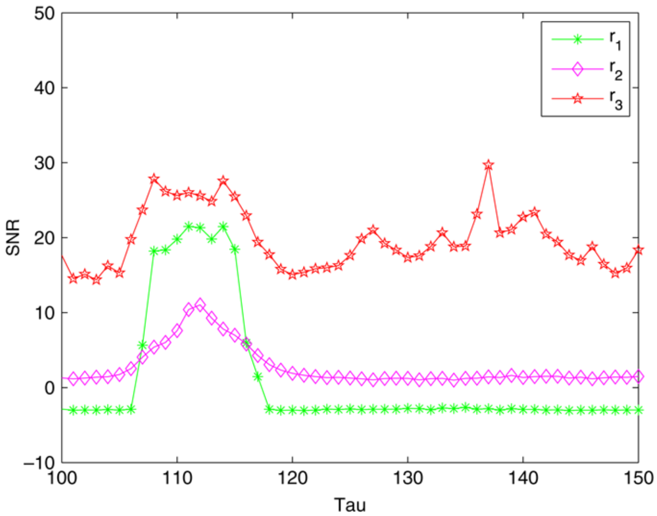

Fig. 8. SNR comparison results of New algorithm2 to reference signals r_1, r_2 and r_3 for artificial ECG signals.

lots of noise, therefore r_2 is an unsuitable reference signal for the extraction of desired FECG. As for r_1, which is a clearer signal with different fundamental period but the same pulse shape as FECG signal, its application improves the performance of the proposed algorithm to some extent when τ falls in the interval [108, 115]. This means that the algorithm's performance is affected by the reference signal, but it shows that even if the reference signal is not selected well, the proposed algorithm is able to provide satisfactory performance, for example in the case of r_1, which shows the robustness of the proposed algorithms to the reference signal.

3.2. Experiments on real-world ECG data

In order to further confirm the validity of the proposed algorithms, we have performed experiments on real-world ECG data which is distributed by De Moor [23]. This data is a famous ECG measured from a pregnant woman (in Fig. 9). One can see the heart beat of both the mother (stronger and slower) and the fetus (weaker and faster). Note that the fetal influence is stronger in the first channel in Fig. 9. The ECG measurements were recorded over 10s and sampled at 250 Hz (although in De Moor's homepage he claims the sampling frequency is 500 Hz, Barros et al. [3] assure it is 250 Hz).

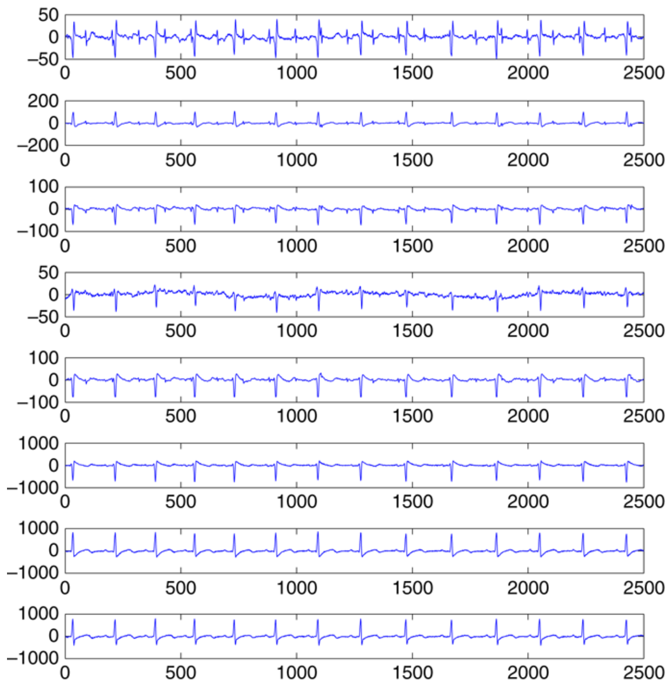

Fig. 9. The 8-channel of ECG recording obtained from a pregnant woman.

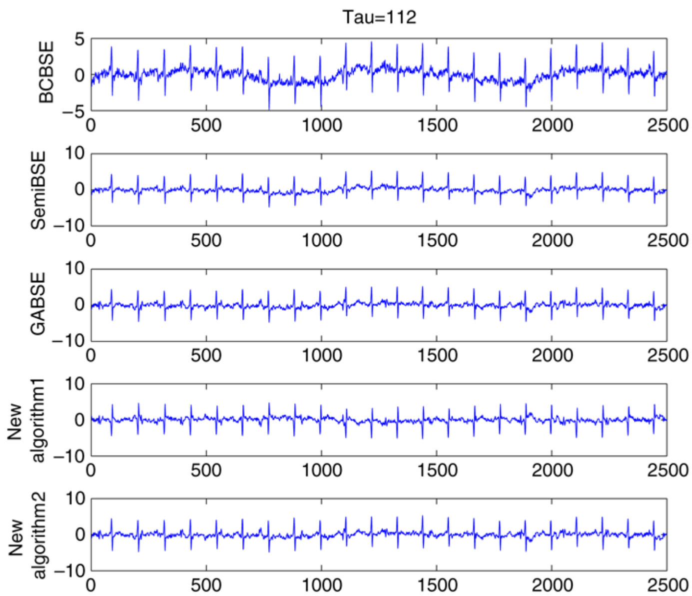

Fig. 10. Comparison of extracted FECGs for real-world ECG data at $\tau = 112$. From top to bottom, the extracted FECGs by BCBSE algorithm, SemiBSE algorithm, GABSE algorithm, New algorithm1 and New algorithm2 respectively.

By using prior information about FECG frequency, we might estimate the optimal time delay $\tau = 112$. The same parameters were chosen as the experiments on artificial data. Fig. 10 corresponds to the extracted FECGs by the above five algorithms. Note that the reference signal of our algorithms was Sig3 in artificial ECG data. From the figure we can see that the desired FECGs are all well extracted, except for the BCBSE algorithm. Since the mixing matrix **A** and the pure FECG signal were not available, the PI and the SNR performance could not be computed as above. But we could perceive distinctly the quality of extracted FECG through experience.

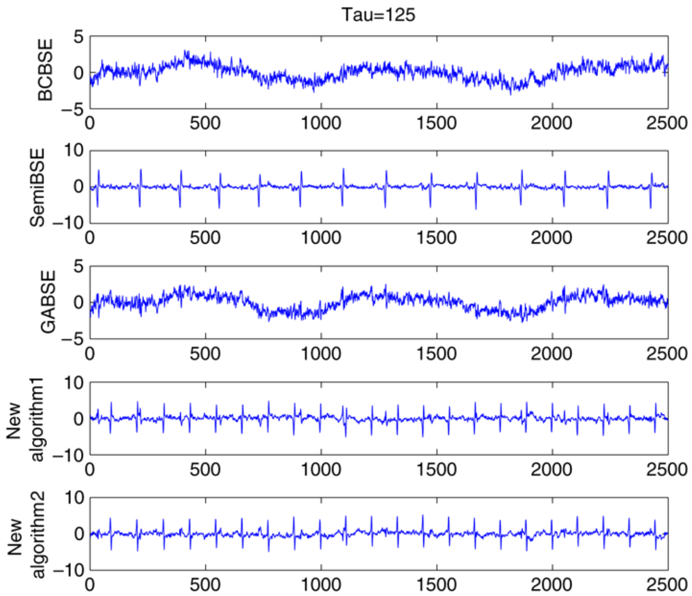

Fig. 11. Comparison of extracted FECGs at $\tau = 125$ for real-world ECG data. From top to bottom, the extracted FECGs by BCBSE algorithm, SemiBSE algorithm, GABSE algorithm, New algorithm1 and New algorithm2 respectively.

In this case, one could also make use of either the fact that a fetal heart rate is around 120 beats per second, which means that the heart should strike every 0.5 s (corresponding to 125 samples for the data) [3,24]. It means that we can simply use $\tau = 125$ in these algorithms without examining the autocorrelation of the sensor signal. We provided the waveforms of the FECG signal recovered by above five algorithms in Fig. 11. Obviously, the extracted FECGs by our algorithms are the clearest, while the one by the SemiBSE algorithm is close to MECG. The results by BCBSE algorithm and GABSE algorithm are the worst ones, which are mixed with lots of respiratory noise.

And we also made 100 independent experiments to examine the robustness of our algorithms when the time delay was changed from 100 to 145. Note that in these experiments, we believed that the optimal desired FECG could be obtained at $\tau = 112$. So we could take the FECG extracted by New algorithm2 at the time delay $\tau = 112$ as the benchmark signal (shown in Fig.10 (New algorithm2)). Based on this benchmark, we computed the correlation coefficients between estimated signal at different time delay and the benchmark signal (all estimated signals are normalized to be zero-mean and unit-variance). The results are plotted in Fig. 12.

Similar to [24], a correlation coefficient of the estimated signal which is higher than 0.9 can be considered to achieve a good extraction level. From the results, we can see that the GABSE algorithm is sensitive to the estimation error of the time delay and the extracted signal is satisfactory only when $\tau \in [108, 115]$. As to SemiBSE algorithm and BCBSE algorithm, their performances are the worst, which are too sensitive to extract desired FECG signal at all. However, our algorithms work well, especially New algorithm1 performs more robustly than the others in the whole interval [100, 145]. Therefore, these results indicate that New algorithm1 is the best one among above algorithms, which is identical with the known facts in [17], that is, the mean squared error(mse) $\varepsilon(y, r) = E\{(y - r)^2\}$ was quite efficient for heart artifact signals. However, it must be noted that these results are not inconsistent with foregoing FECG extraction results at $\tau = 112$, which show New algorithm2 is superior to New algorithm1. Because, when $\tau \in [108, 115]$, the average correlation coefficient of New algorithm2 is 0.9982. It is higher than that of New algorithm1, which is 0.9936.

4. Discussions and conclusions

Due to the low computation load and fast processing speed, blind source extraction has become one of the promising methods in the field of neural networks, especially unsupervised learning, and more generally in advanced statistics and signal processing. Against this background, Shi et al. [25] addressed the semi-blind source extraction problem when the desired source signals have linear or nonlinear autocorrelations. Based on the generalized autocorrelations of the primary sources, they proposed the GABSE algorithm and successfully applied it to the

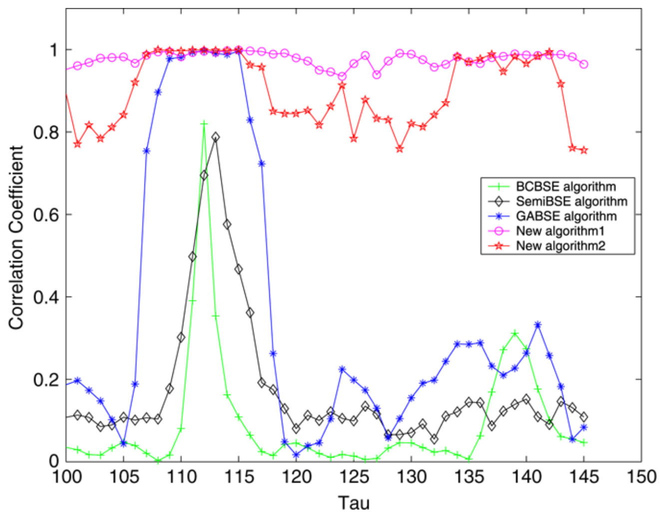

Fig. 12. The correlation coefficients between the estimated signal and the benchmark signal for real-world ECG data.

extraction of the FECG. In many applications, like biomedical applications, some reference signal is explicitly available which corresponds to stimulus. In such cases, it is usually desired to extract the signal which is as close as possible to the reference signal. For this purpose, we develop a new objective function for the extraction of temporally correlated source, which is based on the the generalized autocorrelations and reference information of desired source signal. Maximizing this objective function, we propose a semi-blind source extraction fixed-point algorithm which can extract a clearer FECG and is very robust to the estimated error of the time delay. Experiments with artificial ECG data and real-world ECG data reveal the efficacy and accuracy of the proposed method.

Actually, contrary to gradient-based algorithms, there is no learning rate in the proposed algorithms, which makes it easy to use, and more reliable. However, it should be pointed that the steady good performance of our algorithms may be contributed to the application of a properly reference signal. Fortunately, the proposed method does not greatly depend on the selection of the reference signals, which makes this method suitable for broader applicability. Undoubtedly, the better the reference signal, the better performance of the algorithm. Appropriate estimation of the reference signal is critical for achieving best performance. Therefore the selection of the reference signal still remains one of the important issues, just as in other works [19–22,28]. So our future work will focus on how to design more suitable reference signals so as to improve the quality of the semi-blind source extraction algorithms.

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