2017 International Conference on Computer Network, Electronic and Automation (ICCNEA 2017)

Separating Signals with Specific Temporal Structure

Yongjian Zhao
School of Information Engineering
Shandong University (Weihai)
Weihai, China
E-mail: zhaoyj@sdu.edu.cn

Haining Jiang
School of Information Engineering
Shandong University (Weihai)
Weihai, China
E-mail: jian123cn@sdu.edu.cn

Bin Jiang
School of Information Engineering
Shandong University (Weihai)
Weihai, China
E-mail: jiangbin@sdu.edu.cn

Meixia Qu
School of Information Engineering
Shandong University (Weihai)
Weihai, China
E-mail: qumx@sdu.edu.cn

***Abstract*—Blind signal extraction is particularly attractive to solve signal mixture problems while only one or a few source signals are desired. Many desired biomedical signals exhibit distinct periods. A sequential method based on second order statistics is introduced in this paper. One can choose to recover one source signal or all signals in a specific order. The validity and performance of the proposed method are confirmed by computer simulations.**

Keywords-Component; Period; Order; Mixture; Extraction; Simulation

I. INTRODUCTION

In recent decades, blind signal separation (BSS) has been studied extensively and has become an increasingly important technique for signal analysis [1-3]. Indeed, BSS is a technique aiming to transform multivariate random signal into components that are mutually independent in complete statistical sense. Traditional BSS approach always separates all source signals from their mixtures simultaneously. In many applications, a large number of original sources are available while only one or a few are desired [4,5]. A typical example is the cocktail party problem, which is the phenomenon of being able to focus one's auditory attention on a particular stimulus while filtering out a range of other stimuli. This means the same way that a partygoer can focus on a single conversation in a noisy room. This effect is what allows most people to extract the desired single voice and throw away the others. In such cases, only one source signal is considered interesting and the others are regarded as interfering noise. As a result, simultaneous BSS approach will introduce large computational burden. It is important to introduce an effective approach which enables us to recover the desired source signal, which is potentially interesting and contain useful information, from its mixtures exclusively. This problem is referred to as blind signal extraction (BSE), which is indeed a particular class of BSS.

Recently, several approaches have been proposed for the solution of BSS/BSE problem, which are generally based on the second or higher order statistics of the data [6-8]. For example, Cichocki presented a classical BSE algorithm based on the stochastic property of source signals [3, 4]. It can extract a source signal, whose absolute kurtosis value is the largest among all mixed signals, as the first output. However, it must be mentioned that the high order statistics (HOS) based techniques often have high computation [4, 6]. Second order statistics (SOS) based techniques have the advantage of requiring shorter data records due to their reduced small sample estimation errors, and do not limit the number of Gaussian sources that can be separated to one [5, 9]. SOS based techniques have generally represented the preferred approach to solving the BSS/BSE problem [4, 5]. Recently, there is a trend to exploit BSS/BSE approaches based on SOS techniques.

In many BSS/BSE applications, one is not complete blind about the original sources or the mixing process. In other words, one can know a priori knowledge about one source signal in advance. Fortunately, in many applications such as biomedical signal processing, this type of knowledge is often readily available. A typical example is that the human heart contracts at regular intervals. In fact, when a biomedical source signal is periodic, its fundamental period can be measured based on methods such as heart instantaneous frequency estimation techniques.

Many natural signals such as speech signals or biomedical signals have significant temporal structures [8, 10]. It is valuable to exploit the second order correlations based on time delay for source extraction. Our work is motivated by the observation that majority of measurements obtained from many biomedical applications exhibit some degree of periodicity. In this paper, we focus on separating one or a few desired source signals, which are time delayed correlation, from the observed sensor signals. By analyzing the linear autocorrelation feature of the desired source signal, we have novel insights about source extraction. An objective function based on linear autocorrelation of the desired signal is first designed. Optimizing the objective function, a flexible BSE method is introduced correspondingly. Compared to the traditional BSS/BSE method, the proposed techniques have many good properties in terms of computing time and flexibility. For example, only desired source signal is recovered, lots of computing time and resources can be saved; source signals can be recovered in a specific order according to some properties of source signals. The validity and performance of the introduced techniques are confirmed by computer simulations.

This manuscript is organized as follows. In section II, a constrained optimization problem is introduced based on second order correlations of the desired source. Solving the constrained optimization problem, a batch fixed-point learning algorithm is deduced for estimating the desired source signal with linear autocorrelations. Section III demonstrates the proposed techniques with computer simulations. Some conclusions are drawn in the final section.

II. PROPOSED ALGORITHM

Denote the observed sensor signals $x[k] = [x_0[k],\ x_1[k], \cdots, x_{n-1}[k]]^T$ described by matrix equation

$$\xi[\kappa]=A\sigma[\kappa] \tag{1}$$

where A is an n*m unknown mixing matrix, $s[k] = [s_0[k], s_1[k], \cdots, s_{m-1}[k]]^T$ is a vector of unknown temporally correlated sources (zero-mean and unit-variance), k is the time index, m is the number of sources and n is the number of mixtures. Since the BSS problem is blind, it is difficult to develop new technology. For simplicity, in the following we assume m=n. Fig .1 shows a general BSS architecture for separating all source signals from the observed sensor signals at a time.

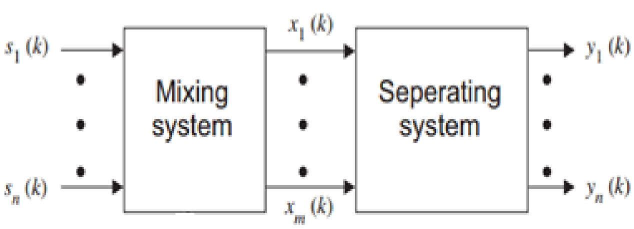

Figure 1. Traditional BSS techniques.

To cope with ill-conditioned cases and make algorithm fast and simple, a linear transformation known as preliminary whitening is often exploited to whiten the sensor mixtures[11,12]. That is to say, one may transform the observed vector x linearly so that a new vector is obtained. As a result, the generated vector becomes white. In other words, components of the new vector are uncorrelated and their variances equal unity. A typical whitening solution is as follows

$$\tilde{x}(k) = Vx(k) = VAs(k) \tag{2}$$

so that $E\{\tilde{x}(k)\tilde{x}(k)^T\} = I$, where V is called whitening matrix. Therefore, after the sensor signals are whitened, the components of $\tilde{x}(k)$ are unity and uncorrelated.

To formulate the BSS problem, one must construct a suitable objective function that is greatly dependent on the parameters of the specified neural network model in (1). Optimizing the objective function will deduce approach to recover all source signals from their sensor mixtures at a time. To recover one source signal exclusively, one should introduce specific prior information about the desired signal into the objective function, thus causing a constrained optimization problem. The use of such prior information about the source signal leads us to call BSE as semi-blind separation [13,14]. Optimization of such an objective function should cause the outputs of the model to satisfy the desired statistical conditions. As a result, the output will be the desired source signal. In general, SOS based approach assumes that the original sources are not correlated with each other and every source signal has a different temporal structure.

It is very often the case with biomedical measurements that we have some prior information about the source signals which we wish to extract from the sensor mixtures. Indeed, many physiologically relevant signals or patterns have certain temporal, spectral or time–frequency characteristics, and in the case of multi-channel (body surface, volumetric) measurements also particular spatial projections. It is efficient and indeed possible to incorporate such prior information into the BSS/BSE model using only minor modifications of the estimation procedures, essentially by imposing constraints on the model, which can act on the spatial projections, or work on the temporal dynamics of the source waveforms. The idea is that we may be able to guide the BSS/BSE solution to include an expected outcome. By introducing prior information into the traditional BSS system shown in Fig .1, we develop improved BSS/BSE techniques to estimate the unknown portions based on the assumptions as have already been covered, thus helping us to interpret the output results. In this paper, we suppose that the desired source signal has property of linear autocorrelations. Our work is to estimate the desired source signal with specific temporal structure from a large number of mixtures exclusively. The main criterion of source extraction is to find a specific vector w, and apply a demixing operation by applying vector w to the signal mixtures. In our work, a single neural processing unit is introduced as follows

$$\tilde{y}(k) = w^T\tilde{x}(k) \tag{3}$$

$$\tilde{y}(k-\tau) = w^T\tilde{x}(k-\tau) \tag{4}$$

Where $w = (w_0, \cdots, w_{n-1})^T$ is the weight vector and τ is a time delay in time.

To estimate one source signal with linear autocorrelation from its mixture exclusively, we introduce the following constrained optimization problem based on second order correlations of the desired source

$$\max_{\|w\|=1} J(w) = E\{\tilde{y}(k)\tilde{y}(k-\tau)\}$$
$$= E\{(w^T\tilde{x}(k))(w^T\tilde{x}(k-\tau))\} \quad (5)$$

where J(w) is called objective function. The parameter τ can be selected as an optimal prior time delay based on some information of the desired source signal. In some cases if the optimal time delay cannot be obtained, the time delay is often set to 1.

Optimizing the objective function contrast J(w) in (5), one can further deduce a batch learning BSE algorithm. The gradient of J(w) with respect to w can be deduced as

$$\frac{\partial J(w)}{\partial w} = E\{\tilde{y}(k-\tau)\tilde{x}(k) + \tilde{y}(k)\tilde{x}(k-\tau)\}. \quad (6)$$

According to the Kuhn–Tucker conditions[1,7], one can note that at a stable point of the optimization problem in (5), the gradient of $\frac{\partial J(w)}{\partial w}$ at w must point to the direction of w. In other words, one can optimize the objective function in (5) by the classical fixed-point algorithm[1,2]. To solve problem in (5), we utilize the fixed-point algorithm that, after each iteration, enforces the constraint $ww^T = 1$ dividing by its norm, then obtaining the following updating rule

$$w \leftarrow E\{\tilde{y}(k-\tau)\tilde{x}(k) + \tilde{y}(k)\tilde{x}(k-\tau)\}$$
$$w \leftarrow w/\|w\|. \quad (7)$$

Approach in (7) is a batch fixed-point learning algorithm, which is utilized to recover the desired source signal with linear autocorrelations. One can find that this approach is very simple. Most of all, in contrast to classical fixed-point algorithm [1,2], it do not need to choose any learning step sizes. After the first desired source signal is recovered, one can exploit a deflation process to remove it from the signal mixtures. Then the remained mixtures may experience another separating process to recover next signal. This procedure can be repeated until each desired source signal is recovered from its mixture. In other words, our work can recover source signals in a prescribed order, which is efficient in many applications. In addition, each source signal can be extracted using different BSE method, according to distinct feature of original sources. A general architecture of batch learning BSS techniques is shown in Fig.2.

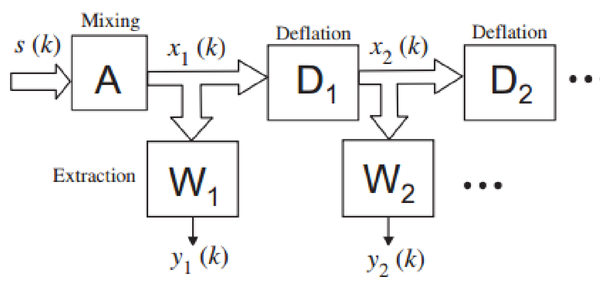

Figure 2. Batch learning BSS techniques.

III. COMPUTER SIMULATIONS

To confirm the performance of the proposed approach, we performed extensive computer simulations. Due to space constraint, only one simulation is illustrated here. The real-world ECG data, distributed by De Moor[15], are a well-known electrocardiogram measured from a pregnant woman (shown in Fig .3). Many classical BSS/BSE approaches utilize these data to verify their separating performance. For the sake of comparison, we also perform simulation on the real-world ECG data.

The electrocardiogram measurements are recorded over 10 s and sampled at 250 Hz with 8 electrodes located at the abdomen and thorax of a pregnant woman. Actually, although in De Moor's homepage he claims the sampling frequency is 500 Hz, Barros et al. [3] believe it is 250 Hz. One can see the heart beat of both the mother (stronger and slower) and the fetus (weaker and faster). The fetal electrocardiogram (FECG) is the recording of the fetal heart's electrical activity, which contains valuable clinical information about the healthy condition of the fetus [3–5]. However, in the dimensional mixtures shown in Fig.3, the desired FECG signal is very weak, which is often contaminated by a variety of noise, such as the maternal electrocardiogram (MECG) with extremely high amplitude, the mother's respiration, and thermal noise from electronic equipment. In fact, even the accurate occurrence time or shape of each complex of FECG is often not easy to obtain, especially when the fetus is in early phase. Therefore, non-invasive extraction of FECG has become vital important from a clinical point of view. However, it must be mentioned that the measured FECG is always contaminated by a large number of other signals and artifacts. Separating FECG by conventional BSS methods may produce hundreds of recordings, which may result in heavy computational load. Our main purpose is to extract a clear FECG signal exclusively, which is the recording of the fetal heart's electrical activity and provides valuable clinical information about the heart performance. Since the FECG signal is always corrupted by a variety of noise, how to develop an efficient method to extract a clear FECG as the first output has become a difficult task.

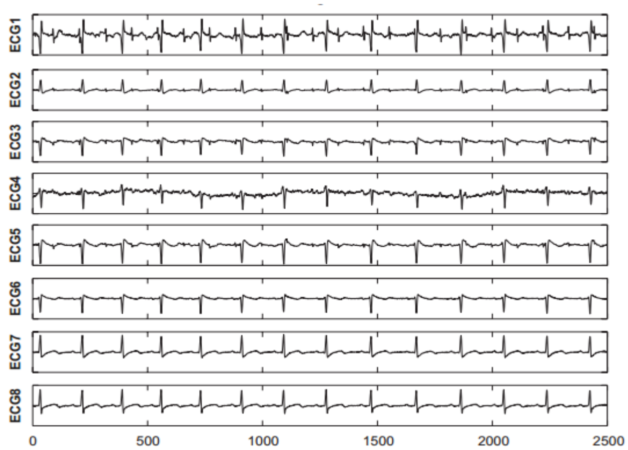

Figure 3. ECG signals obtained from a pregnant woman.

The fetal influence in channel 1 is clearly stronger than that in the other channels [3,5,6]. The fetal heart should strike every 0.5 s or so [5,6]. By carefully examining the autocorrelation of the sensor signal in channel 1, we find that it has a peak at τ=112 sampling period. In fact, it is the optimal time delay for extracting the FECG signal. To estimate the desired FECG, we first whitened the sensor signals and initialized the weight vector by $\mathrm{w} = [1,0,\cdots,0]^T$. In the first simulation, we adopted the optimal time delay as τ=112. The FECG estimated by our algorithm is FECG1 as shown in Fig .4. To compare the performance of our algorithm, we also ran the algorithms in [2] and [5], which were classical methods for FECG extraction. The extracted signals were FECG2 and FECG3 accordingly as shown in Fig .4. In contrast, the algorithm proposed in this paper can separate clear FECG. The signals extracted by the other algorithms contain some contributions of the mother's breathing artifacts. To further compare the performance of our algorithm with the other algorithms in [2] and [5], we selected slightly wrong delays as τ=114. The simulation results are shown in Fig .5. The signals estimated by the proposed algorithm and algorithms in [2] or [5] are FECG4, FECG5 and FECG6 accordingly. From the comparison results shown in Fig.5, one can find that the signal extracted by algorithms in [2] or [5] for τ=114 (FECG5 and FECG6 accordingly) is mostly the respiration artifact. Obviously, the algorithm proposed in this paper outperforms the other two algorithms, as expected, and again the algorithm in [5] performs poorly. The computer simulations illustrate that the proposed algorithm is not sensitive to the estimation error of the time delay as long as the error is not too large, which is valuable in practical applications.

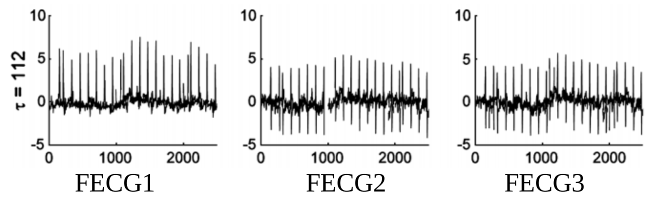

Figure 4. The extracted FECG signals using τ=112.

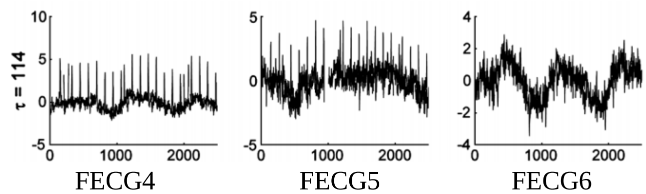

Figure 5. The extracted FECG signals using τ=114.

IV. CONCLUSIONS

In recent decades, the BSE technique has received extensive research attention in various fields such as biomedical signal analysis, speech processing, data mining, and so on. In many applications, the desired biomedical signal exhibits specific temporal structure. In general, it is apparent that BSS/BSE techniques using temporal structure are suited to biomedical signal analysis very well. The temporal and time-frequency information exploited is clearly relevant in biomedical signals. The second order statistics based method is less expansive for the calculation than traditional higher order statistics. If one has specific information on the source signals, it is desirable to exploit BSS/BSE techniques based on the use of second order statistics.

In this paper, we introduce a sequential BSE algorithm for blind separation of source signals with distinct periods, based only on second order statistical information. Indeed, the proposed approach exhibits computational advantages over traditional BSS approach when one's purpose is to recover only one or a few source signals from dimensional mixtures. It must be pointed out that the source signals recovered by the traditional BSS method are subject to the ambiguities of permutation and scaling. Through the proposed algorithm in this paper, after one source signal is estimated, one can choose a deflation process to eliminate it from its mixtures. Then the remained mixtures can experience another estimating process to recover the next signal. In other words, the source signals can be recovered in a specific order according to proper features of original sources. In addition, based on the proposed techniques, different methods can be utilized at different stages of the extraction process. This means that source estimation can be completed according to the features of original source that one wants to estimate at a particular stage, which is important in practice. The simulation results have shown the presented approach can recover the desired signal from its mixtures in a better and faster way. Time structure based techniques will be readily adaptable to provide more valuable applications to biomedical signal processing. The BSE techniques can be in fact utilized to estimate a lot of meaningful information from a set of sensor signals through just a few assumptions about the underlying sources and their mixing process, which is the objective of further research.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China (11473019), Natural Science Foundation of Shandong (ZR2014AM015)

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