Neurocomputing 101 (2013) 204–216

Contents lists available at SciVerse ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Approaches and applications of semi-blind signal extraction for communication signals based on constrained independent component analysis: The complex case ☆

Xiang Wang *, Zhitao Huang, Yiyu Zhou, Xiaotian Ren

Deya Road 50, Changsha, Hunan 410073, China

ARTICLE INFO

Article history:
Received 28 February 2012
Received in revised form
24 August 2012
Accepted 5 September 2012
Communicated by E.W. Lang
Available online 26 September 2012

Keywords:
Blind signal extraction (BSE)
Independent component analysis (ICA)
Constrained ICA
Cyclostationarity
Spatial information
Direction of arrival (DOA)
Initialization

ABSTRACT

Signals of interest (SOIs) extraction are a vital issue in the field of communication signal processing. A promising approach is constrained independent component analysis (cICA). This paper extends the conventional constrained independent component analysis framework to the case of complex-valued mixing model and presents different prior information and different ways to be incorporated into the cICA framework. Two examples are demonstrated, ICA with cyclostationary constraint (ICA-CC) and ICA with spatial constraint (ICA-SC). The adaptive solution using the gradient ascent learning process is derived to solve the new constrained optimization problem in the ICA-CC example, while the rough spatial information corresponding to the direction of arrival (DOA) of the SOI can be utilized to select the specific initial vector for the desired solution before the learning process in the ICA-SC example. The corresponding experiment results show the efficacy and accuracy of the proposed algorithms.

1. Introduction

In general, the goal of blind source separation (BSS) is to recover all the source signals from mixed signals received by sensors. The adjective "blind" emphasizes the fact that, the source signals are not observed, and, no information is available about the mixing situation. But, the assumption is often held physically that the source signals are mutually independent. Recently, BSS in signal processing has received considerable attention from researchers, due to its numerous promising applications in the areas of remote sensing, speech processing, medical diagnosis and wireless communication. However, in many applications, it is desired to extract only one signal of interest or a desired subset of signals. For example, reception of wireless communication signals becomes increasingly difficult as more and more users and types of communication signals increasingly consume the available spectra and therefore we wish to extract the SOIs from the observed mixtures and automatically discard other uninteresting source signals. Thus, it would be important to develop algorithms to extract only the desired signals with given characteristics instead of all sources. In such cases, the BSS problem reduces to a blind signal extraction (BSE) problem, which we focus here.

Many BSE algorithms existing in the literature extract the SOI as the first signal, by using some a priori information. In [1], Barros and Cichocki proposed a fast and simple algorithm exploiting the prior information about the time structure of the desired signal, which requires the precise estimation of an optimal time delay. Zhi-Lin Zhang and Zhang Yi extended the Barro's work and proposed an improved algorithm based on eigenvalue decomposition [2], which is less sensitive to the errors of the time delay. Tsalaile et al. [3] proposed a novel second-order-statistics-based sequential extraction algorithm of quasi-periodic signals with time-varying period, which diagonalizing autocorrelation matrices at lags corresponding to the time-varying period. But most of the communication signals do not possess such characteristics. In array signal processing area, the beamforming is a promising technique, which covers specific cell sectors so that the signal of interest (SOI) can be extracted while suppressing other signals. Traditional beamforming techniques such as MVDR, LCMV [4] are based on the accurate knowledge of the direction vector associated to the SOI and the perfect array calibration, both of which are not often available in practice. Another technique, called independent component analysis (ICA), is perhaps the most widely applied to the BSS problem [5–13]. Most existing ICA algorithms always extract independent components (ICs) whose number is same as the number of the

☆ This work is supported by Program for New Century Excellent Talents in University of China.

* Corresponding author.
E-mail address: christopherwx@163.com (X. Wang).

0925-2312/$ - see front matter © 2012 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.neucom.2012.09.003

observed mixtures while the number of the SOIs is much less than the observations. Once a spanning set is determined, the ICs of interest must be identified and in general this is not a trivial task and automation of this process is nontrivial. Moreover, such methods involve redundant computation, require large memory for estimating unnecessary signals and degrade the equality of the signals recovered. Although some deflation algorithms such as FastICA [8,9,12,13] were proposed to extract all the ICs one by one, the signals can only be recovered up to scaling and permutation ambiguities due to the fact that the information of the mixing matrix and the source signals are assumed to be completely blind which cannot be circumvented without additional assumptions or knowledge. Hiroshi et al. [14] combined ICA and time–frequency masking to extract SOIs, which requires the target sources to have dominant powers at some sensors. Furthermore, in complex-valued BSE research, recent algorithms typically can be applied to both circular and non-circular signals. In [15], Javidi et al. proposed a class of linear predictability based algorithms for blind extraction from noisy complex-valued mixtures and in [16], Javidi et al. exploited higher-order statistics of latent sources to introduce a new class of complex BSE algorithms suitable for the extraction of both circular and non-circular signals.

Recently, Lu and Rajapakse proposed a new technique of constrained independent component analysis (cICA) [17,18], which incorporates the a priori information about the desired signal as the additional constraints into the conventional ICA learning process and means that only a single statistically independent component will be extracted for the given constraint. James et al. have applied with great success the cICA method to artifact rejection in EEG/MEG signal analysis [19]. Lee et al. [20] used the cICA method to the extraction of fetal abdominal ECGs. However, the a priori information in [18–20] is the reference signals (template signals) for each desired signal, and the constraints are denoted by the correlation measure between the recovered signals and their corresponding reference signals, namely ICA-R. It incorporates the reference signals to guide the separation process and extract the desired signals, which are the closest one, in some sense, to the reference signals. De-Shuang Huang et al. proposed a new version of cICA by discussing the characteristic for different closeness measurements [21]. Qiu-Hua Lin et al. [22] proposed a fast ICA-R algorithm by prewhitening and normalizing the weight vector. In practice, it is difficult for us to accurately compensate time delay between the recovered signal and the reference signal in order to make the phase between them is closely matched, let alone that the reference signals are not available in communication applications. James et al. [23] proposed a modified FastICA algorithm, which exploited the spatial topography of selected source sensor projections as the a priori information. Nikolao Mitianoudis et al. [24] proposed a new cICA method exploiting the smoothness constraint to extract the smooth source signals with slowly varying temporal structures. In fact, instead of constraining the domain of the source separation, the a priori information can be incorporated in other ways e.g., by expanding the cost function. Zhenwei Shi et al. [25] developed a new extraction algorithm by combining the time–correlation property into the ICA contrast function to extract the temporally correlated signals such as fetal electrocardiogram. Most of the existing cICA algorithms mentioned above used a "real-valued" instantaneous mixing model (sources have different amplifications in different mixtures). Nevertheless, in practical situations, for example, in array signal processing for radio communications, the so-called attenuation delay mixing model (sources have different amplifications and time delays in different mixtures) is more suitable, which can be considered as complex-valued mixing model as stated in Section 2.

Here, we extend the conventional cICA approach to a general framework for the complex-valued case, and two examples exploiting different additional information are illustrated. Our main results are as follows:

- We give a rounded description of the cICA framework from two aspects: different types of the a priori information and their different ways of incorporation.
- The cICA method is notably extended to the case of complex-valued mixing model including complex mixtures, mixing matrix and source signals.
- We derive a new version of cICA algorithm exploiting cyclostationary property of the SOI denoted by the absolute value of the cyclic autocorrelation function, which is utilized as inequality constraint to form a new constrained optimization problem.
- Spatial constraint is utilized for the extraction of the desired signal, which is denoted by the coarse knowledge about the direction of arrival (DOA) of the desired signal and utilized to obtain a specific initialization of the extracting vector.

The rest of the paper mainly consists of six sections. In Section 2 the attenuation delay mixing model is given, along with the assumptions and the notations. Section 3 describes the new cICA framework and derives its learning rule. Section 4 derives two cICA algorithms with cyclostationary constraint and spatial constraint respectively. Section 5 demonstrates the performance of the proposed algorithm with simulations, where the results are compared to that of the FastICA algorithm and beamforming method, respectively. Finally Section 6 provides the conclusions and discussion.

2. Problem formulation, assumption and notation

2.1. Notations

Conventional notation is used in this paper. Scalars, matrices and vectors are represented by lower case, upper case and boldface lower case letters, respectively. The ith component of vector $\mathbf{x}$ is denoted by x_i. The expectation operators $E\{\bullet\}$. $\mathbf{A}^{\mathrm{T}}$, $\mathbf{A}^*$ and $\mathbf{A}^{\mathrm{H}}$ denote transpose, complex conjugate, and Hermitian transpose of the matrix $\mathbf{A}$, respectively. The identify matrix is denoted by $\mathbf{I}$. Furthermore, $\|\bullet\|$ represents the L2 norm of a vector and $\mathrm{sgn}(\bullet)$ is the sign function.

2.2. Problem formulation

In narrowband (NB) signal processing, the attenuation delay mixing model is more suitable than the instantaneous mixing model. Suppose N narrowband source signals impinge on M sensors, the ith mixture $x_i(t)$ can be formulated as

$$x_i(t) = \sum_{k=1}^{N} b_{ik} s_k(t-\tau_{ik}) \tag{1}$$

where b_{ik} and τ_{ik} are the attenuation coefficients and the propagation time delays associated with the path from the kth source signal to the ith sensor. According to the NB assumption, Eq. (1) can be formulated as complex-valued form

$$x_i(t) = \sum_{k=1}^{N} b_{ik} s_k(t) e^{-j2\pi f_k \tau_{ik}} \tag{2}$$

Eq. (2) can be rewritten as the following matrix form:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \tag{3}$$

where $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_N(t)]^T \subset \mathbb{C}^{N\times 1}$ denotes the source signals and $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_M(t)]^T \subset \mathbb{C}^{M\times 1}$ denotes the observation vector, and $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_N]^T \subset \mathbb{C}^{M\times N}$ is the complex mixing matrix whose kth column $\mathbf{a}_k = \left[b_{1k} e^{j2\pi f_k \tau_{1k}}, \ldots, b_{Mk} e^{j2\pi f_k \tau_{Mk}}\right]^T$ is related to