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Design of signal extraction algorithms based on second order statistics exploiting beamforming techniques

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ABSTRACT

Signal extraction methods are becoming increasingly popular due to lower computational demands and less restrictive requirements than source separation algorithms. Many existing signal extraction algorithms extract interesting signals based on some known features of the sources. However, immediate extraction of the desired signal is not guaranteed, leading to inefficient and ad hoc deflation techniques.

We present a design strategy for efficient signal extraction algorithms. First, by incorporating some amount of prior information in the form of a guess of either the autocorrelation function or the mixing column of the desired source, immediate identification of the desired extraction filter is guaranteed. Second, for a parameterized mixing system new techniques for the design and evaluation of signal extraction algorithms have been developed. These techniques are used to ensure immediate extraction of the desired signal by exploiting knowledge on physical parameters.

The design procedure is flexible in the use of a priori information and leads to extraction algorithms that are robust to noise, deal with incomplete prior information, and handle modeling errors. Furthermore, the extraction algorithms can be used to identify extraction filters with different objectives. The design procedure and the properties of the extraction algorithms are evaluated by examples and experiments.

1. Introduction

Signal extraction problems emerge in a wide variety of application areas, e.g., in the fields of biomedical engineering, telecommunication, and speech enhancement. In such a problem, a single desired source signal is to be extracted from mixtures of multiple source signals such as the speech signal from the person in front of the teleconferencing system or a fetal electrocardiogram (ECG) in biomedical engineering.

Traditionally, in the fields of acoustics and telecommunication mainly beamformers were used to extract the desired source signal from multiple observations. These spatial filters exploit a parameterized modeling of a designed sensor array and its environment [1]. Nowadays blind source separation (BSS) techniques are more and more applied in the fields of acoustics, telecommunication, and biomedical engineering [2,3]. A BSS algorithm separates all observed source signals without using information about the mixing system.

Each of these methods, i.e., beamforming and BSS, has their own imperfections when applied for signal extraction. Beamformers heavily depend on the array configuration at hand and are sensitive to modeling errors and false prior information. Additionally, with the rise of wireless sensor networks [4], modeling of the entire sensor array

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becomes practically impossible. Contrarily, BSS algorithms suffer from a scaling and permutation indeterminacy; therefore, they require a classifier that selects the desired signal.

Alternative signal extraction algorithms can be found in the literature. Some examples of (semi-) blind signal extraction (BSE) algorithms can be found in [2,3,5–8]. The majority of these algorithms are sequential BSE algorithms, which extract sources containing possibly interesting features such as linear predictability and non-Gaussianity. A disadvantage of these methods is that immediate extraction of the desired signal cannot be guaranteed, i.e., a classifier is still required to detect if the desired signal is extracted. If the extracted signal is not the desired signal, then deflation techniques are applied and a new, possibly interesting, signal is extracted. This iterative procedure results in naturally inefficient algorithms and is only applicable in batch mode.

Despite the research conducted in the last decades [2,3,9], BSS algorithms yield insufficient quality for many applications [10,11]. The lack of performance of BSS algorithms has lead to a new research field called informed source separation (ISS) [12,11]. The objective of ISS is to build source separation algorithms that exploit all relevant prior information such that the separation performance increases. Furthermore, it is unrealistic to develop a single algorithm that fits any scenario. “Instead, we must focus our efforts on developing a methodology for designing robust algorithms that are specific to the application at hand.” [12]. In this context, we develop a methodology that can be used to design signal extraction algorithms based on available prior information. The main considerations for the development of such a framework can be brought back into three elements. The framework must be *flexible* in the use of available prior information; moreover, the algorithms derived from the framework have to be *robust* and *efficient*.

In [13] we presented a single stage signal extraction method that guarantees immediate extraction of the desired signal if certain conditions hold on a mold, which consists of some amount of prior information. For robustness and efficiency purposes, the method calculates extraction filters exploiting the second order temporal structure in the data instead of higher order statistics.

In the current paper we expand the work from [13] and our goal is to provide insight into the design of signal extraction algorithms that exploit all available prior information. The main contributions of this paper are that we convert the method from [13], based on a mold, such that it works for both complex and real valued mixtures of signals. Furthermore, we introduce new techniques for developing signal extraction algorithms and we present example designs based on different types and amounts of a priori information about physical parameters. Finally, we show that the presented methodology has strong advantages over beamforming.

Part of this work has already been presented in [14–16]. It was shown in [14] that extraction filters with different objectives on noise and interference reduction can be obtained with the presented method. In [15], a signal extraction algorithm is applied to a combined fixed and wireless sensor network and an example signal extraction algorithm based on prior information about autocorrelation functions of sources is presented in [16].

The outline of this work is as follows. In Section 2 we introduce the mixing model and assumptions on the signals. In Section 3 we present the signal extraction algorithms for real and complex mixtures based on a mold that contains some amount of prior information. The new design techniques and example algorithm designs are derived in Section 4 and experimental results are presented in Section 5. Finally, a discussion and conclusions are given in Section 6.

Notation of vectors and matrices is with bold face, lowercase and bold face, uppercase letters, respectively. Subscript and superscript indices are used to denote, respectively, the row and column elements of vectors and matrices. Row vectors carry an additional tilde symbol $\sim$ in order to distinguish between column and row vectors. For example, $\mathbf{h}^j$ is the jth column vector and $\tilde{\mathbf{h}}_i$ is the ith row vector of the matrix $\mathbf{H}$. Throughout this paper we reserve the index symbols i and j for components related to the sensors and sources, respectively. Index sets are denoted by calligraphic symbols such as $\mathcal{S} = [1, S]$, which contains all integers from 1 until S. Square brackets are used for denoting the time index n. Conjugate, transpose, and conjugate transpose are denoted by the superscript symbols $*$, T, and H, respectively, e.g., $\mathbf{a}^*$, $(\mathbf{a})^T$, and $(\mathbf{a})^H$. The Euclidean inner products for column and row vectors are defined as $\langle \mathbf{a}, \mathbf{b} \rangle \triangleq (\mathbf{a})^H \mathbf{b}$ and $\langle \tilde{\mathbf{a}}, \tilde{\mathbf{b}} \rangle \triangleq \tilde{\mathbf{a}}^* (\tilde{\mathbf{b}})^T$, respectively. Finally, the Euclidean norm for column and row vectors is defined as $\|\mathbf{a}\|_2 \triangleq \sqrt{\langle \mathbf{a}, \mathbf{a} \rangle}$ and $\|\tilde{\mathbf{a}}\|_2 \triangleq \sqrt{\langle \tilde{\mathbf{a}}, \tilde{\mathbf{a}} \rangle}$, respectively.

2. Model and assumptions

Before the design strategy is introduced we discuss the mixing model and assumptions on the source signals.

2.1. Introduction of the mixing model

The observed signals are assumed to be complex instantaneous mixtures of multiple source signals. These mixtures can either be natural instantaneous mixtures, such as in biomedical or narrowband telecommunication applications, or they can be obtained from a DFT filterbank or short time Fourier transform (STFT) such as in speech enhancement applications.

The complex instantaneous mixing system is modeled by a complex matrix $\mathbf{H}$ with D rows and S columns, corresponding to the number of sensors and sources, respectively, i.e.,

$$\mathbf{H} = [\mathbf{h}^1 \;\cdots\; \mathbf{h}^S] = \begin{bmatrix} h_1^1 & \cdots & h_1^S \\ \vdots & \ddots & \vdots \\ h_D^1 & \cdots & h_D^S \end{bmatrix} \tag{1}$$

The structure in the sensor signals for complex instantaneous mixtures is assumed as follows:

$$\mathbf{x}[n] \equiv \mathbf{H}\mathbf{s}[n] + \boldsymbol{\nu}[n] = \sum_{j=1}^{S} \mathbf{h}^j s_j[n] + \boldsymbol{\nu}[n] \tag{2}$$