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Blind separation of partially overlapping data packets ☆

Mu Zhou, Alle-Jan van der Veen *

TU Delft, Fac. EEMCS, Mekelweg 4, 2628 CD Delft, The Netherlands

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The paper discusses the separation of partially overlapping data packets by an antenna array in narrowband communication systems. This problem occurs in asynchronous communication systems and several transponder systems such as Radio Frequency Identification (RFID) for wireless tags, Automatic Identification System (AIS) for ships, and Secondary Surveillance Radar (SSR) and Automatic Dependent Surveillance–Broadcast (ADS–B) for aircraft. Partially overlapping data packages also occur as inter-cell interference in mutually unsynchronized communication systems. Arbitrary arrival times of the overlapping packets cause nonstationary scenarios and makes it difficult to identify the signals using standard blind beamforming techniques. After selecting an observation interval, we propose subspace-based algorithms to suppress partially present (interfering) packets, as a preprocessing step for existing blind beamforming algorithms that assume stationary (fully overlapping) sources. The proposed algorithms are based on a subspace intersection, computed using a generalized singular value decomposition (GSVD) or a generalized eigenvalue decomposition (GEVD). In the second part of the paper, the algorithm is refined using a recently developed subspace estimation tool, the Signed URV algorithm, which is closely related to the GSVD but can be computed non-iteratively and allows for efficient subspace tracking. Simulation results show that the proposed algorithms significantly improve the performance of classical algorithms designed for block stationary scenarios in cases where asynchronous co-channel interference is present. An example on experimental data from the AIS ship transponder system confirms the effectiveness of the proposed algorithms in a real application.

1. Introduction

Co-channel interference is a growing concern in wireless communication applications. One approach for interference mitigation is to use an antenna array. Beamforming techniques allow to receive the target signals and suppress the interference signals, assuming the array response vector of each of the signals is known. Blind beamforming techniques aim to estimate these array response vectors.

In many cases, the interference is intermittent and unsynchronized. For example, inter-cell interference reduces channel capacity in Multiple Input Multiple Output (MIMO) cellular networks [6, 7]. Also, ad-hoc communication systems or wireless sensor networks where devices transmit whenever data is available result in multiple partially overlapping data packets at the receiver. Other examples are Radio Frequency Identification (RFID) systems with multiple tags, the Automatic Identification System (AIS) for ships, wherein transponders periodically report their locations [8,9], the secondary surveillance radar (SSR) [10,11,2] and similar Automatic Dependent Surveillance–Broadcast (ADS–B) transponder systems for aircraft. Another example is multiple unsynchronized Wireless Local Area Network (WLAN) systems in the same service area.

In this paper we consider the separation of partially overlapping data packets using blind beamforming techniques under narrowband assumptions. We consider an observation interval (typically a sliding window) matched to the length of the data packets, and consider packets that are fully inside this window as target signals, and packets that are partially in the window as interfering signals. It is important to realize that, in this scenario, there is no inherent property that defines a “target” or “interference” signal, the classification is based on the position of packets in the observation interval.

The approach is to collect a block of data from an analysis window. The data block is split into two sub-blocks, and we compare

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* Corresponding author.
E-mail address: a.j.vanderveen@tudelft.nl (A.-J. van der Veen).

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the subspaces present in each block. Specifically, a generalized singular value decomposition (GSVD) allows to match basis vectors within the subspaces to each other, and target/interference signal classification is based on detecting differences in signal power between the two blocks. The subspace information from the GSVD directly leads to a beamformer to suppress the interfering signals while keeping the target signals. The analysis window can then shift a number of samples and the process is repeated, allowing previously classified "interference signals" to become properly aligned and be detected as target signals.

It could happen that the resulting subspace contains multiple target signals. In that case, the proposed algorithm return a mixture of the nearly fully overlapping target signals, and other properties should provide further separation, such as constant modulus properties (the Algebraic Constant Modulus (ACMA) algorithm [12]) or related algorithms based on fourth-order cumulants (the Joint Approximation Diagonalization of Eigen-matrices (JADE) [13] and the Multi-User Kurtosis (MUK) algorithms [14]). Such algorithms explicitly assume stationary signals and therefore typically cannot handle intermittent interference or signals with non-stationary properties, and the algorithms in this paper can serve as a preprocessing step both to filter out the intermittent signals and to arrive at a nearly synchronous scenario.

To understand why traditional blind source separation algorithms based on cumulants such as ACMA and JADE fail on intermittent sources, consider first a data matrix $\mathbf{X}$ consisting of N samples of a mixture of *stationary* sources. Based on $\mathbf{X}$, these algorithms estimate a cumulant matrix $\mathbf{Q}$ and derive separating beamformers from it. Each entry of $\mathbf{Q}$ can be written as $S_4/N - S_2/N^2$, where S_4 is a sum of fourth-order products of entries of $\mathbf{X}$, and S_2 a combination of sums of second-order products. If we now augment $\mathbf{X}$ with N "zero" columns to $[\mathbf{X}, \mathbf{0}]$, then S_4 and S_2 do not change, while the weights $(1/N)$ and $(1/N^2)$ scale with factors $(1/2)$ and $(1/4)$, respectively. Very quickly, $\mathbf{Q}$ loses the structure on which the computation of the beamformers rely. This simple example shows that ACMA and JADE are not reliable for separating intermittent sources, and this is confirmed in the simulations in Sec. 8.

The paper has two parts. We first propose a generic algorithm based on the GSVD [15] or the related generalized eigenvalue decomposition (GEVD). We then work out an implementation based on a new tool—the Signed URV (SURV) algorithm [16,17]. This leads to a computationally efficient technique that allows for tracking and improved noise processing. Simulations and an experiment using acquired AIS data are provided to confirm the results.

Interference cancellation using oblique projections has been studied in [18,19], assuming the "target" and "'interference" subspaces are known. Here, we focus on the estimation of the required subspace information so that these tools can be applied. Not many papers consider intermittent interference cancellation based on subspace techniques. For the blind separation of partially overlapping SSR signals, Petrochilos et al. proposed a block-based tracking algorithm [20,21] based on detecting and projecting out rank-1 components representing time segments where only a single source is present. The existence of such segments can be considered as a simplified special case of our scenarios.

Notation

Matrices and vectors are denoted by uppercase and lowercase boldface symbols, respectively. $(\mathbf{A})_{ij}$ denotes the i,jth entry of a matrix $\mathbf{A}$. For a matrix $\mathbf{A}$, $\mathbf{A}^H$ denotes the complex conjugate transpose, and $\mathbf{A}^\dagger$ denotes the Moore–Penrose matrix pseudo-inverse. If $\mathbf{A}$ has full column rank, then $\mathbf{A}^\dagger = (\mathbf{A}^H\mathbf{A})^{-1}\mathbf{A}^H$.

$\mathrm{E}\{\cdot\}$ is the expectation operator.

$\|\cdot\|$ denotes the matrix 2-norm, which is equal to the largest singular value of the matrix.

Subspaces are denoted by calligraphic symbols. The column span (range) of a matrix $\mathbf{A}$ is $\mathcal{A} = \mathrm{ran}(\mathbf{A})$.

2. Data model

2.1. Signals

We consider unknown discrete-time intermittent signals (data packets) $s_i[k]$ where i is the signal index and k is the time index. Each signal consists of a stretch of N_p nonzero values, preceded and followed by zeros. For simplicity of notation, all intermittent signals will have the same packet length N_p (this is generalized at a later stage). There are d signals, and they are stacked in a vector $\mathbf{s}[k] = [s_1[k], \cdots, s_d[k]]^T$.

We assume that the receiver has an antenna array with M antennas, and we stack the (complex-valued) antenna signals into a vector $\mathbf{x}[k] \in \mathcal{C}^M$. In a narrowband scenario, the received signal vector is an instantaneous mixture

$$\mathbf{x}[k] = \mathbf{h}_1 s_1[k] + \cdots + \mathbf{h}_d s_d[k] + \mathbf{n}[k] = \mathbf{H}\mathbf{s}[k] + \mathbf{n}[k] \tag{1}$$

where the vectors $\mathbf{h}_i$, $i = 1, \cdots, d$ are the channel vectors (array response vectors) corresponding to each signal, $\mathbf{H} = [\mathbf{h}_1, \cdots, \mathbf{h}_d] \in \mathcal{C}^{M\times d}$ is the channel matrix, $\mathbf{s} = [s_1, \cdots, s_d]^T$ is the source vector, and $\mathbf{n} \in \mathcal{C}^M$ is the noise vector.

We assume that the unknown channel matrix $\mathbf{H}$ has full column rank. This also implies that $d \le M$. In our applications, we have an inherent scaling indeterminacy between signals and channel vectors; without loss of generality we will assume that the channel vectors are all scaled to $\|\mathbf{h}_i\| = 1$ (this can be achieved by exchanging a scaling factor with $s_i[n]$). No further parametric structure is assumed on $\mathbf{H}$, e.g., we do not consider a calibrated array, with channel vectors functions of source directions and antenna locations. Also, multipath and antenna coupling may be present as this leads to the same instantaneous mixture model (1).

The noise is modeled by i.i.d. zero mean Gaussian vectors, with covariance matrix $\mathbf{R}_n = \mathrm{E}\{\mathbf{n}\mathbf{n}^H\} = \sigma^2\mathbf{I}$. We assume that the noise power σ^2 is known.

If we have collected N_s observations $\mathbf{x}[k]$, then we can collect these into a matrix $\mathbf{X} = [\mathbf{x}[1], \cdots, \mathbf{x}[N_s]]$, and similarly for the source signals and the noise. The corresponding data model is

$$\mathbf{X} = \mathbf{H}\mathbf{S} + \mathbf{N}\,. \tag{2}$$

The sample covariance matrix is $\hat{\mathbf{R}}_x = \frac{1}{N_s}\mathbf{X}\mathbf{X}^H$.

2.2. Separation scenario

We assume that we have obtained N_s samples of data corresponding to an "analysis window". Thus, in the data model (2), $\mathbf{X}$ is known and $\mathbf{H}, \mathbf{S}$ are unknown. Our algorithms are based on splitting this window into two parts and comparing the subspaces determined by each part. The splitting can be done in several ways, each corresponding to different definitions of target signals and interference signals. Here, we limit the presentation to one scenario, explained below. A second scenario applicable to continuously present target signals is described in Appendix A.

We split the analysis window into three blocks (see Fig. 1). A target signal is defined by being centered in the middle block, and the corresponding data matrix is denoted by $\mathbf{X}_1$. Interfering signals are defined by being more present in the first or third block. Samples from these two blocks are combined into a single data matrix $\mathbf{X}_2$ as shown in Fig. 1.

As a refinement of (2), assume that there are d_s target signals and d_f interference signals. The channel vectors of the target signals are collected in a matrix $\mathbf{H}_s$, and those of the interference signals in $\mathbf{H}_f$. We also define $\mathbf{H} = [\mathbf{H}_s, \mathbf{H}_f]$.