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Source Separation and Applications

Data-driven methods are based on a simple generative model such as matrix or tensor decompositions and hence can minimize the assumptions on the nature of the data and the latent variables. They have emerged as alternatives to the traditional model-based approaches whenever the unknown dynamics are hard to characterize. Source separation has been at the heart of data-driven approaches and has found wide applicability in areas as diverse as biomedicine, communications, finance, geophysics, and remote sensing.

Historically, the source separation problem has been posed with flexible and general assumptions and minimal priors, hence leading to the designation blind source separation (BSS). The first methodology for successful BSS was independent component analysis (ICA), and today, source separation includes a broader range of topics that emphasize incorporation of various priors and different types of decompositions to take the natural dimensionality of the observed data into account. New trends of research include the joint analysis of large-scale heterogeneous multidimensional sets of data, e.g., associated to multimodal data acquisition as in hyperspectral or brain imaging. In addition, underdetermined problems, i.e., those with a weak diversity and a large number of sources, are practically very interesting and can be solved through the use of additional priors such as sparsity. Indeed, many connections between source separation and the fields of sparse representations, compressive sensing, and dictionary learning have emerged, leading to new avenues for research. Hence, addressing the theory and problems at the junction of these topics, along with other exciting directions such as sparse component analysis and nonnegative matrix factorization (NMF), is of particular interest.

Our aim in this special issue is to provide a comprehensive view of the main advances in the field through a number of overview articles as well as contributions that emphasize the key topics of development in the area, both in terms of theory and applications. The issue contains 12 articles, where the focus of the last five is on applications.

The first two articles are overviews. The first article "Diversity in Independent Component and Vector Analyses" by Adalı et al. provides an overview of ICA and its extension to multiple data sets, independent vector analysis (IVA). Mutual information rate is used as the cost that allows the use of both non-Gaussianity and sample dependence as the form of diversity—statistical property—for achieving the decomposition, which in the case of IVA, adds the use of one more type of diversity, statistical dependence of the sources across the data sets. For this general case, identification conditions are given for both ICA and IVA, underlining the parallels between the two, and noting that both can identify multiple Gaussians under certain conditions when non-Gaussianity is not the only form of diversity that is used. Many existing algorithms and results are discussed as special cases under this broad umbrella along with performances of a few using medical imaging as the motivating example. While the focus in terms of algorithms for the first overview article is on iterative methods that maximize the likelihood, the second article shifts the focus to another important class—source separation through joint diagonalization.

The joint diagonalization of a set of matrices has been a prominent tool in linear ICA and BSS since, in many mixing models, the underlying key features of the mixed sources—such as their mutual statistical independence—can be expressed in terms of diagonal matrices. In fact, exact or approximate joint diagonalization is an important particular case of a broader family of joint matrix decompositions and transformations, which can be useful in a variety of source separation scenarios. The article "Joint Matrices Decompositions and Blind Source Separation" by Chabriel et al. provides a description of some of the theory and practice behind the different signal models and approaches in which advanced techniques for joint matrix decompositions become instrumental.

In recent years, the field of source separation benefited from the gradual assimilation of multilinear algebra into signal processing, in the form of tensors in general and tensor decompositions in particular. In many practical source separation contexts, the observed signals can be arranged in multiway arrays, and much can be gained by considering them as tensors and by applying tensor analysis and decomposition tools—which, in many cases, can produce not only estimates of the mixing parameters but also denoised versions of the underlying source signals. In his article "Tensors," Comon overviews some of the fundamental properties of tensors, such as their relations with polynomials and different concepts of tensor ranks. Several exact and approximate tensor decomposition approaches are reviewed in a way that can hopefully serve as a solid basis for readers interested in further pursuing these appealing tools.

Nonnegativity is a natural property that one can take into account when achieving source separation, and NMF has indeed

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been an active area. Three articles in the special issue have a focus on nonnegative factorizations. In "Nonnegative Matrix and Tensor Factorizations," Zhou et al. present an overview of the current and novel efficient algorithms for large-scale NMF and their extensions to nonnegative tensor factorizations and decompositions. The performances of the proposed algorithms are demonstrated by several illustrative examples. In "Static and Dynamic Source Separation Using Nonnegative Factorizations," Smaragdis et al. discuss models beyond the standard NMF and provide a unifying approach to nonnegative source separation for both static and dynamic models. They show how they can be easily extended to temporal models that are either continuous or discrete. Their approach enables many alternative formulations of dynamic source separation algorithms with nonnegativity constraints. Finally, in "Putting Nonnegative Matrix Factorization to the Test," Huang and Sidiropoulos give a concise tutorial style derivation for the Cramér–Rao lower bound for standard symmetric and asymmetric NMF. By providing the performance bound, they provide the benchmark against which the performance of the competitive NMF algorithms can be assessed. The proposed approach can be extended to facilitate analogous derivations for related bilinear matrix factorizations problems with constraints other than nonnegativity.

Classical source separation mostly relies on statistical properties of the sources and is usually effective only when the mixing process is invertible, requiring the number of observed mixtures to be equal to (or larger than) the number of sources. Separation of sources from fewer mixtures, and even from a single mixture, is possible when some structural information is available regarding the sources, especially when such information can be expressed using a convex operator—cost function—which promotes the desired structure. The article "Convexity in Source Separation" by McCoy et al. provides an elucidating overview of this emerging field, starting with simple motivating examples and following through with an explanation of underlying theoretical concepts, separability conditions and algorithmic aspects. Li et al. also addresses the underdetermined problem in "Sparse Representation for Brain Signal Processing" and considers an important application area—brain imaging. The problem that has no solution without extra priors has been addressed in the early 2000s based on sparsity assumption on the sources, and the work has led to a wide class of methods known as sparse component analysis, also related to sparse representation and dictionary learning, two very active areas of research. In their article, the authors provide a review and extension of main results in the area and then demonstrate how sparse representation methods can enhance ill-posed inverse problems in brain signal processing.

Audio processing, the original inspiration to the source separation problem by the "cocktail-party problem," has been arguably the most active application area for source separation. Today, the area is still a very active one, and three of the articles in this issue have a focus on audio applications. While initially, most of the work in the area considered the convolutive nature of the mixtures and were based on approaches in the time or frequency domain, the current state of the art and recent advances exploit—most often jointly—many priors on signals, such as sparsity, positivity, and sophisticated models of speakers, of instruments or the rooms, leading to informed source separation. The article "From Blind to Guided Audio Source Separation" by Vincent et al. provides an attractive review of this evolution and critical perspectives for the field. The transition from blind, to semiblind, and semiinformed separation is the focus of another article in the issue. In "Score-Informed Source Separation for Musical Audio Recordings," Ewert et al. address the growing field of music signal processing, which has applications in stereo-to-surround up-mixing, remixing tools, instrument-wise equalizing, karaoke systems, and preprocessing in music analysis tasks. They review recent developments in the field that integrate the prior knowledge encoded by the musical score, a simple prior that is typically available. In addition to use of different priors that lead to an "informed" solution, one can also make use of complementary information, more specifically, visual information, which can be considered to be insensitive to background noise. The article "Audiovisual Speech Source Separation" by Rivet et al. provides an overview of the key methodologies in audiovisual speech source separation. It focuses on three aspects: modeling the audio-video coherence in a common probabilistic framework for modeling the audiovisual features distribution; use of video as secondary modalities for improving speech detection; and use of video information to regularize/control the audio enhancement based on either ICA or time-frequency masking.

Another application area where the mixing model has been useful is chemical analysis. Data recorded through various chemical sensing procedures can be modeled as linear or nonlinear mixtures of concentrations of spectra. Classical methods of chemiometrics can then be enhanced with recent methods of source separation, taking into account special properties of the available data: nonnegativity (of the concentrations, spectra), dependence (due to chemical interactions), and sparsity (mass spectrum) among others. In "Source Separation in Chemical Analysis," Duarte et al. show how chemical data properties can be exploited through various methods, including ICA, geometrical, and Bayesian methods.

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Source separation, we believe, is an exciting area that keeps evolving. We hope that this special issue reflects that sentiment and will help identify some of the new and emerging directions in the area as well as providing critical perspectives on the existing ones.

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