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Introduction to Special Issue on Independent Components Analysis

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Independent Component Analysis (ICA) and Blind Source Separation (BSS) have become standard tools in multivariate data analysis. ICA continues to generate a flurry of research interest, resulting in increasing numbers of papers submitted to conferences and journals. Furthermore, there are many workshops and special sessions conducted in major conferences that focus on recent research results. The International Conference on ICA and BSS is a prime example of the attractiveness and research diversity of this field. In many universities, ICA is now taught in the graduate curriculum of electrical engineering, computer science and statistics departments.

The goal of this special issue is to present the latest research in ICA. We received 43 papers, of which 14 were accepted for publication. The topics covered in this issue cover a wide range of research areas including ICA theories and algorithms, representations such as nonlinear mixing, non-stationary, sparseness, and ICA applications.

Theory and Algorithms: In the first paper in this issue, Cardoso explores the space of multivariate random variables to elucidate the relations among mutual information, entropy and non-Gaussianity. Mutual information is decomposed into the sum of the term due to correlation and that due to non-Gaussianity.

In the second paper, Bach and Jordan present a generalization of ICA, where instead of looking for a linear transform that makes the data components independent, they look for a transform that makes the data components well-fit by a tree-structured graphical model. This tree-dependent component analysis (TCA) provides a tractable and flexible approach to weakening the assumption of independence in ICA.

In the the third paper, Teh et al. present a new way of extending ICA to overcomplete representations. In contrast to the causal generative extensions of ICA, they propose an energy based model where features are defined as deterministic functions of the inputs resulting in conditional independence of the features given the inputs. One of the basic ICA contrasts, mutual information, leads to minimizing the entropies of the found sources.

Parra and Sajda point out that linear blind source separation can be formulated as a generalized eigenvalue decomposition under certain assumptions, and use this insight to identify the conditions necessary for successful separation.

Learned-Miller and Fisher consider entropy estimation without trying to estimate the densities at all. The proposed entropy estimator is based on order statistics and spacings and is compared to several existing algorithms.

Nonlinear Representation: The paper by Almeida presents one possible method for unmixing nonlinearly-mixed independent sources. The criterion used for separation is the well-known Infomax, and the nonlinearities are implemented as Multi-layered Perceptrons, which provide smooth mappings and give the required regularization making separation possible.

In the following paper, Ziehe et al. suggest methods for inverting the post-nonlinearities to reduce the problem to that of linear ICA. Two methods are considered: in the first one, nonlinear transformations are sought which give maximal linear correlation to the outputs. Such transformations optimally invert the post-nonlinearities. In the second method, transformations make the outputs Gaussian and hence similar to the linearly mixed signals before the post-nonlinearity.

Sparse Representation: Kisilev et al. take advantage of the properties of multiscale transforms, such as wavelet packets, to decompose signals into sets of local features with various degrees of sparsity and study how the separation error is affected by the sparsity of decomposition coefficients, and by the misfit between the probabilistic model of these coefficients and their actual distribution.

Jang and Lee exploit sparseness of sources to separate independent sound source signals from a single mixture. The method is based on a signal model in which each source signal is spanned by a set of fixed temporal basis functions, driven by sparse independent coefficients.

Non-stationary Representation: Basalyga and Rattray study the dynamics of on-line learning in ICA theoretically. The trajectory of learning should pass through many unstable fixed points, and the paper elucidates its long symmetry-breaking time by the statistical-physical method.

Waheed and Salam use the general state space approach to obtain algorithms of blind source recovery for non-linear time varying deconvoluted and mixed signals in a unified way.

Sarela and Vigario treated the overlearning phenomena in ICA learning. They show that artificial spike and bump solutions are caused by overlearning, and they suggest practical methods to overcome this difficulty.

Applications: Bounkong et al. present a domain independent ICA-based approach to watermarking in which their method can be used on images, music or video to embed either a robust or fragile watermark. In the case of robust watermarking, the method shows high information rate and robustness against malicious and non-malicious attacks, while keeping a low induced distortion. It is well known that even slight changes in nonuniform illumination lead to a large image variability and are crucial for many visual tasks.

Stainvas and Lowe present a new ICA related probabilistic model where the number of sources exceeds the number of sensors to perform an image segmentation and illumination removal, simultaneously.

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