Development of ICA and IVA Algorithms with Application to Medical Image Analysis

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Overview

Blind source separation (BSS) is an active research area in statistical signal processing due to its numerous applications, including: analysis of medical imaging data, such as functional magnetic resonance imaging (fMRI) data, detection of specific targets in video sequences or sets of images such as multi-spectral remote sensing data, among many others. Independent component analysis (ICA) is a powerful method for BSS that can achieve perfect source recovery through only the assumption of statistical independence of the latent sources. In many applications, a joint analysis of multiple datasets needs to be performed, such as medical imaging data from multiple subjects or at different conditions, motivating the development of methods that can exploit the complementary information across these multivariate datasets. This has driven the development of independent vector analysis (IVA), a recent generalization of ICA to multiple datasets that achieves better performance than performing ICA separately on each dataset by taking the dependence across datasets into account. Though ICA and IVA algorithms cast in the maximum likelihood (ML) framework enable exploitation of all available statistical information—diversity—in reality, they often deviate from their theoretical optimality properties due to improper estimation of the source probability density function (PDF). Therefore, the key issue that enables the application of ICA and IVA algorithms to many problems is the development of effective models for the underlying source density and their estimation. In addition, efficient use of available prior information into both models promises to greatly increase their utility. The objective of this work is the development of effective ICA and IVA algorithms that can face these challenges and study of their application to fMRI data.

Current Results

MGGD Parameter Estimation and Efficient Integration to IVA, [1], [2]

The multivariate generalized Gaussian distribution (MGGD) has been an attractive solution to many signal processing problems due to its simple yet flexible parametric form, which requires the estimation of only a few parameters, *i.e.*, the scatter matrix and the shape parameter [3]. Existing approaches to this problem attempt to estimate the scatter matrix for a given value of the shape parameter, however their accuracy suffers when the value of the shape parameter becomes large [4], [5], which makes them unsuitable for many applications. MGGD provides an effective model for independent vector analysis (IVA) as well as for modeling the latent multivariate variables–sources–and the performance of the IVA algorithm highly depends on the estimation of the source parameters. In this work, we

- Derived a new and efficient maximum likelihood (ML) estimation technique based on the Fisher scoring (FS) that estimates both the shape parameter and the scatter matrix;
- Developed a new fixed point (FP) algorithm, called Riemannian averaged FP (RA-FP) that accurately estimates the scatter matrix for any positive value of the shape parameter;
- Presented a theoretical justification of the convergence of RA-FP;
- Demonstrated significantly improved performance of RA-FP and ML-FS over existing FP and method-of-moments (MoM) algorithms as shown in Fig. 1;

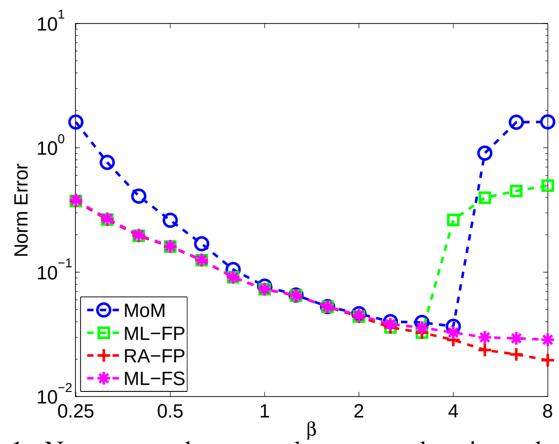

Fig. 1: Norm error between the true and estimated scatter matrices with respect to the shape parameter β.

- Derived a new IVA algorithm, IVA with adaptive MGGD (IVA-A-GGD), that estimates the shape parameter and scatter matrix jointly and takes into account both second and higher-order statistics;

Flexible Probability Estimation Technique for ICA, [6], [7]

Maximum likelihood (ML), an optimal theoretical framework for ICA, requires exact knowledge of the true underlying PDF of the latent sources. However, knowledge of the PDF of the latent sources is generally unknown. Algorithms that utilize a fixed or simple model for the underlying distribution of the latent sources [8], [9] yield poor separation performance when the data deviates from the assumed model. In this work, we

- Developed a new and efficient ICA algorithm based on entropy maximization with kernels, (ICA-EMK), which uses both global and local measuring functions as constraints to dynamically estimate the PDF of the sources with reasonable complexity;
- Derived an optimization framework, enabling parallel implementations on multi-core computers;
- Demonstrated the superior performance of ICA-EMK over the popular ICA algorithms FastICA [9] and ICA-EBM [10] using image data obtained from [11] as shown in Fig. 2;

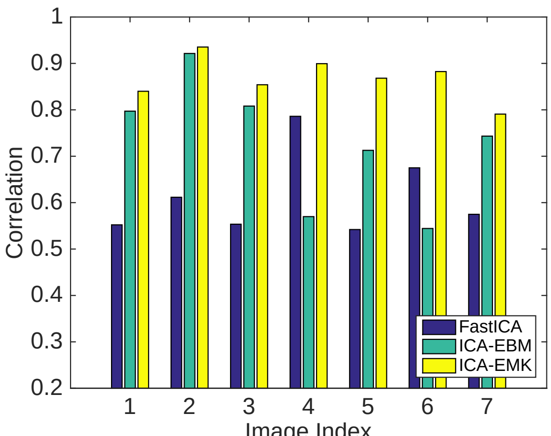

Fig. 2: Correlation between the true and estimated sources for three different ICA algorithms.

Incorporation of Prior Information into the ICA Model, [12]

Though ICA has proven powerful in many applications, complete statistical independence can be too restrictive an assumption in many applications. Additionally, important prior information about the data, such as sparsity, is usually available. Sparsity is a natural property of the data, a form of diversity, which, if incorporated into the ICA model, can relax the independence assumption, resulting in an improvement in the overall separation performance. In this work, we

- Developed a new ICA algorithm, sparse ICA by entropy bound minimization (SparseICA-EBM) through the direct exploitation of sparsity;
- Demonstrated that the proposed algorithm inherits all the advantages of ICA-EBM, namely its flexibility, though with enhanced performance due to the exploitation of sparsity and allow the user to balance the roles of independence and sparsity.
- Studied the synergy of independence and sparsity through simulations on synthetic as well as functional magnetic resonance imaging (fMRI)-like data.
- Explored the trade-offs between independence and sparsity in the ICA optimization framework and provide a guidance on how to balance these two objectives in real world applications where the ground-truth is not available.

Future Work and Expected Results

Multivariate Parameter Estimation Technique For IVA

Current IVA algorithms are based on the assumption that the underlying density model of the sources is both unimodal, symmetric and the samples are independent and identically distributed. These assumptions are often not realistic and can lead to poor separation performance. Motivated by the flexibility and superior performance that ICA-EBM [10] provides in the univariate case, we propose to

- Design of a multivariate probability density function estimator based on the maximum entropy principle to successfully match multivariate sources from a wide range of distributions and take sample dependence into account;
- Proposed approach is quite different from the MGGD-based approach described in the preliminary work, where a density model is chosen and the parameters are estimated during the estimation of the demixing matrix.

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