Effect of Sparse Decomposition on Various ICA Algorithms With Application to Image Data

Asif Khan, Intaek Kim
Department of Communication Engineering
Myongji University
e-mail : asifspecial@gmail.com, kit@mju.ac.kr

Abstract

In this paper we demonstrate the effect of sparse decomposition on various Independent Component Analysis (ICA) algorithms for separating simultaneous linear mixture of independent 2-D signals (images). We will show using simulated results that sparse decomposition before Kernel ICA (Sparse Kernel ICA) algorithm produces the best results as compared to other ICA algorithms.

I. Introduction

In ICA, an N-dimensional vector of observed signals is generated by the product of an unknown N×M mixing matrix A and an M-dimensional vector of unknown source signals. The task is to estimate the mixing matrix and then recover the source signals. In terms of Image the basic ICA model is given by:

$$m_1 = a_{11}\, s_1 + a_{12}\, s_2 \quad (1)$$

$$m_n = a_{n1}\, s_1 + a_{n2}\, s_2 \quad (2)$$

$$M = A \times S \quad (3)$$

where n = {1,2,...,N}, m_1,..., m_n are the N mixed images and s1 and s2 are the source images represented as row vectors and A is the mixing matrix. It is possible to recover sources by estimating the mixing matrix A' ≈ A, and estimating the sources by its inversion:

$$S' = (A')^{-1} \times M \quad (4)$$

In this paper we show what is the effect of sparseness on ICA algorithms, including Infomax [4], Analytic ICA by Farid [1], JADE [5], SHIBBS [5], OGWE [6], Pearson [7], Radical [9] and Kernel [8] and demonstrate that sparseness before Kernel ICA gives the best results.

II. Sparse Decomposition of Images

Zibulevsky et al [3] have noticed that in case of *sparse* sources, their linear mixtures can be easily separated using very simple "geometric" algorithms. Alexander M. Bronstein applied the Sparse ICA [2] for reflection removal. Different classes of signals have their "natural" sparse transformations. We use the wavelet packet transform (WPT) for sparse representation of mixture of images and analyze its effect on the ICA algorithms.

III. Results

We apply ICA algorithms mentioned earlier, first without sprasing and then with sparsing on random mixtures (Figure 1) of two source images. Results of algorithms after sparse decomposition can be seen in Figure 2 , where R1 and R2 represent estimated Source 1 and estimated Source 2 respectively.

a b c d

Figure 1. (a) Source 1. (b) Source 2. (c) Mixture 1. (d) Mixture 2.

Using PSNR (Figure 3), we compare quantitatively the results of sparsing on ICA algorithms, which shows the improvement in results for JADE, SHIBBS, Pearson, and Kernel and deteriorates the estimated Source 2 in case of Farid, OGWE and Radical ICA.

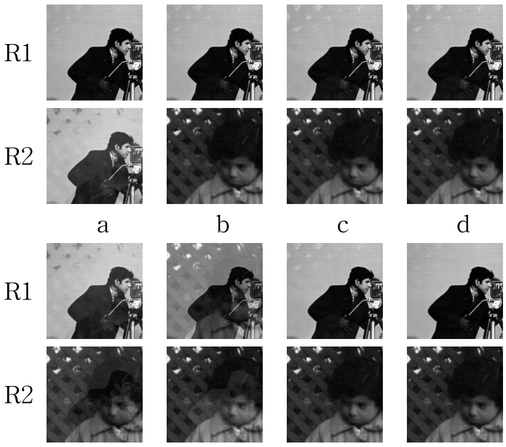

Figure 2. Results of ICA algorithms with sparsing (a) Farid and Adelson (b) Infomax (c) JADE (d) SHIBBS (e) OGWE (f) Pearson (g) Radical (h) Kernel

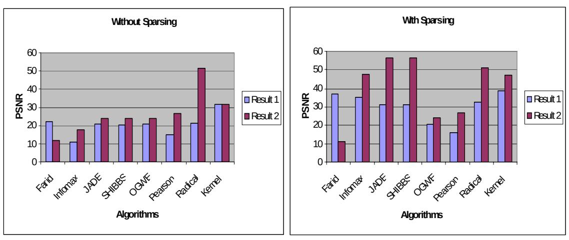

Figure 3. PSNR of estimated source 1 (Result1) and estimated source 2 (Result2), before and after Sparse Decomposition.

Ⅳ. Conclusion

Sparse decomposition considerably improves the result of Infomax, JADE, SHIBBS and Kernel but shows random behaviour to Farid, OGWE and Radical ICA, deteriorating the results for one or both of the sources. We have shown that in BSS problems if we sparse the data and then use Kernel ICA we get the most robust and consistent results but with computational cost.

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