BLIND IMAGE SEPARATION USING FORWARD DIFFERENCE METHOD(FDM)

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ABSTRACT

In this paper, blind image separation is performed, exploiting the property of sparseness to represent images. A new sparse representation called forward difference method is proposed. It is known that most of the independent component analysis (ICA) basis functions, extracted from images are sparse and gives unreliable sparseness measure. In the proposed method, the image mixture is first transformed to sparse images. These images are divided into blocks and for each block the sparseness measure ℓ_0 *norm is applied. The block having the most sparseness is considered to determine the separation matrix. The efficiency of the proposed method is compared with other sparse representation functions.*

KEYWORDS

Blind source separation (BSS), ℓ_0 *norm, sparse representation, Quality measure*

1. INTRODUCTION

Blind source separation (BSS) is the process of extracting the underlying sources called Source Separation from the mixed images or observed signals, and since no *a priori* knowledge of the mixed sources is known or very little information is available, it is called *blind*. Independent component analysis (ICA) is most widely used technique to solve the blind source separation [1-4] problem. BSS is based on the assumptions that source signals are independent with each other. Sparse coding is a method for finding suitable representation of data in which the components are rarely active. It has been shown [5, 6, 7] that this sparse representation can be used to solve the BSS problem. ICA algorithms i.e., FASTICA uses kurtosis as a sparseness measure and since kurtosis is sensitive to the outliers as it applies more weight on heavy tails rather than on Zero, this measure is mostly unreliable. When the sources are locally very sparse the matrix identification algorithm is much simpler. A simpler form, for separation of mixtures from images after sparsification transformation is hence used.

In this work, a new method is proposed called the forward difference method (FDM) to exploit the sparsity representation of images and measure the sparseness, using ℓ_0 norm. The forward difference method provides a powerful approach to solve differential equations, non linear problems and is widely used in the field of applied sciences. The new BSS algorithm, is shown to

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be more efficient and leads to improved separation quality which is measured as Peak signal to Noise ratio (PSNR), Structural Similarity Index Measure (SSIM) and Improvement in signal to Noise ratio (ISR).

The rest of the paper is organized as follows: Section 2 deals with the method used for sparse representation of data, Sparse measure using ℓ_0 norm and the algorithm used for separation. Section 3 illustrates the results where the separated images and the original images are compared, Section 4 gives the conclusion.

2. METHODOLOGY

Consider N images each of size 256x512 and N linear mixtures of these original images are observed. These mixtures can be represented as a linear equation of the form

$$X = AS \qquad (1)$$

Where **s** is the original source to be extracted, X **is** the observation random vector, A is a full rank n x n mixing matrix. As the observed image is a random vector **X**, both A and **s** needs to be estimated. Inverse matrix W can be computed after estimating A. The independent sources are simply obtained by

$$U = WX \qquad (2)$$

Hence the goal of BSS is to find a matrix W, called separator. There are several methods [8], [9],[17] to separate the independent components from the original data. Bell and Sejnowski [10] developed a neural learning algorithm for separating the statistically independent components of a dataset through unsupervised learning. The algorithm is based on the principle of maximum information transfer between sigmoid neurons. The features it gave were not very interesting from a neural modeling viewpoint, and the mixing matrix 'reduces' the sparsity of the original images which motivates us to find better models like exploiting the property of sparseness [11].

2.1. Sparse Representation

In order to restore the sparsity of the representations of the original images that solves the BSS problem, two methods are proposed [5, 6]. We propose a simpler and efficient method to make the image sparse by calculating the forward difference of the image matrix. The analysis systematically starts from Taylor's series expansion by considering the approximation of first-order derivatives. The Taylor series expansion is given by

$$f(x+\Delta x) = f(x) + \sum_{h=1}^{n-1} f^{h} + (\mathrm{x})\frac{\Delta(x)^{h}}{h!} + f^{(n)}(x+\theta\Delta x)\frac{\Delta x^{n}}{n!} \qquad (3)$$

Where 0<θ<1 , f^{n} is the h^{th} derivative of f .considering the last term as order of $(\Delta x)^{n}$, equation (3) becomes,

$$(x+\Delta x) = f(x) + \sum_{h=1}^{n-1} f^{h} + (\mathrm{x})\frac{\Delta(x)^{h}}{h!} + O(\Delta x)^{n} \qquad (4)$$

Rewriting the above forward approximation for the partial derivative $u_{t.}$ i.e.,

$$U(x_i, t_j + \Delta t) = U(x_i t_j) + U_t(x_i, t_j)\Delta t + \mathrm{O}(\Delta t)^2) \qquad (5)$$

Or

$U_{i,j+1} = (U_{i,j}) + \Delta t + O((\Delta t)^2)$

i.e. $$U_{i,j+1} = (U_{i,j}) + \Delta t + O((\Delta t)^2) \tag{6}$$

Hence, approximating the formula for forward approximation

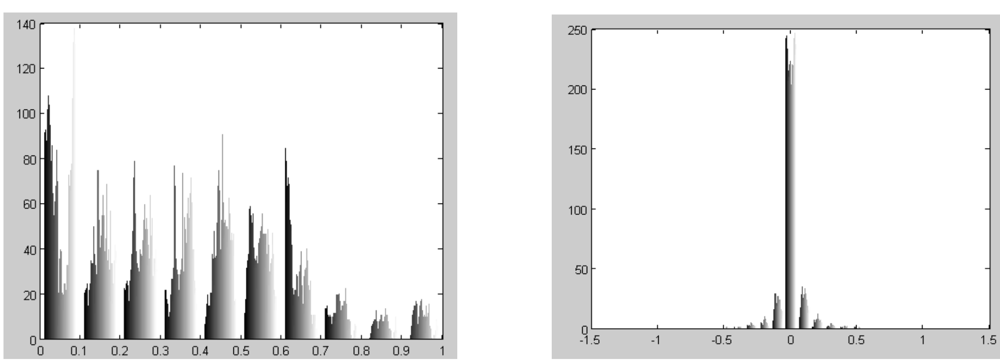
$$(U_t)_{i,j} \approx \frac{U_{i,j+1} - U_{i,j}}{\Delta t} \tag{7}$$

Using finite difference operators the equation (7) can be easily written as $\Delta f_i = f_{i+1} - f_i$ or

$$\Delta_h[f](x) = f(x+h) - f(x) \tag{8}$$

Depending on the application, the spacing *h* may be variable or constant. The forward difference method (FDM) can be used for sparse representation of the image since it acts as an edge detector which provides a two-level image, the edges and the homogeneous background. By using this method, the separation matrix estimated to separate the image mixture is similar to that of the method used (FASTICA) for image separation. In Figure 1, the natural image is displayed as well as the image obtained from the above method and their respective histograms that clearly show the sparsity of the latter.

Fig. 1. Original Image and FDM Image



(a) (b)

Fig. 2. (a) Original Image Histogram and (b) FDM Histogram

2.2. Sparsity Measure

The sparsity property can be measured [15] using ℓ_0 norm defined by David Donoho. Usually ℓ_0 norm is defined as

$$J_0(S) = \sum_{i=1}^{n} \sum_{j=1}^{N} |s_{ij}|^0 \quad (9)$$

the number of nonzero entries of S, is used as a sparsity measure of S, since it ensures the sparsest solution. Under this measure, the sparse solution is obtained by finding the number of non zero elements in a block. The block having the maximum sparse is selected to estimate the separation matrix W equation (1).The fig 3 shows quality measure using ℓ_0 norm for different sparse functions.

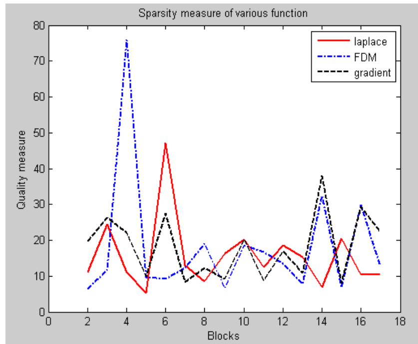


Fig. 3. Quality Measure values for sparse images shown for each block

2.3. Algorithm

In this section, A BSS algorithm using the FDM is proposed.

1. Normalize the N images.

2. Mixed images are formed by linearly mixing with a random matrix

3. Apply forward difference method for each mixed images to get sparse images.

4. The sparse images are divided into blocks.

5. The blocks having same spatial location are considered for evaluation of the sparseness (ℓ_0 norm).

6. The blocks having maximum sparseness is considered for estimating the separation matrix using Infomax algorithm

3. SIMULATION

Simulation experiments are conducted to demonstrate the feasibility of the proposed BSS method. All simulations are carried on 256 x 512. The algorithms are developed on MATLAB environment. The images are mixed with a random matrix 2x2 and the forward difference formula equation (8) is applied on it. This sparse image is divided into blocks of 64x128 for which the ℓ_0 norm is applied to evaluate the quality factor. The blocks which has maximum value of the quality factor is considered for evaluating the separation matrix .The separation matrix is obtained by using Infomax algorithm. The results are shown in Fig 4. The performance of the extracted images is evaluated by an objective image quality measure Peak Signal to Noise Ratio (PSNR) and Improved signal to noise ratio (ISNR) which is defined by the equations (11,12). The

Structural Similarity Index Measure (SSIM) equation (13) a well-known quality metric is used to measure the similarity between two images. It was developed by Wang et al. [16], and is considered to be correlated with the quality perception of the human visual system (HVS). A comparative result is obtained with other sparcifying functions like gradient and Laplace transform for which the random matrix is fixed as in equation (10) . Table 1 shows the Results for all the three methods.

Fig 4. Original Images

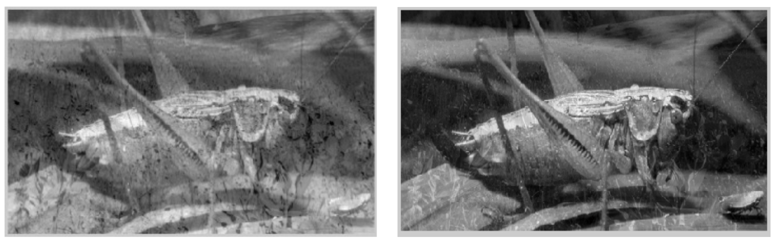


Fig 5. Mixed Images

Fig 6. Separated Images

Random Matrix used:

$$M = \begin{matrix} 0.2944 & 0.7143; \\ -1.3362 & 1.6236; \end{matrix} \qquad (10)$$

$$PSNR = 20 \log_{10} \left(\frac{255}{\sum_{m=1}^{M} \sum_{n=1}^{N} s(m,n) - y(m,n)} \right) \text{dB} \qquad (11)$$

$$ISNR = 10 \log_{10}\left(\frac{s(m,n) - x(m,n)}{s(m,n) - y(m,n)}\right) \text{dB} \quad (12)$$

$$SSIM = \frac{(2\mu_r\mu_d + C_1)(2\sigma_{rd} + C_2)}{(\mu_r^2 + \mu^2{}_d + C_1)(\sigma_r^2 + \sigma_d^2 + C_2)} \quad (13)$$

Table 1. Performance evaluation of sparse functions used for separating the Images

Methods	PSNR in dB		ISNR in dB		SSIM	
	Image 1	Image 2	Image 1	Image 2	Image1	Image2
Laplace	25.4338	17.0934	25.5006	35.8572	0.8570	0.9884
Gradient	25.7711	11.2603	25.1161	35.5613	0.9993	0.9994
FDM	27.2376	24.1159	35.8283	35.8056	0.9999	0.9994

4. CONCLUSION

In this paper, an efficient and simple technique for sparsification of the natural observed mixtures followed by a blind separation of the original images has been proposed. This method uses forward difference function that has low computational complexity. The result shows FDM performs better than other available sparse functions for the same random matrix given in (10).

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