Separation of Image Sources Using AMMCA Algorithm

Nimmy Nice.A [1], V.Vino Ruban Singh[2]
PG student, Applied Electronics, Loyola Institute of Technology and Science,Nagercoil, India[1]
nice24.nimmy@gmail.com[1]
Assistant professor, Dept of ECE, Loyola Institute of Technology and Science,Nagercoil, India[2]

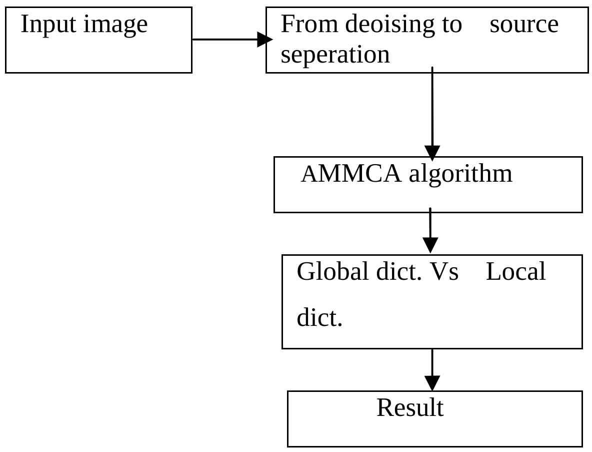
Abstract-Sparsity has been shown to be very useful in source separation of multichannel observations. However, in most cases, the sources of interest are not sparse in their current domain and one need to sparsify them using a known transform or dictionary. If such a priori about the underlying sparse domain of the sources is not available, then the current algorithms will fail to successfully recover the sources. In this paper, we address this problem and attempt to give a solution via fusing the dictionary learning into the source separation. We first define a cost function based on this idea and propose an extension of the denoising method in the work of Elad and Aharon to minimize it. Due to impracticality of such direct extension, we then propose a feasible approach. In the proposed hierarchical method, a local dictionary is adaptively learned for each source along with separation. Image compression is done by using Block Truncation Coding(BTC**).**

Keywords- Blind Source Separation(BSS),Adaptive Multichannel Component Analysis (AMMCA), Block TruncationCoding(BCT).

I. INTRODUCTION

In signal and image processing, there are many instances where a set of observations is available and we wish to recover the sources generating these observations. This problem, which is known as blind source separation (BSS). Blind source separation by Independent Component Analysis (ICA) has received attention because of its potential applications in signal processing such as in speech recognition systems, telecommunications and medical signal processing. The goal of ICA Independent Component Analysis is to recover independent sources given only sensor observations that are unknown linear mixtures of the unobserved independent source signals. In contrast to correlation-based transformations such as Principal Component Analysis(PCA), Independent Component Analysis ICA not only decorrelates the signals (2nd-order statistics) but also reduces higher order statistical dependencies, attempting to make the signals as independent as possible.

There have been two different fields of research considering the analysis of independent components. On one hand, the study of separating mixed sources observed in an array of sensors has been a classical and difficult signal processing problem.



II. IMAGE DENOISING

Consider a noisy image corrupted by additive noise. Elad and Aharon showed that if the knowledge about the noise power is available, it is possible to denoise it by learning a local dictionary from the noisy image itself. In order to deal with large images, they used small (overlapped) patches to learn such dictionary. The obtained dictionary is considered local since it describes the features extracted from small patches. Let us represent the noisy $\sqrt{N}$ x $\sqrt{N}$ image y by vector y of length N. The unknown denoised image x is also vectorized and represented as x . The i th patch from x is shown by vector $\Re_i x$ of r<< N pixels. For notational simplicity, the i th patch is expressed as explicit multiplication of operator $\Re_i$ (a binary r x N matrix) by x. The overall denoising problem is expressed as

$$\min_{D,\{S_i\},x} \lambda\|y-x\|_2^2+\sum_i \mu_i\|S_i\|_0+\sum_i\|D_{s_i}-\Re_i x\|_2^2$$

Where scalars λ and μ control the noise power and sparsity degree, respectively. In addition, $D \in R^{r\times k}$ is the sparsifying dictionary that contains normalized columns (also called atoms), and $\{s_i\}$ are sparse coefficients of length. In the proposed algorithm by Elad and Aharon x and D, and are respectively initialized with y and overcomplete (r < k) discrete cosine transform (DCT) dictionary. The minimization of starts with extracting and rearranging all the patches of x. The patches are then processed by K-SVD, which updates D and estimates sparse coefficients $\{s_i\}$. Afterward, D and are assumed fixed and x is estimated by computing

$$\hat{x}=\left(\lambda I+\sum_i \Re_i^T \Re_i\right)^{-1} \left(\lambda y+\sum_i \Re_i^T D s_i\right)$$

Where I is the identity matrix and $\hat{x}$ is the refined version of x. Again, D and $\{s_i\}$ are updated by K-SVD but this time using the patches from $\hat{x}$ that are less noisy. Such conjoined denoising and dictionary adaptation is repeated to minimize. In practice, is obtained computationally easier since $\sum_i \Re_i^T \Re_i$ is diagonal and the above expression can be calculated in a pixel wise fashion.

It is shown that is a kind of averaging using both noisy and denoised patches, which, if repeated along with updating of other parameters, will denoise the entire image. However, in the sequel, we will try to find out if this strategy is extendable for the cases where the noise is added to the mixtures of more than one image.

Image Separation

Image separation is a more complicated case of image denoising where more than one image are to be recovered from a single observation. Consider a single linear mixture of two textures with additive noise: $y=\chi_1+\chi_2+v(\text{or}\, x_1+x_2+v)$

The authors of attempt to recover and using the prior knowledge about two sparsifying dictionaries $D_1$and D2. They use a minimum mean-squared-error (MSE) estimator for this purpose. In contrast, the recent work in does not assume any prior knowledge about the dictionaries. It rather attempts to learn a single dictionary from the mixture and then applies a decision criterion to the dictionary atoms to separate the images. In another recent work, Peyre et al. presented an adaptive MCA scheme by learning the morphologies of image layers. They proposed to use both adaptive local dictionaries and fixed global transforms (e.g., wavelet and curvelet) for image separation from a single mixture. Their simulation results show the effects of adaptive dictionaries on separation of complex texture patterns from natural images.

All the related studies have demonstrated the advantages that adaptive dictionary learning can have on the separation task. However, there is still one missing piece and that is considering such adaptivity for the multichannel mixtures. Performing the idea of learning local dictionaries within the source separation of multichannel observations obviously has many benefits in different applications. Next, we extend the denoising method in for this purpose.

Global Dictionaries Versus Local Dictionaries

The proposed method takes the advantages of fully local dictionaries that are learned within the separation task. We call these dictionaries local since they capture the structure of small image patches to generate dictionary atoms. In contrast, the global dictionaries are generally applied to the entire image or signal and capture the global features. Incorporating the global fixed dictionaries into the proposed method can be advantageous where a prior knowledge about the structure of sources is available. Such combined local and global dictionaries have been used in for single mixture separation. Here, we consider the multichannel case and extend our proposed.

Consider a known global unitary N x N basis Φ_j for each source. The minimization problem can be modified as follows to capture both global and local structures of the sources:

$$\min_{\{a_j, D_j, \{s_i\}, x_j\}} \lambda_j\|E_j-a_j x_j^T\|_F^2+\beta_j\|x_j^T\Phi_j\|_1+$$

$$\sum_i \mu_i\|s_i\|_0+\sum_i\|D_j s_i-\Re_i x_j\|_2^2$$

Note that term $\|x_j^T\Phi_j\|_1$ is exactly similar to what was used in the original MMCA. All variables in the above expression can be similarly estimated using Algorithm 1, except the actual $\{x_j\}$ sources. In order to find $x_{j:}$, the gradient of with respect to $x_{j:}$ is set to zero, leading to

$$\left(\lambda_j I + \sum_i \Re_i^T \Re_i\right) x_{j:} = \underbrace{\left(\lambda_j E_j^T a_{:j} + \sum_i \Re_i^T D_j s_i\right)}_{\tilde{x}_{j:}} - \frac{\beta_j}{2}\Phi_j \operatorname{sgn}(\Phi_j^T x_{j:})$$

Where sgn(.) is a component wise signum function. The above expression amounts to soft thresholding due to the signum function, and hence, the estimation of can be obtained by the following steps:

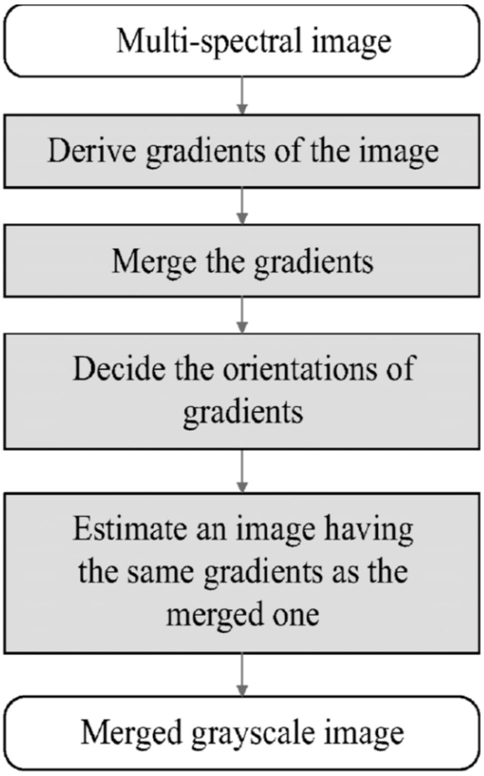
• Soft thresholding of $\alpha_j \triangleq \Phi_j^T \tilde{x}_j$ with threshold β_j and attaining $\hat{\alpha}_j$;

Reconstructing by $\hat{x}_{j:} = \left(\lambda_j I + \sum_i \Re_i^T \Re_i\right)^{-1} \Phi_j \hat{\alpha}_j$

Note that, since Φ_j is a unitary and known matrix, it is not explicitly stored but implicitly applied as a forward or inverse transform where applicable. Similar to the previous section, the above expression can be executed pixel wise and is not computationally expensive.

III. AMMCA ALGORITHM

Morphological Component Analysis Morphological component analysis is a popular image processing algorithm that extracts degrading patterns or textures from images and simultaneously performs in painting. The Morphological Component Analysis (MCA) is a new method which allows us to separate features contained in an image when these features present different morphological aspects. To extend MCA to a multichannel MCA (MMCA) for analyzing multispectral data and present a range of examples which illustrates the results.



FUTURE ENHANCEMENT

BTC Algorithm

Block Truncation Coding is used for future enhancement. After get the resultant image to apply the encryption standard.

Step1:

The given image is divided into non overlapping rectangular regions. For the sake of simplicity the blocks were let to be square regions of size m x m.

Step 2:

For a two level (1 bit) quantizer, the idea is to select two luminance values to represent each pixel in the block. These values are the mean *x* and standard deviation

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad \text{------------(1)}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad \text{------------(2)}$$

Where xi represents the ith pixel value of the image block and n is the total number of pixels in that block.

Step3:

The two values *x* and σ are termed as quantizers of BTC.. We can use “1” to represent a pixel whose gray level is greater than or equal to *x* and “0” to represent a pixel whose gray level is less than

$$B = \begin{cases} 1 & x_i \geq \bar{x} \\ 0 & x_i < \bar{x} \end{cases} \qquad \text{---------(3)}$$

Step 4:

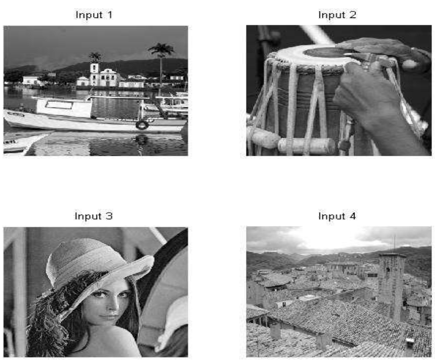
In the decoder an image block is reconstructed by replacing '1's in the bit plane with H and the '0's with L, which are given by:

$$H = \bar{x} + \sigma\sqrt{\frac{p}{q}} \qquad \text{-------------(4)}$$

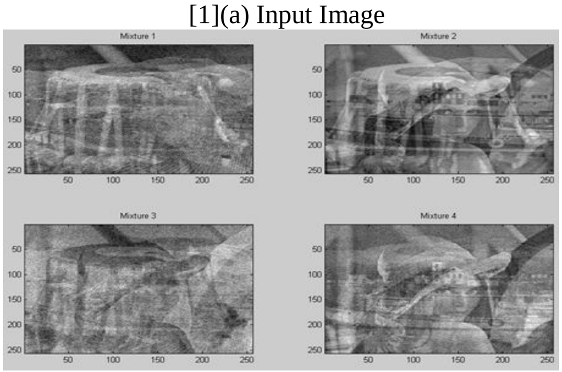
$$L = \bar{x} - \sigma\sqrt{\frac{q}{p}} \qquad \text{---------(5)}$$

Where p and q are the number of 0's and 1's in the compressed bit plane respectively.

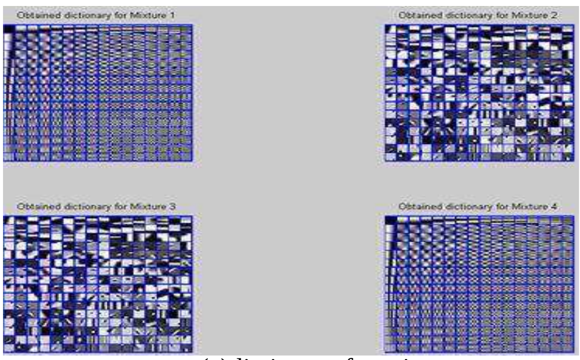
IV. SIMULATED RESULTS



[1](a) Input Image

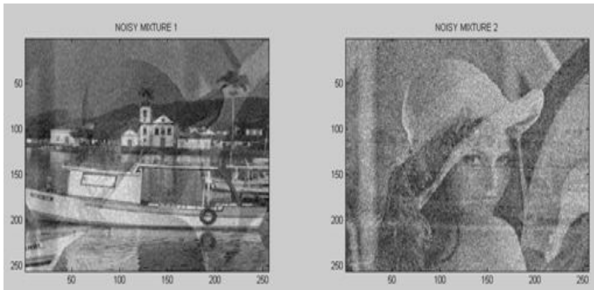


(b)mixture image

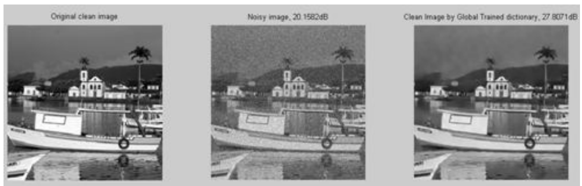


(c)dictionary for mixture

(d)Separated by ammca



[2] (a)noisy mixture for two images



(b)clear image by dictionary

(e)clear image by dictionary

V. CONCLUSION

In this paper, the BSS problem has been addressed. The aim has been to take advantage of sparsifying dictionaries for this purpose. Unlike the existing sparsity-based methods, assumed no prior knowledge about the underlying sparsity domain of the sources. Instead, have proposed to fuse the learning of adaptive sparsifying dictionaries for each individual source into the separation process. Motivated by the idea of image denoising via a learned dictionary from the patches of the corrupted image in, proposed a hierarchical approach for this purpose.

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Author Profile

A.Nimmy Nice,P.G student in Loyola Institute Of Technology & Science.She has completed her U.G(B.E-ECE)degree in Noorul Islam College of Engineering under Anna University.Her Current research is Digital Image Processing .