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MULTI-CHANNEL IMAGE SOURCE SEPARATION BY DICTIONARY UPDATE METHOD

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Abstract- In real world, a large set of mixed signals are available from which each source signal need to be recovered and this problem can be addressed with adaptive dictionary method. In the case of multichannel observations sparsity found to be very useful for source separation. The problem exist is that in most cases the sources are not sparsified in their domain and it will become necessary to sparsify the source by using some known dictionaries. In order to recover the sources successfully a prior knowledge of the sparse domain is required, if not available this problem can be solved by using dictionary learning technique into source separation. The proposed method, a local dictionary is adaptively learned for each source separately along with separation. This approach improves the quality of source separation both in noiseless and different noisy situations. The advantage of this method is that it denoise the sources during separation.

Keywords-Blind source separation (BSS); dictionary learning technique; multichannel morphological analysis; denoising; sparsity.

I. INTRODUCTION

In blind source separation, the aim is to separate independent sources without knowing the mixing parameters from their mixtures. To recover the sources from the mixed observations blind source separation (BSS) is used. The observed mixture can be represented by general matrix model

$$y = A x + B \quad (1)$$

where $y \in \mathfrak{R}^{m \times N}$ is the observation matrix, $x \in \mathfrak{R}^{n \times N}$ is the source matrix, A is the $m \times n$ mixing matrix and B is the $m \times N$ additive noise. The blind source separation method is used to estimate the mixing matrix A and source x from the observations.

Sparsity is very useful in source separation of multichannel observations. The sources have to be sparsified using a known transform or dictionary. By the use of adaptive dictionary learning technique in source separation the prior knowledge about the sparse domain is not required. And this method increases the quality of the source separation even in the noisy situations. Sparsity based approaches for the BSS problem has received much attention recently [1].

The term sparse refers to signals or images with small number of non zeros with respect to some representation bases. In sparse component analysis (SCA), the assumption is that the sources can be sparsely represented using a known common basis or dictionary. Some methods use sparse dictionaries for separation of image mixtures [2]. Also there are many cases where each source is sparse in a different domain, which makes it difficult to directly apply SCA methods to their mixtures. The SMICA exploits

the spectral diversity of the sources and is used to separate sources whether they are noiseless or noisy [3]. An extension of this method is called wSMICA which uses wavelet domain for the process [4]. SPICA is the method used to solve the problem of recovering a scene recorded through semi-reflecting medium [5].

Multichannel morphological component analysis (MMCA) [6] and generalized morphological component analysis (GMCA) [7] have been recently proposed to address the problem of each source having different sparse domain. In MCA, each source is modeled as the linear combination of a number of morphological components where each component is sparse in a specific basis [8].

The main assumption in MMCA is that each source can be sparsely represented in a specific known transform domain. MMCA and GMCA are extensions of morphological component analysis (MCA) to the multichannel case.

The MMCA performs well when a priori knowledge about the sparse domain of each individual source is available. If there is no prior knowledge about the sparse domain is available, then a dictionary learning framework is used to solve the problem.

The extended MMCA algorithm will adaptively learn dictionaries from the mixed images within the source separation process [9]. Thus blind image source separation is performed without any prior knowledge about the sparse domains of the sources and this method enhances the separability of the sources. This

approach provides a better and efficient separation of sources.

II. FROM IMAGE SEPARATION TO MULTI-CHANNEL IMAGE SEPARATION

A. Image Separation

Image separation becomes difficult when one observation contains more than one image source. To separate image from a linear mixture, blind source separation method is used. A linear mixture, y of two images can be represented as

$$y = ax_1 + bx_2 + B \tag{2}$$

where a, b are unknowns and x_1, x_2 are the image sources that has been mixed with an unknown mixing parameter. The additive noise is denoted by B . If prior knowledge of the sparse domain of each source is known, the sources can be recovered using the existing blind source separation methods. But if the prior knowledge of sparse domain is not available, then the problem has to be solved by learning dictionaries for each source separately. The dictionary learning technique has better impact on source separation process.

B. Multi-channel image separation

Here the separation process has been extended into mutli channel image observations. There is no restriction in the obtained image mixtures. The images that have considered for multi-channel observations are 2- D gray scale images. For multi-channel case, the observations considered is more than the number of sources taken ($m \geq n$). The proposed method for multi-channel image source separation is adaptively learning dictionaries from the mixed images for each source separately. The method takes the advantage that the denoising is performed along with the separation process.

III. PROPOSED METHOD FOR IMAGE SEPARATION

An extended Multichannel Morphological Component Analysis method is used for multichannel image separation. The blind separation of images using proposed method provides a better quality of image separation. The blind image separation process assumes that the sources are 2-D grayscale images. The observation mixture is generated by using a linear mixing process which is performed by Kronecker product function and the obtained mixture is then separated by the proposed method in which an adaptive dictionary learning technique is fused with separation process. In separation process the dictionary is initialized by DCT, updated by K-Singular Value Decomposition (K-SVD) algorithm [10] and the sparse coefficients are estimated by

using Orthogonal Matching Pursuit (OMP), sparse coding method [11], [12].

Source images, x

reconstructed data, \hat{x}

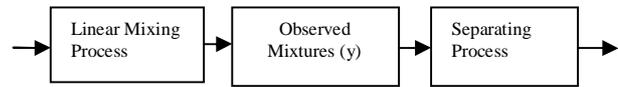


Figure 1. Block of proposed method

C. Image Mixing Process

The linear mixing is performed using the equation,

$$y = (I \otimes A) x + B \tag{3}$$

where y is the observation matrix, $(I \otimes A)$ is a block diagonal matrix obtained as a result of Kronecker product function of I with mixing matrix A and x is the source matrix, B is the additive noise. The BSS model for 2-D sources can be represented by vectoring all images $\{\chi_1, \chi_2, \chi_3, \dots, \chi_n\}$ to $\{x_1, x_2, x_3, \dots, x_n\}$. And then stacking them to form $X = [x_1, x_2, x_3, \dots, x_n]^T$. Since the BSS model cannot be used directly as it requires both X and Y to be single vectors. The vectorized version of these matrices can be obtained by using the properties of Kronecker product. The symbol \otimes represents Kronecker product function.

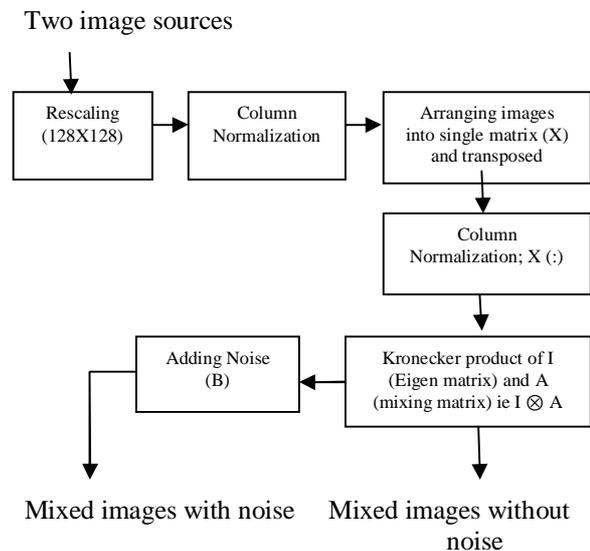


Figure 2. Mixing Process

The Kronecker product function is performed on two matrices which results in a block matrix. It is the outer product from vectors to matrices which will give the matrix with a standard choice of basis. The Kronecker product is different from the usual matrix multiplication. For e.g., if E is a $m \times n$ matrix and F is a $p \times q$ matrix, then the Kronecker product $E \otimes F$ is a $mp \times nq$ block matrix.

D. Image Separation Process

The BSS for multichannel separation is performed by using extended multichannel morphological component analysis (MMCA) algorithm that uses the K-SVD algorithm to update the dictionary. Using this method n dictionaries have to be learned, one for each source. Advantage of this scheme is learning adaptive source specific dictionaries which improve the source diversity. The proposed method could successfully recover the image sources via adaptive learning of the sparsifying performance for both denoising and separation tasks. The proposed method successfully denoises and separates the mixed image observations into individual separate image sources.

The denoising problem can be solved by considering one unknown at a time. From the unknown mixture patches has been obtained for creating the dictionary. Patch size depends on the entire image size and the patterns of the actual sources. But large patches are avoided as they lead to large dictionaries. Here 8×8 patch sizes are considered for experiment, which seems to become a standard size. Dictionary is a collection of atoms, by using more than one combination of different atoms any signal can be obtained. The size of the dictionary depends on the data type and number of training sets. The obtained dictionary is having size 256 atoms. The estimation of dictionary D is performed firstly by initializes the dictionary using DCT and is updated by using K-SVD algorithm.

The OMP method is used for the estimation of sparse coefficients $\{S_i\}$. In K-SVD, the dictionary is updated column-wise using the algorithm single valued decomposition.

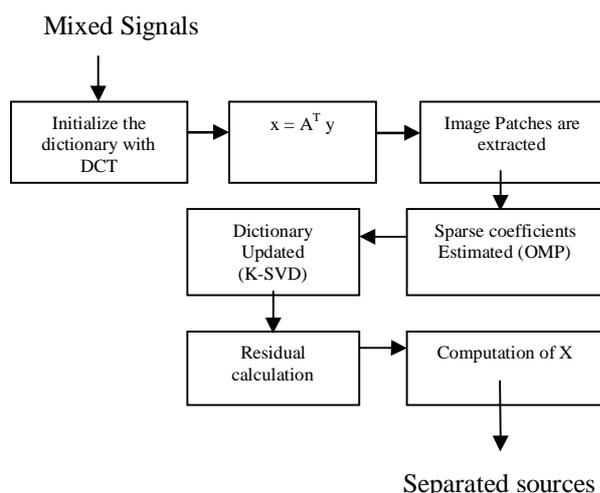


Figure 3. Separation Process

E. Algorithm

The proposed algorithm is;

1. Choose observation matrix y , patch size r , dictionary atoms k , number of sources n , noise deviation σ_v .

2. Initialize the dictionary using over-completes DCT.
3. Obtain x using a random mixing matrix, A .
4. Set the number of iterations M and extract image patches from obtained x .
5. Sparse coefficients have been estimated by orthogonal matching pursuit (OMP) method.
6. Dictionary is updated using K-SVD
7. Source X is estimated.

IV. RESULTS

F. Experiment on Noiseless mixtures

Firstly the experiment was conducted on noiseless mixtures and the mixtures were obtained from two sources. The chosen sources were having different morphologies. A random 4×2 column-normalized matrix has been taken as mixing matrix A and two hundred iterations were set to meet the stopping criterion. The value of regularization parameter, $\lambda = 30/\sigma$ where the σ value starts with 25 and reaches 15 at the end of iterations. The other parameters considered are patch size $r=64$, the dictionary size $k=256$, size of image source, $N=128 \times 128$ and noise gain $C=1$. The performance is evaluated by using peak signal to noise ratio (PSNR) and is calculated by using the equation

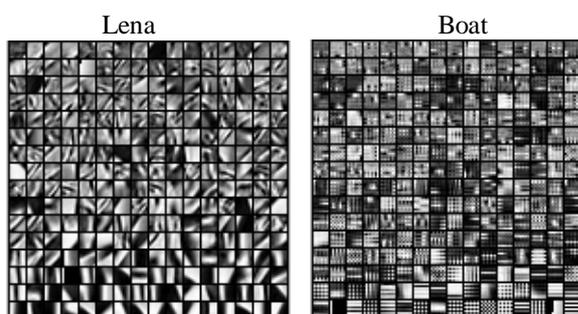
$$\text{PSNR} = (20 * \log_{10} \max(x)^2) / \text{MSE} \quad (4)$$

The obtained PSNR value for the reconstructed images using proposed method are compared with the existing algorithms like generalized morphological component analysis (GMCA), Sparse ICA (SPICA) and Spectral Matching ICA (SMICA). The proposed method recovers the sources using the adaptively learned dictionaries.

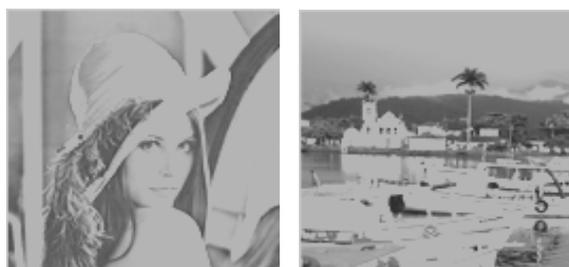




(b)



(c)



PSNR=30.6203dB

PSNR=30.9205dB

(d)

Figure 4. (a)Original sources (b)Noiseless mixtures (c) Dictionaries obtained (d) Reconstructed sources
TABLE I. COMPARISON WITH EXISTING METHODS (NOISELESS)

Method	Lena/Boat Combination	
	PSNR Values	
	Lena(dB)	Boat(dB)
Proposed Method	30.6203	30.9205
GMCA	24.9667	25.9595
SPICA	26.4130	27.2769
SMICA	25.5342	26.4796

TABLE II. DIFFERENT NOISELESS COMBINATIONS

Different Noiseless Combinations	PSNR Values	
	Image 1(dB)	Image 2(dB)
	Lena /Boat	30.6203
Barbara/Boy	32.9588	24.6309

Different Noiseless Combinations	PSNR Values	
	Image 1(dB)	Image 2(dB)
	Cameraman/Peppers	35.2963
House/Woman_Blonde	28.5295	28.1009

G. Experiment on Noisy mixtures

Secondly the experiment is conducted with noisy mixtures and considered different noise mixtures. The recovered image sources are compared with their MSE and PSNR values for performance evaluation. This noisy experiment is performed by considering the same condition as that of noiseless experiment and in addition to that some noise is added in this case. The mean-squared error (MSE) is calculated by using

$$MSE = (X - \bar{X}) / N \quad (5)$$

where X and \bar{X} are the original and recovered images respectively. The proposed method has the ability to denoise the sources during the separation process.

TABLE III. COMPARISON WITH EXISTING METHODS (GAUSSIAN)

Methods	Barbara/House Combination	
	PSNR Values	
	Barbara(dB)	House(dB)
Proposed Method	32.1966	28.3445
GMCA	26.1573	24.3443
SPICA	27.6878	25.4448
SMICA	26.7568	24.7818

TABLE IV. RECONSTRUCTED IMAGES WITH MSE VALUES

Noisy Mixtures	Barbara/House Combination	
	MSE Values	
	Barbara	House
Gaussian	2.8321	4.8592
Salt & Pepper	3.0857	4.9841
Poisson	2.9569	5.2453
Speckle	3.2183	5.5220



(a)

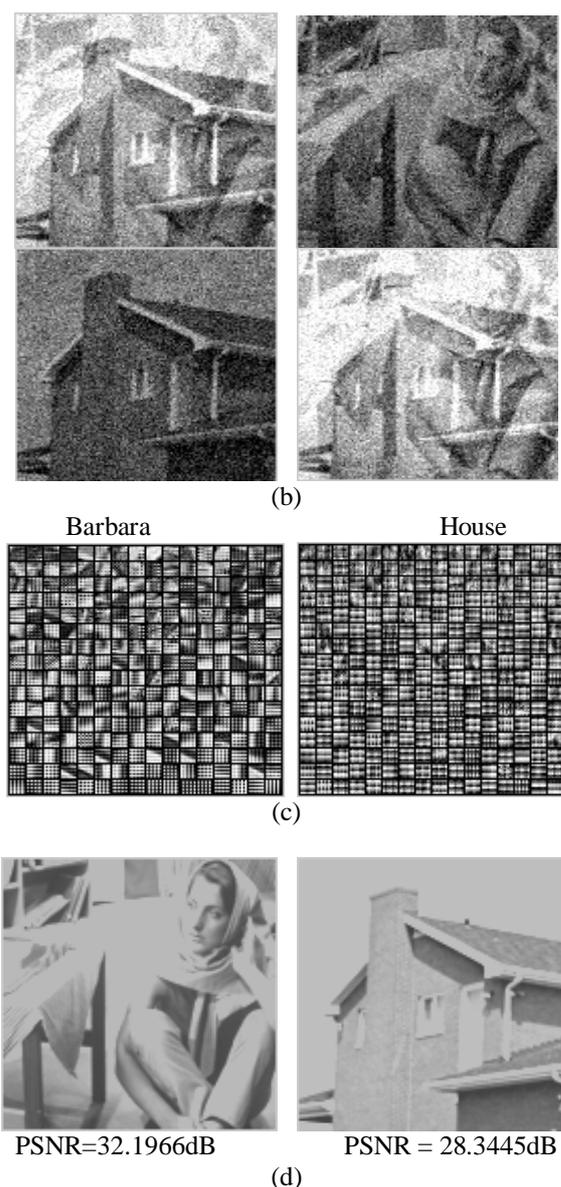


Figure 5. (a)Original sources (b)Noisy mixtures (Gaussian)
 (c) Dictionaries obtained (d) Reconstructed sources

V. CONCLUSION

In this paper, blind image source separation problem has been solved by using dictionary update method. In this method no prior knowledge of the sparse domain of the sources are required. The dictionary has been learned adaptively for each source during the separation process. By this method the denoising is performed along with the separation process and it effectively separates the sources for both noisy and noiseless observation mixtures. The performance of the algorithm is evaluated by PSNR and MSE values.

For noiseless combination of lena and boat, the separated sources are having PSNR of 30.6203 dB and 30.9205 dB. For noisy combination of barbara and house, the PSNR values obtained are 32.1966 dB and 28.3445 dB which is a better value when compared to the existing algorithms.

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