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Blind Separation of Permuted Alias Image with Morphological Diversity Based on NSCT and Waveatom Dictionary

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Abstract

A blind separation algorithm was proposed for the type of permuted alias images with morphological diversity in this paper. Firstly, permuted alias image mode in sparse domain was presented and separation scheme based on sparse domain was proposed. Non-subsampled Contourlet transform and Waveatom transform are respectively used as two type of dictionaries for piecewise cartoon and texture image. Then the permuting image can be separated from permuted alias image by morphological component analysis algorithm. The results show that our algorithm can separate effectively texture image from the permuted alias image not being affected by size, location number and types of texture image for a permuted alias image composed by piecewise smooth part and texture part.

Keywords: *Blind Separation, Permuted Alias Image, Morphological Diversity, Dictionary, NSCT(Non-subsampled Contourlet transform), Waveatom*

1. Introduction

As an important branch of modern signal processing field, the research of blind separation of superposed alias image have been concerned for many years [1-3]. There is growing concern on permuted alias image blind separation as frontier of single channel blind separation research. Blind separation of Permuted alias image is a new type of single channel blind source separation (BBS), which is differ from the traditional BBS. The primary difference between them is the mixture mode that the mixture image is composed of some source images by superposed aliasing or permuted aliasing. The traditional single channel blind separation is a technique for estimating individual source components from their single mixtures composed of several components superposed.

There are several novel characteristics in comparison with the traditional blind separation for images. Firstly, the integrality of the permuted image is impaired because it some regions are permuted by another images (permuting images). Secondly, the locations, size and number of permuted regions are unknown before being separated. Lastly, the source of the permuted image and the permuting one are completely various. All these elements cause the enormous difference between the blind separation of traditional superposed alias image and the blind separation of permuted alias image. Therefore, this resolution of new type of blind separation is much challenged [4].

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A detection and separation scheme was proposed by Fang *et. al.*, that separation were completed by extracting common factor from various source signals and detecting the activated region in appropriate characteristic domain [4].Therefore, it is pivotal in selecting a appropriate characteristic domain for various type of permuted alias images.

For the source images in JPEG format with various compression ratio, a blind separation method based on compression factors estimation was proposed for permuted JPEG image [5]. The permuted alias image is compressed again and the primary compression factors were estimated by calculating the correlation coefficients of image blocks before and after recompression. Using the estimated compression factors, a mapping space was constructed. The permutation mixing matrixes can be accurately estimated by classifying the parameters in the mapping space, thus the source images can be separated. This method can be used in JPEG image tampering detection.

For the sources contain interpolated images, a blind separation method based on interpolation factors estimation was proposed in [6] for permuted interpolated image. The periodic property of difference sequence was detected by finite-difference for permuted image, in the light of the periodic property, the various interpolation factors can be identified. A mapping space was constructed by the estimated interpolation factors. The permutation alias matrixes can be estimated by categorizing the parameters in the mapping space, so that the source images can be separated. At last, the proposed method was used in interpolation image tamper detection. The Results show the validity and robustness of the proposed algorithm [6].

For the permuted alias image composed of blurry image and sharp image, a novel blind separation algorithm based on four-phase-difference and differential evolution was proposed. Firstly, the four four-phase-difference images were obtained by doing differential operating to the permuted alias image in four phases. The fitness function was designed as computing the sum of square errors of normalizing version and binary version obtained by thresholding operation with a threshold vector. The optimal threshold vector was resolved by using difference evolution algorithm, by which a binary image was gotten. The blurry permuting image could be separated by multiplying permuted alias image by the binary image [7].

The research of blind separation of permuted alias image is still in beginning stage. Relevant focus of research is emphasized on selecting the proper characteristic domain in which the separation is effectively implemented according to different types of permuted alias image.

According to a type of permuted alias image with morphological diversity such as piecewise smooth image permuted by texture image, a blind separation approach is proposed, which can separate texture image from the permuted alias image by using morphological component analyzing method.

2. Separation Mode of Permuted Alias Image and Permuted Alias Image Mode in Sparsity Domain

2.1. Separation Mode of Permuted Alias Image Mode

Mode of permuted alias image is represented based on reference [4], where X is composed of one permuted image indicates by X_P and n permuting sub-images indicated by $X_{T1} \cdots X_{Tn}$. A denotes permuted alias matrix, X_P indicates permuted image, X_{Ti} indicates the i^{th} permuting image. The permuted alias image Y is written as:

$$Y = A \bullet X$$
$$= A_P \otimes X_P + A_{T1} \otimes X_{T1} + \cdots + X_{Ti} \otimes A_{Ti} + \cdots + X_{Tn} \otimes A_{Tn} \tag{1}$$

$$A = [A_P, A_{T1}, A_{T2}, \cdots, A_{Ti}, \cdots, A_{Tn}] \tag{2}$$

$$A_{T_1} = \begin{cases} 1 & (i,j) \in U_{T_1} \\ \vdots \\ 0 & (i,j) \in U_{T_i} \\ \vdots \\ 0 & (i,j) \in U_{T_N} \end{cases}, \cdots, A_{T_i} = \begin{cases} 0 & (i,j) \in U_{T_1} \\ \vdots \\ 1 & (i,j) \in U_{T_i} \\ \vdots \\ 0 & (i,j) \in U_{T_N} \end{cases}, \cdots, A_{T_N} = \begin{cases} 0 & (i,j) \in U_{T_1} \\ \vdots \\ 0 & (i,j) \in U_{T_i} \\ \vdots \\ 1 & (i,j) \in U_{T_N} \end{cases} \tag{3}$$

$$A_P = U - [A_{T1} + A_{T2}, \cdots, + A_{Tn}] \tag{4}$$

$$X = [X_P, X_{T1}, X_{T2}, \cdots X_{Ti}, \cdots, X_{Tn}]^T \tag{5}$$

where symbol '$\bullet$' is a specific product, symbol '$\otimes$' indicates $hadamard$ product. A_P is a binary matrix with size $M \times N$, where '1' indicates un-permuted region of Y ,'0' indicates permuted region of Y . A_{Ti} is a $M \times N$ binary matrix, the i^{th} permuting matrix, '1' indicates part of permuting image in permuted alias image, U is a matrix of all 1.and

$$U_P \cap U_{T1} \cap U_{T2} \cdots \cap U_{Ti} \cdots \cap U_{Tn} = \varnothing \tag{6}$$

$$U_P \cup U_{T1} \cup U_{T2} \cdots \cup U_{Ti} \cdots \cup U_{Tn} = U \tag{7}$$

where the intersection of all active region U_{Ti} is empty set, and the union set of them is matrix of all '1'.

2.2. Permuted Alias Image Mode in Sparsity Domain

Recently, sparsity representation of signals draws increasingly attention as a new trend of signal processing community, become an efficient tool for describing structure information of all kinds of signals. Over-complete redundant dictionary is used to represent image which can be represented as a sparse linear combination of these atoms. The representation that uses the least number of atoms is the optimal one, namely the sparsest representation [8-10].

Permuted alias image Y is totally composed of two regions, the one is the part of permuted image Y_P such as piecewise smooth image, the other is the part of some permuting images Y_T such as texture image.

$$Y = A_P \otimes Y_P + A_T \otimes Y_T$$
$$= \begin{cases} Y_P = D_P \alpha_P & Y(i,j) \in U_P \\ Y_T = D_T \alpha_T & Y(i,j) \in U_T \end{cases} \tag{8}$$

where D_P indicates the over-complete dictionary, in which Y_P is sparsely represented as α_P , Y_T is highly inefficient in sparsely representing in D_P ; similarly, D_T indicates the over-complete dictionary, in which Y_T is sparsely represented as α_T , while Y_P is highly inefficient in sparsely representing in D_T , and $U_P = A_P$, $U_T = A_{T1} + A_{T2} \cdots + A_{Tn}$.

From the mode above, it can be seen that the key of separating the permuted images from the permuted alias image is to detect the region denoted U_T composed of parts of texture image. So the permuted alias image can be decomposed into cartoon component and texture component by morphological component analysis algorithm and we can detect location of U_T by location of texture component.

3. Separation of the Permuted Alias Image and Selection of Dictionary

3.1. Separation of the Permuted Alias Image

Their sparseness levels are commonly diversity when different types of image are represented sparsely by different dictionaries. For example, images commonly include the texture type and cartoon type, texture image can be sparsely represented by local discrete cosine transform, but can be not by general wavelet transforms. Cartoon image can be well sparsely represented in biorthogonal wavelet while is not better represented using a discrete cosine transform. This diversity in sparseness level is described as morphological diversity [11-15].

The sparseness levels are commonly diversity when different types of images are represented sparsely by different dictionary according to the model of permuted alias image, the permuted alias image is composed of piecewise smooth section Y_P and texture section Y_T.

$$Y = Y_P + Y_T = D_P\alpha_P + D_T\alpha_T \tag{9}$$

So we can translate resolving separation of permuted alias image into resolving the most sparsest representation of Y.

$$\left\{\alpha_P^{opt}, \alpha_T^{opt}\right\} = \underset{\{\alpha_P, \alpha_T\}}{\operatorname{Arg\,min}}\{\|\alpha_P\|_1 + \|\alpha_T\|_1\} \tag{10}$$

where $\alpha_P^{opt}, \alpha_T^{opt}$ respectively indicate the sparsest solution of Y_P and Y_T on D_P and on D_T. $\|\alpha_P\|_1$ indicates l_1 norm of α_P, $\|\alpha_T\|_1$ indicates l_1 norm of α_T.

In real natural image, noise or additional content, which pertain to piecewise smooth and texture image, are not sparsely represented by both dictionaries. We can accommodate this content to the residual $Y - D_P\alpha_P - D_T\alpha_T$.

$$\begin{aligned}\left\{\alpha_P^{opt}, \alpha_T^{opt}\right\} = \underset{\{\alpha_P, \alpha_T\}}{\operatorname{Arg\,min}}\{&\|\alpha_P\|_1 + \|\alpha_T\|_1 + \\ &\lambda\|Y - D_P\alpha_P - D_T\alpha_T\|_2^2\}\end{aligned} \tag{11}$$

Moreover, the real piecewise smooth part in permuted alias image does not fit strictly to model of piecewise smooth image. It can be resolved by applying Total Variation penalty term for approximating model.

$$\begin{aligned}\left\{\alpha_P^{opt}, \alpha_T^{opt}\right\} = \underset{\{\alpha_P, \alpha_T\}}{\operatorname{Arg\,min}}\{&\|\alpha_P\|_1 + \|\alpha_T\|_1 + \\ &\lambda\|Y - D_P\alpha_P - D_T\alpha_T\|_2^2 + \gamma\,\mathrm{TV}\{Y_P\}\}\end{aligned} \tag{12}$$

where $\gamma TV\{Y_P\}$ indicate Total Variation penalty term.

The optimal solution α_P^{opt} and α_T^{opt} can be obtained by using Block-Coordinate Relaxation Method to resolve equation (12). Piecewise smooth section Y_P and texture section can be respectively separated from permuted alias image Y by $D_P\alpha_P^{opt}$ and $D_T\alpha_T^{opt}$. As shown in equation (13) and equation (14).

$$Y_P = D_P \alpha_P^{opt} \tag{13}$$

$$Y_T = D_T \alpha_T^{opt} \tag{14}$$

MCA decomposition algorithm[]

Task: image decomposition
Parameters: The permuted alias image Y , the dictionary $D = [D_1, D_2] = [D_P, D_T]$, number of iterations N_{iter} , stopping threshold $\lambda_{\min}$, threshold update schedule. $k = 1$ indicates piecewise smooth section, $k = 2$ indicates texture section.
Initialization:
Initial solution $y_k^{(0)} = 0$, $\forall k$.
Initial residual $r^{(0)} = y$.
Initial threshold: let $k^* = \max_k \left\| D_k^T y \right\|_\infty$, set $\lambda^{(0)} = \max_{k \neq k^*} \left\| D_k^T y \right\|_\infty$.
Main iteration:
for $t = 1$ **to** N_{iter} **do**
for $k = 1$ **to** 2 **do**
Compute marginal residuals $r_k^{(t)} = r^{(t-1)} + y_k$.
Update k -th component coefficients by thresholding $\alpha_k^{(t)} = TH_{\lambda^{(t-1)}}(D_k^T r_k^{(t)})$.
Update k -th component $y_k^{(t)} = D_k \alpha_k^{(t)}$
end
Update the residuals $r^{(t+1)} = y - \sum_{k=1}^{2} y_k^{(t)}$.
Update the threshold $\lambda^{(t)}$ according to the given schedule.
if $\lambda^{(t)} \le \lambda_{\min}$ **then** stop.
end
Output: Morphological components $(y_k^{(N_{iter})})_{k=1,2}$.

3.2. Separation Selection of Dictionary

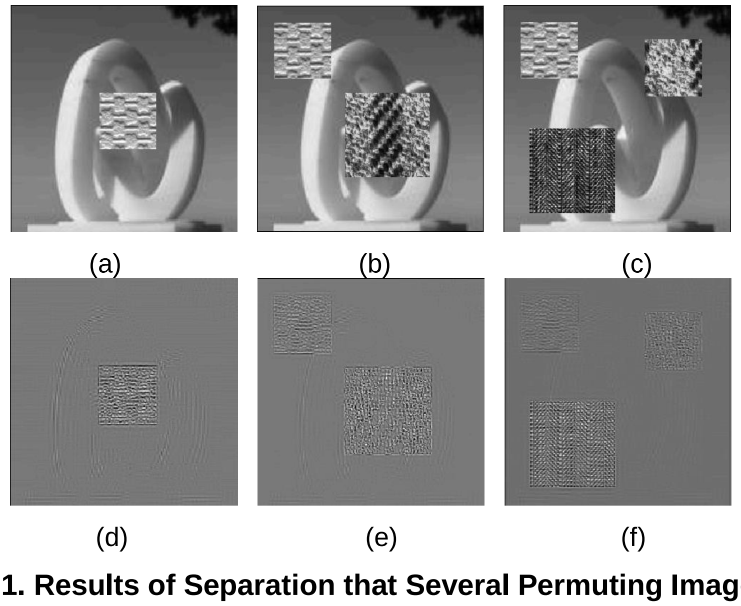
It is very critical to effectively separate images that images can be sparsely represented by selecting appropriate dictionaries based on various types of images. In general, the piecewise smooth images can be sparsely represented by these transforms such as the Bi-Orthogonal Wavelet transforms, the un-decimated Wavelet transforms, the Curvelet transforms, Contourlet transforms, un-sampled Contourlet transforms and so on. There were some inadequacies of each in representing piecewise smooth images. Although bi-orthogonal wavelet transforms can represent sparsely natural scenes, it can only represent elements of images unrelated to scale, but not highly anisotropic elements. There are excessive amounts of redundancy information in sparsely representing by the un-decimated wavelet transforms, though high precision of estimating image feature can be achieved and ringing effect can be restrained effectively. Similarly, there are high redundancy in sparsely representing images by Curvelet transforms to avoid blocking effect. Contourlet transforms, proposed by Do.M.N and Vetterli M., are new type of transform with analyzing image multi-direction and multi-scale analyzing, which approximate image with base structure like contour segment. Support set of contourlet transform base has strip structure varying with various scales, which has directivity and anisotropy. The energy of coefficient representing image edges by Contourlet transform more concentrate, that is, the Contourlet transform can more sparsely represent image edge. Although the Contourlet transform has an advantage of representing natural images multi-directional and multi-scale, designing proper filters for the Contourlet transform is a difficult task. In addition, the Contourlet transform is not shift-invariant, for down samplers and up-samplers are applied in the both directional filter band and Laplacian pyramid. Later, an over-complete transform named non-subsampled Contourlet transform (NSCT) is designed to overcome the defects aforementioned. The NSCT is a fully multidirectional, multi-scale, and shift-invariant transform in addition to fast implementing. So NSCT is selected as the dictionary representing piecewise smooth images for above advantages [15].

Gabor Transform and Local Discrete Cosine Transformation (LDCT) are usually used as dictionaries representing texture image. Gabor transform is used for research of texture image, which is local discrete Fourier transform in essence, localization is obtained by implementing overlapping signal window. DCT is orthogonal transform, which is applicable to sparsely representing smooth or periodic segment. Coefficients of DCT represent similarly frequency content gotten by Fourier analyzing. DCT is mainly used to blocking processing for non-stationary signal, which has higher redundancy for using overlap blocking method. A new multi-scale image analyzing tool named as Waveatoms is proposed by Demanet and Ying, which is a variant of special two-dimensional wave packet and supports of which is isotropic comparing to Curvlets. Wave atom can sparsely represent texture model in comparison with Gabor and LDCT [16].

4. Results and Discussion

To evaluate impartially the results, we structured according permuted alias image base in which all images were composed of texture image and piecewise smooth image. The permuting image came out of Brodatz texture image base which included various type texture images. The permuted images were selected from those images used commonly in image processing community. Experiments were implemented in MATLAB 7.6, on a Lenovo computer, running Windows XP operating system on Pentium(R) Dual-Core processor, with 2GB of RAM.

A. The separation of several permuting images with various size, location and types of textures from the same permuted image



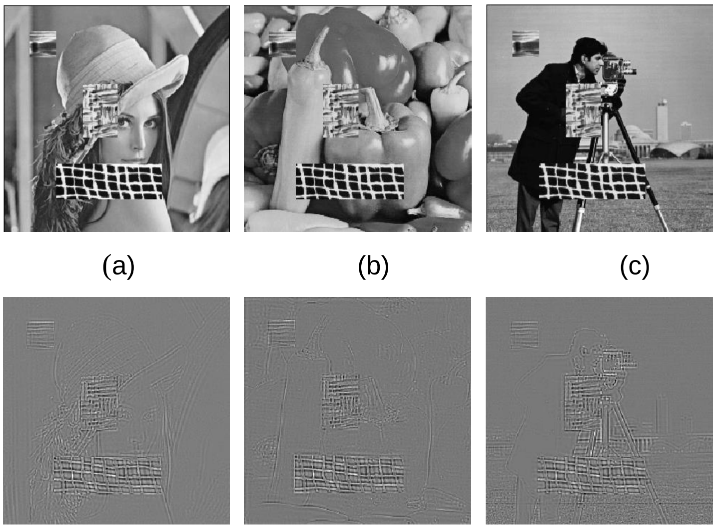
(a) (b) (c)

(d) (e) (f)

Figure 1. Results of Separation that Several Permuting Images with Varioussize, Location and Types of Textures from the same Permuted Image

In the Figure 1, (a-c) are the permuted alias images to be separated, (d-f) are their separating results respectively. It can be seen that the permuting images can be effectively separated from the permuted alias images regardless of the size, location and types of textures, though there are a few edge regions being separated falsely.

B. The separation of several permuting images with various size, location and types of textures from the different permuted images



(a) (b) (c)

(d) (e) (f)

Figure 2. Results of Separation that Several Permuting Images with the Same Size, Location and Types of Textures from the Different Permuted Image

In the Figure 2, (a-c) are the permuted alias images to be separated which were composed of different permuted images, (d-f) are their separating results respectively. In the Figure 2 (d), three permuting images composed of different size, location and types texture can be separated from the permuted image, at the same time, some region not belonging to the permuting images were falsely separated, mainly because there were some parts such as Lena' hat tassels morphology of which were extremely similar to morphology of texture in the permuted image. In the Figure 2 (f), there were some parts mistakenly separated of permuted image.

In brief, the he permuting images can be effectively separated from the permuted alias images regardless of the size, location and types of textures, though there are a few regions being separated falsely for the permuted alias images with complicated background perm.

5. Conclusions

In this paper, a novel blind separation algorithm was introduced which can effectively separate texture image from the permuted alias image composed of texture and piecewise smooth image. NSCT and Waveatom were used as dictionaries respectively representing piecewise smooth image and texture image on the base of analyzing features of various dictionaries. Separation of permuted alias image was effectively implemented by MCA method. The proposed method had some advantages that texture image can be separated from the permuted alias image for different size, location, number and type permuting image.

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