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Blind Separation of Permuted Alias Image with Motion Blurred Using Image Enhancement in NSCT Domain

DUAN Xin-tao[a,b] , WANG Jing-juan[a,b] , PENG Tao[a] , LI Fei-fei[a],
LIU Shang-Wang[a,b] and LIU Tuan-ning[a]

[a]*College of Computer and Information Engineering, Henan Normal University, Xinxiang 453007, China*
[b]*Engineering Lab of Intelligence Business & Internet of Things, Henan Province, Xinxiang 453007, China*
duanxintao@126.com

Abstract

Focused on the issue that motion blurred permuted alias image blind separation, an algorithm using image enhancement based on nonsubsampled contourlet transform (NSCT) domain was proposed. Firstly, permuted alias image was decomposed into low-frequency sub-band and high-frequency sub-bands, which were obtained by spare decomposition based on NSCT domain. Coefficients of high-frequency sub-bands were enhanced according to Bayesian shrinkage threshold and nonlinear gain function, and the enhanced version was got by this method. Then the permuted alias image and the enhanced version were blocked, the correlation coefficients were estimated by each corresponding sub-block, because the permuting image was changed larger, the permuting image could be separated by using threshold method. Experimental results show that the proposed algorithm can separate the permuting image effectively from the permuted alias image in spite of the motion blurred direction, blur degree, size, location and the number of permuting image.

***Keywords**: blind separation; permuted alias image; nonsubsampled contourlet transform (NSCT); image enhancement; Bayesian shrinkage threshold; nonlinear gain*

1. Introduction

Blind source separation has developed rapidly, it has been used in various fields such as digital image processing, wireless communication, audio signal processing, and biomedical signal processing [1-2]. Blind separation of permuted alias image was a new type of single channel blind separation [3]. The permuted alias image was formed by different source image replacement of non-overlapping and different from traditional single channel blind separation. How to detect and separate the permuting image is a key issue with location and blur degree, size, location, source and the number of permuting image are unknown completely[4].

Fang presented the fundamental conception of blind separation of permuted alias image as a new type of blind separation method for the first time[3]. Fang Y *et. al.*, proposed a detection method of the permuting region on account of separable characteristic domain. Duan *et. al.*, proposed an algorithm about the permuted alias image blind separation based noise detection according to a category of permuted alias image including noise in permuting region[5]. Duan *et. al.*, proposed an algorithm about a blind separation based on differential evolution for a type of the permuted alias image with blur difference [6]. Wang *et. al.*, proposed a single channel blind separation algorithm using double blur correlation for blurring permuted images.

In the real world, the permuting and permuted images are always from different sources. This paper proposes blind separation of permuted alias image with Motion

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Blurred Using Image Enhancement in NSCT Domain. Because NSCT has good anisotropy and directionality, Motion blurred permuted alias image were decomposed based on NSCT domain which can better reflect the direction information of motion blurred permuted alias image for effective feature extraction.

2. Permuted Alias Image Mode

The permuted alias image with motion blurred was formed by one permuted and one or more permuting images replacement of non-overlapping. Figure 1 (d), the permuted alias image is composed of two permuting images. Figure 1 (a) is permuted image, permuting images are partial of the motion blurred images as shown as shown in Figure 1 (b) and Figure 1(c).

(a) (b) (c) (d)

Figure 1. Permuted Alias Image

The model of permuted alias image is described in mathematical formula as follows.

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

Where X_P is permuted image, $X_{Ti}(i=1,2,\cdots n)$ is permuting images, $A_{Ti}(i=1,2,\cdots,n)$ is permutation matrix, the permuted alias image denoted as Y which contains two sections of them. $\otimes$ is Hadamard product.

$$A_{T_1} = \begin{cases} 1 & (i,j) \in U_{T_1} \\ \vdots & \\ 0 & (i,j) \in U_{T_i} \\ \vdots & \\ 0 & (i,j) \in U_{T_N} \end{cases}, \cdots, A_{T_i} = \begin{cases} 0 & (i,j) \in U_{T_1} \\ \vdots & \\ 1 & (i,j) \in U_{T_i} \\ \vdots & \\ 0 & (i,j) \in U_{T_N} \end{cases}, \quad \cdots, \quad A_{T_N} = \begin{cases} 0 & (i,j) \in U_{T_1} \\ \vdots & \\ 0 & (i,j) \in U_{T_i} \\ \vdots & \\ 1 & (i,j) \in U_{T_N} \end{cases} \tag{2}$$

$$U_P = U - [A_{T1} + A_{T2}, \cdots, +A_{Tn}] \tag{3}$$

$$U_P \cap U_{T1} \cap U_{T2} \cdots \cap U_{Ti} \cdots \cap U_{Tn} = \varnothing \tag{4}$$

$$U_P \cup U_{T1} \cup U_{T2} \cdots \cup U_{Ti} \cdots \cup U_{Tn} = U \tag{5}$$

Where U is universal matrix, $U_{Ti}(i=1,2,\cdots,N)$ is non-overlapping activated interval. Permutation matrix $A_{Ti}(i=1,2,\cdots,N)$ and activated interval $U_{Ti}(i=1,2,\cdots,N)$ are corresponding relationship. Detection of the permuting image activated interval to realize blind separation of permuted alias image [8].

3. The Basic Principle of NSCT and Definition of the Correlation Coefficients

3.1. The Basic Principle of NSCT

3.1.1 Contourlet Transform: As one of multiscale geometric analysis, the purpose of contourlet transforms is to obtain sparse decomposition of images. contourlet transform has anisotropy and multidirection property. Besides, it inherits wavelets' multiresolution and the local supporting property.

Contourlet transform is composed of directional filter banks and Laplacian Pyramid algorithm. Contourlet transform decomposes images into directional bandpass subband[9]. The structure of contourlet transform is shown as follows.

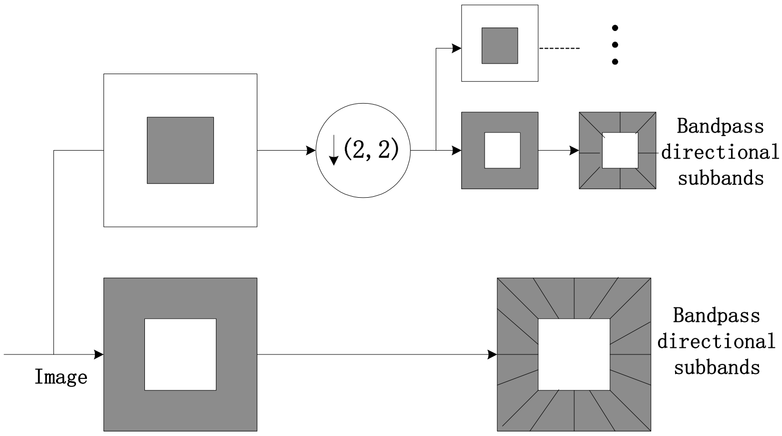


Figure 2. Filter Banks Structure of Contourlet Transform

3.1.2 NSCT: NSCT is proposed based on Contourlet transform. Contourlet transform has the characteristic of anisotropy and fitable for effective representation of images which can detect the intrinsic characteristic of images. Due to the down-sampling contourlet transform is shift variance [10]. With respect to the Contourlet transform, NSCT remove contourlet transform the down-sampling section, which has shift in variance.

NSCT is obtained by the nonsubsampled pyramids (NSP) and the nonsubsampled directional filter banks (NSDFB).Low frequency and high frequency are decomposed by NSP and Decompose High frequency into several directions by using NSDFB. Consequently, different directions and varieties of directional bandpass subband are received [11], as shown in the Figure 3 and Figure 4.

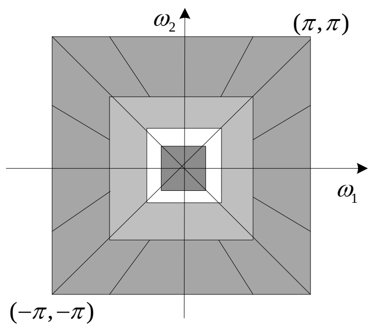


Figure 3. NSCT Frequency Domain Decomposition

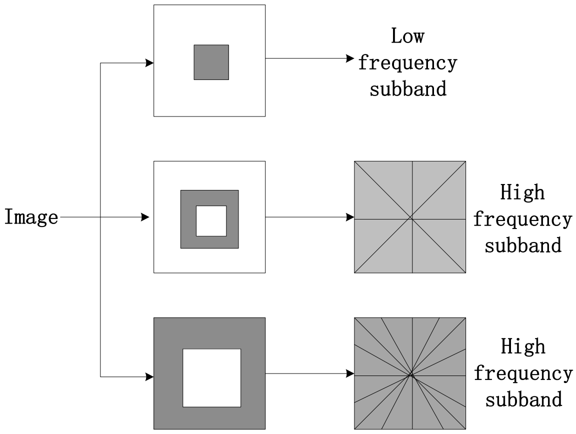


Figure 4. Multi-Dimensional Decomposition Framework of NSCT

3.2. The Definition of the Correlation Coefficient

Focused on the issue that blind separation of motion blurred permuted alias image, this algorithm using image enhancement based on NSCT domain. Compared with the correlation that each sub-block before and after enhanced, this is characterized using the correlation coefficient. Due to the permuting blurred is less than the permuted with the image correlation coefficient before and after comparison, which can set an appropriate threshold to separate the permuting image.

The correlation coefficient is a measure of the degree of correlation between two random variables. Under the premise of discrete, the formula of the correlation of two random variables (m × n matrix) is described as follows [12].

$$\rho_{xy} = \frac{\sum_{i=1}^{m\times n}(x_i - u_x)(y_i - u_y)}{\sqrt{\sum_{i=1}^{m\times n}(x_i - u_x)^2} \cdot \sqrt{\sum_{i=1}^{m\times n}(y_i - u_y)^2}} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \tag{6}$$

Where u_x and u_y are Mean, σ_x and σ_y are standard deviation, σ_{xy} is covariation of X and Y, ρ_{xy} is the correlation coefficient of X and Y, which is ranged from -1 and 1.

① When $\rho_{xy} = 0$, X and Y is irrelevant

② When $\rho_{xy} > 0$, X and Y is positive correlation

③ When $\rho_{xy} < 0$, X and Y is negative correlation

It is generally considered that two variables have strong correlation when $|\rho_{xy}|$ >0.8.

3.3. Image Enhancement based on NSCT Domain

The key to separate the permuting image is to extract variation characters of the permuting image and the permuted one. Hot research area of image is enhanced based on multiscale transform. The direction of motion blurred permuted alias image is varied and varieties of directional bandpass subband coefficients of the image is changed after image enhancement. Extract the variation characteristics of the coefficient before and after enhancement is important.

The wavelet base has no anisotropy and lack multidirection so that the wavelet transform cannot represent image sparely. Shift-variance in contourlet transform caused by critical down-sampling results in visual artifacts called “Gibbs-like” phenomenon. Multi-directional and multi-scale features of image can be reflected based on NSCT, which can dig the direction information of the image and can express sparsely the high abramovich heterosexual. Because the NSCT transform has the translation invariance, which can effectively overcome the Gibbs phenomenon.

The permuted alias image not only includes image edges and details but also contains some noise. Enhance the details while not boost up noise is the purpose of this algorithm. Low-frequency sub-band and high-frequency sub-bands are decomposed based on NSCT. Then coefficients of high-frequency sub-bands are enhanced according to nonlinear gain function and Bayesian shrinkage threshold.

The nonlinear gain function was proposed by A.F. Laine, which expressed as follows.

$$f(x) = a[sigm(c(x-b)) - sigm(-c(x+b))] \tag{7}$$

$$a = 1/[sigm(c(1-b)) - sigm(-c(1+b))] \tag{8}$$

The definition of the sigm function is expressed as follows and it is shown in Figure 5.

$$sigm(x) = 1/(1+e^{-x}) \tag{9}$$

Parameter c control gain strength, which can be set to a fixed value and generally valued from 20 to 50 [13], this paper takes 20. The parameter b controls the gain curve shape, the representatives of the details of the high-frequency coefficients, the gain multiplier must be greater than 1, so the parameters b are determined by the following formula defined:

$$a[sigm(c(T_k^s - b)) - sigm(-c(T_k^s + b))] = T_k^s \tag{10}$$

Where T_k^s is threshold, which is distinguished between the details and noise. This paper uses Bayesian shrinkage method to estimate the threshold. The permuted alias images are disturbed by blurred images, and the coefficients of high-frequency sub-bands of sharp image in general are to obey the generalized Gaussian distribution [14]. Bayesian shrinkage threshold is obtained by Bayesian criterion [15].

$$T_k^s = \sigma_n^2(k,s) / \sigma(k,s) \tag{11}$$

$\sigma_n(k,s) = \text{Median}(|g_k^s(i,j)|)/0.6745$, $\sigma_n(k,s)$ is noise standard deviation. $g_k^s(i,j)$ is high frequency coefficient of the location (i, j).

The standard deviation of the corresponding subbands is described as follows.

$$\sigma(k,s) = \sqrt{\max(\sigma_g^2(k,s) - \sigma_n^2(k,s), 0)} \tag{12}$$

$\sigma_g^2(k,s)$ is the variance of corresponding subband coefficient.

According to the above, the high frequency subband coefficients make adjustment according to the following formula:

$$G_k^s(i,j) = a \cdot \max g_k^s \cdot \{sigm[c(g_k^s(i,j)/\max g_k^s - b)] - sigm[-c(g_k^s(i,j)/\max g_k^s + b)]\}$$

$\max g_k^s$ is the max of the high frequency subband coefficients. $G_k^s(i,j)$ is the adjustment of the corresponding position in the subband coefficients. Finally, NSCT inverse transform through the adjustment of the high frequency subband coefficients, which obtained the enhanced image.

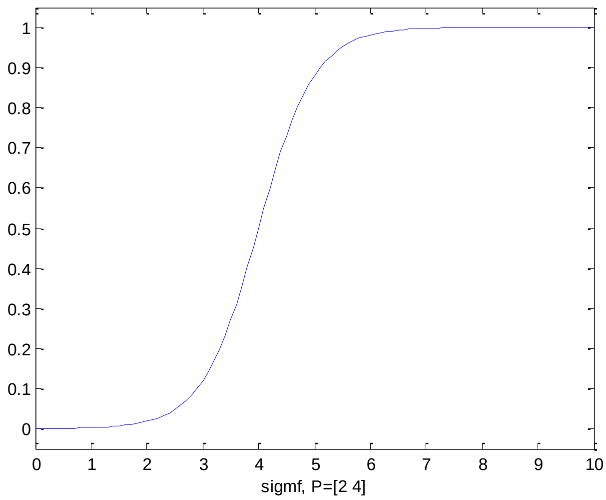


Figure 5. The Diagrammatic Sketch of the Function Sigm

4. The Proposed Approach

This dissertation proposes the methods of blind separation in characteristic domain for permuted alias images. Since the permuting blurred is less than the permuted with the image correlation coefficient before and after comparison, which can set an appropriate threshold to separate the permuting image.

Image enhancement based on wavelet transform is the methods of blind separation for permuted alias image which is extracted by constructing reasonable linear or nonlinear transformation function of wavelet transform coefficient, but due to the direction of the wavelet transform is limited, which is difficult to distinguish the permuting image. NSCT decomposes permuted alias image into low-frequency sub-band and high-frequency sub-bands. Coefficients of high-frequency sub-bands were enhanced according to Bayesian shrinkage threshold and nonlinear gain function, and the enhanced version was got by this method. Then the permuted alias image and the enhanced version were divided into sub-blocks. Due to the permuting blurred is less than the permuted with the image correlation coefficient before and after comparison, which can set an appropriate threshold to separate the permuting image. Lastly, the inverse NSCT is used to reconstruct the enhanced image according to the high frequency coefficients.

According to the theory of algorithms described in this paper, the steps of the permuted alias image blind detection and separation as follow:

Ste.1. Read the image. First read the motion blurred permuted alias image A, which is gray image and size of $\mathrm{M} \times \mathrm{N}$

Ste.2. The permuted alias image A is spare decomposed based on NSCT domain, and low-frequency sub-band and high-frequency sub-bands are obtained in this way. Using an enhanced function adjust the high frequency coefficients.

Ste.3. NSCT inverse transform through the adjustment of the high frequency subband coefficients, which obtained the enhanced image B.

Ste.4. Image A and image B are partitioned into non-overlapping blocks which size of $\mathrm{k} \times \mathrm{k}$, sub-block set $X = (X_1, X_2, \cdots X_m)$ and $Y = (Y_1, Y_2, \cdots Y_n)$ are obtained, respectively. Then every block is processed by the following steps.

Ste.5. Calculated the correlation coefficient of $X_i (i = 1, 2, \cdots, m)$ and $Y_j (j = 1, 2, \cdots, n)$,denoted as ρ_{xy} .

Ste.6. Set the appropriate threshold. Because the differences of subblock pixel values between permuted alias image A and the enhanced version B. When the correlation coefficients are relatively small, they are probably the permuting area. By setting an appropriate threshold value, to detect and locate the permuting image, when the correlation coefficient is less than this threshold, indicating weak correlation corresponding sub-block, it is likely that the block has been replaced.

Ste.7. Repeat the steps from 4 to 6, blind source separation of the permuted alias image.

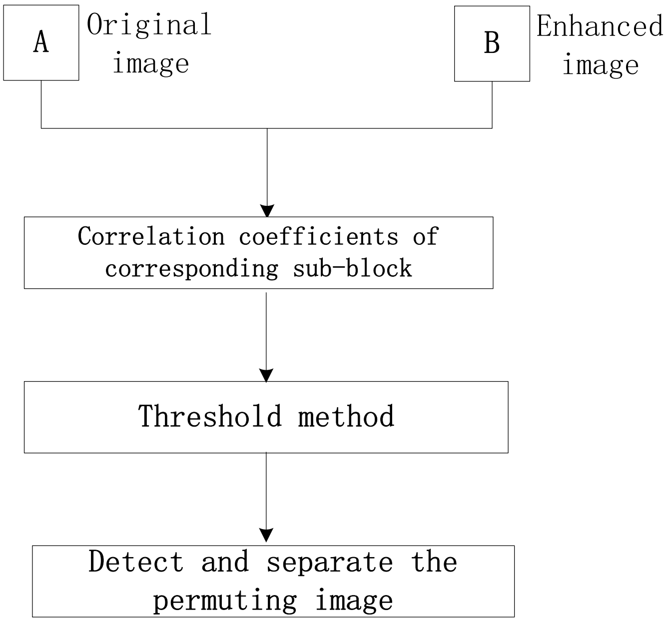


Figure 6. Basic Framework of this Arithmetic

5. Results and Discussion

To investigate the proposed approach, there are conducting five experiments to verify. Select images which are frequently used in the image processing field. The size of the images are 256× 256 pixels, and the size of sub-block are 8× 8 pixels.

5.1. Experiment 1: The Blind Separation with the Different Location and Different Size of the Permuting Image

The permuted image is Baboon, the permuting image is Lena. In Figure 7, the location of permuting image is top left [100,100], the size is 100 × 100 pixels. In figure 8, the location of permuting image is top left [20,100], the size is 120 × 120 pixels.

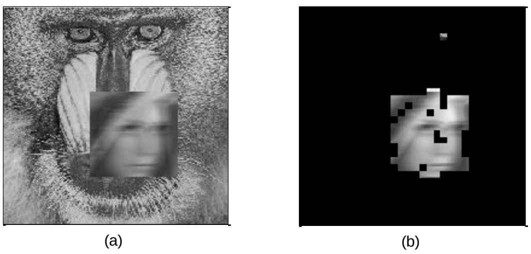
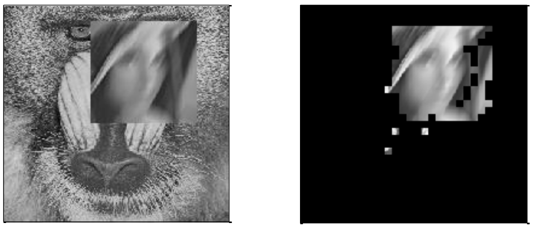


Figure 7. Original Image and Separated Result with Location and Different Size



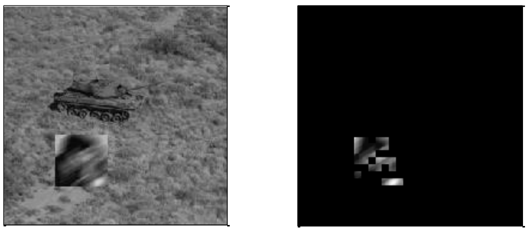
(a) (b)

Figure 8. Original Image and Separated Result with Location and Different Size

Figure 7(b) and figure 8(b) are separated results. It can be seen that the permuting image is perfectly separated from the permuted alias image. Although both the size and location of the permuting image are both different.

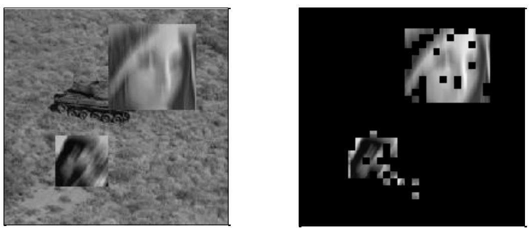
5.2. Experiment 2: The Blind Separation with the Different Direction and Different Number of the Permuting Image

In Figure 9, the permuted image is Tank, the permuting image is Cameraman, which the direction of motion blurred is 30°. In figure 10, the permuted image is Tank, the permuting image are Lena and Cameraman. The direction of Lena is 90° and the direction of Cameraman is 60°. Two images using this algorithm to separate the results as shown.



(a) (b)

Figure 9. Separated Result with Different Motion Blurred Direction and Number of Permuting Image



(a) (b)

Figure 10. Separated Result with Different Motion Blurred Direction and Number of Permuting Image

5.3. Experiment 3: The Blind Separation with the Different Blur Degree of the Permuting Image

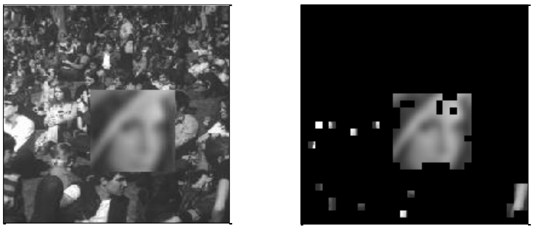
The permuted image is Crowd, the permuting image is Lena. Separated result with different blur degree of the permuting image. Figure 11 (b) is the separation results of the permuting image Lena after using this algorithm with the blurred degree Len=1. Figure 12 (b) is the separation results of the permuting image Lena after using this algorithm with the blurred degree Len=10. Figure 13 (b) is the separation results of the permuting image Lena after using this algorithm with the blurred degree Len=20.

(a) (b)

Figure 11. Original Image and Separated Result with Different Blur Degree

(a) (b)

Figure 12. Original Image and Separated Result with Different Blur Degree



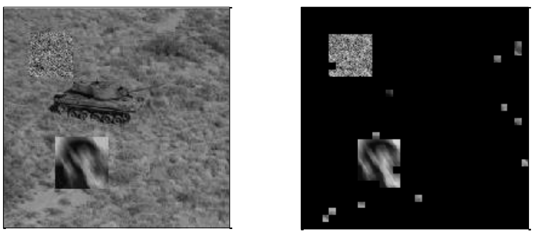
(a) (b)

Figure 13. Original Image and Separated Result with Different Blur Degree

What can be seen from the experiment, the blur degree of the permuting image affect the results of the permuted alias image blind separation. With the blur degree increase, the number of pixels of the permuting image will correspondingly increase.

5.4. Experiment 4: Blind Separation with the Noise of the Permuting Image

The permuted image is Tank in Figure 14 and Figure 15, the permuting image is Cameraman, which the direction of motion blurred is 120°. In figure 14 the top left one is the permuting image with Gaussian noise, in Figure 15 the top left one is the permuting image with salt & pepper noise. Two images using this algorithm to separate the results as follows.



(a) (b)

Figure 14. Separated Result with Motion Blur and Gaussian Noise of Permuting Image

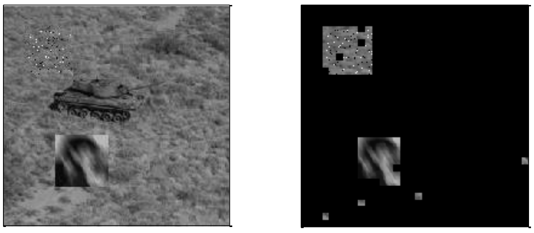


Figure 15. Separated Results with Motion Blur and Salt & Pepper Noise of Permuting Image

From the Separated results in Figure 14(b) and Figure 15(b) two permuted image can be successfully separated from the original image by using this algorithm, though there is some region which detected falsely.

From separate experimental results can be drawn using the proposed algorithm can separate the permuting image, only a very small portion is erroneously detected as the area of permuted image. So the method can effectively separate the permuting image from the permuted alias image irrespective of location, size, direction, blur degree, blurry types and the number of the permuting images.

6. Conclusion

Using the advantage of NSCT with good directionality and anisotropy, it can dig the direction information of the image and can express sparsely the high abramovich heterosexual. Enhancement image is got by NSCT domain in order to achieve the blind separation of permuting image. Simulation results shows that the method can effectively separate the permuting image from the permuted alias image irrespective of location, size, direction, blur degree, blurry types and the number of the permuting images.

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Authors

Duan Xintao, was born in Xinxiang China on April 1972. He received the M.Sc. degree in Computer application technology from Shanghai Normal University in 2004, and D.Sc. degrees in communication and information system from Shanghai University in 2011. He is now Associate Professor at Henan normal university, China. His main research interests include sparse approximation, blind source separation and image processing.