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Blind Separation of Permuted Alias Image Base on Four-phase-difference and Differential Evolution

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Abstract: Blind separation of permuted alias image was a new type of single channel blind separation, which was fundamentally different from traditional single channel blind separation in theory and method. In this paper, a blind separation algorithm based on four-phase-difference and differential evolution was proposed for a type of permuted alias image with blur difference. The model of permuted alias image was briefly introduced. Space domain was selected as characteristic domain after analyzing various detection methods of blur characteristic. First, four-phase-difference versions of permuted alias image are computed and the fitness function was first evaluated by calculating sum of square errors of binary version and its version with a threshold vector. The differential evolution was then performed to obtain the optimal threshold vector for threshold the differential image into binary one. The permuting image could be separated by permuted alias image multiplied with the binary image. Experimental results showed that the proposed approach could effectively separate the permuting image from the permuted alias image without respect to the location, size, number and blurry types of the permuting image. *Copyright © 2013 IFSA.*

Keywords: Blind separation, Permuted alias image, Four-phase-difference, Differential evolution.

1. Introduction

The basic conception of blind separation of permuted alias image was presented for the first time by Fang as a new type of blind separation method [1]. Fang Y *et al.* proposed a detection method of the permuting region based on separable characteristic domain where the activated region was detected with characteristic separation by extracting common factor from various source signals. Therefore, it is important to select appropriate characteristic domain in view of various type of permuted alias images. Wang *et al.* proposed a novel blind detection algorithm based on finite-difference for interpolation permuted image [2]. The periodic property of difference sequence was detected by finite-difference for interpolated signal. According to the periodic property, the various interpolation factors could be identified. The major recent development of blind separation of permuted alias image is still in its infancy as a new type of blind separation. Currently, relevant research concentration is focused on how to select the characteristic domain to various types of permuted alias images, in which the difference is presented between the permuted region and the permuting one.

In the real world, the sources of permuted and permuting image always are varied. Blur difference consist in different regions of permuted alias image for permuting image and permuting images are blurred likely in the phase of acquiring or post processing. So a new algorithm of blind separation

based on four-phase-difference and differential evolution is proposed for the type of permuted alias image which is composed of sharp and blurry image.

2. Permuted Alias Image Mode and Selection of Characteristic Domain

2.1. Permuted Alias Image Mode

The model of permuted alias image is briefly described. In order to describe the mode concisely, the situation was considered that only one permuting region is in the total permuted alias image. Suppose the permuted image belongs to sharp image, denoted as X_S, and permuting image belongs to blurry image, denoted as X_B. So the permuted alias image contains two sections of them, denoted as X.

$$X = f(X_S, X_B) = X_S + X_B \tag{1}$$

In space, only one component is activated in any location of permuted alias image. The permuted image and the permuting image are expressed as follows.

$$X(i,j) = \begin{cases} X_S(i,j) & i,j \in U_S \\ X_B(i,j) & i,j \in U_B \end{cases}, \tag{2}$$

where U_S is the activated region of sharp image, U_B is the activated region of blurred image, U is the total region of permuted alias image. and $U_P \cap U_B = \varnothing$, $U_P \cup U_B = U$.

2.2. Selection of Characteristic Domain

It is can be seen from the mode of the permuted alias image that permuted and permuting images locate in two non-overlapping regions. Therefore, the premise of separating permuting image from the permuted alias image is to detect the activate region. The key of detecting activated region of the permuting image is to select an appropriate characteristic domain in which characteristic difference is shown between the permuting image and the permuted one, as well as characteristic difference between sharp image and blurred one. This is similar to detecting characteristic of blurry image. Marziliano P. *et al.* proposed a method to detect whether the image is blurry by analyzing the width of edges in the image and different blur extent of image [3]. Chung Y. *et al.* discriminated the blurred image by both the distribution of standard deviation of gradient and gradient value of edge together. It provided a reliable method for judging blurred image [4]. Tong H. H. *et al.* proposed a blur detection scheme based on the edge type and sharpness analysis using Haar wavelet transform, which can determine whether an image is blurred or not and to what extent an image is blurry [5]. Wang J. W. *et al.* analyzed the features of the image edges using non-subsampled contourlet transform, by which the image edges can be classified. Then the authors could distinguish whether the edge is blurred by the differences between the normal edge and the blurred edge [6]. Liu R. T. *et al.* used the local power spectrum slope to determine whether image is blurred or not [7]. Tsomko E. *et al*. propose a method based on computing the prediction residue between neighboring pixels in the images and computing the sample variance to estimate the image quality without reference. The gradient of the evolution curve through scale is then used to produce a "blur graph" representing the probability of a picture being blurred or not [8, 9].

The methods for judging whether the image is blurred are mostly based on detecting the width of edge. It is very difficult to select an appropriate threshold to detect one edge which is disturbed by the noise in the image. The methods based frequency domain analysis don't depend on detecting edge and have some of robustness of detection, but lack the location information of the blurred image. The detecting methods based on space domain have the advantages of small computation and simple operation.

Besides low frequency information, sharp image contains high-frequency information reflecting the edges and details, blurred image contains more low-frequency information for lacking details. Moreover, a blurred picture shows significant correlation between successive samples. That is, the variance between the pixels is smaller for a blurred picture than for a sharp version of the same picture. Once the image is blurred, its amount of gradients decreases, and the mean and standard deviation also decrease. So the statistics of the image gradients can be used for detecting the blurred images.

In space domain, the variance of gradient of blurred images is greatly less than the variance of gradients of sharp ones. With an appropriate threshold, the variance of the gradient image is greater than threshold for clear images, vice is blurred images. But for the permuted alias image, it also includes a sharp part and blur parts, location and size of which are unknown. Therefore, it is a reasonable choice that the location of blur region can be detected by partitioning the whole image into sub-blocks and computing gradient variance value of each sub-block. However some experiments show that, for different sized blocks of various images, the variance of gradient image changes with the block size. How to select size of sub-block will be considered.

The general difference method is implemented by subtracting neighbor pixel along single direction. Although gradient information is obtained in this direction, gradient information in other direction is weakened. So a four-phase-difference method is employed in order to acquire more comprehensive gradient information [10]. Four-phase-difference

images are gotten by translating and subtracting the original image respectively in 0°, 45°, 90°, 135°.

3. Blind Separation of Permuted Alias Image with Blur Difference Based on Four-phase-difference and DE

3.1. Four-phase-difference of Blur Image

As for this type of permuted alias image, there are sharp image blocks and blurred ones in total region. So the permuted alias image is partitioned into non-overlapping blocks. Then variance value of every blocks are computed and compared with threshold to classify it as blurry or not, until the permuting region U_B are detected completely [11].

Algorithm process as follows:

1) Permuted alias image X is moved towards 0°, 45°, 90°, 135°.

$$Y_0(m,n) = X(i, j+1) , \tag{3}$$

$$Y_{45}(m,n) = X(i-1, j+1) , \tag{4}$$

$$Y_{90}(m,n) = X(i-1, j) , \tag{5}$$

$$Y_{135}(m,n) = X(i-1, j-1) , \tag{6}$$

Y_0 , Y_{45} , Y_{90} and Y_{135} denote respectively moved images along 0°, 45°, 90°, 135°. X denotes permuted alias image, i , j denote pixel coordinate of X , *m* and *n* is pixel coordinate of Y_p , *p*=0, 45, 90, 135.

2) Obtain the difference images D_p as follows:

$$D_p = Y_p - X \tag{7}$$

3) All difference images D_p are calibrated as follows:

$$D_0(m,n) = D_0(m,n-1) \tag{8}$$

$$D_{45}(m,n) = D_{45}(m+1,n-1) \tag{9}$$

$$D_{90}(m,n) = D_{90}(m+1,n) \tag{10}$$

$$D_{135}(m,n) = D_{135}(m+1,n+1) \tag{11}$$

4) Partition each D_p into non-overlapping sub-blocks respectively and computing variance of each sub-block.

3.2. Differential Evolution

Differential Evolution (DE) is a population-based, reliable, efficient, versatile, and direct search method developed by Storn R. and Price K. [12-16]. We choose DE since it provides fast convergence ratio, simple implementation, and capability of working with real numbers. Like nearly all evolution algorithms, DE starts with an initial population vector, which is randomly chosen when preliminary knowledge is unavailable. Let suppose that $X_{i,g}(i = \{1,2,\cdots,N_p\})$ are N_p N_d -dimensional parameter vectors of generation g (N_p is a constant number which denotes the population size, N_d is dimensional of each parameter vector). For classical DE, it mainly includes the mutation, crossover, and selection procedures as follows:

Mutation- a mutant vector $V_{i,g}$ is defined by.

$$V_{i,g} = X_{r1,g} + F(X_{r2,g} + X_{r3,g}) , \tag{12}$$

where $i = \{1,2,\cdots,N_p\}$ and r_1 , r_2 , and r_3 are mutually different random integer indices chosen from $\{1,2,\cdots N_p\}$. The scale factor, $F \in (0,1+)$, is a positive real number that controls the evolving rate of the population. Larger values for F result in higher diversity in the generated population and the lower values generate faster convergence. While there is no upper limit for F , effective values are seldom greater than 1.

Crossover DE employs the crossover operation to increase diversity of the population. It is defined by as following:

$$U_{i,g} = u_{j,i,g} = \begin{cases} v_{j,i,g} & if\,(rand_j(0,1) \le Cr, \quad or, j = j_{rand} \\ x_{j,i,g} & otherwise \end{cases} \tag{13}$$

The crossover probability, $Cr \in [0,1]$, is a predefined constant value which controls the fraction of parameter values that are copied from the mutant. $rand_j(0,1)$ is j^{th} $\in [0,1]$ evaluation of uniform random generator.

Selecting a member from vector ($X_{i,g}$ or $U_{i,g}$) should be decided to turn into new generation $g+1$. Vector with higher fitness values is chosen.

$$X_{i,g+1} = \begin{cases} U_{i,g} & if \quad f(U_{i,g}) \le f(X_{i,g}) \\ X_{i,g} & otherwise \end{cases} \tag{14}$$

where $f(U_{i,g})$ and $f(X_{i,g})$ indicate the fitness function of $X_{i,g}$ and $U_{i,g}$, respectively.

3.3. The Proposed Approach

For a picture of permuted aliasing image, at least one permuting region is blurred. Dissimilarity between sharp and blur region can be detected by calculating variance value of gradient of permuted alias image. Therefore, a binary image can be obtained by thresholding the gradient image. The permuting image can be separated from permuted alias image by multiplying with binary image.

The key to separate permuting image from permuted alias image is to select an appropriate threshold for every sub-block. If the selected threshold is too small, there will be a lot of missing blurred sub-blocks being. If the selected threshold is too large, blurred ones can be checked out, and at the same time, some sharp ones will also be detected by mistake. So the thresholding task can be counted as an optimization problem with differential evolution.

Supposing an input permuted alias image X, getting its differential image $Diff$, dividing $Diff$ into $M \times N$ sub-blocks of size $b \times b$, calculating variance value of each sub-block, and getting a binary image B by comparing the variance value with the corresponding threshold T_{mn}, the objective function $F\cos t(T)$ is defined as follows:

$$F\cos t(T) = \sum_{m=1}^{M}\sum_{n=1}^{N}\left|D_{mn} - B(T_{mn})_{mn}\right|, \qquad (15)$$

$$T_{opt} = \min\{F\cos t(T)\}, \qquad (16)$$

where D indicates version of $Diff$ normalized in [0, 1].

The optimal threshold T_{opt} can be obtained by minimizing the objective function illustrated in (15). Then the permuting image (blurred image) will be separated from the permuted alias image with the optimal threshold. The proposed algorithm is shown below detailed (See Algorithm 1).

Algorithm 1. Blind separation algorithm of permuted alias image based on four-phase-difference and DE.

1) Random population initialization P_0, number and bounds of parameters of the objective function, scale factor and crossover probability, termination condition.
2) Compute objective value for each individual in the population.
3) While (satisfying termination condition) do
    1) Mutation
    2) Crossover
    3) Compute objective;function value
    4) Selection
    end (while)
4) Thresholding the permuted alias image with the found optimal value of threshold T_{opt}.
5) Optimizing the permuting image with morphological operations. Separating the permuting images.

Computation of objective value

a) Calculating the four-phase-difference version of the permuted alias image, splitting differential image into sub-blocks, calculating the variance value of each sub-block.
b) Comparing the variance value with corresponding threshold of sub-block, if less than threshold marking it as blur, otherwise marking it as sharp.
c) Calculating objective function value according to (15).

4. Results and Discussion

In order to investigate the performance of the proposed approach, a permuted alias image databases were built which are frequently used images in the image processing field.

Some results for our method are provided. Our method was implemented in MATLAB R2008a, on a Dell PC, running Windows XP Professional SP3 on an Intel Core Duo processor, with 2GB of RAM. And the size of sub-block are respectively 4×4, 8×8 and 16×16 pixels.

The following various control parameters are set for experiments with no attempt to achieve their optimal values.

Population size, N_p=(size(image)^2/blocksize^2)*4.

Differential scale factor, F =0.6.

Crossover probability factor, C_r =0.6.

Strategy: DE/rand/1/bin.

In the images above, Fig. 1 is original permuted alias image, where the permuting image is blurred by motion blur Fig. 2 - Fig. 4 are separated results of Fig. 1 respectively with using different size sub-blocks. It can be seen that permuting image "Lena" can be perfectly separated from the permuted alias image with size 4×4 pixels, but a few regions are falsely separated. Separation effect with sub-block size 8×8 is same as the one with sub-block size 4×4, though a very small region about two sub-blocks at top left corner is not separated, as shown in Fig. 3. With sub-block size increasing, partial permuting image can not be separated from permuted alias image, as shown in the Fig. 4.

Fig. 1. Original image.

Fig. 2. Separated image with 4×4 pixels.

Fig. 3. Separated image with 8×8 pixels.

Fig. 4. Separated image with 16×16 pixels.

This is mainly because the size of sub-block is slightly big and the marginal regions of permuting image contain some region of sharp image. So it is effective to separate the permuting images with sub-block size of 8×8 pixels.

In Fig. 5, the permuted alias image is composed of two permuting images, the top left one is motion blur and the middle one is Gaussian blur with different location and size. Separated result is shown as Fig. 6 it can be seen that two permuted image can be successfully separated from Fig. 5, though there is some region detected falsely.

So our method can effectively separate the permuting image from the permuted alias image irrespective of size, location and blurry types of the permuting image.

Fig. 5. Original image.

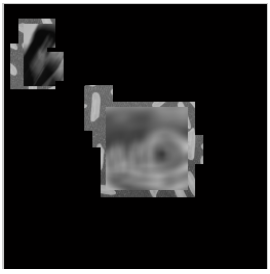

Fig. 6. Separated image with 8×8 pixels.

5. Conclusion

The conception of permuted alias image was proposed for the first time as a novel type of blind separation in the reference. Research of them is still very much in its infancy. This paper proposes a novel method of blind separation based on differential evolution in view of a class of permuted alias image with blur difference. First, space domain is selected as characteristic domain after analyzing various detection methods of blur characteristic. A four-phase-difference image is partitioned into sub-blocks which correspond to a testing threshold vector. DE algorithm was performed to obtain an optimal threshold vector by minimizing the objective function. The permuting image can be separated from the permuted alias image with binary image threshold by the optimal threshold vector. Simulation results shows that our method can effectively separate the permuting image from the permuted alias image irrespective of size, location and blurry types of the permuting image.

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