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Out-of-Focus Blur Estimation for Blind Image Deconvolution: Using Particle Swarm Optimization

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***Abstract*—This study addresses the blind image deconvolution which uses only blurred image and less point spread function (PSF) information to restore the original image. To identify the blind image it is a very important step for restoring the image. Therefore, the first step is to look for PSF model. In this paper, particle swarm optimization (PSO) is utilized to seek the unknown PSF. The objective function is based on the wavelet transform. It can identify the parameters of PSF exactly. Finally, the feasibility and validity of proposed algorithm are demonstrated by several simulations.**

Keywords—out of focus, blind image deconvolution, point spread function, particle swarm optimization, Wiener filter, wavelet transform.

I. INTRODUTION

The objective of image restoration is to reconstruct the original scene from a degraded observation which is commonly blurred by a point spread function (PSF). However, the PSF is usually unavailable a prior in many applications, the recovery process becomes a blind image deconvolution (BID) problem. It has also taken a lot attention in many different technical areas, for example photography [1], medical imaging [2], astronomical imaging [3], and so forth.

Referring to the classification [4], BID approaches could be classified into two chief categories according to the stage of blur identifying:

1) A priori blur identification methods: with this approach, the PSF is identified separately from the original image, and later used in combination with one of the classical image restoration algorithms in order to restore the original image. Generally, a parametric blur model may be used.

2) Joint identification methods: with this approach, most of they use an alternative approach to estimate an original image and the PSF rather than truly finding the joint solution.

Initially, D. Kundur and D. Hatzinakos proposed the restoration procedure involves recursive filtering of the blurred image to minimize a convex cost function blindly. The feasibility has been confirmed when it is applied on a scene consists of a finite support object against a uniformly black, grey, or white background [5], [6]. After that, different advanced conditions for BID and shortcomings in conventional methods have been addressed and improved respectively. For instance, since the requirement of a hard-decision on whether the blur satisfies a parametric form before their formulations in these algorithms, the precondition inhibits the incorporation of parametric blur knowledge domain into the restoration schemes [7]. The recursive soft-decision approach is therefore proposed by K. H. Yap and et al. Further, they proposed a computational reinforcement learning scheme to overcome the drawbacks of conventional methods, for instance, inter-domain dependency and falling into a local solution [8]. C. Vural and et al. thought that conventional methods require either a special parametric PSF form or complex computation; hence, they proposed a non-linear adaptive filtering to minimize dispersion of image. Because this method does not impose constraints on the phase of the blur, its implementation is easy for real applications [9].

Recently, aiming at seeking a higher quality of restoration, several evolutionary techniques have been presented, such as genetic algorithm (GA) [10], [11] and evolutionary algorithm [12]. The feasibility and benefits are verified by simulation results in [10], [11], and [12]. Most of these algorithms belong to a priori blur identification method because the parameters of blur model are suitably committed to the evolutionary learning. According to the same purpose, this paper applies another evolutionary technique, particle swarm optimization (PSO), to tackle BID problem. Each particle presents a probable PSF and evolutes according to the objective function which designed based on wavelet of its restoration. Because edge of a blurred image is thicker than that of an original image, the edge of a restoration with implied a well estimation for unknown PSF. For verifying the validity and efficiency, the simulations which use different blur levels respectively are designed. Because the method [10] with GA is not held on the same assumptions, it does not be compared in simulations.

This paper is organized as follows: Section II introduces the fundamental of blind image deconvolution. Section III presents the proposed methods, such as how PSO is used to seek the parameters of PSF and how the objective function is designed. Section IV presents and analyzes performance of the proposed method and the compared method by computation simulations. Section V draws a brief conclusion for this work.

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II. BLIND IMAGE DECONVOLUTION

The BID problem is an advanced image restoration problem because the received image does not uniquely define the convolved signals. Nevertheless these are many applications where the received images have been blurred either by an unknown or a partially known PSF. Generally speaking, a framework of BID consists of blur model, PSF estimation, and image restoration. In this section, a brief explanation about blur model and image restoration used in this work is given as following.

A. Blur Model

In many imaging applications, blurring procedure is modeled as following [11]:

$$g(x,y) = f(x,y) * h(x,y) + n(x,y) \tag{1}$$

where $g(x,y)$, $f(x,y)$, $h(x,y)$ and $n(x,y)$ denote the observed image, original image, point spread function (PSF) and additive noise, respectively. The symbol $*$ denotes two-dimensional (2-D) linear convolution operator. In (1), $f(x,y)$ and $h(x,y)$ are unavailable information a prior and n is assumed a white Gaussian noise. Therefore, restore the origin image $f(x,y)$ requires the deconvolution of the degraded image $g(x,y)$ from the $h(x,y)$.

The general model of degradation function for out-of-focus images is presented [11]-[14]:

$$h(x,y) = \begin{cases} \dfrac{1}{\pi R^2} & ,\sqrt{x^2 + y^2} \le R \\ 0 & ,\text{otherwise} \end{cases} \tag{2}$$

Even thought, this equation is a simple geometric model ignoring diffraction in which the radius R reflects the degree of blur. It has been shown in [15] that an accurate and complex physical model does not result in significantly better restoration than this geometric model.

B. Wiener Filter

The Wiener filter is a restoration technique for deconvolution. When the image is blurred by a known PSF, it is possible to recover the image. The Wiener filter is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The filter is usually applied in the frequency domain. Given a blur image $g(x,y)$, one takes the Discrete Fourier Transform (DFT) to obtain $G(u,v)$. The original image spectrum is estimated by taking the product of $G(u,v)$ with the Wiener filter $W(u,v)$:

$$F(u,v) = G(u,v)W(u,v) \tag{3}$$

The inverse DFT is then used to obtain the original image from its spectrum. The Wiener filter can be stated as follow:

$$W(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \dfrac{P_n(u,v)}{P_s(u,v)}} \tag{4}$$

Here, $H(u,v)$ is Fourier transform of the PSF, P_n is power spectrum of the noise and P_s is power spectrum of the signal. P_n/P_s can be interpreted as the reciprocal of the signal-to-noise ratio (SNR). Where the signal is very strong relative to the noise, $P_n/P_s \approx 0$ and the Wiener filter simplify $H^{-1}(u,v)$. When the signal is very weak, $P_n/P_s \to \infty$ and $W(u,v) \to 0$.

III. PSF IDENTIFICATION

This section will first present the optimization tool for PSF. Next, the difference between an original image and a blurred image is analyzed by wavelet transform process respectively. The design of objective function is explained as follows. The final subsection presents the procedure of the proposed algorithm.

A. Particle Swarm Optimization

The particle swarm optimization is a population-based optimization technique that was proposed by Eberhart and Kennedy [16] in 1995. PSO simulates the behavior of bird flocking. Suppose the following scenario: a group of birds are randomly searching for food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But, during each iteration, the team via their inter communications, how far the food is. So the best strategy to find the food is to follow the bird which is nearest to the food.

In PSO, each single solution is a "bird" in the search space. We call it "particle". Each particle represents a potential solution to the optimization task. All particles can find possible solving repeatedly. Each particle moves to a new position according to the new velocity which includes its previous velocity, the past best solution and global best solution. Therefore, when a particle discovers a new probable solution, other particles will move to it for exploring the region with more depth in the process [17].

A swarm in PSO consists of a number of particles. In the swarm has some parameters, the particle's current position p_i, current velocity v_i and past best position Pb_i, for particles in the search space to present their features. Each particle in the swarm is iteratively updated according to the aforementioned parameters. Assuming that the objective function f is to be minimized, the new velocity of every particle is updated by (5).

$$\begin{aligned} v_i(g+1) = w \cdot v_i(g) + c_1 \cdot r_{1_i}(g)\left[Pb_i(g) - p_i(g)\right] \\ + c_2 \cdot r_{2_i}(g)\left[Gb(g) - p_i(g)\right] \end{aligned} \tag{5}$$

For all $i \in 1, \ldots, \mathrm{N}$, v_i is the velocity of the ith particle, the w, c_1 and c_2 denote the acceleration coefficients, r_1 and r_2 are elements from two uniform random sequences in the range

(0,1), and t is the number of generations. The new position of a particle is calculated as follow:

$$p_i(t+1) = p_i(t) + v_i(t+1) \tag{6}$$

The past best position of each particle is updated by:

$$Pb_i(t+1) = \begin{cases} p_i(t+1) & \text{,if } f(Pb_i(t)) > f(p_i(t+1)) \\ Pb_i(t) & \text{,otherwise} \end{cases} \tag{7}$$

And the global best position Gb :

$$Gb(t+1) = \arg\min_{Pb_i} f(Pb_i(t+1)) \tag{8}$$

The velocities of the particles on each dimension may be clamped to a maximum velocity v_{max} . If the sum of accelerations causes the velocity on that dimension to exceed v_{max} , then this velocity is limited to v_{max} .

B. Discrete Wavelet Transform

The first discrete wavelet transform (DWT) was invented by Alfréd Haar, a Hungarian mathematician. In numerical analysis and functional analysis, a DWT is very useful.

At first, we need to define some signals and filters. $I[x]$: dispersed input signal. $L[x]$: low pass filter. $H[x]$: high pass filter. One-dimensional wavelet transform can be defined as follow:

$$\begin{cases} I_{1,L}[x] = \sum_{k=0}^{K-1} I[2x-k]L[k] \\ I_{1,H}[x] = \sum_{k=0}^{K-1} I[2x-k]H[k] \end{cases} \tag{9}$$

In 2-D, the input signal is regarded as $I[x, y]$. Therefore, the transfer process becomes more complicated, interpret as follows:

$$\begin{cases} I_{2,L}[x,y] = \sum_{k=0}^{K-1} I[x,2y-k]L[k] \\ I_{2,H}[x,y] = \sum_{k=0}^{K-1} I[x,2y-k]H[k] \end{cases} \tag{10}$$

where $I_{2,L}$ and $I_{2,H}$ is calculated by passing I through a high pass filter and low pass filter to y direction.

$$\begin{cases} I_{2,LL}[x,y] = \sum_{k=0}^{K-1} I_{2,L}[2x-k,y]L[k] \\ I_{2,LH}[x,y] = \sum_{k=0}^{K-1} I_{2,L}[2x-k,y]H[k] \\ I_{2,HL}[x,y] = \sum_{k=0}^{K-1} I_{2,H}[2x-k,y]L[k] \\ I_{2,HH}[x,y] = \sum_{k=0}^{K-1} I_{2,H}[2x-k,y]H[k] \end{cases} \tag{11}$$

Then to $I_{2,H}$ and $I_{2,L}$ through a high pass filter and low pass filter to x direction. Through (10) and (11), two steps can be regarded as one stage which 2-D DWT.

C. Objective Function

Because this work focuses on the restored out-of-focus image, PSF model can use the Eq. (2) to express. By the Eq. (2), the parameter of R can be estimated and examined, then it can be used to infer PSF model.

For PSO process, it will calculate an objective function value for each particle. According to the objective value that all particles are calculated, can determine past best solution and global best solution, and then determine the movement direction of the particle. Finally, particles can convergence to global optimal position. Originally, the objective function is set as follow:

$$PSNR = 10\log_{10} \frac{255^2}{\frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} \left(f(x,y) - \hat{f}(x,y) \right)^2} \tag{12}$$

where f, $\hat{f}$, M and N denote the original image, restored image, image width and image length respectively. Following Eq. (12), a larger objective value shows the image of estimate is closed to the primitive image. The excellent estimated R can be obtained by Eq. (12). But it must know the original image f in advance, this condition does not accord with reality. Therefore, we need a new objective function. Mainly employ the high-frequency information that the DWT in the new objective function. As leaving $I_{2,LH}$ and $I_{2,HL}$ can be regarded as the edge detected. Let $I_{2,LH}$, $I_{2,HL}$ and $I_{2,HH}$ turns into binary image. Figure 1. (a) can find the edge of the blur image is formed by thicker line. Figure 1. (b) can find the edge of the clear image is formed by several line. Therefore, the objective function is set as (13), the smaller objective value shows that the restored image is more clear.

$$s = \sum_{x=1}^{M} \sum_{y=1}^{N} J[x,y] \tag{13}$$

where J is the binary image of wavelet transform, it is described as following:

$$J[x,y] = \begin{cases} 0 & \text{,if } I_{2,HL}[x,y] = 0 \text{ and } I_{2,LH}[x,y] = 0 \\ 1 & \text{,otherwise} \end{cases} \tag{14}$$

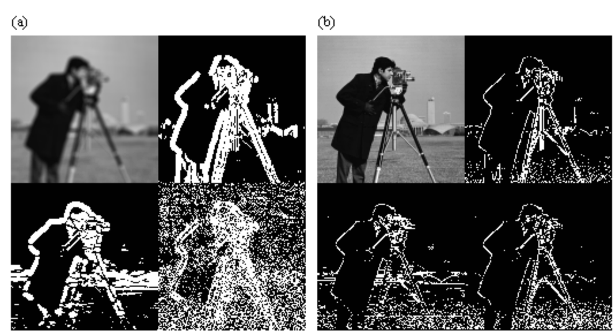

Figure 1. Comparing the DWT of the clear Cameraman image (a) with the DWT of the blurred Cameraman image (b)

D. Framework of the Proposed Algorithm

The framework of the proposed algorithm is shown as Figure 2. and each step is explained as follows:

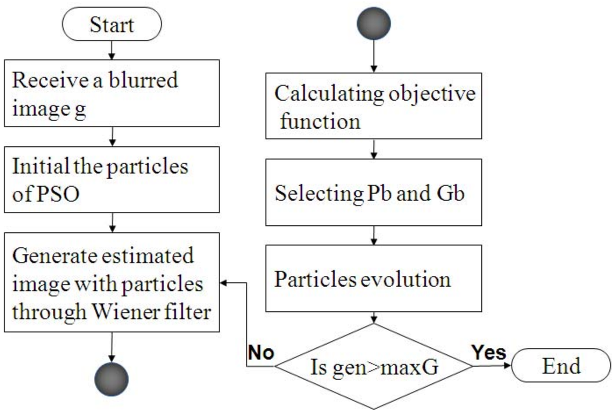

Figure 2. The flowchart of proposed algorithm

1) First, we must assume that a real *R*. Receive a blurred image *g* which is convoluted by (1).

2) Initial the particles of PSO randomly.

3) Applying Wiener filter on each particle to restore estimated images by (3) and (4).

4) The values of objective function are calculated on each estimated image.

5) *Pb* and *Gb* are selected by (7) and (8).

6) Particles move according to (5) and (6).

7) To check the number of generation is less than the maximal generation (maxG) or not. If it isn't done, then redo the step 3 to step 7. Otherwise, the learning is terminated.

Eventually, the optimal PSF could be obtained from final *Gb* which is able to generate the restored image with the best of objective function.

IV. EXPERIMENTAL RESULS

For the simulation design, two popular benchmarks, Lena and Cameraman, are the original images which are shown in Figure 3. (a) and (b) respectively with the size 256×256. The PSF model is the only knowledge a prior, besides a degraded image. For all simulations, the Entropy Evaluation [18], GA and proposed algorithm are implemented for over 30 independent runs. And there GA uses the proposed objective function. Entropy evaluation and proposed algorithm settings of related parameters are given as: particle number = 30, c_1=1.193, c_2=1.193, w=0.79 and maxG=20. GA settings of related parameters are given as: population number = 30 and iterative number = 20.

The measurement of restoration quality commonly uses the Peak Signal-to-Noise Ratio (PSNR) of the image. The formula for PSNR is then given as Eq. (12). Another measurement, Improvement in Signal-to-Noise (ISNR), evaluates the two PSNR differences between the degraded image and the restoration as:

$$ISNR = 10\log_{10}\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}\left(f(x,y)-g(x,y)\right)^2}{\sum_{x=1}^{M}\sum_{y=1}^{N}\left(f(x,y)-\hat{f}(x,y)\right)^2} \quad (15)$$

Here four simulations involve different radius $R(3,5,7,9)$ and ignores additive noise. In the first simulation, the PSNR of degraded Lena image is 27.7 dB, and the PSNR of degraded Cameraman image is 22.9 dB. In the second simulation, the PSNR of degraded Lena image is 25.0 dB, and the PSNR of degraded Cameraman image is 21.0 dB. In the third simulation, the PSNR of degraded Lena image is 23.5 dB, and the PSNR of degraded Cameraman image is 20.0 dB. In the fourth simulation, the PSNR of degraded Lena image is 22.4 dB, and the PSNR of degraded Cameraman image is 19.2 dB. From (9) and (10), it can be understood that ISNR is the difference between PSNR of a degraded image and PSNR of a restoration. Consequently, only the ISNR is presented in following simulation results.

Figure 3. The original image (a) Lena; (b) Camera man

After all the simulations finish for each algorithm, the results are summarized in TABLE I. to TABLE IV. which shows the estimated R and ISNR comparison for three algorithm (Entropy, GA and Proposed) for Cameraman and Lena, respectively. In each table, the "Avg." means the average of estimated *R* or ISNR of all runs; and the "Var." presents the variance of estimated *R* or ISNR of all runs. When the result has smaller Var., it means the algorithm has robust and stability. From the results in these tables, it could be observed that the proposed algorithm has closer real *R* in estimated *R* and has better value in ISNR Avg. than Entropy algorithm. It means that the proposed algorithm is accuracy to estimate PSF. Moreover, the proposed algorithm can obtain a small variance in estimated *R* and ISNR, which implies a well stability.

From the below simulation results, the proposed algorithm has superior feasibility and efficiency than entropy algorithm since it results estimated *R* approximate real *R*, larger ISNR and smaller variances. For Lena, it has some better estimated *R* in entropy algorithm. However, it can not precise identify to *R* for Cameraman. Therefore, entropy algorithm has not robust and stability enough. To the running time, the entropy algorithm spends 1124 sec and the proposed algorithm only spends 123 sec.

TABLE I. ESTIMATED *R* OF RESTORE CAMERAMAN

Real *R*	Method			
		Entropy	***GA***	***Proposed***
3	Avg.	4.9753	2.2648	2.8465
	Var.	24.9007	0.9590	0.2450
5	Avg.	4.7122	5.0398	5.0408
	Var.	10.1283	1.2428e-04	1.2036e-004
7	Avg.	4.5870	7.1310	7.1098
	Var.	0.2310	6.9548e-06	4.7769e-004
9	Avg.	6.4839	9.1718	9.1690
	Var.	2.0794	7.3554e-04	9.7159e-004

TABLE II. ISNR OF RESTORE CAMERAMAN

Real *R*	Method			
		Entropy	***GA***	***Proposed***
3	Avg.	0.4333	3.5502	6.4477
	Var.	26.1316	7.8947	5.8706
5	Avg.	0.0299	5.5700	6.2048
	Var.	9.4046	0.0049	0.0057
7	Avg.	-1.2097	5.2378	5.4229
	Var.	0.7141	0.0183	0.0137
9	Avg.	0.0875	4.8465	4.9469
	Var.	3.7561	0.0198	0.0282

TABLE III. ESTIMATED *R* OF RESTORE LENA

Real *R*	Method			
		Entropy	***GA***	***Proposed***
3	Avg.	3.1771	2.498	2.7546
	Var.	0.0249	0.9197	0.4900
5	Avg.	5.2089	5.0583	4.6764
	Var.	8.6577e-0005	2.0033e-04	1.2711
7	Avg.	7.3120	7.1007	7.1018
	Var.	3.5068e-005	6.9547e-04	3.3016e-005
9	Avg.	9.5371	9.0998	9.1031
	Var.	1.7758e-005	1.8440e-06	2.2329e-005

TABLE IV. ISNR OF RESTORE LENA

Real *R*	Method			
		Entropy	***GA***	***Proposed***
3	Avg.	3.8593	0.8567	4.3570
	Var.	2.2256	1.9607	2.9369
5	Avg.	3.7883	2.7056	3.5904
	Var.	0.0013	1.1593e-04	2.0527
7	Avg.	2.9387	2.8717	3.4245
	IVar.	1.4934e-004	7.8114e-05	0.0015
9	Avg.	2.8186	3.6212	3.8889
	Var.	6.1110e-005	3.9439e-07	3.6666e-006

GA and PSO are general evolutionary algorithms. Therefore, we compare these two performance of algorithms in the same conditions. For TABLE I. and II, most of the performance of PSO is better than GA. However, TABLE III. and IV, most of the performance of PSO is better than GA. In the implementation of time, PSO and GA are almost equal.

For the Figure 4. to Figure 7. , the blur images and estimated images are restored by the proposed algorithm which are labeled by (a) and (b) respectively, are contrasted for two different *R* and two benchmarks. From these figures, it could be observed that the detail of the restorations is quite clear and integer of the restorations approximates to the original image in Figure 3.

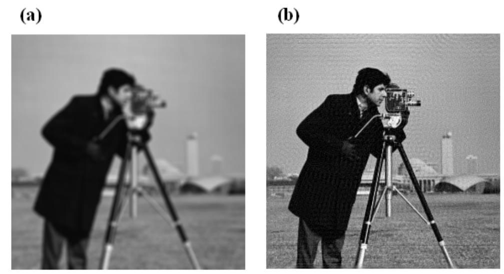

Figure 4. The received degraded Cameraman image (a) and restoration (b) by the proposed algorithm in *R*=3.

Figure 5. The received degraded Cameraman image (a) and restoration (b) by the proposed algorithm in *R*=5.

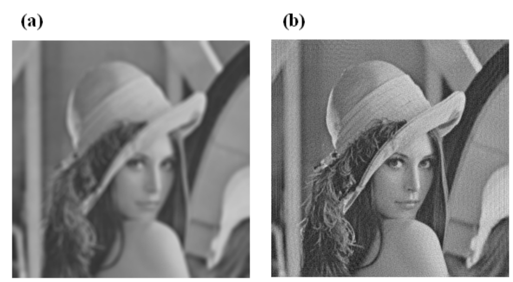

Figure 6. The received degraded Lena image (a) and restoration (b) by the proposed algorithm in *R*=3.

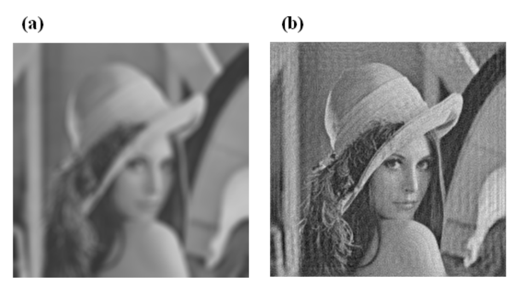

Figure 7. The received degraded Lena image (a) and restoration (b) by the proposed algorithm in *R*=5.

V. Conclusion

To aim the higher quality of blind restoration, this paper presented an algorithm that use PSO to explore the unknown PSF and use wavelet transform to design the objective function; moreover, it associates Wiener filter to restore the estimated image. From simulation results, the proposed algorithm is able to efficiently deconvoluted without information of the original image. Further, the proposed algorithm can obtain several better results in BID problem. The proposed algorithm can be used for various images, experiments demonstrated that the proposed algorithm have high quality restoration and robust efficiency.

In section IV, PSO and GA have similar performance because they are explore a simple solution in the one-dimensional space. In the future, the various PSF will be combined, such as the motion blur and the noise etc., lead to the parameters increase, the solution space will become more complicated. In the multi-dimensional space, PSO may have better performance to explore better solution.

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