

PSO-based Estimation for Gaussian Blur in Blind Image Deconvolution Problem

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Abstract—This study focuses on Gaussian blur estimation for blind image deconvolution (BID) problem. In BID problem, it only uses blurred image and less information of point spread function (PSF) to restore the received the blurred image. Due to restore the received image, the first step is to identify the proper PSF model. The received image does not uniquely define the PSF. Nevertheless these are many applications where the received image have been blurred either by an unknown or a partially know PSF. Therefore, this paper choose Gaussian blur image for further research, which utilized the particle swarm optimization algorithm to search for the unknown PSF. The objective function for searching the parameters of PSF is based on edge detection and image morphology. It can identify the parameters of PSF exactly. Finally, the feasibility and validity of proposed algorithm are demonstrated by several simulations.

Keywords—Gaussian Blur, Blind Image Deconvolution, Point Spread Function, Particle Swarm Optimization, Wiener filter, Edge Detector

I. INTRODUCTION

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, medical imaging, astronomical imaging, and so forth.

Referring to the classification [1], 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 alternating approach to estimate 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 [2], [3]. 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 [4]. The recursive soft-decision approach is therefore proposed by K.H. Yap and el al. Further, they proposed a computational reinforced learning scheme to overcome the drawbacks of conventional methods, for instance, inter-domain dependency and falling into a local solution [5]. C. Vural and el al. thought that conventional methods require either a special parametric PSF form or complex computation; hence, they proposed a non-linear adaptive filtering to minimum dispersion of image. Because this method does not impose constraints on the phase of the blur, its implementation is easy for real applications [6].

Recently, aiming at seek a higher quality of restoration; several evolutionary techniques have been introduced, for example genetic algorithm [7] and evolutionary algorithm [8]. The feasibility and benefits are verified by simulation results in [7], [8]. Most of these algorithms belong to a priori blur identification method because the parameters of blur model are suitably committed to the evolutionary learning. In the preliminary studies, we have utilized particle swarm optimization (PSO) to tackle different issues about BID problem [14], [15]. In [16], we have observed that the edge of a blurred image is thicker than that of an original image. Therefore, following this observation, the edge of a restoration with implied a well estimation for unknown PSF will be presented using PSO in this study. Each particle of PSO presents a probable PSF and evolves according to the objective function which designed based on edge detection of its restoration.

This paper is organized as follows: Section II introduces the fundamental of blind image deconvolution. Section III is the description of the proposed method. PSO and edge detector used in this work describes first. And then presents

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the objective function and how PSO is used to seek the parameters of PSF. Section IV presents the simulation and results. The conclusion and future works are described in Section V.

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, BID must consider three key issues: 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 image applications, blurring procedure is modeled by a two-dimensional (2D) linear convolution as following [1]:

$$g(x, y) = f(x, y) * h(x, y) \quad (1)$$

where $g(x, y)$, $f(x, y)$, $h(x, y)$ denote the observed blurred image, original image, and point spread function (PSF), respectively. In (1), $f(x, y)$ and $h(x, y)$ are unavailable information in advance. 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 Gaussian blurred images is presented as following [9]:

$$h(m, n) = K \exp\left\{-\frac{(m^2 + n^2)}{2\sigma^2}\right\} \quad (2)$$

where m and n present the horizontal and vertical space of $h(\cdot)$. K is a normalization constant to ensure the summation of $h(\cdot)$ matrix is one. σ is the standard deviation for the magnitude distribution of $h(\cdot)$.

B. Wiener Filter

The Wiener filter is a image restoration technique for the deconvolution with a priori known PSF. The Wiener filter is usually applied in the frequency domain. Given a blurred 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 $W(u, v)$:

$$F(u, v) = G(u, v)W(u, v) \quad (3)$$

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

$$W(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + \rho} \quad (4)$$

where $H(u, v)$ denote Fourier transform of the PSF. Since the $W(u, v)$ have the possibility to produce the pulse while the $|H(u, v)|^2$ approaches zero. Hence, in (4) adopted ρ to prevent this situation. The ρ value supposes too slightly, is unable to improve the pulse situation effectively; the ρ value supposes

too large, will cause $W(u, v)$ to be too small, and will cause the recover image effect variation. After many experiments of the simulation proved that the ρ value about 0.0005 may obtain a good recovered image.

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 edge detection 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 PSO is a population-based optimization technique that was proposed by Eberhart and Kennedy [10] in 1995. PSO simulates the behavior of bird flocking. The population is referred to as a *swarm*. The particles examine fast convergence to local and/ or global optimal position(s) over a small number of generations. In PSO, 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 [11].

A swarm in PSO consists of a number of particles. Each particle represents a potential solution to the optimization task. All of the particles iteratively discover the probable solution. Each particle moves to a new position according to the new velocity which includes its previous velocity, and the moving vectors according to the past best solution and global best solution. The best solution is then kept; each particle accelerates in the directions of not only the local best solution but also the global best position. If a particle discovers a new probable solution, other particles will move closer to it in order to explore the region with more depth [11]. In general, there are three attributes, the particles' current position p_i , current velocity v_i and local best position $Pbest_i$, for particles in the search space to present their features. Each particle in the swarm is iteratively updated according to the aforementioned attributes. Assuming that the cost function J is to be minimized so that the particles contain N dimensions, the new velocity of every particle is updated by

$$v_i(t+1) = wv_i(t) + c_1 \times r_1 [Pbest_i(t) - p_i(t)] + c_2 \times r_2 [Gbest(t) - p_i(t)] \quad (5)$$

For all $i \in 1, \dots, N$, v_i is the velocity of the i th 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:

$$p_i(t+1) = p_i(t) + v_i(t+1) \quad (6)$$

The past best position of each particle is updated by:

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

and the best position Gb found from all particles in its search dimension during the previous three steps is defined as:

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

B. Edge Detector

The edge detector [12] employed in this paper is based on a set of filters obtained from a basis filter d_0 and through successive rotations depicted as Fig. 1. The other filters were obtained by rotating basis filter with bicubic interpolation and by angles multiple of 45° . Designating by d_θ the filters of the set presented as

$$g_\theta(x) = d_\theta * x \quad (9)$$

The output of the edge detector is given by a combination of those filters' outputs through an L_2 norm

$$f(x) = \sqrt{\sum_{\theta \in \Theta} g_\theta(x)^2} \quad (10)$$

where Θ denote the set of filter orientations under consideration.

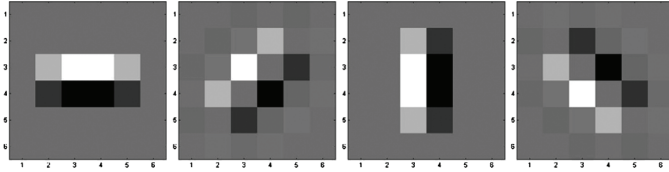


Figure 1. Set of edge detection filters, in the four orientations that were used. The leftmost filter is the basis filter d_0

As an example of the detector's operation, Fig. 2 shows the edges that were extracted from the "Cameraman" image by the proposed edge detector.



Figure 2. Edges of "Cameraman" by the proposed edge detector

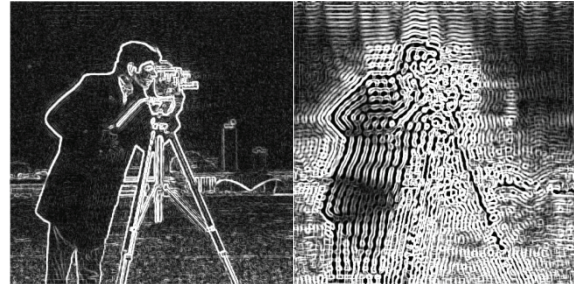
C. Object Function

In this study, the proposed objective function is based on the results of edge detection for blurred image and recover image respectively. Many observations of image after edge operation are shown as Fig. 3. The observed blurred image presents thick curve of edge as Fig. 3 (a). However, the edge of correct restored image shown as Fig. 3 (b) presents thin curve and the mean brightness of image is bright. Fig. 3 (c) shows the edge of an over-recovered image. Although the edge mean

brightness is also bright, it exhibits the existence of the unnecessary ringing phenomenon. Therefore, based on the comparison of difference information of image edge curve, a suitable objective function could be possible defined to distinguish different situations of image.



(a)



(b)

(c)

Figure 3. The edge detector of Cameraman image (a) The edge of blurred image (b) The edge of correct restored image (c) The edge of over-recovered image

The main profile of a blurred image could be obtained following below:

$$\hat{g} = f(g) - \frac{1}{n} \sum f(g) \quad (11)$$

where g is blurred image; $f(g)$ is the blurred image after edge detection via (10); n is the total amount of image pixels. The obtained $\hat{g}$ will convert to binary image and its opposition processing. And then, we can obtain the *essential* edge and *non-essential* edge of blurred image as shown in Fig. 4(a) and (b) respectively. With the concept of morphology, the erosion followed by dilation tends to smooth an image, to break narrow joins, and to remove thin protrusions, as shown in Fig. 4(c) (d). The value of the blurred image through edge detection filled the *essential* edge and *non-essential* edge as below:

$$\begin{cases} ged = f(g) \times ed \\ gned = f(g) \times ned \end{cases} \quad (12)$$

where ed is *essential* edge of blurred image; ned is *non-essential* edge of blurred image.

For each stage of the restored image through edge detection, also made the same blurred image with the *essential* edge and *non-essential* edge part information as below:

$$\begin{cases} xed_i = f(x_i) \times ed \\ xned_i = f(x_i) \times ned \end{cases} \quad (13)$$

where $f(x_i)$ denote the edge detection of the i^{th} estimation image.

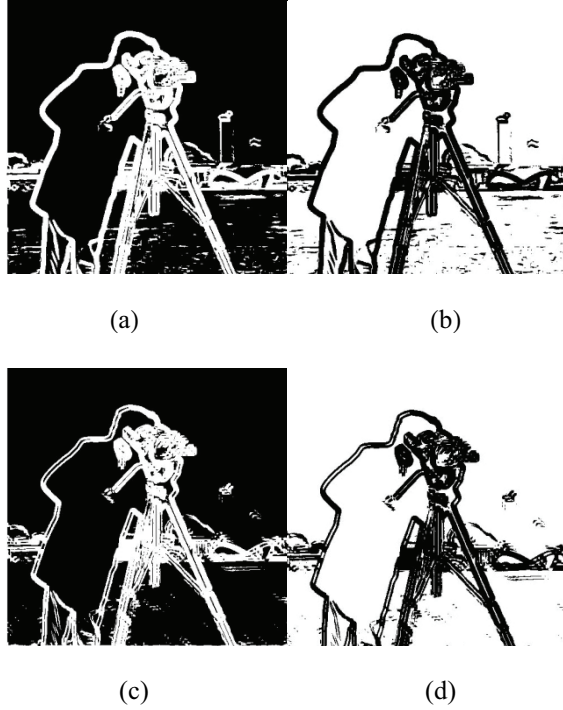


Figure 4. (a) The white place is the essential edge (b) The white place is the non-essential edge. The erosion followed by a dilation of (c) essential edge (d) non essential edge

The relationship between the blurred image and the i^{th} estimation image can be obtained as below:

$$\begin{cases} \text{ered}_i = \text{xed}_i - \text{ged} \\ \text{erned}_i = \text{xned}_i - \text{gned} \end{cases} \quad (14)$$

Then, ($ERed$ & $ERned$) refers to only take information of the edge ($ered$ & $erned$), as follows:

$$\begin{aligned} ERed &= \{\text{ered} \mid \text{ered} \neq 0\} \\ ERned &= \{\text{erned} \mid \text{erned} \neq 0\} \end{aligned} \quad (15)$$

Through the concept of entropy [13], [14] to calculate the diversity of the edge as following:

$$\begin{cases} Hed = -\sum_{i=1}^m P(ERed_i) \log P(ERed_i) \\ Hned = -\sum_{i=1}^m P(ERned_i) \log P(ERned_i) \end{cases} \quad (16)$$

where $P(ERed_i)$ and $P(ERned_i)$ are the distribution probability of the $ERed_i$ and $ERned_i$ respectively. Therefore, the objective function is set as (17), the large objective value shows that the restored image is more clear.

$$J = Hed - Hned \quad (17)$$

D. Framework of the Proposed Algorithm

The framework of the proposed algorithm is shown as Fig. 5, and each step is explained as follows:

- Receive a blurred image g which is convoluted by (1).
- Initial the particles of PSO randomly.
- Applying Wiener filter on each particle to restore estimated images by (3) and (4).
- The values of objective function are calculated on each estimated image.
- Pb and Gb are selected by (7) and (8).
- Particles move according to (5) and (6).
- To check the size of PSF particles average velocity is less than the threshold value (this paper set the threshold value is one) or not. If it isn't done, then redo the step (c) to step (g). 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

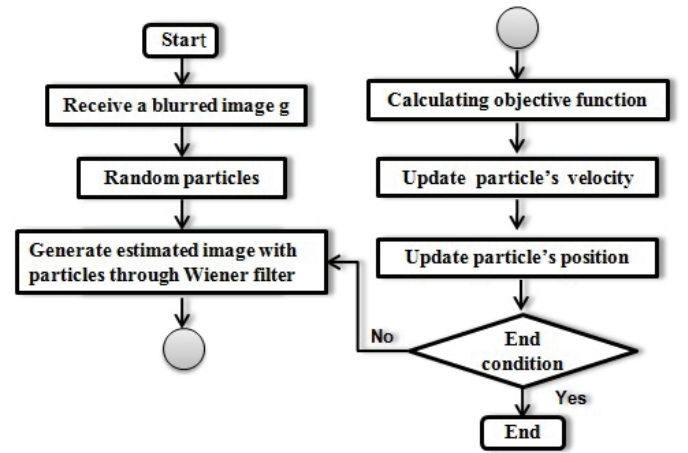


Figure 5. The flowchart of proposed algorithm

IV. EXPERIMENTAL RESULT

For the simulation design, two popular benchmarks, Lena and Cameraman, are the original images which are shown in Fig. 6 (a) and (b) respectively and with the size 512×512. The PSF size is the only knowledge a prior, besides a degraded image.

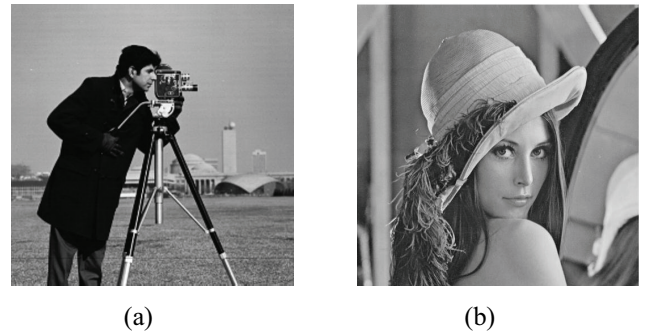


Figure 6. The original image (a) Cameraman (b) Lena

The measurement of restoration quality commonly uses the Peak Signal-to-Noise Ratio (PSNR) of the image as below:

TABLE I. ESTIMATION PSF OF RESTORE LENA

Lena									
NO.	PSF of Gaussian blur		Identify of PSF for Gaussian blur				PSNR(db) of blurred image	PSNR(db) of estimation image	
	Size	σ	Size		σ			Avg.	Std.
			Avg.	Std.	Avg.	Std.			
1	5	3	5.3333	1.8257	4.4773	1.4472	77.4935	82.1522	3.3066
2	7	3.5	7.0667	0.2537	4.7291	1.4152	75.6562	80.1690	1.8435
3	9	4	9.9667	1.9384	4.6593	1.4007	74.4668	77.2082	2.9095

TABLE II. ESTIMATION PSF OF RESTORE CAMERAMAN

Cameraman									
NO.	PSF of Gaussian blur		Identify of PSF for Gaussian blur				PSNR(db) of blurred image	PSNR(db) of estimation image	
	Size	σ	Size		σ			Avg.	Std.
			Avg.	Std.	Avg.	Std.			
1	5	3	5.3333	1.8257	4.4346	1.3870	77.3059	83.0344	3.6688
2	7	3.5	7.0667	0.2537	4.5743	1.4676	74.6235	80.3489	2.5050
3	9	4	9.9333	1.7407	4.4366	1.3325	73.0687	76.8471	3.2187

$$PSNR = 10 \log_{10} \frac{\sum_{i=1}^M \sum_{j=1}^N 255^2}{\sum_{i=1}^M \sum_{j=1}^N (f(i, j) - \hat{f}(i, j))^2} \quad (18)$$

where f , $\hat{f}$, M and N denote the original image, restored image, image width and image length respectively. Here three simulations involve different PSF size (5×5 , 7×7 , and 9×9) and standard deviation (3, 3.5, and 4), the proposed algorithm are implemented for over 30 independent runs. The results are summarized in TABLE I and TABLE II. In each table, the “Avg.” means the average PSNR value of estimated image of all runs; and the “Std.” presents the standard deviation of PSNR of estimated image of all runs. When the result has smaller Std., it means the algorithm has robust and stability.

From Fig. 7 to Fig. 12, the blurred images and estimated images restored by the proposed algorithm are labeled by (a) and (b) respectively. These figures are contrasted for three different PSF size and standard deviation with two benchmarks. From these figures, it could be observed that the detail of the restorations is quite clear and the estimated results of the restorations approximate to the original image in Fig. 6. Although the proposed method was unable to find the correct standard deviation of PSF, it did not have to the result affects too greatly.



Figure 7. (a) The received degraded Cameraman, PSF size: 5×5 , σ : 3.
(b) Estimation image and PSF size: 5×5 , σ : 4.2476



Figure 8. (a) The received degraded Lena, PSF size: 5×5 , σ : 3.
(b) Estimation image and PSF size: 5×5 , σ : 4.1038

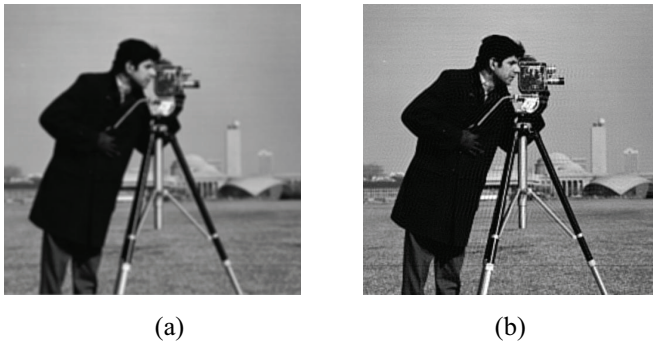


Figure 9. (a) The received degraded Cameraman, PSF size: 7×7 , σ : 3.5.
(b) Estimation image and PSF size: 7×7 , σ : 3.5532



Figure 10. (a) The received degraded Lena, PSF size: 7×7 , σ : 3.5.
(b) Estimation image and PSF Size: 7×7 , σ : 3.5591

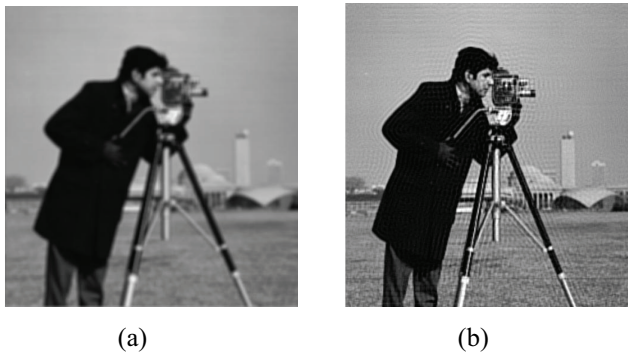


Figure 11. (a) The received degraded Cameraman, PSF size: 9×9 , σ : 4.
(b) Estimation image and PSF Size: 9×9 , σ : 4.1908



Figure 12. (a) The received degraded Lena, PSF size: 9×9 , σ : 4.
(b) Estimation image and PSF Size: 9×9 , σ : 4.2907

V. CONCLUSION

To aim the higher quality of blind restoration, this paper presents an algorithm that use PSO to explore the unknown PSF and deploys edge information to design the objective function. Moreover, it associates Wiener filter to restore the estimated image. From simulation results, as general-purposed in parameter definition, high quality restoration is demonstrated.

The proposed algorithm can identify and recover the image only for Gaussian Blind Image, not for real BID problem. The future work, we will study for identifying each kind of blur situation. So that it can identify encounter all the possible with photograph.

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