A Spread Function Based Image Deblurring Technique Employing Particle Swarm Optimization Algorithm

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Abstract : Image blurriness is one of the primary causes of poor image quality in image acquisition and can significantly degrade the structure of sharp images. Atmospheric turbulences, out-of focus and the motion of camera or scene would cause the blur. Atmospheric conditions such as dust storm condition, hazy environment results in poor quality image and it can increase the noise component of the picture. When images with poor quality are used for analysis, errors are likely to be generated. In this project heuristic particle swarm optimization technique, is being developed to optimize the parameters of the Point spread function PSF. The advantage of using this method is to get higher resolution, better quality and deblurring can be conducted on the noisy/ blurred image and thus the image quality can be improved. Experimental results show that the proposed method, the PSO Regularized technique, can improve the image quality significantly. Better results in terms of PSNR, SNR and image quality index are achieved.

***Keywords* :** PSF, PSO, image processing, deblurring, image quality index,

I. INTRODUCTION

Image restoration is to improve the quality of the degraded image. It is used to recover an image from distortions to its original image. It is the process of recovering the original scene image from a degraded or observed image using knowledge about its nature. Blurs found in the images can be uniform or non uniform that needs the estimation of point spread function (PSF) [1]. Image deconvolution is an inverse problem with the aim of recovering a true image from an observed degraded image. Image deblurring has recently received significant attention and has been a continuing problem in the image processing and computer vision fields. Image deblurring can be classified into two types, blind and non-blind deconvolution [2]. Deblurring is more difficult and ill-posed problem when the blur kernel is unknown, which is classified as blind deconvolution. When the blur kernel is known all practical solutions can be stronger than the prior information is unknown about the kernel. These techniques are classified as non-blind deconvolution [3]. Nevertheless, all those techniques suffer from heavy mathematical baggage implicated to carry out the task and more complexes formulas developed. According to literature those techniques have given good results but suffer from complexities .that's why, In this paper the application of the particle swarm optimization technique (PSO) is used. This paper proposed a new technique of image deblurring based on spread function, estimated the parameters of the Gaussian point spread function (PSF) and proposes a novel image deblurring algorithm that can be used to remove motion blur using Regularized filter.

Thus, the present paper is organized as follows: Methodology described in section II, proposed method Particle swarm Optimization technique is presented in section III, and Results and Discussion in section IV and conclusion is in section V.

II. METHODOLOGY

In this section, the problem of image deconvolution is described. A blurred or degraded image can be approximately described by this equation:

$$g(x,y) = PSF * f(x,y) + r(x,y) \qquad \ldots(1)$$

Where: g the blurred image,"*" is the discrete convolution operator, PSF is a distortion operator called Point Spread Function, f the original true image and r is the Additive noise, introduced during image acquisition, that corrupts the image [4]. The objective of restoration is to obtain an estimate $\hat{f}(x,y)$ of the original image such that the estimated image to be close as possible to the original input image. In this paper, PSO algorithm is used to find the elements of a filter mask. The corrupted filter mask minimizes the difference between artificially degraded image and obtained restored image by the regularized filter mask. Find a good filter mask such that it can be represented as a suitable inverse of the corruption function [5]. For linear spatial filtering the above process consists simply of moving the filter mask window from point to point in the corrupted image of size MxN with a regularized filter mask of size mxn is given by

$$\hat{f}(x,y) = \sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t)\, f(x+s)(y+t) \qquad \ldots(2)$$

Where a = (m-1)/2 b = (n-1)/2

Finding m×n coefficients of the regularized filter mask by PSO is the objective of this paper. Therefore, in the following section a brief explanation of PSO mechanism is given.

III. PARTICLE SWARM OPTIMIZATION

The particle swarm optimization (PSO) algorithm belongs to the category of Swarm Intelligence methods [6]. It was developed and first introduced as a stochastic optimization algorithm by Eberhart and Kennedy in 1995. PSO gained increasing popularity due to its effectiveness in performing difficult optimization tasks. PSO is a population-based algorithm that exploits a population of individuals to probe promising regions of the search space. In this context, the population is called a *swarm* and the individuals are called *particles*. Each particle moves with an adaptable velocity within the search space, and retains in its memory the best position it ever encountered. In the *global* variant of PSO the best position ever attained by all individuals of the swarm is communicated to all the particles. In the *local* variant, each particle is assigned to a neighborhood consisting of a pre specified number of particles. In this case, the best position ever attained by the particles that comprise the neighborhood is communicated among them [6]. 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. 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

$$v_i(t+1) = wv_i(t) + c_1 \times r_1[Pbest_i(t) - p_i(t)] + \\ c_2 \times r_2[Gbest(t) - p_i(t)] \quad ...(3)$$

For all $i \in 1,\dots,N$, v_i is the velocity of the ith particle, the w is the inertial weight, 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 follows:

$$p_i(t+1) = p_i(t) + v_i(t+1) \quad \dots(4)$$

The past best position of each particle is updated by :

$$Pb_i(t+1) = \begin{cases} P_i(t+1), iff(Pb_i(t) > f(p_i(t+1)) \\ Pb_i(t), otherwise \end{cases} \quad \dots(5)$$

And the best position G*b* found from all particles in its search dimension during the previous three steps is defined as

$$Gb(t+1) = \arg\min_{pb_i} f(Pb_i(t+1)) \quad \dots(6)$$

The constants c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each particle toward pbest and gbest positions. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement toward, or past, target regions [7].

Suitable selection of inertial weight w provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. Usually the large inertia value is high at first, which allows all particles to move freely in the search space at the initial steps and decreases over time. This decreasing inertia weight w has produced good results in many optimization problems [8]. To control the balance between global and local exploration, to obtain quick convergence, and to reach an optimum, the inertia weight whose value decreases linearly with the iteration number is set according to the following equation.7 [8]. As originally developed, w often decreases linearly from about 0.9 to 0.4 during a run.

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad \dots(7)$$

Where $w_{\max}$ and $w_{\min}$ are the initial and final values of the inertia weight respectively, $iter_{max}$ is the maximum number of iterations and iter is the current number of iterations [8]

Generally, the basic PSO procedure works as shown in flow chart: the process is initialized with a group of random particles (solutions). The ith particle is represented by its position as a point in search space.

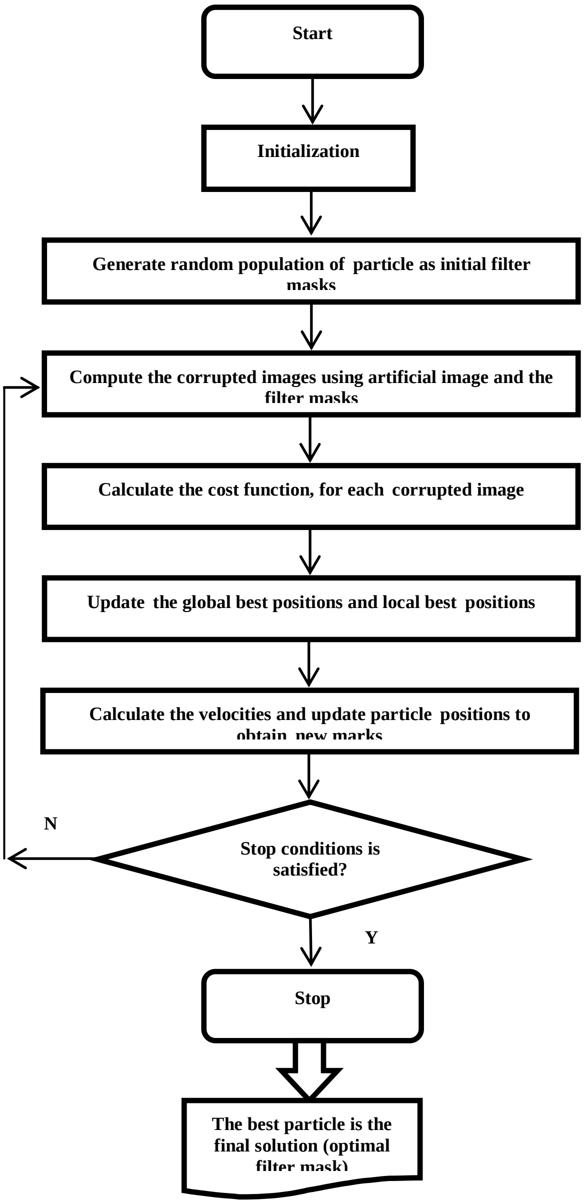


Fig.1: Methodology of Particle Swarm Optimization [Source : 5]

Throughout the process, each particle moves about the cost surface with a velocity. Then the particles update their velocities and positions based on the best solutions[5]. This process continues until stop condition(s) is satisfied (e.g. a sufficiently good solution has been found or the maximum number of iterations has been reached).Each particle represents coefficients of a filter mask. Parameters such as initial speed vector, population size, inertial coefficient, acceleration constants and value of the maximum number of iterations are also initialized. Afterwards, each particle is used to calculate corrupted image and then to calculate cost function of each particle. The best particle and the local best particles and their corresponding costs are saved. Then, the new positions, as the new better solutions (filter masks), are produced by equations (3) and (4). Now, using the computed filter mask, one can be restore other similar corrupted image. The proposed method is linear, simple and intelligent.

IV. RESULTS AND DISCUSSION

The proposed algorithm was implemented for different standard images and the results are shown in this study. Subjective as well as objective measurements are done. the PSO Regularized technique, can improve the image quality of the deblurred images in terms of PSNR ,SNR and Image Quality Index. Regularized filter was used as the deblurrer in the proposed method (here in after referred to as PSO-Regularized technique) and was engaged with the optimal alignment parameters determined by the PSO discussed in “Optimization of PSF” For this purpose, we use Matlab software Image Processing Toolbox to produce degradation functions and additive noise.

peak signal to noise ratio equation is given as

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right)dB \qquad \ldots(8)$$

Mean square error equation is given as

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}(f(x,y) - \hat{f}(x,y))^2 \qquad \ldots(9)$$

Where M x N denotes the size of the image $f(x,y)$ and $\hat{f}(x,y)$ denotes the pixel values at $(x,y)^{th}$ location of original and restored image respectively. The PSNR has been utilized to calculate similarity between the original image and the restored image. he higher the PSNR and lower the MSE in the deblurred image, the better is its quality.

signal to noise ratio is calculated as follows

$$SNR = 10\log_{10}\frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\hat{f}(x,y)^2}{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y) - \hat{f}(x,y)]^2} \qquad \ldots(10)$$

Signal-to-noise ratio is define as the ratio of the power of a signal and the power of background noise. where $f(x,y)$ is original image and $\hat{f}(x,y)$ is restored image. If the value of SNR is 40-60 db the image quality comes under excellent and if value is above 20 db then quality image is good.
Image quality index is calculated as follows

$$Q = \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x^2 + \sigma_y^2)[(\bar{x})^2 + (\bar{y})^2]} \qquad \ldots(11)$$

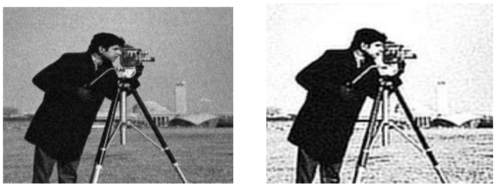
where

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N}x_i \qquad \bar{y} = \frac{1}{N}\sum_{i=1}^{N}y_i$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2 \qquad \sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{y})^2$$

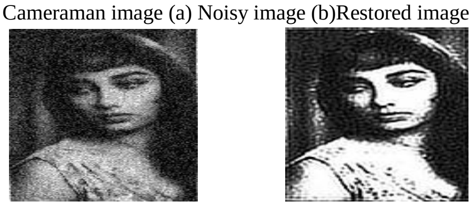
$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})$$

where x and *y* be the original and the restored images respectively. The dynamic range of Q is (-1,1). The best value 1 is achieved if and only if *yi*=*xi* for all *i*=1,2,...*N*. [9]



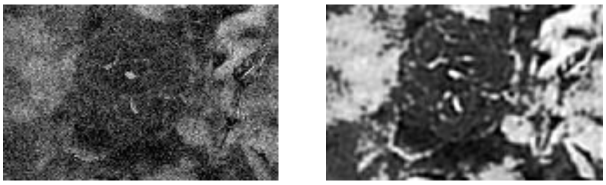
(a) (b)

Fig2: Cameraman image (a) Noisy image (b)Restored image with PSO algorithm



(a) (b)

Fig 3 : Sadhana image (a) Noisy image (b)Restored image with PSO algorithm



(a) (b)

Fig 4 : Flower image (a) Noisy image (b)Restored image with PSO algorithm

Table 1
Results with PSO Algorithm

Test images	PSNR	SNR	Image quality index
Cameraman	24.5596	24.1738	0.351572
Sadhana	24.2741	22.0314	0.724679
Flower	24.4433	21.6907	0.503655

We have evaluated the results for different images and the results are shown for the three images in terms of PSNR ,SNR IMAGE QUALITY INDEX. From the above Images (a) is noisy image and (b) is obtained from proposed method , With the particle swarm optimization method the quality of the image enhances (See Table 1) and we got better quality of image in terms of PSNR, SNR and Image quality index . The higher the PSNR and lower the MSE in the deblurred image better is quality. The dynamic range of Q is (-1,1) and If the value of SNR is 40-60 db the image quality comes under excellent and if value is above 20 db then quality image is good.

V. CONCLUSION

In this paper, a method is proposed to determine the image quality based on optimal PSF, in order to improve the image quality of the deblurred image. A heuristic method, particle swarm optimization, is being developed to optimize the parameters of the PSF. Hence, deblurring can be effectively performed using the optimal PSF. The advantage of using this method is to get higher resolution and better quality. When an appropriate PSF is determined deblurring can be conducted on the blurred image and thus image quality can be improved. Experimental results show that the proposed method, the PSO Regularized technique, can improve the image quality of the deblurred images in terms of PSNR, SNR and Image Quality Index .

REFERENCES

[1] *Vishakha Chourasia and Sanjay Agrawal, “Critical Analysis of Techniques used for Image Deblurring,” in International Journal of Advanced Research in Computer Science and Software Engineering, 2014*

[2] *Nimali Rajakaruna, Chamila Rathnayake, Kit Yan Chan and Iain Murray, “Image Deblurring for Navigation Systems of Vision Impaired People Using Sensor Fusion Data,” in IEEE Ninth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP) Symposium on Computational Intelligence Singapore, 21–24 April 2014.*

[3] *Kundur, D. and Hatzinakos, D., “Blind image deconvolution,” Signal Processing Magazine, IEEE, vol.13, no.3, pp.43,64, May 1996.*

[4] *Ratnakar Dash and Bansidhar Majhi, “Particle Swarm Optimization based regularization for image restoration,” World Congress on Nature & Biologically Inspired Computing (NaBIC-2009), IEEE Transactions, 2009.*

[5] *Mohammd Pourmahmood Aghababa, Amin Mohammadpour Shotorbani, Easa Narimani, "Estimation of image corruption Inverse Function and Image Restoration using a PSO based Algorithm," International Journal of Computer Applictions, Vol.13, No.1, January 2011.*

[6] *Konstantinos E. Parsopoulos and Michael N. Vrahatis, “On the Computation of All Global Minimizers Through Particle Swarm Optimization,” IEEE Transactions on Evolutionary Computation, Vol.8, No.3, June 2004.*

[7] *Chih Cheng Khao, “Application of Particle Swarm Optimization in Mechanical Design,” July 2009.*

[8] *Satyabroto Talukder, Mathematical modeling and applications of particle swarm optimization, M.Sc. Thesis, Blekinge Institute of Technology, Feb.2011.*

[9] *Zhou Wand and Alan C. Bovik, A universal image quality index, IEEE Signal Processing Letters, March 2002.*