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IMAGE RESTORATION USING NON-BLIND DECONVOLUTION APPROACH – A COMPARISON

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ABTRACT

The Image restoration is the process of recovery of an image that has been corrupted by some degradation phenomenon. Degradation occurs due to motion blur, gaussian blur, noise and camera mismatch. In this paper an attempt has been made to recover image from the corrupted image using Particle Swarm Optimization (PSO) algorithm in the presence of gaussian blur. For this purpose, a heuristic particle swarm optimization technique has been developed to optimize the parameters of the Point Spread Function (PSF). Higher resolution, better quality image is obtained by deblurring the noisy/ blurred image using this method. The algorithm performance is compared with Lucy Richardson algorithm. Experimental results indicated that the PSO regularized technique will improve the image quality significantly. Better results in terms of PSNR, SNR and image quality index are achieved.

Keywords: Point Spread Function, Particle Swarm Optimization, PSNR, SNR, Image quality index

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1. INTRODUCTION

Images are produced for recording useful information. However, due to imperfections in the imaging and capturing process the recorded image invariably represents a degraded version of the original scene. The degradation causes an image blur, affecting identification and extraction of the useful information from the images. The blurring degradation may be space invariant or space-in variant. Image deblurring methods can be divided into two classes: nonblind, in which the blurring operator is known and blind, in which the blurring operator is unknown. Image deconvolution is a linear image restoration problem where the parameters of the true image are estimated using the observed or degraded image and a known PSF (Point Spread Function). Blind image deconvolution is a more difficult image restoration where image recovery is performed with little or no prior knowledge of the degrading PSF. The advantages of deconvolution are higher resolution and better quality [1].

In the present paper attempt has been made to improve the image quality using Particle Swarm Optimiation (POS) technique and compare with the commonly used Lucy Richardson (LR) technique.

2. RELATED WORK

The issues related to image deblurring for navigation system of vision impaired people using sensor fusion data was analyzed by Rajkaruna et.al. [2]. In his paper non-deconvolution method is used where PSF is known. Particle swarm optimization is used to determine optimal Point Spread Function (PSF) and the improved quality of image can be readily used for object and path identification for blind people.

Wei Wang et al. [3] discussed a new image deblurring method by fractional differential (FD) based image deblurring approach combining with Total Variation (TV) constraint. An additional regularization algorithm is used to overcome the drawbacks compared to TV method to show better results and PSNR. FD method is very effective for edge detection and image texture enhancement.

Kundur et al. [1] discussed the two types of image deblurring methods viz., blind deconvolution and non-blind deconvolution. The former is more difficult since the blur kernel (PSF) is unknown.

3. DEGRADATION MODEL

The image is blurred using filters and additive noise in a degradation model. Image can be degraded using Gaussian Filter and Gaussian Noise. Gaussian Filter represents the PSF which is a blurring function. The degraded image can be in the form of the following equation (1)

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

Where: $g(x,y)$ the blurred image,"*" is the discrete convolution operator, PSF is a distortion operator called Point Spread Function, $f(x,y)$ the original true image and $r(x,y)$ is the additive noise, introduced during image acquisition, that corrupts the image [1]. 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.

3.1. Blurring Parameters

Parameters needed for blurring an image are PSF, blur length, blur angle and type of noise. When the intensity of the observed point image is spread over several pixels, this is known as PSF. Point Spread Function is a blurring function.

Blur length is the number of pixels by which the image is degraded. It is number of pixel position shifted from original position. Blur angle is an angle at which the image is degraded. Available types of noise are gaussian noise, salt and pepper noise, poisson noise, speckle noise which are used for blurring. In the present paper, a Gaussian noise is used which is also known as White noise. The Gaussian noise requires mean and variance as parameters [4].

3.2. Gaussian Blur

In gaussian blur pixel weights aren't equal - they decrease from kernel center to edges according to a bell-shaped curve. The gaussian blur effect is a filter that blends a specific number of pixels incrementally, following a bell-shaped curve. The blurring is dense in the center and feathers at the edge. Gaussian blur to an image is applied when more control over the blur effect is needed. Gaussian blur depends on the Size and alfa [4].

3.3. Gaussian Noise

The ability to simulate the behavior and effects of noise is important to image restoration. Gaussian noise is a white noise with constant mean and variance. The default values of mean and variance are 0 and 0.01 respectively [4].

4. DEBLURRING TECHNIQUES

In the present paper deblurring techniques applied are:

4.1. Lucy-Richardson Technique (LR)

The non-blind de-convolution is the category of deconvolution methods in which the PSF is known. Initially it was derived from Bayes theorem in the early 1970's by Richardson and Lucy. It is mainly used in Astronomy and Medical imaging. The Lucy Richardson (LR) algorithm is an iterative nonlinear restoration method. The L-R algorithm arises from maximum likelihood formulation in which image is modeled with poisson statistics. Maximizing the likelihood function of the model yields an equation that is satisfied when following iteration converges [5].

$$\hat{f}_{k+1}(x,y) = \hat{f}_k(x,y)[h(-x,-y) * \frac{g(x,y)}{h(x,y) * \hat{f}_k(x,y)}] \quad \textbf{(2)}$$

In this method it is difficult to claim any specific value for the number of iterations; a good solution depends on the size and complexity of the PSF matrix. The algorithm usually reaches a stable solution very quickly (few steps) with a small PSF matrix. But if one stops after a very few iterations then the image may be very smooth. On the other hand, increasing the number of iterations not only slows down the computational process, but also amplifies noise and introduces the ringing effect. Thus for the "good" quality of restored image, the optimal number of iterations are determined manually for every image as per the PSF size [6]. In addition, this algorithm functions in the event of noise presence but the noise would be increased throughout the raised number of iterations [4]. The equation of the Richardson-Lucy algorithm is [6]

$$f^{n+1} = f^n H^*(\frac{g}{Hf^n}) \quad \textbf{(3)}$$

Where f^{n+1} is the new estimate from the previous one f^n, (g) is the blurred image, (n) is the number of the step in the iteration, (H) is the blur filter (PSF) and (H*) is the adjoint of (H).

5. PARTICLE SWARM OPTIMIZATION

The PSO algorithm was first described by Kennedy and Eberhart [1998] [7]. The basic PSO (BPSO) algorithm begins by scattering a number of "particles" in the function domain space [8]. Each particle is essentially a data structure that keeps track of its current position *x* and its current velocity *v*. Additionally, each particle remembers the "best" position it has obtained in the past, denoted p_i. The best of these values among all particles (the global best remembered position) is denoted p_g. At each time step, a particle updates its position and velocity by the following equations:

$$v_i(t+1) = wv_i(t) + c_1 \times r_1[Pbest_i(t) - p_i(t)] + c_2 \times r_2[Gbest(t) - p_i(t)] \quad \textbf{(4)}$$

For all $i \in 1,\ldots,N$, 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:

$$p_i(t+1) = p_i(t) + v_i(t+1) \quad \textbf{(5)}$$

The past best position of each particle is updated by:

$$Pb_i(t+1) = \begin{cases} P_i(t+1), \text{iff}(Pb_i(t) > f(p_i(t+1)) \\ Pb_i(t), \text{otherwise} \end{cases} \quad \textbf{(6)}$$

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

$$Gb(t+1) = \arg\min_{pb_i} f(Pb_i(t+1)) \quad \textbf{(7)}$$

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. 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: As originally developed, w often decreases linearly from about 0.9 to 0.4 during a run.

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad \textbf{(8)}$$

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 [9].

6. PSO METHODOLOGY

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 [10]. 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

$$\hat{f}(x,y) = \sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t) f(x+s)(y+t) \tag{9}$$

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.

7. RESULTS AND DISCUSSION

The blurred/noisy image and deblurred images are processed by the PSO method and Lucy-Richardson method. The proposed algorithm was implemented for different standard images and the results are shown in this study. Subjective as well as objective measurements are carried out. Peak signal to noise ratio is the performance metrics considered for comparison. The computed PSF was used in the deblurring methods. Regularized filter was used as the deblurrer in the PSP method. The results show the relative improvements when the LR method is compared with the PSO-Regularized technique, where the relative improvement is the difference between the results obtained by the PSO-regularized technique and LR method. Peak signal to nise ratio is given as [11]

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

Mean square error equation is given as

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(f(x,y) - \hat{f}(x,y)\right)^2 \tag{11}$$

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. The higher the PSNR and lower the MSE in the deblurred image, the better is its quality.

Signal to noise ratio is calculated as follows

$$SNR = 10\log_{10}\frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\hat{f}(x,y)^2}{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left[f(x,y) - \hat{f}(x,y)\right]^2} \tag{12}$$

Signal-to-noise ratio is defined 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

$$Q = \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x^2 + \sigma_y^2)[(\bar{x})^2 + (\bar{y})^2]} \quad \textbf{(13)}$$

where

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

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

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

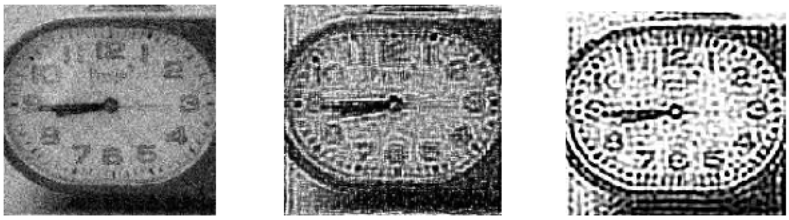
where x and *y* be the original and the restored images respectively. The dynamic range of Q is (-1,1). the best value 1 is achieved if and only if *yi=xi* for all *i*=1,2,...*N.* [12].

(a) Noisy Image (b) LR Method (c) PSO Method

Figure 1 Cameraman Image

Table 1 Objective Parameters of Cameraman Image

Parameters	**Deblurring Methods**		
	Lucy-Richardson	Blind Deconvolution	PSO
PSNR(db)	20.2464	17.8386	24.5596
Image Quality Index	0.38	0.19061	0.351572
SNR(db)	19.98	14.7135	24.1738

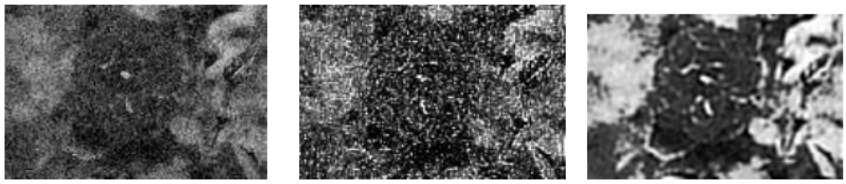


(a) Noisy Image (b) LR Method (c) PSO Method

Figure 2 Clock Image

Table 2 Objective Parameters of Clock Image

Parameters	Deblurring Methods		
	Lucy-Richardson	Blind Deconvolution	PSO
PSNR(db)	18.7786	16.0763	23.0279
Image quality index	0.350495	0.12355	0.271811
SNR(db)	21.2324	13.4175	25.7396



(a) Noisy Image (b) LR Method (c) PSO Method

Figure 3 Flower Image

Table 3 Objective Parameters of Flower Image

Parameters	Deblurring Methods		
	Lucy-Richardson	Blind Deconvolution	PSO
PSNR(db)	22.4469	21.4667	24.4433
Image quality index	0.371479	0.371479	0.503655
SNR(db)	19.8491	14.8114	21.6907

The results evaluated for three different images are presented in Table 1, Table 2 and Table 3. In the images shown in Fig.1, Fig.2 and Fig.3 (a) is noisy image and (b) is image obtained from Lucy Richardson method and (c) is obtained from PSO method. The results indicates that the PSO regularized filter works better under noise conditions. With the particle swarm optimization method the quality of the image enhances (See Table 1 to Table 3) and better quality of image in terms of PSNR, SNR and Image quality index are obtained as compared with LR method. 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. The results shows the relative improvements when LR method is compared with the PSO-Regularized technique, where the relative improvement is the difference between the results obtained by the PSO-Regularized technique and the LR method with better quality of image.

8. CONCLUSION

In the present paper, a method is proposed to determine the image vision 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 noisy image and thus image quality can be improved.

Experimental results show that the PSO Regularized technique, can improve the image quality of the deblurred images. Also, significant improvement can be achieved when compared with the commonly used deblurring filters like Lucy-Richardson method, in terms of PSNR, Image Quality Index and SNR.

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