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Comparative Analysis and Implementation of Image Debluring system using Particle Swarm Optimization

Rakhi Choudhary[1], Mr. Ram Nivas Giri[2]

[1]*M.Tech. Scholar, CSE Department, RITEE, Raipur*
[2]*Asst.Professor, CSE Department, RITEE, Raipur*

Abstract: *Image deblurring is an old issue in image processing, yet it keeps on pulling in the consideration of specialists and experts alike. The blurring, or degradation, of an image can be caused by many factors such as movement during the image capture process, by the camera or, when long exposure times are used, by the subject, out-of-focus optics, use of a wide-angle lens, atmospheric turbulence, or a short exposure time, which reduces the number of photons captured or scattered light distortion in confocal microscopy In this paper work, an efficient image deblurring model is proposed based on Particle Swarm Optimization (PSO) algorithm. This paper deals with the motion blurred images and how to improve the quality of those images by estimating PSF values using trajectory curve that can help to deblur an image. Particle swarm optimization (PSO) is a computational strategy that optimizes a problem by iteratively attempting to improve a candidate solution with respect to a given measure of value. PSO optimizes a problem by having a number of candidate solutions, here named particles, and moving these particles around in the search space according to simple mathematical formulae and moving these particle as indicated by particle's position and velocity. Experimental results illustrate performance proposed approach.*

Keywords: Image Deblurring, PSFs, PSO, PSNR, MSE.

I.INTRODUCTION

The recent rapid popularization of digital cameras permits individuals to capture a large number of digital photographs effortlessly. As the number of normal photographers increases, so does the number of “failure” photographs including over/under-exposed, noisy, blurred, and unnaturally- unnaturally-hued pictures. This circumstance makes automatic avoidance and correction of failure images vital. Additionally, the blur can be brought about by atmospheric turbulences, incorrect focus settings, camera movement and movement within the scene. For smart phones or tablets, significant blurs are probably to be generated by body movement when the users are performing navigation. In fact, automatic corrective functions of digital cameras including auto-exposure, automatic white balance, and noise reduction capabilities steadily improve to resolve exposure, color, and noise issues. Although fast shutter speeds could reduce the blurs, image noise could be generated Likewise, they are normally not accessible in smart phones or tablets, as camera with these fuctions are extremely costly. Potential risks for the vision-impaired individuals can be caused when poor image captions are utilized for object detection and path identification in the navigation system [1]. To improve the image quality, deblurring algorithm can be applied by evacuating the blurred effects.

Recovering an un-blurred image from a single, motion-blurred photograph has for quite some time been a principal research issue in digital imaging. If one expect that the blur kernel or point spread function (PSF) is move-invariant, the issue reduces to that of image deconvolution. Image deconvolution can be further isolated into the blind and non-blind cases. In non-blind deconvolution, the motion blur kernel is thought to be known or computed somewhere else, the only task left is to evaluate the unblurred latent image. Conventional methods such as Weiner filtering [2] and Richardson-Lucy (RL) deconvolution [3] were proposed decades back, yet are still generally used in many image restoration tasks nowadays because they are simple and productive. In any case, these techniques tend to experience the unsavory ringing artifacts that appear near strong edges. On account of blind deconvolution [4; 5], problem is essentially more ill-posed, since both the blur kernel and latent image are assumed unknown. The complexity of natural image structures and diversity of blur kernel shapes make it easy to over- or under-fit probabilistic priors [4].

This paper deals with the motion blurred images and how to improve the quality of those images by estimating PSF values using trajectory curve that can help to deblur an image. Particle swarm optimization (PSO) is a computational strategy that optimizes a problem by iteratively attempting to improve a candidate solution with respect to a given measure of value. The rest of the paper is organized as follows: Section II illustrates the complete details about the earlier image deblurring techniques developed to remove the deblurring form images. Section III gives an idea about the problem identification. The complete details about the proposed approach are illustrated in section IV. Section V explores the simulation results and finally the conclusions are given in section VI.

II. RELATED WORK

Various approaches are proposed in earlier to perform image deblurring and to achieve an optimal performance. The complete approaches are categorized as blind deconvolution and non-blind deconvolution techniques. In the approaches based on non-blind deconvolution, the blur kernel is known and only a latent image must be recovered from the observed, blurry image, whereas in the blind deconvolution, the blur kernel is also unknown. The most widely recognized non-blind deconvolution technique is Richardson-Lucy (RL) deconvolution [3], which processes the latent image with the assumption that its pixel intensities conform to a Poisson distribution. Jiunn-Lin Wu et.al [13] proposed an Improved Richardson-Lucy Algorithm for Single Image De-blurring Using Local Ext-rema Filtering through the modification in the old Richardson-lucy algorithm of de-blurring. One of the advantages of this algorithm is that it is noise invariant and it is also an iterative algorithm. This method minimizes the difference between predicted and blurred image with the help of poisson statistics. Ringing effect and more computational time for more iteration are the two drawbacks of this approach. Zohar-al-ameen et.al [14] proposed A Comprehensive Study on Fast image Deblurring Techniques to describe iterative poison Map algorithm which is also an iterative algorithm. This algorithm is same as Richardson-Lucy algorithm with only difference is that this algorithm uses formula in the form of exponential. Computational it is complex due to the use of exponential function and hence require more time. Zohar-al-ameen [14] proposed A Comprehensive Study on Fast image Deblurring Techniques to describe Laplacian Sharpening filter based image de-noising. Laplacian sharpening filter is basically used for sharpening the image. Image sharpening operation can be considered as the image de-blurring operation. Laplacian filter is basically 3x3 window matrix which is of three different types depending upon the weight given to the centre pixel. These filters are shown in the figure given below. It is very fast algorithm and not a iterative sort of method. Donatelli et al. [6] utilize a PDE-based model to recover a latent image with lessened ringing by incorporating an anti-reflective limit condition and a re-blurring step. Several methodologies proposed in the signal processing community solve the deconvolution issue in the wavelet domain or the frequency domain [7]; a lot of these papers lack experiments in de-blurring real photographs, and few of them endeavor to model error in the estimated kernel. Levin et al. [8] utilize a sparse derivative prior to abstain ringing artifacts in deconvolution. Most non-blind deconvolution method assume that the blur kernel contains no errors, however, and as we show later with a correlation, even small kernel errors or image clamor can lead to significant artifacts. Finally, many of these deconvolution techniques require complex parameter settings and long computation times. Some techniques make the problem more tractable by leveraging additional input, such as multiple images. Rav-Acha et al. [9] leverage the information in two motion blurred images, while Yuan et al. [10] utilize a pair of images, one foggy and one noisy, to encourage capture in low light conditions. Other motion deblurring systems frameworks take advantage of additional, specialized hardware. Ben-Ezra and Nayar [11] attach a low-resolution video camera to a high-resolution still camera to help in recording the blur kernel. Raskar et al. [12] flutter the opening and closing of the camera shutter during exposure to minimize the loss of high spatial frequencies. In their technique, the object motion path should be specified by the user. In contrast to all these strategies, our method operates on a single image and requires no additional hardware. Michael H. Ferris et.al., presented [15] an Extension of No-Reference Deblurring Methods through Image Fusion"(IEEE). In this method, first of all optimal information from the blurred image is obtained without taking a reference image. Image fusion is used in this method for obtaining the optimal information about the blurring in the image. In this method first a de-blurring is applied to a no reference image and then fused it with the blurred image. One of the limitations of this algorithm is that it loses some amount of information. The results revealed the facts that this method has increasing relationship with the blurriness of the image. Tao Yue et.al. [16] Proposed a Hybrid Image De-blurring by Fusing Edge and Power Spectrum Information based on the edge-based and power spectrum based approach. This method first of all, extracts the edges from the images. This edge information is then used for estimating accurate power spectrum of the kernel. Edge and power spectrum information are then combined for estimating the kernel accurately by optimization techniques. One of the drawback of this method that is not able to handle the significant non-uniform blur. It is due to the fact that power spectrum estimation is computed on global level and does not count spatially-varying blur.

III. PROBLEM IDENTIFICATION

Significant research effort has focused on image deblurring [17] [18] [19] [20] and attract the interest on digital image processing. In earlier various approaches were proposed to perform image de-blurring, however the main problems with these approaches are outlined as Synchronization problem was observed during the provision of image sensor alignment with IMU data, due to the very small exposure time. Also used highly expensive cameras which were limited for only offline image de-blurring applications.The accuracy of the accelerometer and the distortion caused by deblurring which can generate ringing artifacts. Some method shares common limitations with other uniform motion deblurring methods. Due to the limitation of the blur model based on convolution, saturated pixels from strong lights and severe noise would not be properly handled. Another disadvantage is that some methods make prohibitive assumptions on the PSF or the true image that limits the algorithm's portability to various applications. In basic, deblurring filters are applied on the degraded images without the knowledge of blur and its adequacy. Roughly speaking, we must specify a real number for every setting of the world model parameters. They are also a bit slower as compared to other deblurring methods.

IV. PROPOSED METHOD

In the proposed method a color image is taken as an input and it was subjected to motion blur to obtain a blurred image, motion blur function is going to generate a set of motion blurred Images and a set of PSF values .In order to obtain a motion blurrred image, a create trajectory function and create PSF function is used. After generating a set of PSFs values and motion blurred image, Particle swarm optimization is used to optimize those PSF values. After optimizing those PSF values apply those on blur images and obtain a deblur image. Figure.1 represents the block diagram of proposed approach.

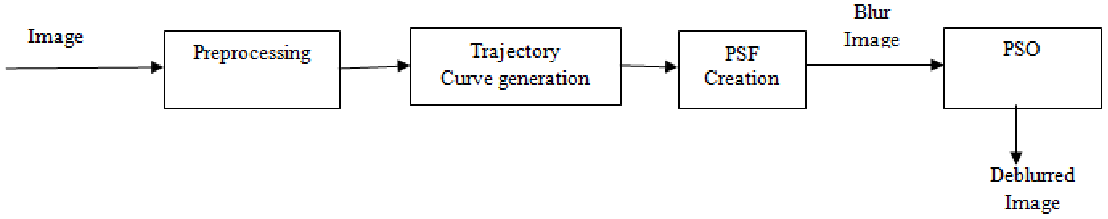


Figure.1 Block diagram of proposed approach

A. Trajectory curve creation

A trajectory or flight path is the path that a moving object follows through space as a function of time. The object might be a projectile or a satellite. For instance, it can be an orbit the path of a planet, a space rock, or a comet as it goes around a central mass. A trajectory can be described mathematically either by the geometry of the way or as the position of the object over time. The createTrajectory function produces a assortment of random motion trajectories in continuous domain as in [21]. Each trajectory is represented by a complex-valued vector comparing to the discrete positions of a particle taking after a 2-D random motion in continuous area. The particle or molecule is initially characterized by a velocity vector which, at each iteration, is affected by a Gaussian perturbation and by a deterministic inertial segment, directed toward the previous particle position. In addition, with a little probability, an impulsive (abrupt) perturbation aiming at inverting the particle velocity may arises, copying a sudden movement that happens when the user presses the camera button or tries to compensate the camera shake. At every step, the velocity is normalized to ensure that trajectories corresponding to equivalent exposures have the same length. Each perturbation (Gaussian, inertial, and impulsive) is governed by its own parameter. Rectilinear Blur can be obtained by setting the anxiety parameter to 0 (when no impulsive changes occurs)

B. PSF generation

The point spread function (PSF) describes the reaction of an imaging framework to a point source or point object. A more broad term for the PSF is a system's impulse response, the PSF being the impulse response of a centered optical framework. The PSF in numerous contexts can be considered of as the extended blob in an image that represents an uncertain object. The degradation producing ill- impact of blur is termed as the point spread function, psf. Any sort of blur is characterized by the PSF .The electromagnetic radiation or other imaging waves proliferated from a point source or point object is known as the psf. The quality of any imaging framework relies on upon the degree of spreading(blurring) of the point object. The PSF defines the impulse response of a point source. When an image is captured by any recording framework, the intensity of a pixel of the recorded image is directly proportional to the intensity of the corresponding segment of the sight be captured. But this is ideal situation. For all intents and purposes, the recorded intensity either gets affected by the noise or blur. The PSF is significant not just for determining the resolution performance of different objectives and imaging frameworks, but also as a fundamental concept used in deconvolution. Deconvolution is a mathematical transformation of image data that lessens out of focus light or blur. Blurring is a critical source of image degradation in three-dimensional (3D) wide field fluorescence microscopy. It is nonrandom and emerges within the optical train and specimen, to a great extent due to diffraction. A computational model of the blurring procedure, in view of the convolution of a point object and its PSF, can be utilized to deconvolve or reassign out of focus light back to its point of origin. Deconvolution is utilized frequently in 3D wide field imaging. However, even images produced with confocal, spinning disk, and multi-photon microscopes can be improved using image restoration algorithms.

C. Particle Swarm Optimization

PSO was originally developed by Kennedy and Eberhart in 1995[22]. PSO optimizes a problem by having a number of candidate solutions,here named particles, and moving these particles around in the search space according to simple mathematical formulae and moving these particle as indicated by particle's position and velocity. Each particle's movement is influenced by its local best known position however then again, is guided toward the best known positions in the pursuit-space, which are updated as better positions are found by various particles. This is expected to move the swarm toward the best solutions[23].

PSO is instated with a group of random particles (solutions) and afterward looks for optima by updating generations. In each iteration, every particle is refreshed by taking after two "best" values. The first is the best solution (fitness) it has achieved so far. This value is called pbest. Another "best" value that is followed by the particle swarm optimizer is the best value, acquired so far by any particle in the population. This best value is a global best and called gbest.

PSO Algorithm

Let d be the dimension of the search space, then x_i = (x_{i1},x_{i2}.... x_{id}) denotes the position of the particle i ∈ 2 (1, 2, . . . ,N) of the swarm, and p_i = (p_{i1}, p_{i2}, . . . , p_{id}) denotes the best position it has ever visited. The index of the best particle in the population (the one which has visited the global best position) is represented by the symbol g. At each time step t in the simulation the velocity of the i^{th} particle, represented as v_i= (v_{i1}, v_{i2}, . . . , v_{id},), is adjusted along each axis j following the equation:

$$v_{ij}(t+1) = v_{ij}(t) + \varphi_p.\left(p_{ij}(t) - x_{ij}(t)\right) + \varphi_g.\left(p_{gj}(t) - x_{ij}(t)\right) \qquad (1)$$

where ψ_p is a random number uniformly distributed in [0, p_{incr}]. and ψ_g is a random number uniformly distributed in [0,g_{incr}]. p_{incr} and $g_{incr}$are the same positive constants used in flock's simulations and are respectively called the cognitive and social acceleration coefficient.
Moreover, the particle's velocity can be constricted to stay in a fixed range, by defining a maximum velocity value $V_{\max}$ and applying the following rule after every velocity updating:

$$v_{ij} \in [-V_{max}, V_{max}] \qquad (2)$$

In this way the probability of particles leaving the search space is decreased, although indirectly, by constraining the maximum distance a particle will cover in a single step, instead of restricting the values of x_i. The new position of a particle is calculated using:

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (3)$$

The personal best position of each particle is updated using:

$$p_i(t+1) = \begin{cases} p_i(t) & if\ f(x_i(t+1)) \geq f(p_i(t)) \\ x_i(t+1) & if\ f\left(x_i(t+1)\right) < f(p_i(t)) \end{cases} \qquad (4)$$

While the global best index is defined as:

$$g = arg\min_i f\left(p_i(t+1)\right), \quad 1 \leq i \leq N \qquad (5)$$

An essential feature of the PSO algorithm is the way in which the local and global best positions, pi and pg, and their respective acceleration coefficients, are involved in velocity updates.

V. EXPERIMENTAL RESULTS

This section shows the result of PSO on the set of ten test sequence. In this section, the results of various set of images are shown ,we have used 8 color images to demonstrate the results. First image is original image in each set and then the image is motion blurred which is shown with the second image and third image is deblurred image in each set .The experimental results are carried out on color images by using PSO algorithm which gives pretty good results as shown in the below figures. PSNR,MSE and other numerical values of the deblurred image are shown in table 1 and comparative analysis of various method is shown in table 2.. Figure 3 shows the comparative analysis of the proposed approach with the other methods with the help of bar charts.

Calculation of PSNR

The PSNR block computes the peak signal-to-noise ratio,between two images. This ratio is often utilized as a quality estimation between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image.

$$PSNR = 10 * \log({(255)^2}/_{MSE}) \qquad (1)$$

Calculation of MSE

The Mean Square Error (MSE) *and the* Peak Signal to Noise Ratio (PSNR) are the two error metrics used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error.

$$MSE = sum(sum(X_o - X_r))/(M * N) \qquad (2)$$

Where X_o is original image and X_r is the deblurred image.

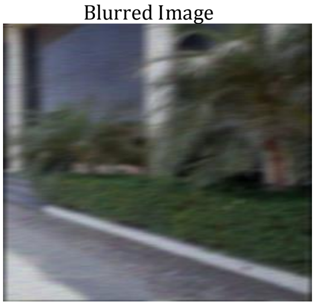
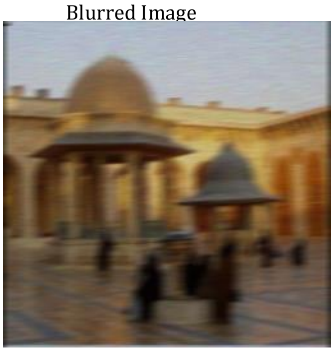
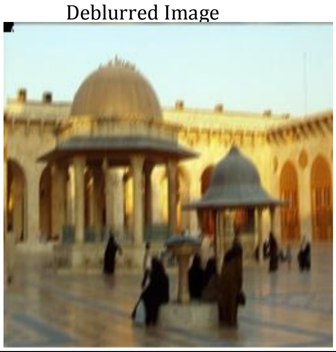
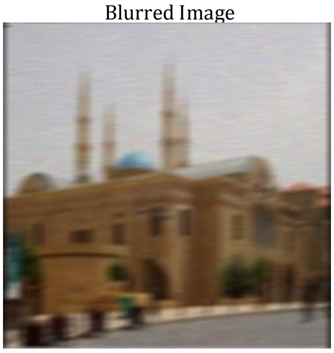
Image 1	Original Image 	Blurred Image 	Deblurred Image 
Image 2	Original Image 	Blurred Image 	Deblurred Image 
Image 3	Original Image 	Blurred Image 	Deblurred Image 
Image 4	Original Image 	Blurred Image 	Deblurred Image 

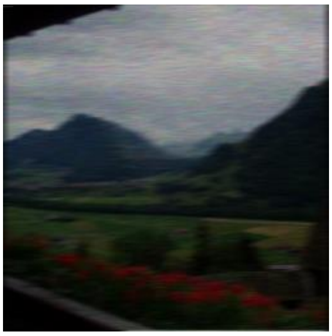
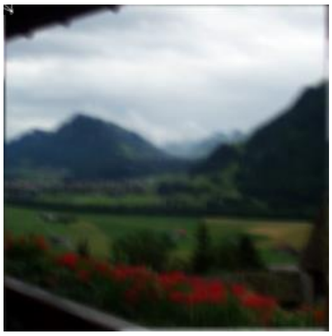
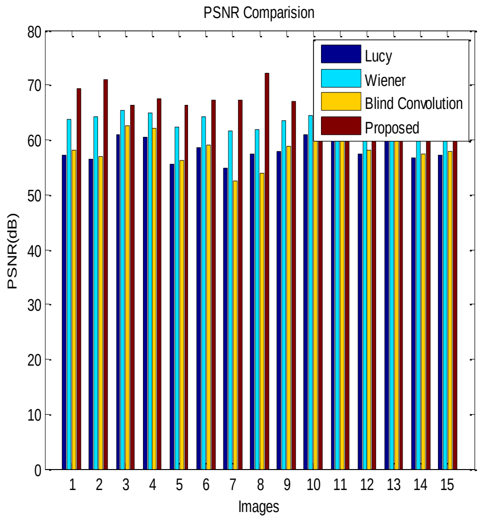
Image 5	Original Image 	Blurred Image 	Deblurred Image 
Image 6	Original Image 	Blurred Image 	Deblurred Image 
Image 7	Original Image 	Blurred Image 	Deblurred Image 
Image 8	Original Image 	Blurred Image 	Deblurred Image 

Figure 2 Observed Image Results Original Image,Blur image and Deblur Image

Table.1 Observed Numerical Evaluation for proposed approach

Image (Deblur)	**PSNR**	**MSE**	**Normalized Cross Correlation**	**Average Difference**	**Structural Content**	**Maximum Difference**	**Normalized Absolute Error**
Image 1	69.3535	0.0075	0.9380	0.0073	1.0660	0.8180	0.1830
Image 2	71.0277	0.0051	0.9824	0.0045	1.0101	0.7509	0.1065
Image 3	66.3296	0.0151	1.0295	0.0231	0.9329	0.6473	0.0845
Image 4	67.4241	0.0118	1.0992	0.0718	0.8028	0.3925	0.2006
Image 5	66.3706	0.0150	0.9909	0.0202	0.9762	0.7414	0.1598
Image 6	67.2055	0.0124	0.9230	0.0036	1.0812	0.9890	0.2154
Image 7	67.2723	0.0122	0.9612	0.0039	1.0521	0.9367	0.1068
Image 8	72.2680	0.0039	1.0142	0.0134	0.9547	0.5274	0.1028



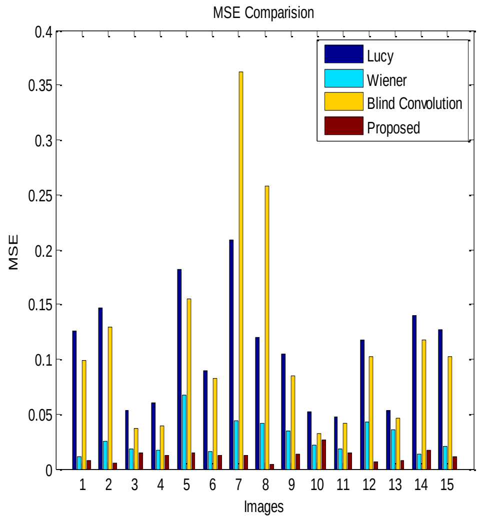


Figure 3. Comparative Analysis of the proposed approach with the other methods based on PSNR and MSE

Table.2 Comparative Analysis of various method with the proposed approach

Image	Parameter	Lucy	Weiner	Blind Deconvolution	Proposed Method(PSO)
Image 1	PSNR	57.1535	63.6523	58.2032	69.3535
	MSE	0.1252	0.0112	0.0983	0.0075
	NCC	0.4045	0.9922	0.3455	0.9380
	AD	0.3143	0.0460	0.2742	0.0073
	MD	0.9988	0.8439	1.000	0.8180
	NAE	0.5892	0.2241	0.6443	0.1830
Image 2	PSNR	56.4730	64.1889	57.0310	71.0277
	MSE	0.1465	0.0248	0.1288	0.0051
	NCC	0.3461	0.8934	0.3461	0.9824
	AD	0.2914	0.0324	0.2914	0.0045
	MD	0.8883	0.8164	0.8883	0.7509
	NAE	0.6499	0.3208	0.6499	0.1065
Image 3	PSNR	60.9155	65.4935	62.4734	66.3296
	MSE	0.0527	0.0184	0.0368	0.0151
	NCC	0.6175	0.8527	0.6474	1.0295
	AD	0.2067	0.0350	0.1886	0.0231
	MD	0.9107	0.6996	0.9107	0.6473
	NAE	0.3827	0.2232	0.3510	0.0845
Image4	PSNR	60.3701	64.9043	62.1712	67.4241
	MSE	0.0597	0.0166	0.0394	0.0118
	NCC	0.4915	0.9609	0.5803	1.0992
	AD	0.2079	0.0851	0.1643	0.0718
	MD	0.9974	0.4107	0.9974	0.3925
	NAE	0.4860	0.2496	0.3895	0.2006
Image 5	PSNR	60.3701	64.9043	62.1712	66.3706
	MSE	0.0597	0.0166	0.0394	0.0150
	NCC	0.3230	0.8266	0.3704	0.9909
	AD	0.3678	0.0355	0.3383	0.0202
	MD	0.9483	0.8770	0.9483	0.7414
	NAE	0.6718	0.2772	0.6185	0.1598
Image 6	PSNR	58.6370	64.1991	58.9589	67.2055
	MSE	0.0890	0.0156	0.0826	0.0124
	NCC	0.3687	0.9184	0.4021	0.9230
	AD	0.2419	0.0308	0.2244	0.0036
	MD	0.9988	0.9918	0.9988	0.9890
	NAE	0.6232	0.2680	0.5832	0.2154
Image 7	PSNR	54.9364	61.6640	52.5410	67.2723
	MSE	0.2087	0.0443	0.3622	0.0122
	NCC	0.2430	0.8352	0.1399	0.9612
	AD	0.3503	0.0384	0.3982	0.0039
	MD	0.9475	0.9994	0.9715	0.9367
	NAE	0.7550	0.4281	0.8581	0.1068
Image 8	PSNR	57.3531	61.9643	54.0220	72.2680
	MSE	0.1196	0.0414	0.2576	0.0039
	NCC	0.3310	0.8582	0.0037	1.0142
	AD	0.2526	0.0566	0.3769	0.0134
	MD	0.9528	0.6821	0.9716	0.5274
	NAE	0.6685	0.4616	0.9963	0.1028

VII CONCLUSION & FUTURE SCOPE

Advances in image deblurring and similar methods are vital both to the development of modern photography and to the restoration of images and videos that are not as sharp as they can be. In the proposed technique, an optimization method is developed to determine the optimal PSF through which a blurred image gets deblurred effectively. For this purpose the most popular artificial intelligence technique, particle swarm optimization algorithm is used and observed an effective result. To evaluate the performance of the proposed deblurring approach ,a numerical evaluation is carried out through Peak signal to noise ratio(PSNR) and Mean square error (MSE). The results demonstrate the values we calculated for PSNR and MSE is pretty good .A Comparative analysis is also carried out with other basic deblurring methods and the result evaluated is better than earlier methods of image deblurring. Additionally, we gained an understanding about some of the confinements that are present in image deblurring because of the shortcoming of credulous methods.
Through the simulation result it was observed that on an average the PSNR achieved is 68.781425 an MSE is 0.010375.

In the future, the other research directions can be focused. In the proposed method optimization method is only developed by incorporating particle swarm optimization. Incorporation of PSO with other intelligence methods such as fuzzy system, genetic programming and neural networks can be studied in order to further improve the searching effectiveness.

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