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Estimation of Motion Blur Based on Combination of PSO and GA

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Abstract: In Digital Image processing image restoration is the process of reconstructing or deblurring an image which has been affected of various unwanted factors or noise. In this paper, we propose a method for image deblurring technique based on combination of PSO and GA. The main drawbacks in a digital image is the presence of noise and degradation during the camera shake by human error, long exposure time, the movement of an object, and not focus the target. Image restoration is very important and necessary in digital image process avoiding the blur and get original Image. We derive a blurring function, namely point spread function (PSF) which deblur the captured image by reversing the motion effect. It aims to incorporate the advantages of the two methods, where the PSO is effective in localizing the global region, is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality and the Genetic algorithm is effective in converging optimization and search problems. Image restoration is a technique which is used to make picture sharp and useful by using mathematical models of different Algorithms.

Keywords: Image deblur, blur, PSF, degradation model, motion blur, blind deconvalution.

I. INTRODUCTION

Digital image processing is the technology of applying a number of mathematical algorithms to process digital image. The result of this process can be either images or properties of the original; image. Digital image is an important research area. Digital image processing consists of denoising, image restoration, image enhancement, image segmentation, image compression, object detection, etc. the application of digital image processing is in robotics system, medical image system, remote sensing, photography and forensics [1]. An image may be defined as a two-dimensional function f (x, y), where x & y are spatial coordinates, & the amplitude off at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y & the amplitude values of 'f' are all finite discrete quantities, we call the image a digital image. The field of DIP refers to processing digital image by means of digital computer. The digital image is composed of a finite number of elements, each of which has a particular location & value. The elements are called pixels [2].

Vision is the most advanced of our sensor, so it is not surprising that image plays the single most important role in human perception. However, unlike humans, who are limited to the visual band of the EM spectrum imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can also operate on images generated by sources that humans are not accustomed to associating with image. There is no general agreement among authors regarding where image processing stops & other related areas such as image analysis& computer vision start. Sometimes a distinction is made by defining image processing as a discipline in which both the input & output of a process are images. This is limiting & somewhat artificial boundary. The area of image analysis (image understanding) is in between, image processing & computer vision.

Imaging devices are used for a wide variety of application from machine vision, astronomy, 3D microscopy, medical imaging, etc. A typical machine vision task is the inspection of a manufactured product for quality. An example machine vision application is inspection of a manufacturing product for better quality and better result, in this system rejected pencils that do not have erasers properly attached to the end. This is done in the production line itself so as to avoid error propagating from one stage of production to the other. The imaging device used in machine vision application suffers from blurring smooth the edges and hence some information is lost due to degradations.

In such case image deblurring algorithm have to be used to process the images before performing a machine vision task. Microscopes are used to magnify and view or record image of very small objects. In fluorescence microscopy, different part of cell, e.g. cell nucleus are stained width a day that is illuminated by specific wavelengths of light. Several images of the illuminated set of point are taken by moving the specimen along the axis perpendicular to the imaging device. In medical imaging analysis deblurring may be used to enhance the quality of the image to assist

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the physician. In this thesis transformation spread function (TSF) is used to effectively model the blur caused by camera motion [3].

II. METHODOLOGY

A. Implementation of Images

Ideally, when an image is generated from a physical process, its values are proportional to energy radiated by a physical source. And hence, the resultant image, i(x, y), is nonzero and finite [4].

$$I(x; y) \in Z \qquad (1)$$

Where Z is a finite set of integers, and x, y denote spatial coordinates. Hence, an image is interpreted as a two-dimensional light intensity function, i(x; y), and the value of i, at any point (x; y) is proportional to the brightness (or grey level) of the image at that point. A digital image can be considered as a matrix whose row and column Indices represent point in the image and the corresponding matrix element known as picture element, pixels value identifies the grey level at that point [5]. The digital image processing takes as input an image always but the output can be an image or some relevant information retrieved after applying some function on the given input image.

B. Image Formulation

The image is characterized by two major components: illumination and reflectance components. But, practically apart from these two components, the image formation also depends on the characteristics of the object being captured, environmental conditions during capture, and the imaging system being used. These other components produce an ill-effect during image acquisition to produce a degraded image, c. The process of reconstructing the original scene from a degraded version is the goal of image restoration. The ill-effect causing functions, df is known as the blur. The additive noise effect is also considered as another cause of degradation. Thus, the image degradation model is,

$$c = dfi + \eta \qquad (2)$$

Given c, some knowledge about the degradation function df, and some knowledge about the additive noise term η, the objective of restoration is to obtain an estimate i of the original image. This estimate, i, should be as close as possible to the original input image. In general, the more knowledge we have about df and η, the closer i will be to i. Figure 1 shows the image degradation and restoration process.

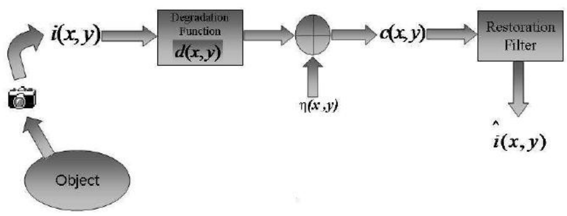

Fig.1 Image Degradation and Restoration Process

C. Estimation of Point Spread Function (PSF)

The point spread function (PSF) describes the response of an imaging system to a point source or point object. A more general term for the PSF is a system's impulse response, the PSF being the impulse response of a focused optical system. The PSF in many contexts can be thought of as the extended blob in an image that represents an unresolved object. In functional terms it is the spatial domain version of the transfer function of the imaging system. It is a useful concept in Fourier optics, astronomical imaging, electron microscopy and other imaging techniques such as 3D microscopy (like in confocal laser scanning microscopy) and fluorescence microscopy. The degree of spreading (blurring) of the point object is a measure for the quality of an imaging system. In non-coherent imaging systems such as fluorescent microscopes, telescopes or optical microscopes, the image formation process is linear in power and described by linear system theory [6]. This means that when two objects A and B are imaged simultaneously, the result is equal to the sum of the independently imaged objects. In other words: the imaging of A is unaffected by the imaging of B and vice versa, owing to the non-interacting property of photons. The image of a complex object can then be seen as a convolution of the true object and the PSF. However, when the detected light is coherent, image formation is linear in the complex field. Recording the intensity image then can lead to cancellations or other nonlinear effects.
If the imaging system is linear, the image of an object can be expressed as:

$$g(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x, y; \alpha, \beta) f(\alpha, \beta) d\alpha d\beta + \eta(x, y) \qquad (3)$$

Where η(x, y) is the additive noise function, f (α, β) is the object, g(x, y) is the image, and h(x, y; α, β) is the Point Spread Function (PSF). The “;” is used to distinguish the input and output pairs of coordinates in this case.

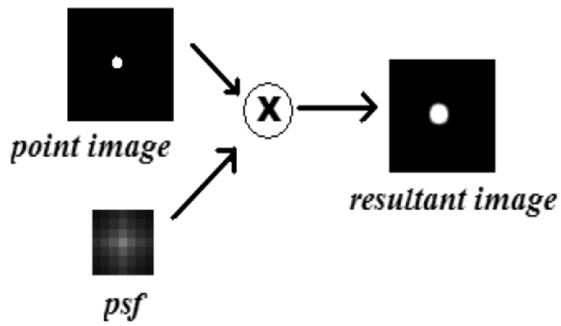

Figure 2 Image formations with PSF

D. Estimation of Transformation Spread Function (TSF)

The blur caused by camera motion is limited by six degrees of freedom of a rigid body motion, most commonly decomposed to three rotations and three translations [7]. A camera has 6 degrees of freedom viz. 3 translation (t_x , t_y, t_z) and 3 rotation (θ_y , θ_x, θ_z). For hand-held cameras, variation t_z is treated as negligible. t_x , t_y and

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θ_z are 3D transformation space [8]. The final blurred intensity image in terms of the TSF can expressed as

$$Z = f\left(\sum_{K=1}^{N_H} h_T\,(\Gamma_k)\Gamma_K(E)\Delta t\right) \quad (4)$$

Where the value of $h_T(\Gamma)$ denotes the fraction of the total exposure for which the camera was stationary in the position that caused the transformation. We can write Z = f (KEΔt) where K is a large sparse matrix with the non-zero elements derived from TSF coefficients and bilinear weights. Δt denotes exposure time and E is irradiance of image.

The local PSFs of a blurred image can be related to the TSF as

$$h(i, j; m, n) = \sum_{k=1}^{N_H} h_T(\Gamma)\delta_d(m-(i_\Gamma - i), n-(j_\Gamma - j)) \quad (5)$$

Where (i_Γ, j_Γ) denotes the position when transformation Γ^{-1} is applied on (i, j), h is the PSF at (i, j),and δd denotes the 2D kronecker delta function. If N_p such PSFs are known, each PSFs can be related to the TSF as h**p**l=$M_l h_T$, where l=1…….N_p. M_l is matrix whose entries are determined by location **p**l of the blur kernel and interpolation coefficients [9]. The cost function to derive the TSF which is consistent with the observed blur kernels is given by

$$\text{argmin}h_T||h - Mh_T||_2 + \lambda_s||h_T||_1 \quad (6)$$

E. Optimization using PSO

Optimizing PSO is difficult due to the huge number of possible poses of the camera in the pose space, and the problem is converted to searching the optimized weighted parameters in a high dimensional space. In this paper, we propose to use the PSO algorithm to solve this issue [10].

x^i_k-Particle position
u^i_k- Particle velocity
p^i_k- Best "remembered" individual particle position
p^g_k- Best "remembered" swarm position
c_1, c_2- Cognitive and social parameters
r_1, r_2- Random numbers between 0 and 1

Position of individual particles updated as follows:

$$x^i_k+1 = x^i_k + u^i_{k+1} \quad (7)$$

With the velocity calculated as follows:

$$u^i_{k+1} = u^i_k + c_1\, r_1(p^i_k - x^i_k) + c_2\, r_2\,(p^g_k - x^i_k) \quad (8)$$

F. Optimization using GA

In this work, a GA technique was used due to its generality and capability to heuristically overcome situations where an exhaustive solution would be too computationally demanding. Its goal was to identify the correct image among those whose properties are stored in the database, as well as its initial and final positions. The correct solution should be able to recreate the blurred image as it was captured [11].

i. Population:

The image species was identified by an integer index which referred to its position in the database, in which the image was recorded by increasing size. Nearby indexes pointed to image of similar size, albeit not necessarily similar shape. Two parameters consisted of the coordinates of the displacement vector Δx, Δy of the centroid measured in pixels, while the last indicated the total angle of rotation Δθ around the centroid of the image [12].

ii. Cross-over:

The cross-over is performed on randomly selected couples by performing a linear combination of the corresponding components:

$$\{P_{a,}P_b\} \rightarrow P_{new} = \alpha.P_a + (1 - \alpha\,.P_b) \quad (9)$$

The components of the random parameter vector α were selected as $\alpha_i \in [-0.5, 1.5]$ in order to access parts of the population space not lying in between the two parent vectors. The first component of P new was rounded to the nearest integer index among those accepted as possible candidates. The diversification arising from this cross-over procedure does not guarantee that new individuals inherit or improve the fitness value of their parents. For this reason the best two or more individuals of a population are transmitted to the new generation without changes, in a process known as elitism.

iii. Mutation:

The mutation is coded as a vector of random changes ΔP in all components of the offspring individuals:

$$P_{new} \rightarrow P_{new} + \Delta P \quad (10)$$

The first component of ΔP is chosen out of the set [−1, 0, 1] , while the others are limited to a predefined maximum equal to 10% of the largest value of all corresponding components. This mutation is applied to all new individuals in order to explore the vicinity of groups of similar individuals rather than explore different and faraway image motions.

iv. Fitness:

The fitness of an individual had to be related to the effectiveness in reproducing the geometrical features of the blurred image of the object. For each individual, the binarized image of the relevant image was obtained from the database and treated as the initial position. According to the translation and rotation values, the final and three intermediate positions were calculated and the resulting images were superposed to the initial one.

G. Hybrid PSO with GA

The main limitation of PSO is that the swarm may prematurely converge. The major fact of this problem is that, for the global best PSO, particles converge to a single point, which is on the line between the global best and the personal best positions. This point is not able to locate a local optimum [13].

Another reason for this problem is the fastest rate of information change between particles. There for result in

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the creation of similar particles with a loss in diversity that increases the possibility of being trapped in local optima and reach best values.

Increasing the inertia weight (w) will raise the speed of the particles resulting in more exploration (global search) and less exploitation (local search) or on the other hand, reducing the inertia weight will decrease the speed of the particles resulting in more exploitation and less exploration. So tack decision the best value for the parameter is not a simple task and it may differ from one problem to another. Therefore, from the above, it can be concluded that the PSO performance is problematic-dependent. The problem-dependent performance can be optimized through hybrid mechanism. It combines different approaches to be a better solution from the advantages of each approach. To reduce the drawback of PSO, hybrid algorithms with GA is proposed.

The main aim of this hybrid approach is expected to have the merits of PSO with those of GA. The main advantage of PSO over GA is its algorithmic simplicity. Another useful difference between PSO and GA is the ability to control convergence. Crossover and mutation rates can deftly affect the convergence of the GA, but this doesn't be analogous to the level of control achieved through manipulating of the inertia weight.

In fact, the decrease of the inertia weight dramatically increases the swarm's convergence. The main problem with PSO is that it prematurely converges to stable point, which is not necessarily maximized. To prevent the occurrence, position update of the global best particles is changed and reduced limitation. The position update is done through some hybrid mechanism of GA.

There are three different hybrid approaches are proposed

i. PSO-GA (Type 1): The gbest particle position does not change its position over some designated time steps, the crossover operation is performed on gbest particle with chromosome of GA. In this model both PSO and GA run in parallel.

ii. PSO-GA (Type 2): The stagnated pbest particles are changing their positions by the mutation operator of GA.

iii. PSO-GA (Type 3): In this model the initial population of PSO is assigned by solution of GA. The total numbers of iterations are equally shared by GA and PSO. First half of the iterations are run by GA and the solutions are given as initial population of PSO. Remaining iterations are run by PSO.

III. RESULT

The simulation of proposed work is done in MATLAB. To evaluate the performance of different deblurring techniques, synthetic and both images are used. Real images have been captured using Digital camera in this paper used synthetic image.

The hybridization of PSO and GA is applied to image to evaluate the performance of the algorithm. Figure 4 shows different push button having a different option like as Generate blur, Optimize PSF, PSO & GS, PSO & GA, and Result button show different Image quality parameters. Figure 5 show Motion Blur with 0.75, 0.85, 0.95, and 1.0 Second.

Fig.3 Original Image

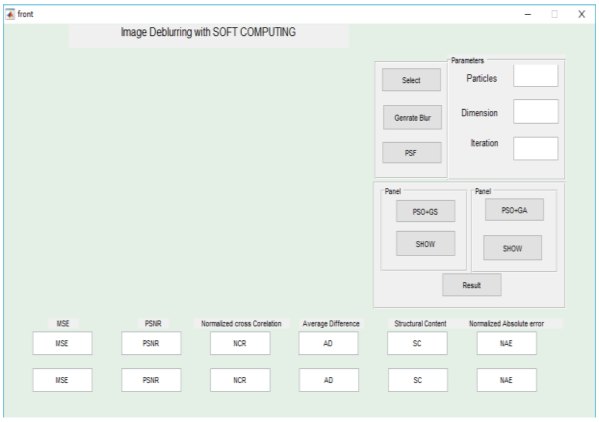

Fig. 4 Workspace of our program

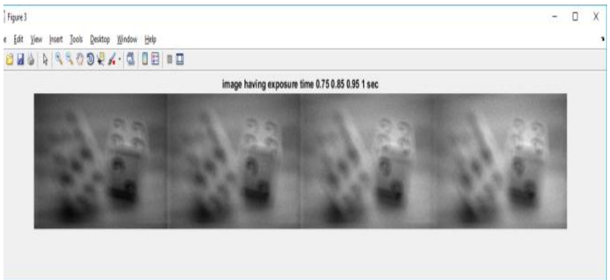

Fig.5 Image Having Motion Blur with Different Exposer Time

i. Image Deblurring using Iteration value 5:

The Image reconstruction algorithm is applied the original Image after generate blur and applied different Iteration value here applied Iteration value 5.

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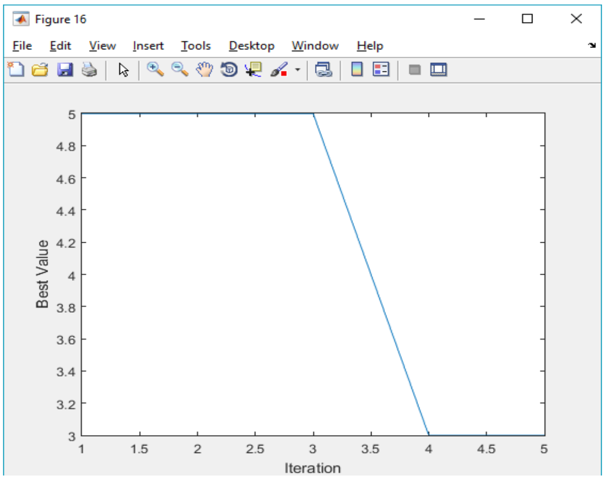

Fig. 6 PSF Graph between Best value and Iteration for PSO and GA

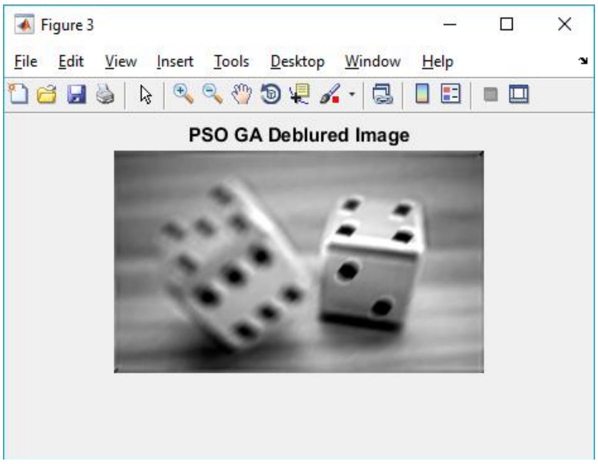

Fig.7 Deblured Image using PSO and GA

ii. Image Deblurring using Iteration value 10:
The Image reconstruction algorithm is applied the original Image after generate blur and applied different Iteration value here applied Iteration value 10.

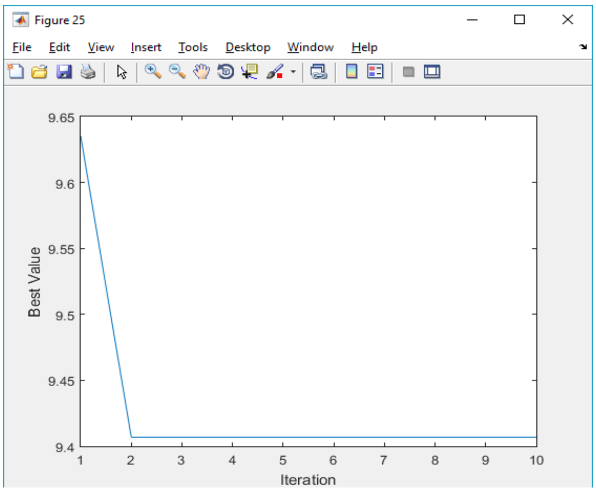

Fig. 8 PSF Graph between Best value and Iteration for PSO and GA

Fig. 9 Deblured Image using PSO and GA

iii. Image Deblurring using Iteration value 30:
The Image reconstruction algorithm is applied the original Image after generate blur and applied different Iteration value here applied Iteration value 30.

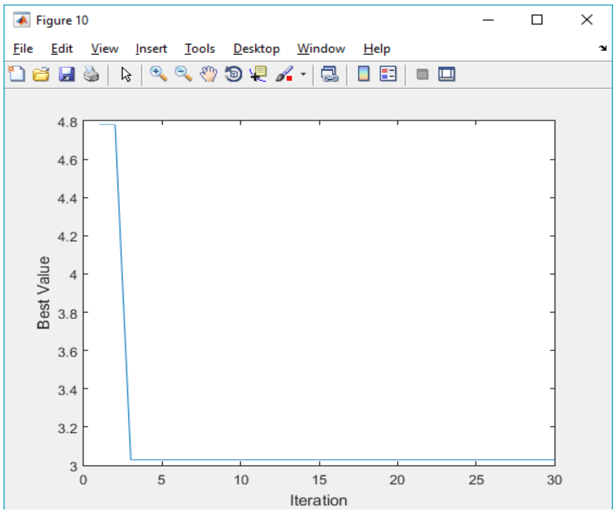

Fig. 10 PSF Graph between Best value and Iteration for PSO and GA

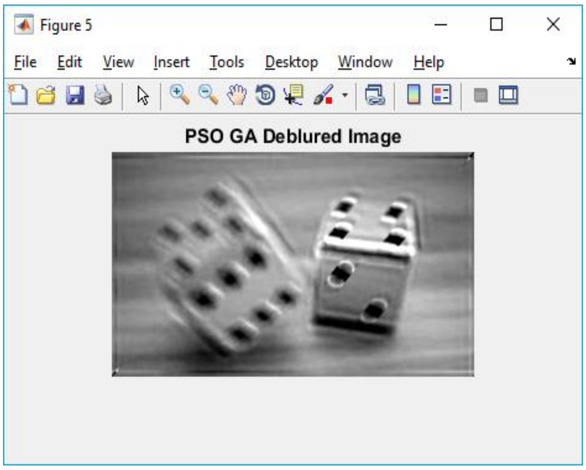

Fig. 11 Deblured Image using PSO and GA

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TABLE 1 NUMERICAL VALUES OF DIFFERENT QUALITY MEASURE PARAMETER USING PSO AND GA

Parameters	Iteration value 5	Iteration value 10	Iteration value 30
MSE	0.0011904	0.0054414	0.025044
PSNR	77.3738	70.7737	74.1437
Normalised cross correlation	0.98416	0.90874	0.9448
Average Difference	0.022901	0.059357	0.038619
Structural Content	0.97185	0.83363	0.89704
Normalized Absolute error	0.040356	0.1046	0.068054

TABLE 2 NUMERICAL VALUES OF DIFFERENT QUALITY MEASURE PARAMETER USING PSO AND GS

Parameters	Iteration value 5	Iteration value 10	Iteration value 30
MSE	0.032363	0.064566	0.13857
PSNR	63.0304	60.0308	56.7142
Normalised cross correlation	0.69322	0.56553	0.36144
Average Difference	0.17568	0.24813	0.36351
Structural Content	0.1825	0.3227	0.13418
Normalized Absolute error	0.30957	0.43726	0.64058

Comparison of deblurring methods and the comparison of quality measurement parameter are done with the help of a bar graph

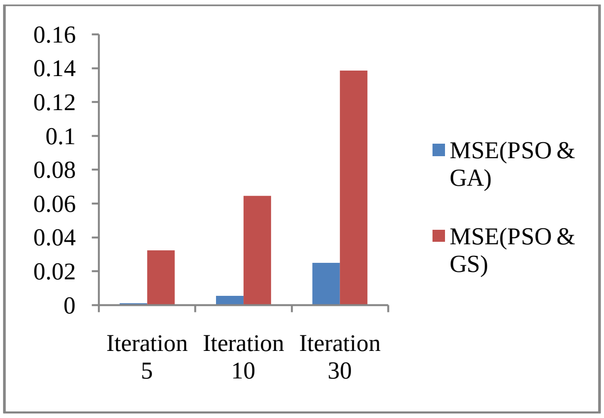

Fig. 12 Comparison of MSE for Deblurr Image

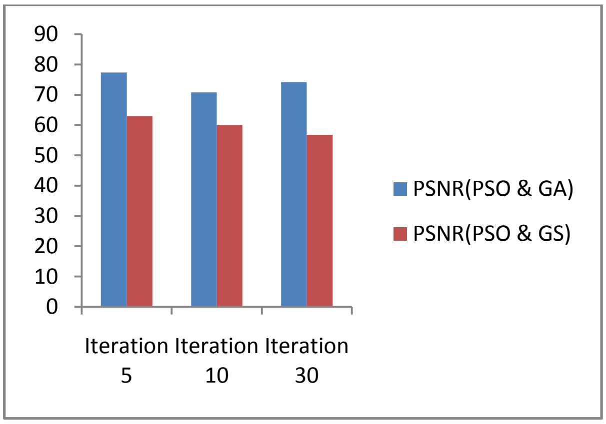

Fig. 13 Comparison of PSNR for Deblurr Image

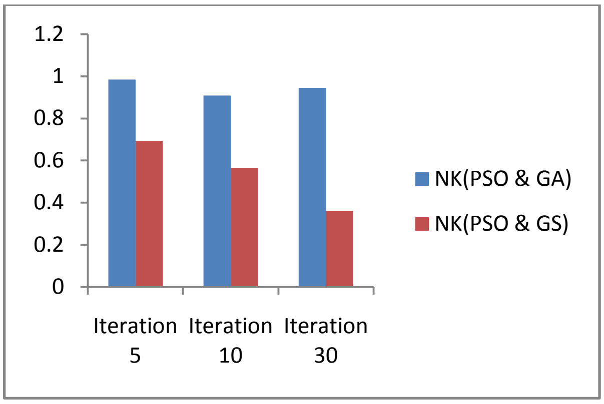

Fig. 14 Comparison of NK for Deblurr Image

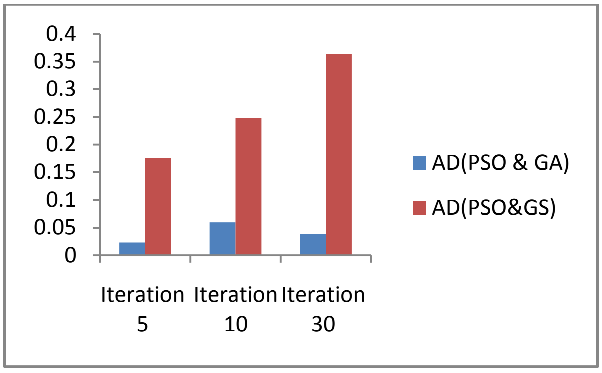

Fig. 15 Comparison of AD for Deblurr Image

IV. CONCLUSION

This thesis has presented a simple and practical method for deblurring and Image reconstruction. It is clear from visual interpretation of results that the technique is best among all the discussion method. In the conclusion of Winner filter method output, as the SNR value increased, the quality of image is also degraded. In Lucy-Richardson method, the output is better as compared to Winner filter. But as the iteration number is increased then ringing artifacts is introduced in output image. The TSF is estimated by locally estimated PSF. In estimation of PSF, show the camera motion. Hybridization of two method

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PSO and GS is better performance of these methods. Our method PSO and GA is better performance than PSO and GS.

Quality measurement parameter has been calculated for all method which is discussed in this thesis. The quality measurement parameter is displayed in the tabular from for comparison purpose for both synthetic and real images. The PSO and GA method is giving higher value for PSNR as compared to PSO and GS.

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