Improvement in PSF Estimation Accuracy in Blind Image Restoration using PSO

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Abstract: An image can convey lots of information about the picture quality. Picture quality is the most notable and distinctive feature of the image providing an information in the specified area. An image can also be identified by its pixel range, shape, of an image but level information retrieval is very high in case of the restoration. Image restoration is a key aspect related to image processing generally categorized as verification and identification or (recognition). Motion blur, out of focus, camera shake are some common distractions to human appearance becoming the pitfall for the image restoration system. For the realization of image restoration systems, one of the well-known feature extraction methods is Blur Stein's Unbiased Risk Estimation (SURE). This method is based on Point Spread Function (PSF) estimation. This method is a filtered version to calculate the PSF from the degraded image. Blur SURE method is usually envisaged as wiener filtering process. It minimized the blur MSE and then applies blur-SURE estimation over blur MSE. To enhance result for point spread function here particle swarm optimization technique is used. For the estimation of the PSF, particle positions are calculated by the PSO. Parametric form of the gaussian kernel is used for the estimation of function. When these parameters are calculated then PSF estimation is done. SURE LET deconvolution is used for the whole process with particle swarm optimization is done for deconvolution process of blind and non blind.
Keywords- Image restoration, Blind Image, Deconvolution, PSF, PSO

Introduction

1.1 Image Restoration

An image can convey lots of information about the picture quality. Picture quality is the most notable and distinctive feature of the image providing an information in the specified area. An image can also be identified by its pixel range, shape of an image, but level information retrieval is very high in case of the restoration. Image restoration is a key aspect related to image processing generally categorized as verification and identification or (recognition). Image restoration can be realized as verification of an image from his deconvolution features that can be accomplished by the application of various computational algorithms. Image restoration system is one of the most cost effective methods for the use of computing resources in comparison to the verification and identification. Motion blur, out of focus, camera shake are some common distractions of image appearance becoming the pitfall for the image restoration system.

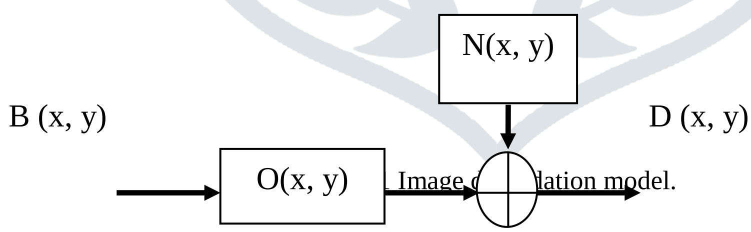

Image degradation model.

The model of image degradation is described as in figure. Original image is represented as B(x,y) in given model, The real image could seen as blurred image due to motion by the help of the image degradation system which is represented in the degradation system as function is O(x, y), this function O(x,y) is also called as point spread function of the degradation system. The original image or blurred image B(x,y) and the point spread function O(x,y) are convolved with each other and the effective outcome is further influenced from N(x, y), after the convolution original image and blurred function over the influence of the noise the degradation system gives the output as degraded image in the form of D(x,y). This function can formed as blurred image. This procedure is formulated as [1].

$$D(x,y) = O(x,y) * B(x,y) + N(x,y) \tag{1}$$

1.2 Point Spread Function

Image processing has many real applications in which point spread function (PSF) cannot be obtained more accurately and easily. So the process of the blind and non blind deconvolution occurs in the process. In the blind deconvolution the process of the estimation of the original image and the point spread function occurs simultaneously. But in the case of the non blind deconvolution first of all estimate the Point Spread Function and then process the estimated image with non blind deconvolution to restore the original image [5].

In the computer vision and image processing the most considerable problem is blur kernal estimation and blind image deconvolution. There is very ill-possed problem of the recovering of the point spread function from a single blurred image because of the reason that there is loss of the information during blurring. This problem can be processed by the bayesian framework [3]. When an image is captured from camera, the blur image comes in effect from different steps of camera. In an image vague impression is objectionable, then it may be removed from the image by using the deconvolution method [1].

In image processing the reconstruction of the original image from the degraded image is the main aim of the image restoration. In real application of the image, the problem of the image restoration is forever blind, that shows blur function of the blurred image is always blind in the restoration process but it is identified only in bunch of parameters. Generally the main image restoration, with the known point spread function and given parameters the blur function can be assumed which give the results whose does not match with the main imaging model of the some devices which reduce restoration execution. So to overcome this problem blind image super resolution process comes in effect and estimating the high resolution image and blur function at the same time. The main problem arises in the blind de-blurring is that it gives the incomplete convolution result. Cut off frequency destroyed the relationship between the convolution and boundaries and make the process more complicated to recognize the blur function of the image [4].

With the known PSFs the image is processed with the method of improving sharpen version of the blurred image. Blurring process is generally the process of the convolution of the point spread function with the original image and the process of the deblurring the image is called the inverse of the convolution which is known as deconvolution. Direct inverse filtering is the simplest method of the image deconvolution in frequency domain. From the inverse filtering the frequency response of the vagued image is calculated by splitting the image element wise by that of the point spread function [6].

The deblurring of image is essential for users of remote sensing which is done by using image restoration method. In the former methods of the image deblurring, the point spread function is recognized proceeding to the restoration, but in the past research PSF is estimated in the frequency domain by using the image according to phase information. The estimation function in remote sensing images can be characterized by using the unique parameters (point sources, edges, etc.) of the uncleared image, for this knife edge method, tarp-based target method, pulse method are commonly used methods [7].

The process of blind deconvolution of an image using image restoration can be processed into many major steps. These are PSF estimation by PSO, variation bayesing, Up sampling and image restoration which is represented in fig. 3.1. The first step for the restoration model is PSF estimation, which takes image as input and detects the main image. Deblurred image detection is followed by full resolution estimation in which unique and most informative properties of blind deconvolution are extracted from blurred image. Using these feature images is further processed with the variation bayesing, up sampling, which is done in loop over scale to estimate the full resolution of the image. The stopping criteria are providing for the whole process to extract the best result in the Deblurred image.

For the realization of the image restoration systems various methods are used. The very first step in this research is concentrated on PSF estimation of the image with blind deconvolution. These methods are insensitive to illumination. But most of the methods are not enough for image restoration. To remove drawbacks of the PSF estimation based restoration, a blind deconvolution with PSO techniques came into the picture, which provides better results as compared to the blind deconvolution with PSF estimation of an image.

Various holistic point spread function estimation techniques have been developed, which do not compare in high frequency pixels directly. Partical Swarm Optimization (PSO), Variational Bayesing, Up Sampling methods have been developed which gave the better performance and reduced the blurness of the image. The Point Spread Function is used in blur sure method to reduce the blur. Many types of blurness occurred by the factors like camera shake, motion blur, and defocus, gaussian blur etc. are used in most of the image based restoration methods. To improve the performance and robustness of the blurred image wiener filter deconvolution is used. This method was named as sure let deconvolution method. Point Spread Function estimation is also done by using variational bayesian frame work with different techniques. To obtain this method MAP technique is used to find out the position and direction of edges in blurred image, use sub-pixel value for the blind estimation to predict the sharp edge image. Later on various techniques were proposed in this series among them Partial Spread Function can be found commonly.
The discussed methods fail in blind deconvolution where variation in illumination is present. Thus, the deconvolution analysis community has proposed various deconvolution based descriptor methods. Among them some general methods such as Partical Swarm Optimization (PSO), Variational Bayesing, Up Sampling, are used in image restoration.

2. Design Methodology

1. Selection of the blurred image.
2. Selection of the high frequency patch and initial blur size.
3. Apply PSF estimation by PSO technique in single patch region.
4. Estimation of PSF is solved for the entire region of the image by variational Bayesing technique and applies the stopping criteria.
5. Restore the image with blind deconvolution techniques.
6. Design simulation.
7. Comparison is made in terms of PSNR and restoration rate of the blurred image.

3. Implementation Strategy

The proposed blind image deconvolution system is shown in fig.3.1. The main steps involved in blind deconvolution are selection of high frequency patch with initial blur size of the image followed by the PSF estimation with PSO. These processes are performed on variation Bayesing as well as up sampling with loop over scale method. Explanation of the diagram is presented in steps as follows:

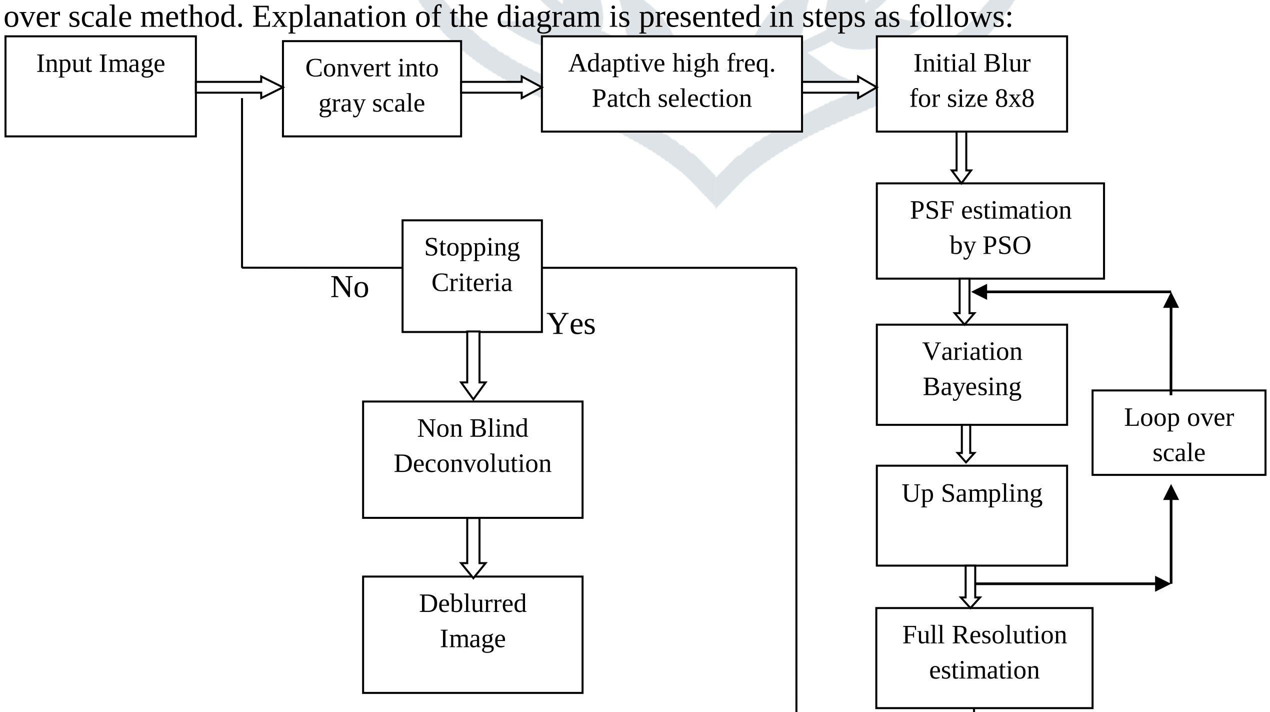

Fig. 3.1: Flow chart of proposed image restoration system.

1. Input the image and read it with grey scale conversion.
2. Apply one of the methods to select the high frequency patch.
3. Apply one of the texture based size extraction method on the initial blurred image.
4. Successively PSO estimation is used for initial blurred image to optimize the restoration factor.
5. Estimate the full resolution by the variational Bayesian of the initial blurred image by above techniques.
6. Finally the stopping criteria are used for non blind deconvolution for extracting the Deblurred image.

4. PSF Estimation Simulations

4.1 Point Spread Function Estimation

Deconvolution of an image is an important task for inverse problem of many decades in image processing systems. In many applications of the image processing like in medical imaging, microscopy imaging, satellite imaging, remote sensing and most popular imaging is photography, in these applications PSF cannot be estimated so easily. Because it depends upon some parameters which can be identified firstly and then estimation is done in the image processing. These parameters are some time known and some time it is partially known; like in blind image deconvolution process point spread function is unknown for image deconvolution. To overcome this identified problem for estimation of the PSF and original image only technique is used as blind deconvolution [8]. Further for the enhancement of the result which cannot be achieved by the traditional method, the function consists of regularity condition by Bayesian prior technique for point spread function and original image and calculate the results for accurate estimation. The specific techniques for prior techniques are observed in many decades. Image deconvolution and PSF estimation both are calculated simultaneously by other methods also which can be described in many techniques [9].

Restoration of the image can be done by many other methods where PSF and degraded image are calculated separately. In this process estimation of point spread function is done and then non blind deconvolution is used, for the restoration of the image. From the calculation it is found that estimation of parameters separately are more helpful instead of when they are estimated in combined way. This can happen with the non blind deconvolution and high class algorithm when PSF is estimated [10]. It is very important that point spread function estimation is accurate for deconvolution process and the failure is shown by the estimation of kernel and results. The estimation of parameters for PSF is obtained in blind deconvolution by two processes. One of them is by non parametric form and another by parametric form. These two forms of the estimation depend upon various techniques of image deconvolution.

4.1.1 Non Parametric Form

When deconvolution process is done, at that time discrete pixel values are obtained by the PSF, in the absence of parametric form of function. The function is estimated at that time by the bayesian and regularization techniques which depend upon point spread function theory. Blur kernel can be estimated by different techniques which can includes the different process:

- Tikhonov ℓ^2-Normalization: this technique can estimate the gaussian blur for PSF technique.
- Out of focus and motion blur can be estimated by the total variation technique.
- Sparsity technique can estimate the blur kernels of the motion blur and camera shake images [11, 12].

4.1.2 Parametric Form

In many applications parametric form of PSF estimation is calculated by theoretical or practical form. When point spread function is calculated in small parameters then degree of freedom is reduced. In parametric form PSF estimation used the linear motion blur for blur orientation and cepstrum is used for calculation of blur length, this can also be defined by another method of radon transformation and steerable filter method [13]. Size of the blur is estimated by gaussian kernel defined by the gaussian variance. Fast fourier transformation is used for decreasing the gaussian kernel by fixing gaussian blur in the blurred image. We can also define many edge based estimation method with the help of gaussian technique.

Estimation of point spread function is done in parametric form by obtaining it with optimization process with the help of the Bayesian or regularization methods. In standard techniques gaussian function for blur estimation use the total variation technique with the help of the Lucy Richardson technique. The generalized cross validation is also used for PSF estimation. But unfortunately auto regressive method makes it very complicated and raises its computational cost very high. GCV performs on many local minima and gives the performance of global minima with the assurance of validation. Point spread function is estimated over the linear approach with gaussian noise performance.

4.1.3 SURE Based Approach

Steins unbiased risk estimation is used to solve the linear inverse problem for non Bayesian technique which use the gaussian noise for blur the image. Image restoration used this technique for calculating the MSE to denoising the original image and also used for image deconvolution for non blind image restoration. This technique needs not any prior information of the original image for the restoration process. SURE based technique is used for the estimation of parameters of blind point spread function. Scaling factor is used to control the blur size of PSF in this approach and also estimate degraded image factor. When point spread function estimated and its factors are also estimated then this technique further used for the non blind deconvolution process [5].

4.2 Estimation of Blur MSE

4.2.1 Estimation of parameter H

Parameter h of the Point Spread Function is calculated by degradation model. This model function y is the estimated data of original image X, real image denoted by matrix h_0 by linear distortion. Vector n define as the noise with covariance matrix. For the parameter estimation processing function F is applied to the calculated data y. Original image X is define for the estimation parameter to assume the MSE. This can be further explained in following formulas:

$$y = h_0 X + n \tag{2}$$

$$\mathrm{MSE} = \frac{1}{M} \epsilon_a \{ \| F(y) - X \|^2 \} \tag{3}$$

$$\text{Blur MSE} = \frac{1}{M} \epsilon_a \{ \| hF(y) - h_0 X \|^2 \} \tag{4}$$

This blur estimation is defined as the mean square error estimation due to reason that it calculates two blur functions. After the calculation of this blur function further we calculate the parameter of point spread function.

$$\mathrm{Min}\, h \frac{1}{M} \| hF_h(y) - h_0 X \|^2 \tag{5}$$

From the above equation it is found that function h in F_h is totally depends upon the processing function F. Further this function is used for matrix h in non blind deconvolution process [16].

4.2.2 MSE Minimization

Blur mean square minimization is estimated by wiener filtering. From the degradation model equation shown in (2) defines the point spread function matrix by h, this function is then minimized by the wiener filter with the help of ideal linear function W_h of the equation (3);

$$W_h = Ah^t(hAh^t + B)^{-1} \tag{6}$$

Mean Square Error cannot be used for estimation of frequency response for the wiener filter, due to the reason because in this process phase variation cannot be linked with amplitude variation, so due to this here we use only zero phase value. This zero value of phase is considered because many real applications of the image may not have phase value so they assumed as zero [14].

4.3 Estimation Of PSF By Blur SURE

4.3.1 MSE Estimation for Blur

In image deconvolution process blur mean square error may not be estimated directly because parameter h_0X is not defined for the estimation. This can be overcome with the help of the process that blur MSE is replaced with blur SURE estimation which depends upon the degradation model; this can be effective in nature due to reason that in this process only calculated data Y is measured. For calculations of blur SURE consider equation as follow:

$$\epsilon = \frac{1}{M}\|hW_h y - y\|^2 + \frac{2\sigma^2}{M} t_r(hW_h) - \sigma^2 \tag{7}$$

When above equation is used for the estimation of the blur SURE based mean square error then it is found that blur steins unbiased risk estimation almost same as in blur MSE, this may comes in effect due to reason that in this process pixel values increased after the processing. From the above equation it is found that noise variance calculation is must for the estimation of the blur. This noise variance depends upon the blur size. To calculate the blur size first of all noise variance is calculated [2].

4.3.2 Exact Wiener Filter

Power spectral densities are not defined in the PSF estimation so wiener filter cannot used practically in the blur SURE. For the calculation of the above function it is replaced with parameter $£\|\beta\|^2$, where estimated parameter is defined as β. Now for exact wiener filtering the approximated blur steins unbiased risk estimation is calculated as:

$$W_{h,£}(\beta) = \frac{h^*(\beta)}{|h(\beta)|^2 + £\|\beta\|^2} \tag{8}$$

PSF estimation is done by minimizing the blur SURE by given equation:

$$\underbrace{\min}_{h,£} \underbrace{\frac{1}{M}\left\|hW_{h,£}y - y\right\|^2 + \frac{2\sigma^2}{M} t_r\left(hW_{h,£}\right) - \sigma^2}_{\text{blur SURE: } \epsilon(h,£)} \tag{9}$$

Minimization of the blur MSE with the help of blur steins unbiased risk estimation can follow the following steps.

1. Estimation of parameter h and £.
2. Calculation of the parameter $W_{h,£}$ by wiener filtering process.
3. Estimate the blur SURE minimization.
4. At the end of the process with the help of the estimated parameter h calculate the non blind deconvolution.

4.4 PSF Estimation Types

4.4.1 Estimation with Blur SURE

From the estimation of the PSF it is found that parameter h is equivalent to parameter h_s which can define as the unknown parameter $S = [s_a, s_b, \ldots\ldots s_p]$. The ground truth value is represented by the parameter s_0. Equation (9) further can be explained as:

$$\underbrace{\min}_{s,£} \underbrace{\frac{1}{M}\left\|h_s W_{s,£} y - y\right\|^2 + \frac{2\sigma^2}{M} t_r\left(h_s W_{s,£}\right) - \sigma^2}_{\text{blur SURE: } \epsilon(s,£)} \tag{10}$$

With due effect of £ PSF estimation is minimized for both h and £ by blur SURE [15].

4.4.2 Parametric Point Spread Function Estimation

4.4.2.1 Gaussian Kernel

For the calculation of the gaussian kernel a parametric equation is define in (11). In this equation parameters l and m defines the coordinates in two dimensions. Here N is defined as the normalization parameter. In this equation parameter s is defined as unknown parameter and it could be estimated.

$$h_s(l, m; s) = N \cdot \exp\left(-\frac{l^2+m^2}{2s^2}\right) \tag{11}$$

4.4.2.2 Non Gaussian Function With Scaling Factor

Gaussian kernel of the function may define the parameter s in the form of the scaling factor which can use as controlling the blur size. So this function is defined in non gaussian form with the help of the two another functions, which can explained as below in following equations:

a. **Jinc Function** estimation of optical diffraction in PSF estimation this function is used

$$h_s(r; s) = N \cdot \left[\frac{2J_1(r/s)}{r/s}\right]^2 \tag{12}$$

From the above equation function J_1 is define as Bessel function for isotropic function and radius of optical diffraction is defined by $r = \sqrt{l^2 + m^2}$.

b. **Anisotropic Gaussian Function** This function may defined as following formula:

$$h_s(l, m; s) = N \cdot \exp\left(-\frac{(i\cos\theta - j\sin\theta)^2}{s \cdot \sigma_1^2} - \frac{(i\sin\theta + j\cos\theta)^2}{s \cdot \sigma_2^2}\right) \tag{13}$$

The above function defines the value θ as a main direction, this direction is define with horizontal line and size of the blur is defines along the perpendicular directions which can define by the parameters σ_1 and σ_2.

5. SIMULATION RESULT

In this research we have to calculate the performance of the point spread function with PSO. For the evolution of this we perform the deconvolution process. This process concludes the results with the help of the multi wiener SURE LET deconvolution, because this proves the state of the art [27], [41]. Our research is depend on the two sets of the real images these are of the 256x256 and 512x512.

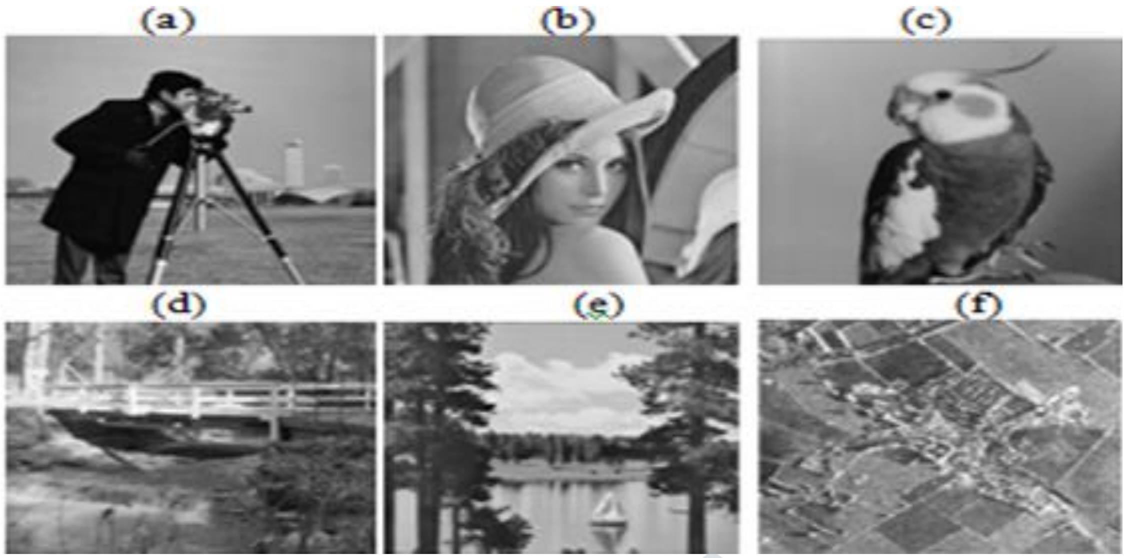

Fig. 1 Natural images (a) Cameraman 256 x256, (b) Leena 256 x 256, (c) Parrot 256 x 256, (d) Bridge 512 x512, (e) River 512 x512, (f) Satellite image 512 x512.

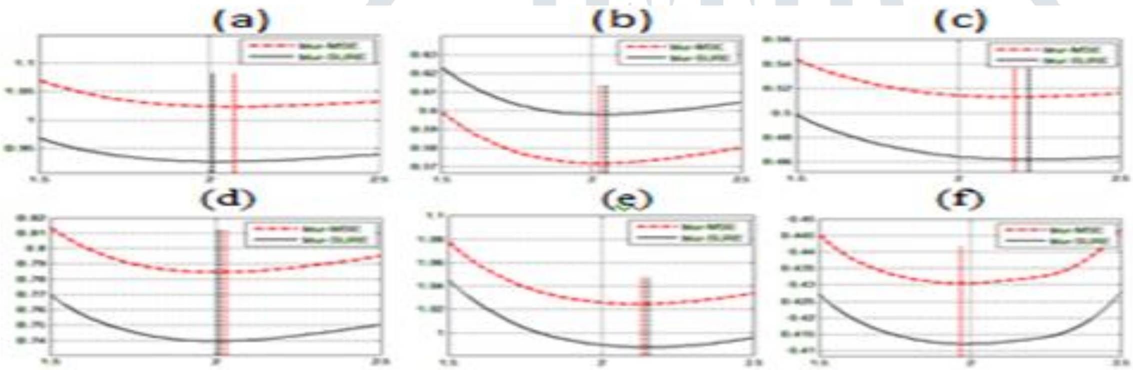

Fig. 2 Blur SURE minimization with the help of the Blur MSE of BSNR 25.06dB.

TABLE I
Estimation of Gaussian PSF with scaling factor s

True $s_0 = 2.0$						
	BSNR 25.06dB			BSNR 31.00dB		
Image Type	Blur SURE	Blur MSE	Time	Blur SURE	Blur MSE	Time Sec.
Camera man	2.0102	2.0714	0.94	1.9694	1.9694	0.93
Leena	2.051	2.0306	0.92	2.0714	2.051	0.89
Parrot	2.2143	2.1735	0.97	2.0918	2.1122	0.92
Bridge	2.0102	2.0306	2.76	2.0306	1.9694	2.71
River	2.1531	2.1327	2.81	2.1122	2.0918	2.74
Sattelite Image	1.9694	1.9694	2.99	1.9898	1.949	2.71

The blind and non blind deconvolution is processed with the help of the SURE LET algorithm [42]. Restoration of blurred image is done by SURE LET technique and calculates the results in terms of the PSNR. The PSNR is defined as:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\|\hat{y}-y\|^2/N}\right) \qquad (19)$$

TABLE II
Calculation of PSNR and SSIM for Blind Deconvolution

Image Types	BSNR 25.06dB		BSNR 31.00dB	
	PSNR	SSIM	PSNR	SSIM
Cameraman	25.02	0.793	25.58	0.813
Leena	28.70	0.856	29.51	0.880
Parrot	31.92	0.912	33.69	0.931
Bridge	24.82	0.887	25.37	0.916
River	27.63	0.934	28.37	0.950
Sattelite Image	18.56	0.810	18.97	0.851

TABLE III
Calculation of PSNR and SSIM for Non Blind Deconvolution

Image Types	BSNR 25.06dB		BSNR 31.00dB	
	PSNR	SSIM	PSNR	SSIM
Cameraman	25.02	0.793	25.61	0.814
Leena	28.74	0.858	29.66	0.882
Parrot	33.29	0.923	33.98	0.934
Bridge	24.82	0.887	25.37	0.915
River	27.98	0.937	28.69	0.952
Sattelite Image	18.58	0.616	18.98	0.853

6. CONCLUSION

In the research, we projected a technique for point spread function estimation with the help of the Particle swarm optimization and further it is based on the blur SURE. In this research we have to show that wiener filtering is used for blur SURE minimization and also for PSF estimation PSO give more accurate results. Results shows, this approach for PSF estimation while using for the non blind SURE LET deconvolution has more accurate results in pictorial and in terms of the numerical form. In this paper blur kernels used in the form of the subset of models only. In this paper it is noted that blur SURE technique is not specified for the two dimensional images but it can also perform on the three dimension images. This research also show that it is not depends only particular noise type but it can perform on any noise type which can performed on unbiased risk estimation of the devise. Hence instead of its limitation on the phase, we consider that this research has more probability for restoration of images in various applications.

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