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PSF Estimation with PSO and SURE LET Deconvolution for Blurred Image

Ritesh Pawar, Maiytree Dutta

Abstract: ***In this research we proposed a technique for the Point spread function estimation in the form of the particle swarm optimization, here also use unbiased risk estimation for the MSE in filtered version with blur stein's unbiased risk estimation in the form of the novel criterion to calculate only PSF from the blurred image which is unknown. This process of minimization of PSF is obtained by the wiener filtering. On the estimation of this blur kernel, non blind deconvolution is done with the SURE LET deconvolution algorithm. The best positions of the particles are calculated by the PSO. Here we use gaussian kernel for parametric form. In this research we found that position calculation from PSO gives the more accurate PSF parameter estimations, this may lead the high accuracy in restoration of degraded images which is as similar to the exact PSF, when whole result is performed with the help of the SURE LET deconvolution algorithm. From the result it is found that non blind deconvolution has highly accurate results in the form of the visually and computationally form.***

Index Terms: PSF estimation, PSO, Exact Wiener filtering, SURE LET, Blur SURE.

I.INTRODUCTION

In a camera blur in image is introduced in many stages. Such blur can be introduced in the form of the motion, defocus or out of focus, sensor resolution, pixel size and sensor with anti aliasing filters in the sensors of the camera [1]. When an image is degraded by the blur it can be illustrated in the form of the linear problem. For this linear problem deconvolution of the image is an important issue for many decades [2]-[4]. PSF in many real applications like medical imaging, remote sensing, photography etc. [5]-[7] cannot be easily estimated. To overcome from this problem some regularity approach is applied on the estimated PSF of original image, these can be derived in the form of the Bayesian techniques [8], [9]. Some time it is necessary to estimate point spread function with original image simultaneously [10], [11]. Image can be degraded with the help of the blur and some additive noise. This can be described in the form of image degradation model shown in figure 2. In this degradation model R(x, y) is defined as the original image. This original image is seen as the motion blurred image with image degradation model as a function of H(x, y). In the degradation model point spread function is defined by H(x, y).

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PSF and original image performed a convolution process which is further influenced by the noise N(x, y). On the processing of this operational result a degraded image is performed in the form of D(x, y) [12]. This can be formulated in equation (1):

$$D(x, y) = h(x, y) * r(x, y) + a(x, y) \qquad (1)$$

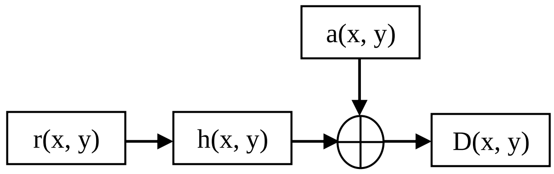

Fig. 1 Image degradation model

Convolution process around the boundaries of the degraded image may affect the cut off frequency; this may lead to identify the blur function in the degraded image more difficult. As we know that from the prior research common blur function is defined as the gaussian PSF. To estimate the parameters of point spread function wiener filtering is used. This may help by processing the threshold distance in the curves, and then PSF is estimated [13]. When parametric form is absent then pixel value may be in discrete form which shows the point spread function. To overcome this discrete values regularization is used for this process. For the regularization of the estimation blur kernels may includes:

- Tikhonov process in which PSF estimation is done by gaussian blur [14]-[16].
- Out of focus and motion blur Total Variation is used [17], [18].
- Camera shakes and motion blur Sparsity Prior is used [19], [20].

In the parametric form of the PSF estimation when it defines in many numbers of parameters then it reduces the degree of freedom [21], [22]. Parameters of PSF blur used as linear motion blur and length of this motion blur is calculated by cepstrum, radon transform and steerable filter [23]-[25]. Bayesian or regularization process mostly used in the parametric point spread function. This process can be performed by optimization technique. Optimization process followed the regularization technique in the estimation of the PSF on putting this function into objective function [26]. The non Bayesian technique for the Stein's risk estimation is based upon the minimization of the gaussian noise. SURE is used for the mean square error and non blind deconvolution of the blurred image. The main purpose to use this technique is that it does not know any knowledge about the real image [27]-[32].

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II.PAPER LAYOUT

This paper is classified into many steps. In section III we solve the PSF estimation which is a novel criteria based on the estimation of the function with mean square error. This error is solved by the filter version called wiener filtering. Section IV defines the estimation of the blur MSE with the help of the novel criteria of the blur SURE. For this we can use many types of the PSF, but to improve the quality of the blurred image in deconvolution process we use Particle Swarm Optimization in section V. At last in section VI simulation results is done for the experiment.

III.ESTIMATE BLUR MSE

A. Statement for Problem

It is observed form the degradation model:

$$D = h_0 r + a \quad (2)$$

In equation (2) D is the degraded image of the original image r, h_0 defines the matrix of distortion in terms of the linear model. In the degradation model equation covariance matrix define by n which represents the additive gaussian noise. The main purpose is to estimate the PSF h which is as close to the ground truth matrix h_0.

B. Estimation of h by Blur MSE

On processing the function for parameter estimation we applied it on research data of linear model D. The MSE is defining for the real image r by estimating it with formula [33]-[36]:

$$\text{MSE} = \frac{1}{L}\xi_a\{\|F(D) - r\|^2\} \quad (3)$$

$$\text{Blur MSE} = \frac{1}{L}\xi_a\{\|hF(D) - h_0 r\|^2\} \quad (4)$$

This estimation is defined as the blur mean square error, due to the reason that it measures the both blurred data. For the calculation of h:

$$\min_h \frac{1}{L}\{\|hF_h(D) - h_0 r\|^2\} \quad (5)$$

In this equation h in F_h is defined as the dependency over the function processing on h. F is used as the processing function in non blind deconvolution [37], [38].

C. Wiener filter minimization in MSE

Wiener filtering is defined for the blur mean square error minimization. This ideal process is denoted by notation W_h [39].

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

MSE may not be taken for the frequency response estimation, due to the reason that amplitude variation may not link with phase variation. So takes only zero phase [40].

IV.PSF ESTIMATION BY BLUR SURE

A. Blur SURE Estimation of Blur MSE

Blur mean square error may not be minimized directly because $h_0 x$ is not defined in the function. To calculate this MSE is changed with the blur Stein's unbiased risk estimation depends on the degradation model (2), in this model only D is measured as proved in theorem 3.1 [41]. It can be calculated by:

$$\epsilon = \frac{1}{L}\|hW_h D - D\|^2 + \frac{2\sigma^2}{M}T_r(hW_h) - \sigma^2 \quad (7)$$

By the calculation the result shows that blur SURE is very close to the blur mean square error due to the reason that pixel quantity is increases. From this equation it is found that in blur SURE requirement of noise variance estimation is must.

B. Exact Wiener Filter Estimation

Due to unknown prior knowledge of the spectral density blur Stein's Unbiased Risk Estimation is not used practically in the exact wiener filtering. With due effect of this it is replaced by the function $\lambda\|\propto\|^2$, here λ is defined as the estimated parameter. Now wiener filtering for blur SURE is defined as:

$$W_{h,\lambda}(\alpha) = \frac{h^*(\alpha)}{|h(\alpha)|^2 + \lambda\|\alpha\|^2} \quad (8)$$

Along the parameters h and λ blur SURE is minimized for the PSF estimation by the formula:

$$\underbrace{\min}_{h,\lambda} \underbrace{\frac{1}{L}\left\|hW_{h,\lambda}y - y\right\|^2 + \frac{2\sigma^2}{L}\mathrm{Tr}\left(hW_{h,\lambda}\right) - \sigma^2}_{\text{blur SURE: } \xi(h,\lambda)} \quad (9)$$

Blur Stein's Unbiased Risk Estimation is summarized for the blur MSE minimization in following steps: 1). First estimate the parameter H, λ. 2). Calculate the $W_{H,\lambda}$ by wiener filtering. 3). Calculate the blur SURE minimization. 4). At last calculate the non blind deconvolution with estimated H.

V.PSF ESTIMATION METHODS

A. Blur SURE PSF Estimation

While the estimation of the blur from unbiased risk than we know that PSF h is equal to the h_s, which represents the unknown parameters $S = [s_1, s_2 \ldots s_p]^T$ [42], [43]. The parameter s_0 is representing the ground truth. Now previous equation (9) can be formulated as:

$$\underbrace{\min}_{s,\lambda} \underbrace{\frac{1}{L}\left\|h_s W_{s,\lambda}y - y\right\|^2 + \frac{2\sigma^2}{L}\mathrm{Tr}\left(h_s W_{s,\lambda}\right) - \sigma^2}_{\text{blur SURE: } \xi(s,\lambda)} \quad (10)$$

B. Parametric PSF Estimation

1). Gaussian Kernel: To estimate the Point Spread Function kernel is expressed in the form as:

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

The co-ordinates l, m defines the dimension in a plan or in a two dimensions and factor N represents the coefficient of normalization. Here parameter s is unknown which is to be estimated.

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2). Non gaussian function by scaling factor s:

It is found that parameter s is a scaling factor in equation (11) of gaussian function. In non gaussian function we have two functions to define the scaling factor s.

- ***Jinc Function,*** This function is commonly used for the optical diffraction [44].

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

J_1 is Bessel function of an isotropic function of radius $r = \sqrt{p^2 + q^2}$.

- ***Anisotropic Gaussian function***, this function is given by:

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

Here θ is the main direction along the horizontal line, σ_1 and σ_2 shoes the blur size along the perpendicular line.

3). Particle Swarm Optimization

PSO consist the swarm of the individual particles. These particles show for the optimization candidate solution individually. There are generally three types of the attributes. (1). Current position of particle P_i. (2). Current velocity V_i. (3). Local best position PB_i, this position is defined for the space search for their feature extraction. Here we can assume the minimization of cost function J to particles for N dimensions. Here for every particle new velocity is updated by:

$$V_i(q+1) = WV_i + A_1 \times R_1[P_{best_i}(q) - P_i(q)] + A_2 \times R_2[G_{best}(q) - P_i(q)] \qquad (14)$$

Here A_1 and A_2 and W represent the coefficient of acceleration, Uniform random sequence R_1 and R_2 represent the elements in range (0, 1). Number of generation shows by q. Now new position is calculated for particle is:

$$P_i(q+1) = P_i(q) + V_i(q+1) \qquad (15)$$

Previous best position and best position of G_{best} is defines below [45], [46].

$$P_{best_i}(q+1) = \begin{cases} P_i(q+1), \text{if } F\left(P_{best_i}(q)\right) > F\left(P_i(q+1)\right) \\ P_{best_i}(q), \qquad \text{otherwise} \end{cases} \qquad (16)$$

$$G_{best}(q+1) = \arg\min_{P_{best_i}} F(P_{best_i}(q+1)) \qquad (17)$$

3). Outline of the Proposed Algorithm

The proposed algorithm is explained in steps as below:
a).Input blurred image convolution by equation (1).
b).Randomly taken the particles of particle swarm optimization.
c).Blur SURE and blur MSE is estimated by applying wiener filter.
d).Every estimated image values of objective functions is calculated.
e).P_{best} and G_{best} are calculated by equation (16), (17).
f).Movement of particles by equation (14), (15).
g).By setting the threshold value check the size of PSF. If size is not calculated then repeat the steps from (c) to (g). Final G_{best} gives the optimal PSF which generate best objective function for the restoration of the image.

VI.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.

A. Research Setting

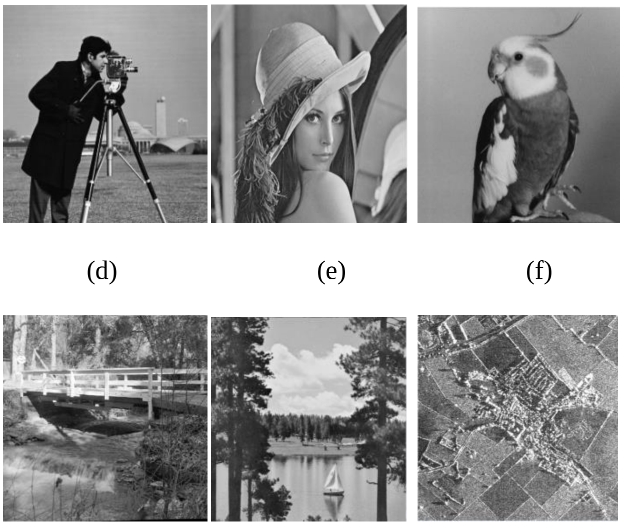
Let us consider convolution kernel defined by scaling factor s:

- Gaussian kernel defined in (11).
- Non gaussian kernel is defined in (12), (13).
- PSO is calculated for PSF by equation (14)-(17).

Blurred image is distorted by gaussian noise with variance σ^2 So BSNR is defined as:

$$BSNR = 10\log_{10}\left(\frac{\|H_0x - mean(H_0x)\|^2}{N\sigma^2}\right) \qquad (18)$$

(a) (b) (c)



(d) (e) (f)

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.

The test images we have consider is in two set of total 6 images of size 256 x 256, 512 x 512 shown in the Fig.1, which includes the whole range of the natural images. Fig. 2 shoes the noisy blurred image in the presence of the BSNR factor of 25.06dB and Fig. 3 shows the images of blur SURE and blur MSE Plot.

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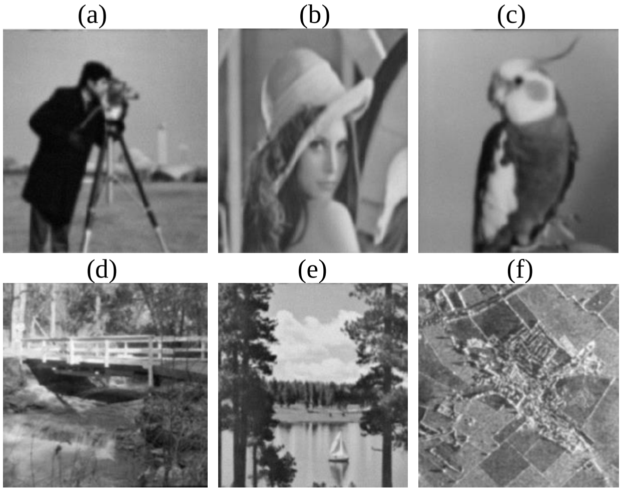

Fig. 2 Noisy Blurred image with BSNR 25.06dB (a) cameraman; b)Leena; (c)Parrot; (d)Bridge; (e)River; (f)Satellite Image.

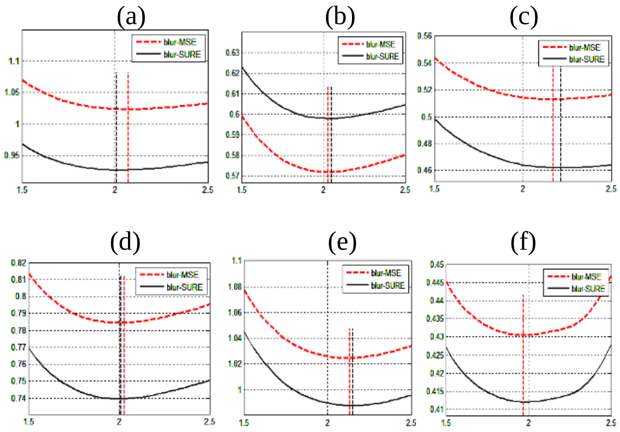

Fig. 3 Blur SURE minimization with the help of the Blur MSE of BSNR 25.06dB.

Fig. 4 shows the noisy blurred image of BSNR 30dB and Fig. 5 shows the images of blur SURE and blur MSE Plot. Table I gives the blur SURE/MSE estimation with computational time of BSNR 25.06dB and 31.00dB.

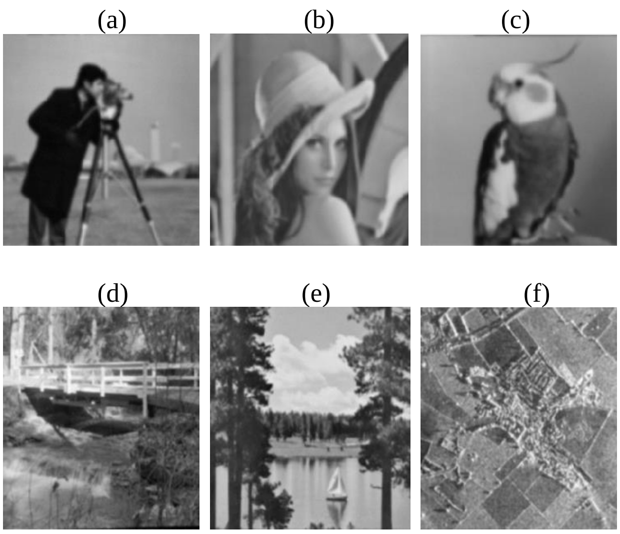

Fig. 4 Noisy Blurred image with BSNR 30dB (a) cameraman; b) Leena; (c)Parrot; (d)Bridge; (e)River; (f) Sattelite Image.

(a) (b) (c)

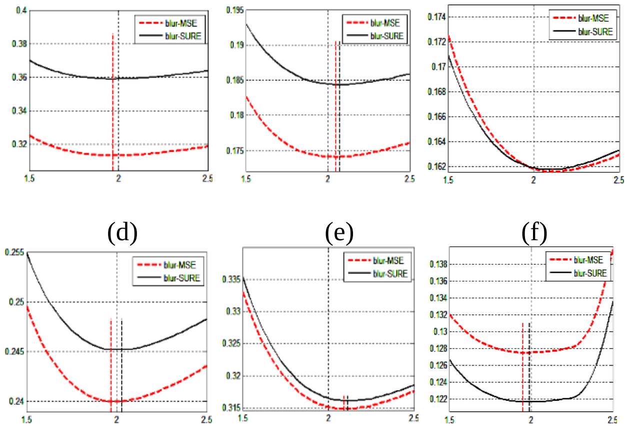

Fig. 5 Blur SURE minimization with the help of the Blur MSE of BSNR 31.00dB.

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:

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

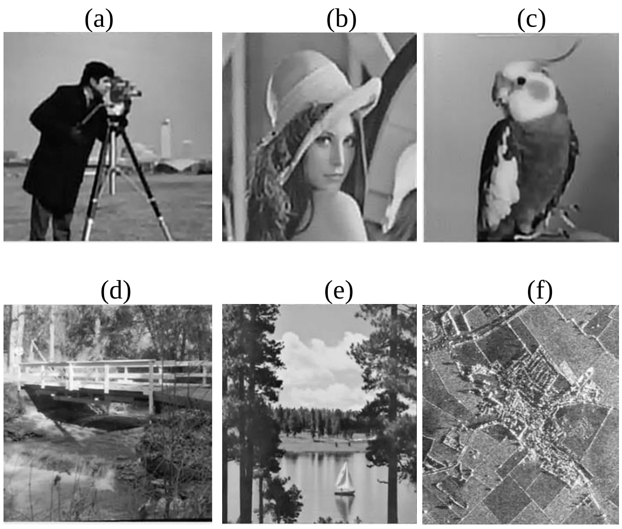

Fig.6 Restoration of images in blind deconvolution

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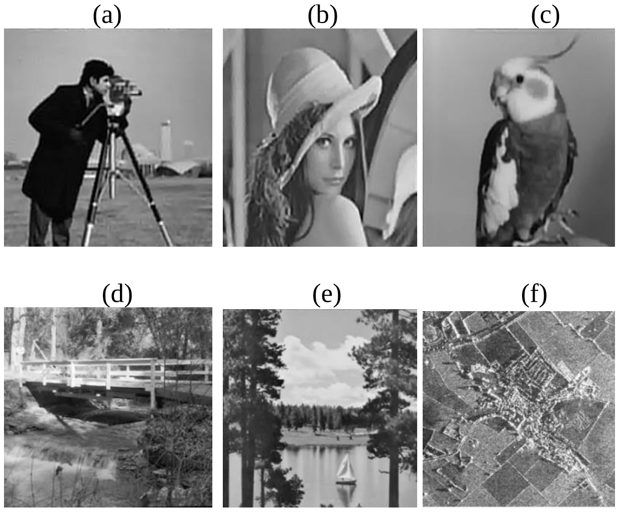

Fig.7 Restoration of images in non blind deconvolution, fig.6 and fig. 7 shows the result of the restoration of images. Sure LET technique is used to calculate the PSNR value of the blind and non blind deconvolution of the images, which is shown in table II.

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

VII.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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