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A Review on Image Restoration With PSF Estimation Techniques

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ABSTRACT

The image restoration can be improved with the help of different kind of the techniques. But some of the techniques can improve the image degradation model. It can improve the image factor in terms of blur due to motion, defocusing of the image and noise introduced at the time of capturing the image. These blurs are depends upon the image restoration factor of PSF. This factor is not defined for the image deconvolution technique in blind process. In the estimation of the point spread function some methods and techniques are applied. Here for the estimation of this technique some method and techniques are compared for the different authors for the image restoration of the blind deconvolution of image restoration. This technique is compared on the bases of the some standard parameters of image in the form of PSNR, Gaussian blur, Motion blur. The compiled analysis is done for point spread function where wiener filtering shows the good results in motion blur radon transformation and blur due to defocused image as compared to others.

Keywords: Point Spread Function, Motion Blur, Image restoration, Gaussian Blur.

I. INTRODUCTION

Deconvolution of the image in blind and finding the kernel of image is very difficult which leads to the major problem for the image restoration [1]. In the real world processing of the image restoration generates the effects with linear problems in inverse form. So in PSF estimation different images is processed which filed as in medical, photographic etc. is not determined easily [2]. By applying correlation method in gradient form, patch selection for the degradation of the image etc. are used for the calculation f this function. Here result can be achieved in the form of the true image which can be observed by the relation in between the true and the blurred image, which can be classified by the formula which is having correlation in factor F and the point spread function with added noise in this relation is defined as:

$$G = F * H + N \qquad (1)$$

Where factor N is used for the noise which is having some standard sample sets of different kind of the noises where it can be calculated in Gaussian noise of the variance factor and produce the convolution in between the estimation factor of point spread function in two dimension form [3]. With the help of this relation we can easily find how blur is introduced in the image with the help of motion, size of the pixel, resolution of the sensor etc. These can be removed with the help of the deconvolution method. At the time of the PSF estimation there must be a proper knowledge of the blur kernel. When estimation technique is applied on the blurred image the common problem occurred in the form of that information can be lost of the original image.

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This technique for the estimation of PSF is used for the image restoration in original form with combination of different point spread function [4]. In degradation image model F(x, y) defined for true image in the above equation. Where blurred image can be find with the help of degradation model in the form of H (x, y) function, which is defined as PSF for the degraded system. Where F and H function is convoluted for outcome result which affected due to noise of function N. In convolution of the image degradation function produced the influenced effect on the original and blurred image with the help of G. In this degradation model all function is defined in two dimensions with parameter in the form of (x, y) which is expressed for the blurred image as [5].

$$G(x,y) = H(x,y) * F(x,y) + N(x,y) \qquad (2)$$

In image processing deconvolution of the image is most important topic for several decades. Image processing has many real applications in which point spread function (PSF) cannot be obtained more accurately and easily. [6].

In image restoration when processing of the image is done in the blind deconvolution method estimation of blur kernel is very difficult. For reducing this problem with the estimation technique of PSF is very less because in this the real information is lost in this process. It can be processed with Bayesian technique [7]. The aim of the image processing is that in this original image is constructed from the degraded image. In the application the blurred image is always blind in the process. But it can be resumed if there is known PSF in the processed image with the predefined parameters. So the result is occur in the form of the real image and also defined that which one is matched with the real image. It will find that blind image processing is the best restoration method to find the restored image in the mean time with the defined blur kernel. Blind restoration process gives the convolution result incomplete in the de-blurring of the image [8].

Sharp image can be restored from the deblurring with known point spread function of the image. PSF convolution is the process for blurred image with the real image is convolution in inverse called as deconvolution of image. The frequency domain is used for the direct method of the inverse deconvolution [9].

In this paper the complete proces is defined in four catogory. These sections are estimation of the blur, estimation of point spread function with different techniques followed by the results and conclusion.

II. Blur Parameter Estimation

This parameter is estimated for the given image by using the general noise method as gaussian, blur in the motion and image capturing by defocusing the image.

A. Parameter of Guaussian Noise

Noise will put the effect in the image it will ruined the original image this can be done by different kind of the noise. General noise is used in the image restoration as gaussian noise. In the restoration of the image different methods is used to reduced the noise from the original image. This can be defined in the form of:

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$$n(a,b) = \frac{1}{2\pi\sigma^2} e^{-(a^2+b^2/2\sigma^2)} \qquad (3)$$

From the above equation σ is standard deviation in gaussian noise model which is unknown in PSF estimation and some time it is to be assumed [10,17] while estimating the PSF, the gaussian point spread function in different imaging systems is commonly used so to determine its parameters wiener filter is used. To identify these parameters e.g. point spread function size is estimated by setting the threshold value. The Gaussian PSF is generally used as the blur function in different optical measurements and imaging models. This function is generally described as:

$$G(m,n) = \begin{cases} \frac{1}{\sqrt{2\pi}\delta} \exp\left\{-\frac{1}{2\delta^2}(m^2+n^2)\right\}, (m,n) \in R \\ 0 \qquad\qquad\qquad\qquad\qquad \text{Otherwise} \end{cases} \qquad (4)$$

Here standard deviation is defined by δ, supporting region defined by the R, this R is used as the matrix size of L x L, where L is odd number. So in this function basically two parameters are to be estimated, that are the standard deviation (δ) and PSF size (L) with the help of the wiener filtering [11]. For the inverse gaussian group the two gaussian parameters are found with PDF. The homogeneity of the scale like parameters λ is the main assumption for the inverse gaussian mean; these can be calculated by the given formula [12,13,15].

$$hx(x|\mu,\lambda) = \left\{\frac{\lambda}{2\pi x^3}\right\}^{1/2} \exp\left\{-\frac{\lambda}{2\mu^2 x}(x-\mu)^2\right\} \qquad (5)$$

Where $x > 0$ and $\lambda > 0$.The generalized gaussian distribution with probability distribution function is used in many cases like digital image processing, blind signal separation of speech etc. The GGD is a generalized form of the Gamma distribution family. GGD function with mean μ, scale parameter β and shape parameter α is defined as:

$$f(x:\alpha,\beta,\mu) = \left[\frac{\alpha}{2\beta\Gamma(1/\alpha)}\right] e^{\left[-\left|\frac{x-\mu}{\beta}\right|^{\alpha}\right]} \qquad (6)$$

Where $\beta = \sqrt{\frac{\sigma^2\Gamma(1/\alpha)}{\Gamma(3/\alpha)}} = \sigma\sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}}$, $\Gamma(z) = \int_0^\infty e^{-t} t^{z-1} dt$ is the gamma function; $-\infty < x < \infty, \alpha > 0, \beta > 0$; and σ is standard deviation [14]. In the parametric PSF estimation the blur stein's unbiased risk estimation is depends upon the parameters of the gaussian (s, λ), these parameters can be estimated by minimization of the blur SURE with the help of the exact wiener filtering. The parametric PSF estimation can be characterized by the gaussian kernel as:

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$$G_s\,(i\,,j\,;s) = M \cdot \exp\left(-\frac{i^2+j^2}{2s^2}\right) \tag{7}$$

Where s^2 is the variance and (I, j) shows the 2D coordinates, M is the coefficient of the normalization. The projection operator P_G is formulated for 1D in gaussian Blur parameter estimation is as [2,16,18]:

$$P_G(f)(x) = m_0 G_s(x) = \frac{m_0}{\sqrt{2\pi}s}\, e^{-\frac{x^2}{2s^2}} \tag{8}$$

B. *MOTION BLUR PARAMETERS*

In image restoration process degradation model can described in the form of uniform linear motion. Generally uniform linear motion has been taken because of the reason that sometime this motion taken as the non uniform linear motion in certain condition. The basic formula of the motion blur model in 2D plan is define below,

$$G\,(x,y) = \int_0^T \left[f\left(x - x_0(t), y - y_0(t)\right)\right] dt \tag{9}$$

When relative motion occurs between the camera and object while capturing the image then motion blur is define in the form of a translational, a rotation and change in scale or combination of these. Uniform linear motion blur model generally defined in image restoration can be formulated as below in equation (10). Where parameter l defined as the blur length and θ is define for the blur orientation of image. When these two parameters of the uniform motion blur model is determined then the point spread function H(x,y) is also determined [19,20].

$$H(x,y) = \begin{cases} \frac{1}{2l}, x\cos\theta + y\sin\theta = 0, x^2 + y^2 \le l^2 \\ 0, \qquad otherwise \end{cases} \tag{10}$$

When we calculate the Motion blur parameters over the directional and orientation pyramids then we can introduced the adaptive thresholding to compute the sharpened sub-bands of the edges of the image. This will help in reducing the sub-band value in to some small finite value [21]. The motion Blur is also modeled as in linear shift invariant and the formula is derived as

$$\lambda\int_0^T y\left(x - s(t)\right)dt = \lambda\int_0^T \left(y \circledast \delta_{s(t)}\right)(x)dt \quad = \lambda\left(y \circledast \int_0^T \delta_{s(t)}dt\right)(x)$$
$$= \lambda\,(y \circledast h_T)(x) \tag{11}$$

The parameter h_T belongs to the motion blur PSF, while $\delta_{s(t)}$ define as Dirac delta function at s(t) ∈ R^2 [22]. Frequency domain estimation is also used for motion blur image restoration process. This process is characterized by the PSF estimation which decomposed in to motion kernel and defocusing kernel. Further this motion kernel is estimated by the frequency domain, which performs the matching

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of the parameters in orientation and two axis lengths [23]. Motion blur angle detection most common Gabor filter is used, because when on applying the threshold value the small errors can cause the large variation in estimation of blur angle. The orientation parameters of filter give blur angle.

$$h(x,y) = \frac{1}{\sqrt{2\pi\sigma_x\sigma_y}} e^{-\left(\frac{(x\cos\theta + y\sin\theta)^2}{2\sigma_x^2} + \frac{(-x sin\theta + y cos\theta)^2}{2\sigma_y^2}\right)} \tag{12}$$

$$G(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \mathrm{e}\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] \times e[-j\omega(x cos\phi + \ y sin\phi)] \tag{13}$$

The function σ_x and σ_y denotes as standard deviation, ϕ and ω are the orientation and frequency of the Gabor filter [24]. Different types of motion blur may be distinguished between the relative motion of capturing device and picture. When picture is recorded with camera at a constant velocity and angle in horizontal axis on the exposure interval, then this may defined in 1D by defining the length of motion L= $v_{\text{relative}}\, t_{\text{exposure}}$, then PSF is derived as [25]

$$\mathrm{B(x,y;L,\phi)} = \begin{cases} \frac{1}{L} \ \ if \ \sqrt{x^2+y^2} \le \frac{L}{2} and \frac{x}{y} = -tan\phi \\ 0 \qquad\qquad\qquad\qquad elsewhere \end{cases} \tag{14}$$

Motion Blurred image in frequency spectrum shows the parallel lines gives very low values near to zero by orthogonal to motion orientation. For finding these dominant parallel lines we can choose different method like Radon transform, haugh transform, cepstral method or any other methods, these are discussed as below.

1. Haugh Transform Method

The haugh transform is used for patterns like lines, circles and ellipses in an image. This method is generally useful in line detection, which is depends on the polar representation of line

$$\rho = x cos\theta + y sin\theta \tag{15}$$

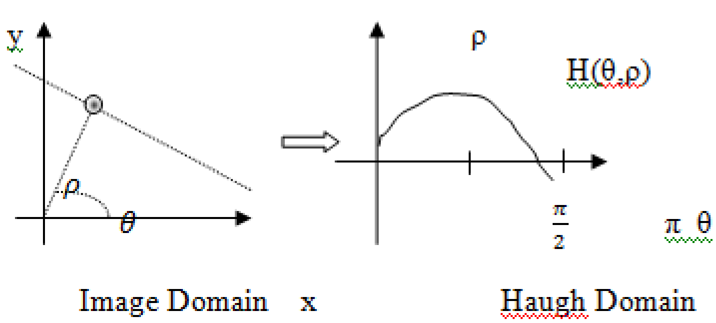

Fig. 1 Haugh Transform

2. Radon Transform Method

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Along the straight line the radon transform consist of integral function of the integral transform. These real valued function $\phi(x,y) \in R^2$, at angle θ and distance ρ from the origin is given in equation (16). Where δ denotes the Dirac delta function. The modified radon transform define over two ways: (i) Radon transform with same area for different angle; (II) polar coordinate integration is formulated directly.

$$R(\phi,\rho,\theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \phi(x,y)\delta(\rho - x\cos\theta - y\sin\theta)dxdy \quad (16)$$

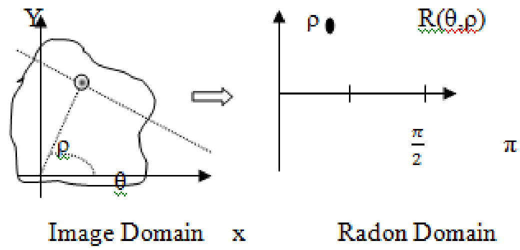

Fig. 2 Radon Transform

3. Cepstral Method

Motion blur length estimation can found with the help of the radon transform and cepstral method. The cepstral transform can use for blur component and image components separation. It is defined in an image f(x,y) as follows [26,10,27,28].

$$C\{f(x,y)\} = F^{-1}(\log|F(f(x,y))|) \quad (17)$$

C. DEFOCUS BLUR PARAMETERS

While taking a photograph some common type of blur is to be detected in the picture. These blur are in the form of the small number of pixels in the image that are comes in the frame due to defocus of the image. These small blurs contains the important clues of the depth of image. This type of blur is called as Just Noticeable Blur. These small blurs cannot distinguish with unblurred structure which is based on the local information. So to find this sparse edge representation and blur strength estimation is used.

$$\min_{x_i} \|y_i - Dx_i\|_2^2 \qquad s.t. \|x_i\|_0 \leq k \quad (18)$$

Where $D \in R^{d\times m}$ is an complete dictionary captured atoms of blurred image and D_{xi} represents the sparsely recovered signal which is close to original one. After calculating the sparse edge we can find the blur strength estimation with the help of the formula given below, where a, b, c, d are fitted variables, σ is the standard deviation and f is the sparsity feature [29].

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$$f = \frac{a}{1+\exp(b\sigma+c)} + d \tag{19}$$

Spatially varying degradation model is also used for obtaining the defocus blur kernels, space invariant gaussian kernels can approximated region wise for defocus blur kernels and it may be restored in the form of FIR filter. Where G(x,y) is out of focus image and F(x,y) is in focused image, h(s,t) is space invariant PSF [30].

$$G(x,y) = \sum_s \sum_t h(s,t)F(x-s,y-t) + \eta(x,y) \tag{20}$$

In single image estimation of spatially varying defocus blur is estimated by re blurred the image with the help of the gaussian kernel and defocus blur is estimated from ratio of the gradient of input and re blurred image.

$$\nabla i_i(x) = \nabla\big(i(x) \circledast G(x,\sigma_0)\big) = \nabla((au(x)+b) \circledast G(x,\sigma) \circledast G(x,\sigma_0)\, \frac{A}{\sqrt{2\pi(\sigma^2+\sigma_0^2)}}$$
$$= \exp\left(-\frac{x^2}{2(\sigma^2+\sigma_0^2)}\right) \tag{21}$$

Where σ_0 standard deviation is defines for the re-blur gaussian kernel. Ratios of gradient magnitude between original and re-blurred edges are given in equation (22). The unknown blur amount is calculated by equation (23) [31,33].

$$\frac{|\nabla i(x)|}{|\nabla i_1(x)|} = \sqrt{\frac{\sigma^2+\sigma_0^2}{\sigma^2}} \exp\left(-\left(\frac{x^2}{2\sigma^2} - \frac{x^2}{2(\sigma^2+\sigma_0^2)}\right)\right) \tag{22}$$

$$R = \frac{|\nabla i(0)|}{|\nabla i_1(0)|} = \sqrt{\frac{\sigma^2+\sigma_0^2}{\sigma^2}}, \quad \sigma = \frac{1}{\sqrt{R^2-1}}\sigma_0 \tag{23}$$

In an image 2D map of scale parameter called defocus blur map in which different levels of local blur at each pixel is indicated. The PSF estimation scale for each pixel is depends upon the local probability estimation and coherent map estimation.

$$\hat{S} = \left(\sum_i \rho i(\hat{S})\right)^{-1} \sum_i \rho i(\hat{S}) \frac{\left|g_i^{\nabla}[X]\right|^2 - \sigma_{ni}^2}{\sigma_i^2(r)}, \tag{24}$$

Where $$\rho i(\hat{S}) = \left(1 + \frac{\sigma_{ni}^2}{\hat{S}\sigma_i^2(r)}\right)^{-2} \tag{25}$$

Here $\sigma_i^2(r)$ is defined as defocus blur spectra and $\hat{S}$ is optimal maximization of defocus blur. The coherent map estimation is achieved by minimizing the energy function, which consist of the data term and smoothness parameters. This parameter can control the strength of the constraints. R= $\{r_x\}_x$ is defined as the whole pixel solution in image [32].

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$$E(R) = \sum_x D_x(r_x) + \sum_{(x,v)\in v} \lambda_{x,v} V(r_x, r_v) \tag{26}$$

III. PSF ESTIMATION TECHNIQUE

Image restoration process may achieve with the different types of the estimation techniques. Point spread function is estimated by various techniques in the blind image deconvolution.

A. Novel SURE Parametric PSF Estimation

In this paper author used a novel technique which is based on the blur SURE criteria used for the estimation of the PSF. This is a filtered version for MSE in blur estimation. Here the point spread function is the unknown parameter which is to be estimated. To estimate this unknown parameter from minimization they used wiener filtering. From this blur kernel estimation image deconvolution is done with the help of the proposed algorithm. This research shows that minimization of the blur SURE gives exact PSF estimation similar to exact point spread function when they use developed SURE based deconvolution algorithm [34].

B. Blind Image Restoration for PSF Estimation

In this paper for imaging model blur function is estimated with blind image restoration technique is used for enhancement in image for better quality. Here authors calculate parameters of the gaussian PSF of the image. Multiple curves of error are generated in different parameters by wiener filter algorithm. Size and standard deviation of PSF are estimated from these curves. Wiener filter is used for the restoration of the blurred image. From the experiment they shows that PSNR gets highest value around PSF and gets lowest when it is far away from point spread function [35].

C. Multiscale Patch Based Image Restoration

In this paper processing is based on the overlapping of the patches into the target image, restore the each patch separately and then by plain averaging merge the results for the final output. The prior techniques are focused on the intermediate results of patch, instead of the final outcomes from the restoration. So to overcome this problem expected patch log likelihood method was come in frame. In this paper author wants to extend that research and improve the EPLL by multi scale patches from the target image which are of the same size and the footprints of the target image changes due to sub sampling of the image. In the prior research of patch based restoration algorithm serves the local patch as global stochastic phenomenon. In this research the use of the multi scales EPLL by motivating the use of the simple gaussian case. This method is used for the image denoising, deblurring and super resolution [36].

D. Image Restoration by Wavelet Image Fusion

In this research authors want to show the new technique for the restoration of the image by fusion process. Firstly motion blurred image is recovered with LR and wiener filtering method. The new

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technique is applied then as for image fusion depends on wavelet process. From the research authors found this technique has good performance for image restoration [37].

E. Sparse and Adaptive Method

In this paper sparse representation is used for the iterative image deblurring for uniform, non uniform single image. This technique is further used for the training dictionaries for the purpose of the showing image contents accurately. Here adaptive dictionary and sparse method used together for deblurring the image more accurately [38].

F. Radon Transformation and Bilateral Filter

For motion blur photography is the challenging task. Image is blurred due to long exposer time taken by camera. Camera high gain may cause the dark and noisy image with short exposer time. The proposed algorithm is used to remove these types of the effects. For this firstly check that from which factor image is blurred and then restore it from deconvolution process. In this paper blur kernels is estimated by blurred edges. These kernels are estimated by inverse Radon transform. The comparison is done in between wiener filter, LR, inverse filter and proposed method [39].

G. Sparse Representation for Blind Image Restoration

This research shows basic two dimensional patterns is modeled from blur kernel in the form of sparse linear combination. This technique is based on modeled method over competitive edge blur kernels, due to reason that this design is more flexible for dictionary design customization. This may help for various applications in the formation of adaptive design. Here Kronecker is used as a product for gaussian kernels. Authors also take the results in PSNR value and compare it with previous technique [40].

H. Mixed Gaussian and Impulse Noise Removal by Alternating Direction Method

In this paper Blurred image corrupted by gaussian noise and impulse noise together is restore with high order total variation method. This method is done with the help of the alternating direction method of multipliers. The demonstration of the results shows the efficiency of the proposed technique with its performance [41].

I. Two Phase Approach for Deblurring Images

In different research papers blurred image restoration is a difficult task with impulse noise. These researches tackle this task by variational methods with data fidelity. Due to this in pixel location systematic errors needs the optimization process. For these errors proposed method is used for to solve the problem and enhance the results. This is a theoretical method depends on model of decoupling the method in two stages. Firstly remove the pixel that are corrupted by noise from the data set and then from free data deblurred and denoised the image simultaneously [42].

Table I

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Parameters and Their Values for Leena

Blur Types	PSF Techniques					
Gaussian Blur	SURE-LET [34]		Wiener Filter[35]		EPLL [36]	
	S_0	PSNR dB	S_0	PSNR dB	S_0	PSNR dB
	2.0	30.51	0.9	33.20	50	28.99
Motion Blur	Image Fusion [37]		Sparse method [38]		Radon Transform [39]	
	S_0	PSNR dB	S_0	PSNR dB	S_0	PSNR dB
	0.005	29.09	0.5	32.79	0.0003	48.96
Defocus Blur	Sparse method [40]		MNID-ADMM [41]		Two-Phase Method [42]	
	r	PSNR dB	r	PSNR dB	r	PSNR dB
	3	31.20	3	33.0	3	38.70

IV. CONCLUSION

In this review paper the main purpose is to carry the comparative study for the restoration of blurred image. The different restoration algorithms used different types of parameters for their restoration purpose. The restoration is done in this review paper is based on the three types of blur like Gaussian blur, Motion blur, Defocus blur. These blurs are having the different parameters as standard deviation, radius and peak signal to noise ratio. Different restoration techniques has been developed and applied such as wiener filtering, multiscale-EPLL, fusion image deconvolution, two phased method etc. Now a days graphical user interface is used for the analysis of image restoration of blurred image.

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