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# A Survey on Various Image Deblurring Methods

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**Abstract:** Image blur is one of the main types of degradation that reduces image quality. Image deblurring is an attempt to invert blurring process by using mathematical model to get best estimation of latent (sharp) image. Blurring can be modeled mathematically as a convolution process between two functions which are image and Point Spread Function (PSF). PSF can be classified into more than one type depending on the reason for blurring. Gaussian is the type of PSF this study will focus on, and an implementation of such PSF to compare different deblurring methods. Based on the availability of prior knowledge about the degradation kernel (PSF), the deblurring methods can be divided into two major categories which are non-blind deconvolution and blind-deconvolution. Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) are the tools used to estimate the performance of these methods.

**Key words:** Blur, deblur, deconvolution, degradation, PSF, Gaussian, Latent, outliers

## INTRODUCTION

Digital Images have been used in many applications such as monitoring, astronomy, medical, military and so on. Digital images are made up by assembling elements of a picture known as pixels and arranging these pixels in a grid. Captured image in real world is considered as a degraded version of the original one (Hamid *et al*., 2015). Image artifacts occur during capturing process because of the noise and blurring. Therefore, image degradation can be described mathematically as a linear process causing the image to become degraded and it can result from two operations. The first operation is the process of convolution between the latent (sharp) image and Point Spread Function (PSF), while the noise addition to the resulted image is considered as the second operation. Eq. (1) described the relation between latent (sharp) image and captured (degraded) image (Jia, 2007):

$$f = h \otimes g + n \tag{1}$$

Where:

f = The blurred image
h = The Point Spread Function (PSF)
g = The latent (sharp) image
$h \otimes g$ = Additive noise
g = The convolution of PSF and g

There are more than one reason produce blurry images such as capturing an image with imperfect resolution equipment (Al-Ameen *et al*., 2012; Perrone and Favaro, 2014)). Other reasons include the use of long exposure time, relative movement between object and capturing devices (Singh *et al*., 2008) and Gaussian noise which comes during image acquisition process e.g. temperature, low illumination (Hamid Ainul Azura Abdul *et al*., 2015) which leads to sensor noise and transmission (electronic circuit noise) (Bhosale *et al*., 2014). The removal of Gaussian noise leads to over-smooth of sharp edges i.e. increase image blurring (Bhosale *et al*., 2014). Thus deblurring is the process of restoring the latent (sharp) image by using mathematical model.

To describe blurring process, let the latent (sharp) image be a single bright (white) pixel surrounded by dark (black) area. The captured image will spread as a single bright pixel over the dark area, the bright pixel will be considered a point source while the response of the imaging system can be described by Point Spread Function (PSF). PSF indicates the impact degree of blurring of the imaging system (Al-Amri and Ali, 2011) while the Fourier transform of PSF is called Optical Transfer Function (OTF) (Khare and Nagwanshi, 2011). Image deblurring is the process of trying to obtain a good approximation of the original image. One of the solutions to deblur an image is blind deconvolution which tries to estimate the PSF using image intensities and gradients to deblur captured image. Equation 1 contained noise term which resulted from imperfection of the acquisition device. Several techniques of image deblurring are

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proposed. Techniques that require prior knowledge about PSF are known as non-blind while in the blind deconvolution, prior knowledge of PSF is not conditional because in this approach the estimation of PSF will be considered. In this paper we will study both deblurring techniques (blind and non-blind deconvolution).

The significance of this study is to focus on the deblurring methods applied in image processing fields such as astronomy, medical images, microscopy, iris recognition, surveillance systems, military application and so on. The Gaussian blur will be the focus of this study. To simulate the original degradation process and to obtain blurry and noisy image a Gaussian PSF function will be generated. The generated PSF will be used to convolve it with a sharp image, and white Gaussian noise will be added to form blurry noisy image. The resulted blurry noisy image will be used to evaluate deblurring techniques.

## BLURRING

An image is clear if we accurately recognize the shape of all details inside it. The best way to recognize the objects inside an image is by the edges of these objects (edges can be recognized by brightness contrast) for example if we could distinguish between nose, mouth, eyes etc. in face image this image will be considered clear. Blurring demands that the transition from one color to another be very smooth so that the color contrast will be reduced which means the observer cannot distinguish the content details. Sometimes zooming process leads to blurred image (if the pixel replication and large zooming factor are used). Blurring also resulted from applying some filter to the original image, such as average filter, weighted average filter, motion filter and Gaussian filter. The average filter has three properties. The first one is that it is odd ordered; the second property is that the summation of its entire element is equal to one and the last property is that all elements are equal in value. The blurring is increased when the size of kernel increases and this happens because a large number of neighbor pixels are included in one smoothing transition. The weighted average filter focuses on the centre area by giving higher weight to it therefore the impact of center area is higher than the border area. In motion blur the effect of fast moving object in still image will be highlighted (Soe and Zhang, 2012). Motion blur occurs due to rapid motion of the object or because of long exposure time in other words motion blur occurs when there is relative movement between the object and image capturing device in the form of rotation, translation or when scale changed suddenly or by combination of them (Singh and Sahu, 2013). The blur produced by motion is a filter which adds blur in specific direction relative to the direction of movement. To find the transformation value for each pixel of image a Gaussian Function is used to produce the Gaussian blur. It is considered as a low pass filter which used to noise minimization to enhance the structureof image at all scales. The bell-shaped curve is used to describe the Gaussian function so applying the Gaussian filter gives higher weight to the center pixel and the weight decreases until the border pixels. The Gaussian filter mixes specific pixels values (which is under bell-shaped curve) incrementally. The blurring is high in the center pixels while it will be light at the edge pixels (Gupta and Kumar, 2013). The blur of Gaussian filter can be controlled by using two factors, area size and variance.

## DEBLURRING TECHNIQUES

**General linear model:** In this model, blurring process is the process of converting images with sharp edges into blurred images assumed to be linear (Hansen *et al*., 2006). This assumption is very important in applications of the blur process approximation. In addition the original sharp image and the captured blurred image are assumed to be digital grayscale images with the size of (m x n), assuming that the blur is the simplest case of blurring. In this case the blurring of columns is performed independently of the blurring of rows. The two matrices of Ac of size m x m and $A_r$ of size n x n are considered in this case. The relation between latent (sharp) and the recorded (blurred) images are shown as in Eq. 2:

$$B = A_c I A_r^T \tag{2}$$

When, the phrase $A_c I$ remark concerns the application of blurring to all columns of image I and $IA_r^T$ is the application of blurring to all rows of image I. The simplest solution for linear model is explained in Eq. 3:

$$I = A_c^{-1} B (A_r^T)\text{-}1 \tag{3}$$

In the real world, the reconstructed image is not reflected in the original one because off the omission of noise during the process of image capturing. Image noise is caused by random variation of intensities and it is generated because of the imperfection of imaging devices. Thus extraneous and spurious information will be introduced to the captured image. Therefore the noise term will be considered in this model as shown in Eq. 4:

$$B = A_c I A_r^T + E \quad (4)$$

where E is the image noise and the image size is m x n. We can find the sharp image by applying Eq. 5:

$$I = A_c^{-1} B (A_r^T)^{-1} - A A_c^{-1} E (A_r^T)^{-1} \quad (5)$$

Where, the part $A^{-1}_c E (A^T_r)^{-1}$ can be considered as inverted noise which is an estimate of the contribution of additive noise in the sharp image reconstruction process. We can notice that the inverted noise dominates the process of reconstruction.

**Singular value decomposition:** In this section the blurring model (Hansen *et al.*, 2006) will be discussed. This model of blurring is more general compare with the previous one. According to this model the blurring process is perform simultaneously in columns and rows of the image. At first the shape of the matrices of sharp image I and blurred image B will be changed by resizing the dimension of I and B into two vectors of size N = mn. The new vectors will be $I_{vec}$ and $B_{vec}$ The relation between the vector of sharp image and the vector of blurred image in blurring general linear model can be described by Eq. 6:

$$B_{vec} = A I_{vec} + e \quad (6)$$

It is assumed that matrix A is blurring matrix of size N X N and it is known but in real world it is constructed by imaging system. The column vector of noise image E are denoted by term e. So the reconstructed of sharp image can be solving by Eq. 7:

$$I_{vec} = A^{-1} B_{vec} - A^{-1} e \quad (7)$$

Where, the term $A^{-1}$ represents the inverted noise. If the impact of the inverted noise is high on the reconstructed image, the deblurred image will become highly distorted. Applying singular value decomposition (SVD) on the blurring matrix achieving achieved two orthogonal matrices (U and V) and diagonal matrix as shown in Eq. 8:

$$A = U \Sigma V^T \quad (8)$$

Where, $U^T U = V^T V = I_N$ and = diag ($\sigma_i$) is a diagonal matrix of N X N which contains nonnegative values (singular values). These values are organized diagonally in a nonincreasing order ($\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \ldots \geq \sigma_n \geq 0$). The determination of the rank of A depends on the positive singular value number. The right singular vector is the name of V columns while the columns of U are called left singular vector. The singular value is decreased when i increased. If there is no singular value equal to zero, the conclusion of the inverse of blurring matrix can be explained using Eq. 9:

$$A^{-1} = V \Sigma^{-1} U^T \quad \mathbf{(9)}$$

Where, $^{-1}$represents diagonal matrix where all of its values in main diagonal are equal to $1/\sigma_i$ where I = 1, 2, 3, ..., N. We can rewrite Eq. 8 and 9 according to the singular vector of left side $u_i$, the singular vector of right side $v_i$ and the singular values $\sigma_i$ as expressed in Eq. 10 and 11.

$$A = \sum_{i=1}^{N} \sigma_i u_i v_i^T \quad (10)$$

$$A^{-1} = \sum_{i=1}^{N} \frac{1}{\sigma_i} v_i u_i^T \quad (11)$$

And Eq. 7 can be reformulated as expressed in Eq. 12:

$$I_{vec} = \sum_{i=1}^{N} \frac{u_i^T B_{vec} v_i}{\sigma_i} - \sum_{i=1}^{N} \frac{u_i^T e v_i}{\sigma_i} \quad \mathbf{(12)}$$

If percentage of singular value to the last singular value $\sigma_1/\sigma_N$ is very large the solution is very sensitive to the errors of rounding and perturbations.

**Richardson-Lucy Deconvolution:** The deconvolution of Richardson-Lucy, also known as the Lucy-Richardson algorithm (the original paper by Richardson (Yang *et al.*, 2007) and the original study by Lucy (Chang *et al.*, 2012) is a technique used to restore the original sharp image from the blurred one when the blurring is caused by known point spread function PSF, a technique introduced by William Richardson and Leon Lucy. The process of this technique is to represent the pixels of blurred image in terms of the original sharp image and point spread function. A several researchers use Richardson-Lucy algorithm such in (Singh and Jain, 2013; Chang *et al.*, 2012; Tai *et al.*, 2011; Prasad, 2002; Al-Ameen *et al.*, 2012; Wu *et al.*, 2012; Yang *et al.*, 2012; Khan *et al.*, 2013; Wu *et al.*, 2013; Tai *et al.*, 2011; Ding *et al.*, 2014; Chu *et al.*, 2012; Zhou *et al.*, 2015; Yang *et al.*, 2014; Torres, 2008; Liu *et al.*, 2015a, b; Dai, 2016; Su *et al.*, 2015; Yamauchi *et al.*, 2015a, b; Almeida *et al.*, 2015; Strohl and Kaminski, 2015). The functions h, f and g are explained in the following system Eq. 13-14 (Carasso, 1999):

$$Hf = g \tag{13}$$

$$\sum_j h_{ij} f_j = g_i \tag{14}$$

Where:

$$h_{ij} \geq 0,\ f_j > 0,\ g_i > 0$$

and;

$$\Sigma_j h_{ij}\ f_j = 1,\ \Sigma_j f_j = \Sigma_j g_j = N$$

Are considered as probability density functions and these are not normalized necessarily. The value of fi/N can be considered as a probability of an event p(fi) in ith location of the latent(sharp) image array f. At the same time p(gk) is equal to gk/N which is considered the probability of an event located in $k^{th}$ location in the blurred image array g. After the realization that P(gk/fi) hki, we get:

$$p(f_i \mathrm{l} g_k) = \frac{p(g_k|f_i)p(f_i)}{\Sigma_j p(g_k|f_j)p(f_j)} \tag{15}$$

So:

$$p(f_i) = \sum_k p(fi|g_k)p(g_k) = \sum_k \left( \frac{p(g_k|f_i)p(f_i)p(g_k)}{\Sigma_j p(g_k|f_j)p(f_j)p(f_j)} \right) \tag{16}$$

Using p ($f_i$) = $f_i$/N, p ($g_k$) $g_k$/N and p ($g_k$|$f_i$) , we get:

$$f_i = f_i \sum_k \frac{h_{ki}\, g_k}{\Sigma_j\, h_{kj}\, f_j} \tag{17}$$

The desired solution fof of above nonlinear Eq. can be found by the following iterative technique:

$$f_i^{n+1} = f_i^n \sum_k \left( \frac{h_{ki}\, g_k}{\Sigma_j h_{kj} f_j^n} \right) \tag{18}$$

Which can be written as:

$$f^{n+1} = f^n H^{\bullet} \left( \frac{g}{Hf^n} \right) \tag{19}$$

**Neural network approach:** Neural network approach can be employed to generate a sharp image from a blurred one. The principle of this approach is by training the system using blurry images and its corresponding sharp images. At first the system is fed a list of blurred images and a list of the desired output of corresponding sharp images. Training on various types of blurring images enables the system to predict the sharp image corresponding to the blurred one. Some neural network based techniques of restoring sharp image from captured blurred version are used in (Yang *et al*., 2007; Kumar *et al*., 2012a, b). Two training algorithms were explained by Jubien and Jernigan (1991) which were used to restore blurred image based on neural network and applied in blind image deconvolution. One of them was based on the rule of Least Mean Square (LMS) while the other one was dubbed algorithm-X. Subashini *et al*. (2011) suggested a solution based on the rule of gradient decent and network of back propagation which contains three layers. Highly nonlinear neuron of back propagation used in image restoration failed to achieve high quality of restored image, high computational speed, less complexity of computation because of the less number of used neurons and the fast convergence with short training method. Saadi *et al*. (2013) improved neural network training by proposing novel optimization swarm algorithm known as Artificial Bees Colony (ABC). It is inspired from the intelligence of honey bees used in food seeking.

**Iterative methods:** Biemond *et al*., 1990 explained the use of iterative restoration of linear image blurs caused by pointwise nonlinearity such as additive noise and film saturation. It illustrated that the iterative deconvolution methods can use various types of a prior knowledge about the class of possible solutions to remove non-stationary blurs. They explain the problems of convergence of algorithm and compare well known algorithms such as Wiener filters, constrained least square filters and inverse filter which are shown to be limiting solutions of variations of the iterations. Finally the regularization was introduced to prevent exceeding the allowed limit of noise amplification caused by ill-conditioned inverse problems such as deconvolution problems. In addition, the effect of noise can be terminated after a number of finite iterations.

Beck and Teboulle (2009) studied class of Iteration Shrinkage-Thresholding Algorithm (ISTA) to solve the problems of linear inverse which occurs in image processing. They mentioned that these are attractive methods because of their simplicity but it is well known that the convergence is very slow. They also show the Fast Iterative Shrinkage-Thresholding Algorithm (FISTA) which achieves the simplicity of computation of ISTA and the convergence with global rate which is significantly better.

Herring (2010) represented the impact of three projected iterative methods on image deblurring: projected Landweber method, projected Successive Over-Relaxation method (SOR) and an interior point gradient method. Nagy *et al*. (2004) introduced a number of Matlab tools using methods of iterative image restoration. They implemented an efficient matrix vector multiplication by using Matlab and combined the capabilities of graphics and the powerful computing in Matlab to make programming with object-oriented method and operator overloading.

**Wiener filtering:** The most widely used technique in image deblurring field is Wiener filter. The performance of this filter to remove image blur resulted from focused optic or linear motion is very high, although sometimes image blurring resulted from poor sampling. In digital images each pixel represents the value of intensity of stationary point in the front of the image capturing device. If the shutter time is relatively long or if the camera is moving, a given pixel will represent a mix of intensities of pixels along the camera motion line (Singh *et al*., 2008; Dwivedi and Singh, 2013). The performance of Wiener filter is optimal in trade-off between noise smoothing and inverse filter because of the blurring inversion and noise removal simultaneously. Some techniques which used Wiener filtering method can be found in (Kumar *et al*., 2010; Wang *et al*., 2005; Bojarczak and Lukasik, 2007; Zheng, 1989; Yang *et al*., 2014b; Sankhe *et al*., 2011; Mohamed and Hardie, 2015; Xiao *et al*., 2015; Carrato *et al*., 2015). The description of model is shown in Eq. 20:

$$b(x,y)=h(x,y)\times s(x,y)+n(x,y) \tag{20}$$

where the recorded blurred image is b (x, y), h x, y) represent the impulse response of linear invariant system, s(x, y) is the unknown latent sharp image. Wiener filter tries to estimate s(x, y) by calculating g(x, y) as shown in Eq. 21:

$$\hat{s}(x,y)=g(x,y)\times b(x,y) \tag{21}$$

s (x, y) is the estimation of s (x, y) which minimizes the mean square error. Wiener filter works in the environment of frequency domain. So, to find s (x, y) the frequency domain of s (x, y) must be calculated as shown in Eq. 22:

$$G\ (u,v)=\frac{H(u,v)\ W\ (u,v)}{|H(u,v)|^2\ W(u,v)+N(u,v)} \tag{22}$$

Where, G (x, y), H (x, y) is the Fourier transformation of g and h respectively, the mean power spectral density of s (x, y) is represented by W (u, v) and N (u, v) is the mean spectral density of n (u, v). Therefore the performance of filter in frequency domain can be expressed by Eq. 23:

$$\hat{S}(u,v)=G(u,v)B(u,v) \tag{23}$$

Where:

$\hat{S}$ (u, v) = The estimated sharp image in frequency domain

B (u, v) = The blurred image in frequency domain

If the information of the same point is contained by three pixels in a line, the image will be convolved in time domain with three-point of boxcar (Dwivedi and Singh, 2013). Above equation seems to be based on inverse filter. There are a number of restrictions related to the Wiener filter implementation such as the unknown H requires guessing, it sometimes gives good results but it requires more effort to try suitable one. In addition, Wiener filter sometimes fails because in some cases the sine function is equal to zero at some values of x and y.

**Blind deconvolution approach:** For image restoration purpose, Wiener filters and inverse filters requires the estimation of degradation function to be highly accurate. The information of noise model is also required. Trying to obtain the above information from a practical point of view seems very hard. In blind deconvolution a calculation of an initial estimation of degradation function will be done. Then the system of blind deconvolution uses iterative process until obtaining an accurate estimation by minimizing the mean square error. Discussion of blind deconvolution can be found at (Singh and Jain, 2013a, b; Patel and Jariwala, 2014; Poulose, 2013; Levin *et al*., 2011; Umale and Sahu, 2014; Kundur and Hatzinakos, 1998; She *et al*., 2015; Prato *et al*., 2015; Zelenka and Koch, 2015; Zhou *et al*., 2015; Perrone *et al*., 2015). In blind deconvolution there are two main approaches. The first is named projection based blind deconvolution and the second is named maximum likelihood restoration. Initial estimation for degradation function (Point Spread Function (PSF) will be implemented in the first approach. After that another initial estimation for the original image will be done, the process will be repeated until the predefined criteria of convergence are met. The usefulness of this method is its robustness against the support size inaccuracies and there is no sensitivity to noise. A disadvantage of this approach is that if the local minima are not initiated appropriately it will lead to error. Maximum likelihood is used in the second approach to estimate the parameters like matrix of covariance and PSF. The approach takes into consideration some parameters like size, symmetry and other parameters because PSF estimation is not unique. Low complexity of computations is considered an advantage of this approach while the disadvantage is converging to the local minima of the estimated cost function.

## EXPERIMENTAL RESULTS

The performance evaluation process of the deblurring techniques needs the measure of latent image quality. There are two methods of image quality evaluation (Umale and Sahu, 2014) which are subjective and objective measures. The subjective measures are more accurate than the objective measures because this type of evaluation tries to accommodate the perception and satisfaction of different types of users and requirements and it doesn't depend on numerical calculations. The objective method is entirely based on mathematical formulas and a numerical value which resulted by applying these formulas is used to evaluate different types of deblurring techniques. The popular objective metric formulas are: Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM). PSNR is used widely in image quality measurements and the evaluation of the resulted image is by db (decibel), Eq. 24 and 25 represent the PSNR calculations:

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{i=0}^{N-1}[I_{ij}-X_{ij}]^2 \quad (24)$$

$$PSNR = 10\log\downarrow 10(MAX\uparrow 2 / MSE) \quad (25)$$

Where:

MSE = The mean squared error
I = Original image
X = Deblurred(sharp) image
M = Row number
N = The column number and Max is the maximum values of possible intensity. The calculations of Structural Similarity (SSIM) (Wang and Tao, 2014) can be expressed as in Eq. 26:

$$SSIM = \frac{(2\mu_I\mu_X + c_1)(2\sigma_{iX} + c_2)}{(\mu_I^2 + \mu_X^2 + c_1)(\sigma_I^2 + \sigma_X^2 + c_2)} \quad (26)$$

Where:

$\mu_I$ and $\mu_x$ = The means of I and X
$c_1$ and $c_2$ = Used to stabilize the division with weak denominator
$\sigma^2_I$ and $\sigma^2_I$ = The variance of I and X

Table 1 represents results of implementation of various deblurring methods where the input blurred images are twenty five synthetically blurred images each of these images are degraded by convolve it with Gaussian kernel with variance value equal to 2 and additive Gaussian noise with standard deviation equal to 0.01 to simulate the Gaussian degradation.

Table 1: Evaluation of various deblurring methods

| Author | PSNR | SSIM |
|---|---|---|
| Yang *et al.* (2012) | 33.723 | 0.73 |
| Chu *et al.*(2012) | 34.121 | 0.72 |
| Kumar *et al.* (2012) | 22.450 | 0.63 |
| Hongying *et al.* (2006) | 20.852 | 0.63 |
| Zheng (1989) | 27.772 | 0.70 |
| Yang *et al.* (2014a) | 31.430 | 0.74 |
| Biemond *et al.* (1990) | 26.542 | 0.73 |
| Herring (2010) | 29.328 | 0.74 |

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