ANALYSIS OF DECONVOLUTION ALGORITHMS FOR IMAGE RESTORATION

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I, VIDHI , Roll No. 2K17/SPD/20 student of M.Tech. SIGNAL PROCESSING AND DIGITAL DESIGN, hereby declare that the project Dissertation titled "ANALYSIS OF DECONVOLUTION ALGORITHMS OF IMAGE RESTORATION" which is submitted by me to the Department of ELECTRONICS AND COMMUNICATION, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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I hereby certify that the Project Dissertation titled "ANALYSIS OF DECONVOLUTION ALGORITHMS OF IMAGE RESTORATION" which is submitted by VIDHI, 2K17/SPD/20, ELECTRONICS AND COMMUNICATION Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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……………………..

VIDHI

ABSTRACT

This report describes the latest developments in the field of image deblurring.The methods of image restoration try to remove the noise and blurring while capturing the image .The concept of deblurring is to generate a better representation of the original blurred image. Combination of the blurring and random noises make image deblurring process very problematic.To create the well-posed solution we need to merge additional information about the ideal image. From several decades significant progress is continuously being made in image restoration field. The applications of image restoration are in the field of medical imaging, space exploration, stegnography etc. In this study analysis of various blind and non blind methods is done for restoring the picture .Various non blind methods like inverse filtering, pseudo inverse filtering and Weiner filtering ,Lucy Richardson(LR) are studied. All these methods are non blind methods so they have knowledge of PSF .But in case of absence of known PSF these methods would not work .These methods have drawbacks like weiner filtering method shows slow convergence rate, LR method shows ringing effect and high processing time and inverse filter is very sensitive to noise .But as we studied Blind methods then we analyzed that blind methods are giving better results as compared to non blind methods. Blind methods do not contain the information regarding PSF. So there is a need to estimate the PSF. Advantage of blind methods is that they improve the convergence rate of the process to get deblurred image. These methods remove the ringing effects from the restored image and take less processing time and also preserve

the edges to restore the better results in terms of image intensity around the edges. The applications of this method exist in the field of aerospace and defence sector, also in field of medicine and robotics. In this study we analyzed various methods and their simulation and experimental results were compared with each other.As a result we observed that deblurring using blind deconvolution is getting better results as compared to other methods in terms of better convergence rate and less mean square value.

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LIST OF SYMBOLS, ABBREVIATIONS

1.1 PSF Point Spread Function

1.2 LR Lucy Richardson

1.4 RVIN Random Valued Impulse Noise

2.1 M-P Moore-Penrose

2.1 AWGN Additive White Gaussian Noise

2.2 W Weight Matrix

2.3 T-M Tikhonav-Miller

2.4 R Regularization Matrix

2.5 λ Regularization Parameter

2.6 ANN Artificial Neural Network

2.7 IBD Iterative Blind Deconvolution

3.1 R-L Richardson Lucy

3.2 OTF Optical Transfer Function

3.3 I R Image Restoration

4.1 NAS-RF Non Negative And Support Constraints Recursive Inverse Filtering

4.2 SD Standard Deviation

4.3 TD Threshold

4.4 PSF Point Spread Function

5.1 PSNR Peak Signal To Noise Ratio

5.2 MSE Mean Square Error

CHAPTER 1

INTRODUCTION

In so much applications of the machine vision, image processing require image preprocessing to compensate the image distortion appeared in the formation of the image . In this report we center around the issue of restoration of the image which is distorted by the movement of object during exposure time of camera. Image restoration uses knowledge about the degradation. The distortion in image can be formulated or modeled as noise or degradation function. Although, all the images are more or less blurry. This is due to the fact of the inclusion of a considerable measure of obstruction in the camera.

1.1 IMAGE RESTORATION

Fig.1.1 Restoration of an old and damaged photograph

Pictures are conveyed to record or show supportive information. In any case, due to blemishes in the imaging, the recorded picture, unendingly, addresses a spoiled interpretation of the primary scene. The use of deblurring techniques aims to remove or minimize known degradations in a picture, using an earlier knowledge of the degradation phenomenon.

Fig.1.2 Image deblurring of a defocused image

Image can be restored in a number of types. Image can be stored colorwise and black and white too .Restoring an unblurred picture from a solitary, movement obscured photo has for some time been a basic research issue in computerized imaging. As we know that Point Spread Function (PSF) is space invariant, we can get back the original picture by using deconvolution. Along these lines, blind deconvolution and non-blind deconvolution are the two categories in which picture deblurring can be sorted into. In non-blind deconvolution, the movement obscure Point Spread Function is thought to be known or processed somewhere else. The main errand remaining is to gauge the unblurred inactive picture. Conventional strategies, for example, Weiner and Richardson-Lucy deconvolution were proposed decades back, however are still generally utilized in many picture rebuilding errands these days since they are straightforward and proficient.

Fig 1.3 Restoring colored and black and white images

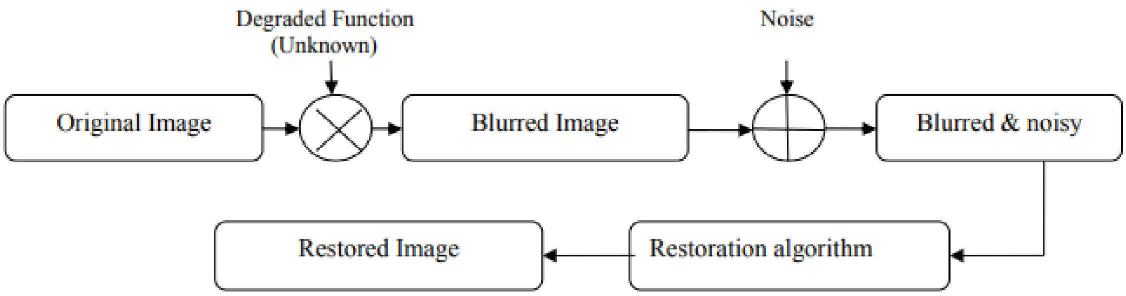


Fig 1.4 Block Diagram of Image Restoration

1.1.1 Formulation of the problem

a(j,k) is an initial picture which is not distorted where the value of a(j,k) is the the pixel brightness having coordinates (j,k), $0 \leq j \leq J$, $0 \leq k \leq N$ where N,J – height and weight of image, correspondingly, let b(j,k) be distorted image of a(j,k) and c(j,k) is the impulse response (IR) of the distortion operator. We denote $\hat{a}(j,k)$ as an estimate value of image a(j,k) and K(j,k) as noise which is independent of image. Distortion model is given as

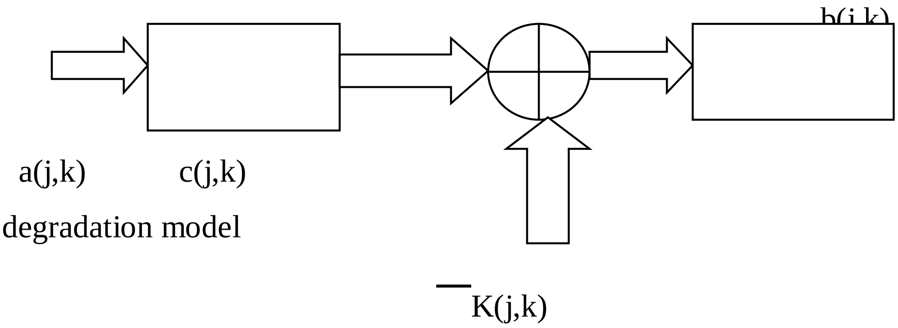


Fig.1.5 Degradation Model

$$b(j,k)=c(j,k)*a(j,k)+K(j,k), \qquad (1.1)$$

where «*» signifies discrete convolution in two measurements. This portrayal depicts the contortion as sifted by discrete two-dimensional direct framework having drive reaction c(j,k), with included commotion.

Since distortion we are describing is by the method of convolution, it is possible to restore image by the inverse operation of convolution which is deconvolution. There are many methods for solving this problem of blurring of images. And also there are various types of noise models exist.

1.2 POINT SPREAD FUNCTION – PSF

The distortion operator c(j,k), known by PSF models the blurring of the image, and is showing properties of linearity and shift-invariance. By linearity

$$C[af1(j,k)+bf2(j,k)]=aC[f1(j,k)]+bC[f2(j,k)] \qquad (1.3)$$

and by shift-Invariance:

$$C[f(j-m),(k-n)]=b(j-m,k-n) \quad (1.4)$$

The PSF can be seen as the irradiance distribution that results from a single point source. Although the source may be a point, as a consequence of the diffraction of light and the presence of defects in the image device, the image of a point source occupies an area of finite dimensions, rather than a point. In this sense, the picture of a mind boggling item can be viewed as a convolution of the genuine article and the PSF. In a frameworks viewpoint, the PSF speaks to the motivation reaction of an engaged optical framework, i.e., the reaction of an imaging framework to a point object.In frequency domain degradation function c(s,t) is otherwise called the optical transfer function (OTF).

1.3 BLUR/NOISE MODELS

The spatial part of noise depends on the measurable lead of the power esteems. These might be considered as irregular factors , described by a likelihood thickness work (PDF). Some usually discovered blur models and their comparing PDFs are given beneath.

1.3.1 Gaussian Blur Model

Also known as Gaussian Smoothening. Gaussian blur is commotion having density function of the ordinary circulation (otherwise called Gaussian distribution). As it were, the qualities that the blur can hold on are having distribution of Gaussian type. It occurs as result when we blur a picture by gaussian capacity. Numerically applying gaussian haze is same as doing convolution of the picture with gaussian capacity. . If r is a random variable which shows blur, then its distribution function is given by

1

$$p(r) = \sqrt{\ }_{2\pi\sigma}\ e{-}(r-\mu)^2/2\sigma^2 \quad (1.5)$$

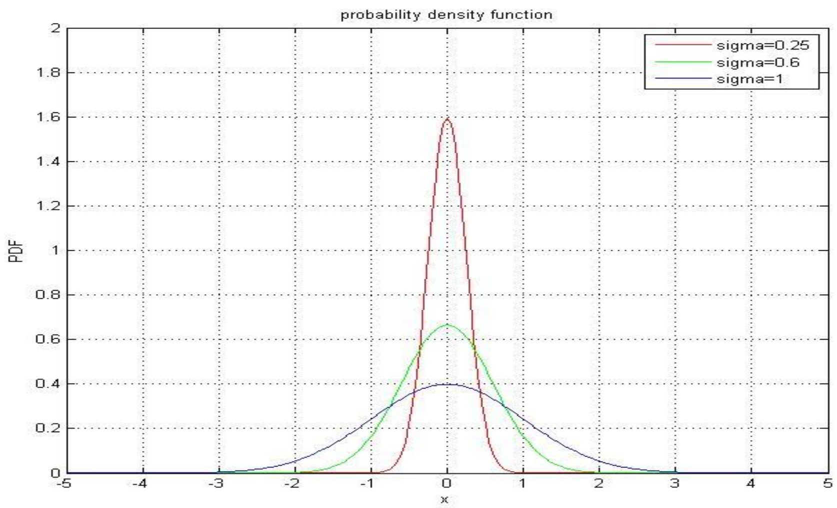


Fig.1.6 gaussian distribution curve

1.3.2 Uniform Noise

Uniform noise is another image noise observed commonly. With uniform probability, this noise can acquire esteems in an [i,j] in this case. The PDF of uniform noises are

$$p(r) = 1/(j-i) \quad \text{if} \quad i \le r \le j \quad (1.6)$$

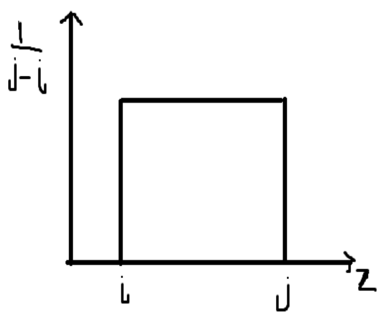


Fig.1.7 uniform distribution

1.3.3 Impulse Noise

Impulse noise is depicted by a commotion spike replacing the real pixel esteem. Impulse noise is additionally partitioned into two classes. Random Valued Impulse Noise(RVIN) and salt and pepper noise(SPN). In RVIN, the impulse value at a specific pixel might be an arbitrary incentive between a specific interim. In any case, in SPN the impulse are either the base worth or the greatest worth permitted in the force esteems. For example, 0 and 255 because of 8-bit picture.

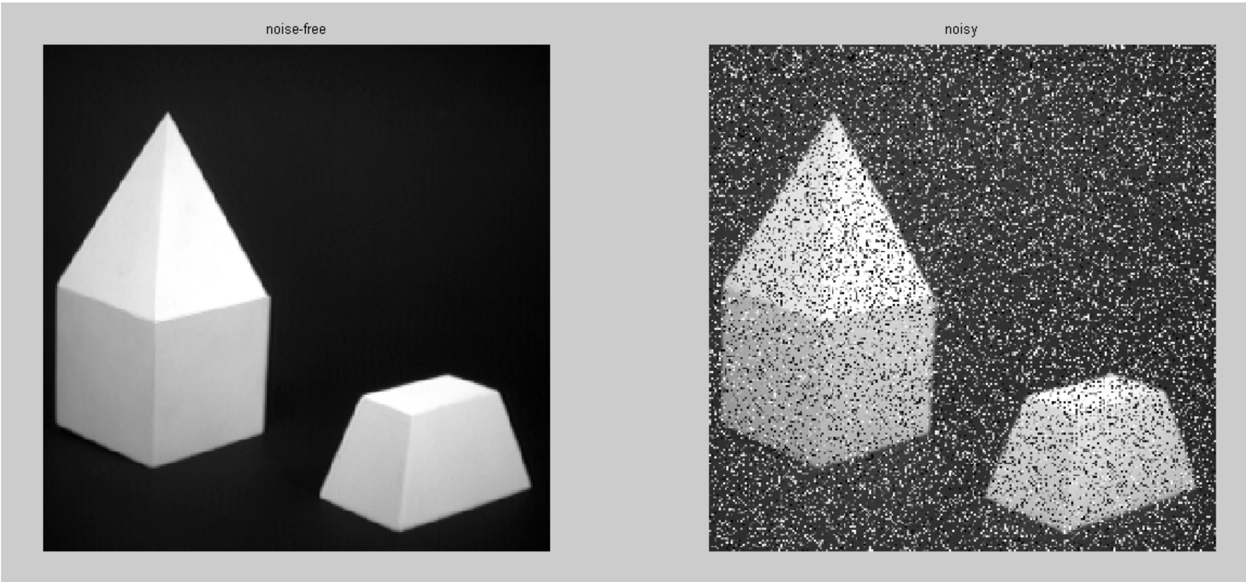


Fig.1.8 impulse noise

1.3.4 Motion Blur

This type of blur occurs when camera capturing the image moves so quickly. Some times the time is so brief that camera can take only instantaneous clicks and sometimes high speeding object or long lenth of outing time shows blurring . Consider the velocity v,the relative velocity and with the horizontal axis at an angle θ and T to be the duration of exposure, meaning the blur length is $N = vT$ and hence the motion blur PSF can be taken as

$$h(x, y) = \begin{cases} 1/N & \text{if} \quad 0 \leq |x| \leq N\cos\theta; \quad y = N\sin\theta \\ 0 & \text{otherwise} \end{cases}$$

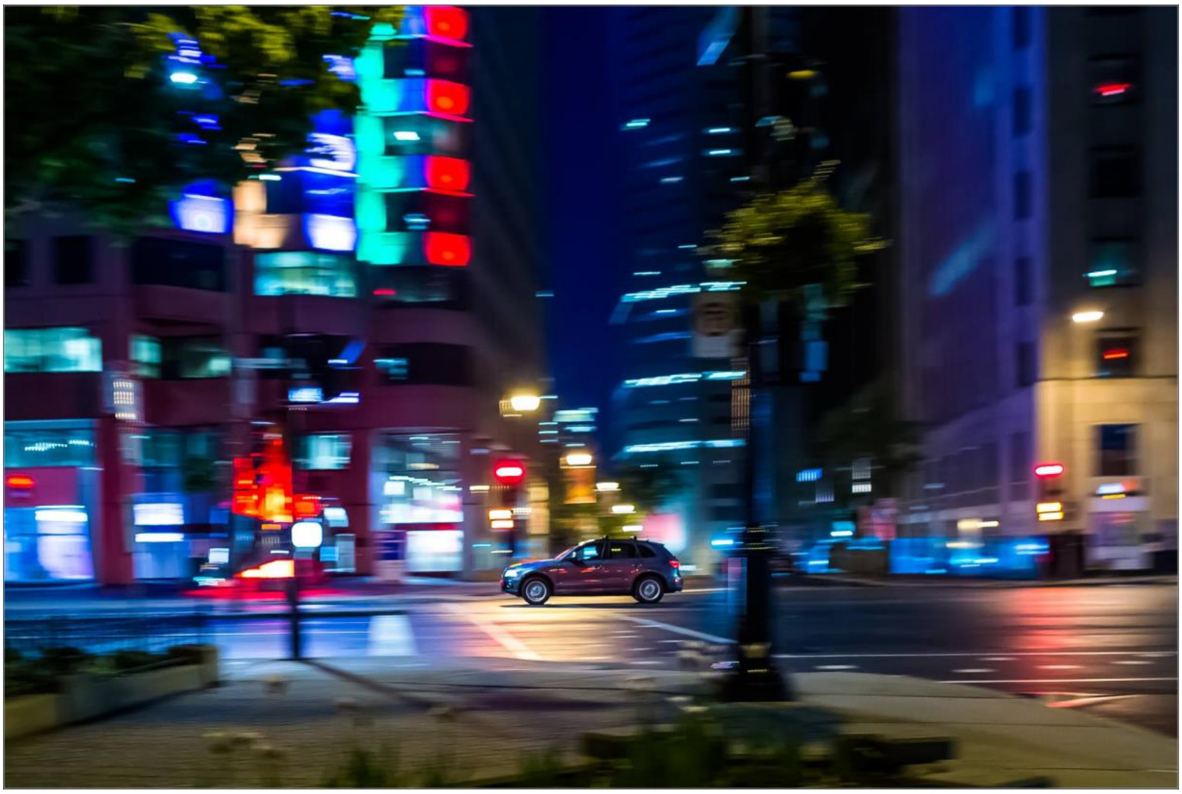


Fig.1.9 Motion blur

1.3.5 Defocus Blur

Another common blur is the result of improperly focused camera. When focus of camera being not proper or properly set then defocus blur exists in the image. The amount of resolution is basing on the quantity of blurring done .Occurrence of more resilience in the picture results in the low resolution. If we want good resolution then there must be minimum defocus. If we assume the system of lens to be circular in aperture with radius m, then spread function

$$h(q, r) = \begin{cases} 0 & \text{if } \sqrt{q^2 + r^2} > m \\ 1/\pi m^2 & \text{otherwise} \end{cases} \quad (1.8)$$

Fig .1.10 Defocus Blur

1.4 TYPES OF NOISE

Noise is basically non wanted changes in the image. It changes the visual picture of the image. Images relating to digital signals often get corrupted by different types of noise. Some of those commotions are Gaussian clamor, salt and pepper commotion, uniform clamor, motivation commotion, Brownian clamor, inverse noise.

1.4.1 SALT AND PEPPER NOISE

It is likewise called as drive commotion. It is created because of sudden aggravations in the picture flag. It is spoken to as inadequately happening white and dark pixel. Median filter is utilized to expel this sort of clamor.

Fig.1.11 salt and pepper noise

1.4.2 BROWNIAN NOISE

Also can be known as red noise. It is formed due to Brownian motion so alternatively called as random walk noise. These kind of noises are strong in longer wavelengths.

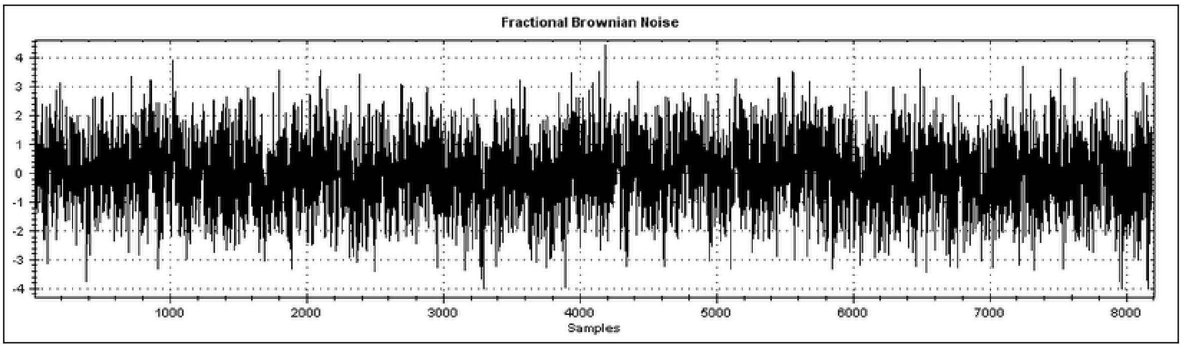


Fig.1.12 Brownian Noise

CHAPTER 2

DENOISING TECHNIQUES

2.1 SPATIAL FILTERING

- Mean Filtering
- Order-Statistics Filtering
- Adaptive Filtering

2.1.1 Arithmetic mean filtering

Technique center pixel estimation of the channel window is supplanted with the average of all the pixel esteems inside the channel window. It just mends neighborhood varieties in a picture. Blur is diminished because of this smoothening, yet edges inside the picture get blurred.

$$\frac{1}{9} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Fig. 2.1 Mean filter

2.1.2 Median filter

It is a factual technique. In this strategy, we locate the median of the pixels and supplant that by the middle of the dark dimensions of the area of those pixels. It is utilized to evacuate the salt and pepper clamor. It generally creates less blurring as compared to other linear smoothening filters of same size. After filtering, this filter removes noise while keeping the edges.

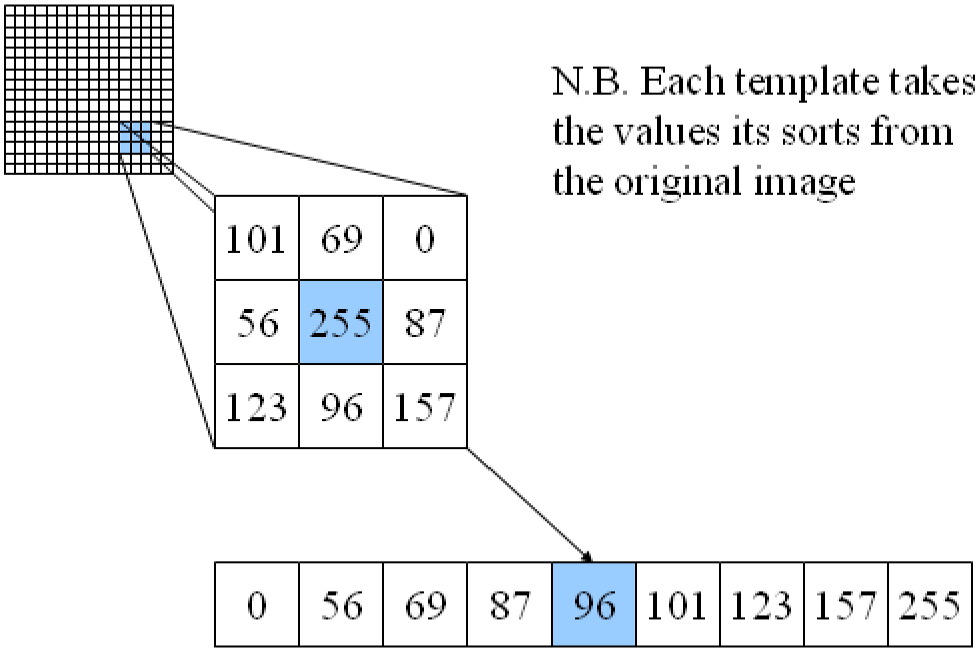
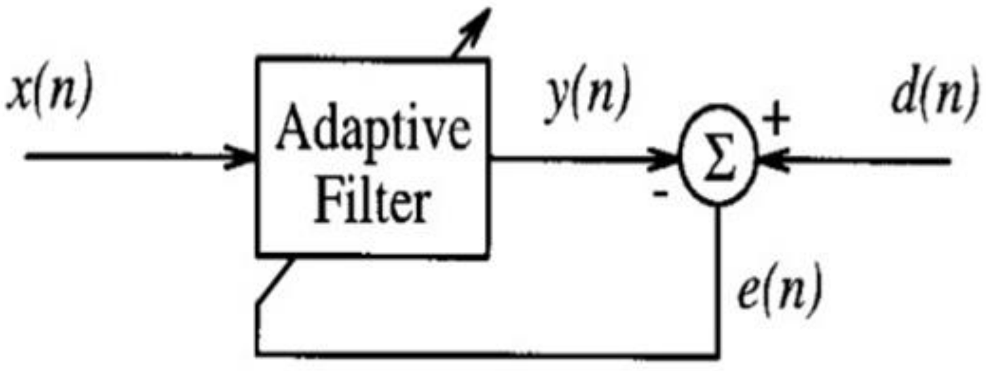


Fig.2.2 Median filter

2.1.3 Adaptive filtering

A linear filter with factor parameter controlled transfer function. This utilizes shading and dark space for evacuating imprudent commotion. This sort of channel is additionally used to expel the impact of speckle clamor. This filter shows better results in preserving edges, image details and thin lines as compared to other filters.



Where x(n)=input digital signal d(n)=desired response

y(n)=output digital signal e(n)=error signal

Fig.2.3 Block diagram of Adaptive Filter

2.2 DECONVOLUTION

We know that after having information about the point spread capacity h(x, y)which is causing corruption then we can get back the first picture by deconvolution. Classical picture deblurring methods and blind deconvolution techniques. Old style deblurring, earlier learning of the PSF which caused the corruption is present. Blind deconvolution procedures are utilized when earlier learning of the corruption procedure is absent.

2.3 CLASSICAL RESTORATION TECHNIQUES

Traditional deblurring procedures demands prior information of the blurring procedure. Following techniques help in determine this process

- Determined by image observation.
- Determined by experimentation
- Determined by modeling

After determining the spreading function, the following methods given below can be used for deconvolution.

2.3.1 Inverse Filter

To deal with restoration, Direct inverse filtering is least dangerous way. Fourier transform of degraded image is divided by the Fourier transform of the degradation function to calculate the Fourier transform of the image L(i,j).

$$L\hat{}(s,t)=G(s,t)/H(s,t) \quad (2.1)$$

No additive noise in the degraded image is suited here. So , degraded image is g(i,j) = l(i, j)∗h(i, j).Be that as it may, on the off chance that noise gets added to the degraded picture, at that point the aftereffect of direct inverse filtering is poor. The advantage of this method is that it needs only the blur PSF as an earlier knowledge. Thus, the inverse filter generates perfect deblurring in the absence of noise. It comes in the scene via channel through which the picture is made (disperse impacts), by the chronicle medium (sensor noise), by recording because of the restricted precision of the account framework, and by quantization of the information for computerized stockpiling. Thus, taking noise into account, dividing again both sides of equation 2.1 by H(s,t) we will obtain an estimate of the form:

Taking for G(s,t) in the above equation, we get

$$L(s,t) = G(s,t)/H(s,t) = F(s,t) + N(s,t)/H(s,t) \quad (2.2)$$

From this equation, it is wanted to have the second term as small as possible, so the estimate can better approaches the real image's Fourier transform.

Nevertheless, inverse filter may not exist due to the presence of zeros in H(s,t) at the selected frequencies (s,t). Not reaching zero but remains significantly small, the blurring function spectral representation H(s,t) and the inverse filtered noise,in the second term which increases many fold leads the inverse filtered image to be amplified noise dominated. This division is to be formed

$$L(s,t)=G(s,t)/H(s,t) \quad (2.3)$$

And we should limitize the range to very less very close to (0,0) because zeroes exist very few near (0,0) and the value is highest in this area.

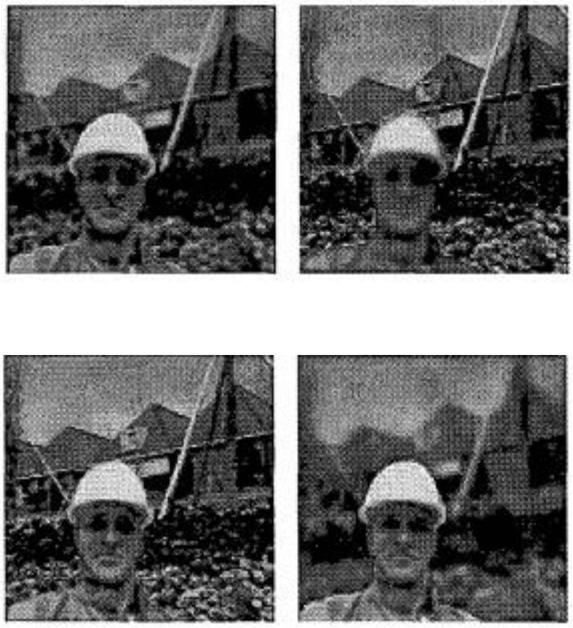


Fig 2.4 a) Test image g1 b) Fig Test image g2 c) restructured g1 d) restructured g2

2.3.2 Pseudo-inverse filtering

The image degradation model can alternatively be expressed using the following matrix-vector form:

$$g = Hu^{o} + v, \qquad (2.4)$$

where $\mathbf{g} \in R^{n}$, $\mathbf{u}^{o} \in R^{l}$ and $\mathbf{v} \in R^{n}$ are the degraded picture, the real picture and the blur, respectively, plus blurring matrix $H \in R^{n\times l}$ be defined using blur PSF H. The blurring matrix H is normally singular or degenerate, making it non-invertible. If the columns of H are linearly independent, however, Utilizing the Moore-Penrose pseudo-inverse, the inverse solution can be taken care of:

$$u = (H^{T} H)^{-1} H^{T} g. \qquad (2.5)$$

The pseudo-inverse approach assumes that the eigenvalues of $H^T H$ occur away from the origin, making it more well-posed than the inverse approach.

2.3.3 Non Negative And Support Constraints Recursive Inverse Filtering

This calculation makes an estimation of target picture based on given picture. This estimation is given based on limiting the mistake work containing the data of the pixel of the picture. Its answer makes the mistake work all around upgraded. Knowledge of the parameters of PSF plus earlier data of the first picture is not required. It is needed to ensure the picture's estimation is nonnegative. It is touchy to clamor yet has leverage it has a procedure which makes the capacity to be focalized to the worldwide minimum.

2.3.4 Block Matching

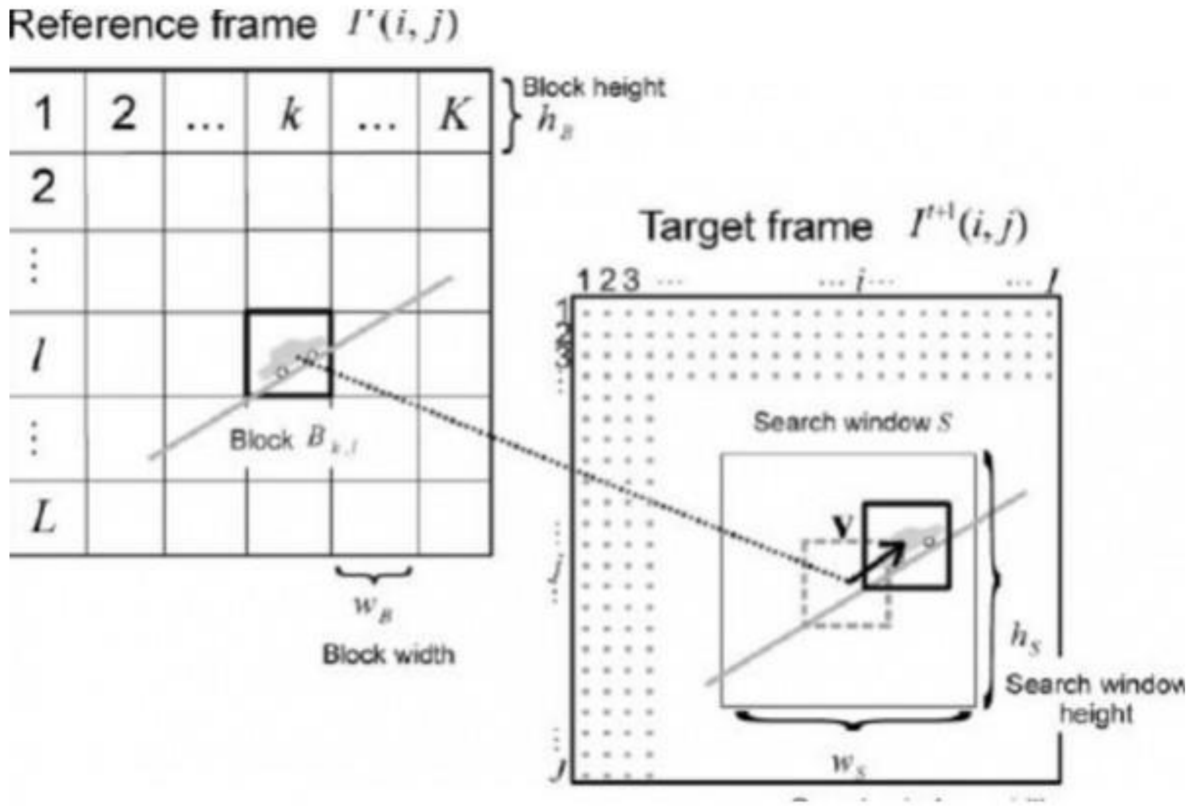


Fig.2.5 Block matching algorithm

Block matching is for discovering the hinders with high center connection since it has exactness being disabled because of noise's nearness. Use of block closeness measure that plays out an introductory denoising within nearby 2-D changed area. In this technique, picture is to be partitioned into blocks and clamors are to be expelled from each block.

2.3.5 Weiner Filter

Degradation function as well as qualities of commotion are both included into restoration process. This incorporates commotion as irregular process and its goal is to discover a estimate capacity of uncorrupted picture by limiting the mean square error. This mean square mistake is communicated as

$$s(\omega_x, \omega_y) = E(|L_j(\omega_x, \omega_y) - \hat{L}j(\omega_x, \omega_y)|2) \tag{2.6}$$

Where E(.) denotes expectation. The solution is given according to which minimizes this error .

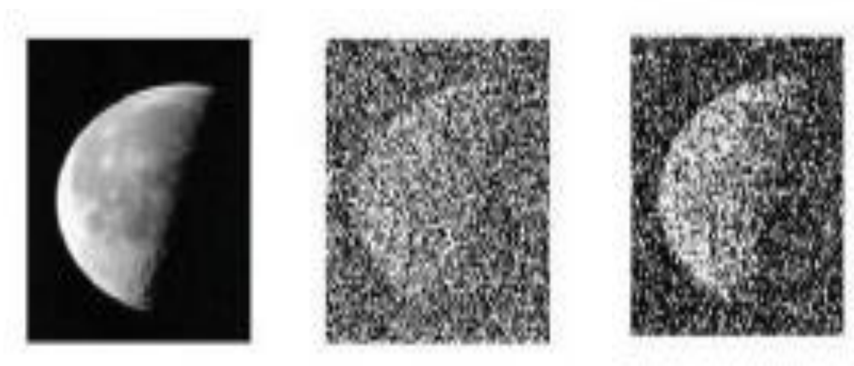


Fig 2.6 a) Original image b) noised image c) weiner filter output

2.4 Regularized image restoration

Regularization methods were developed to make the image restoration problem more well-posed by introducing information about the original image $\mathbf{u}^o$. In all the senses of Hadamard, a hurdle is well faced, if

:

1. There exists a solution,
2. The uniqueness of it, and
3. The dependency of it continuously on the data.

To satisfy the very first condition, the restoration problem must account for noise. For example, the equality $\mathbf{g} = H\mathbf{u}$ will not always have a solution because it does not account for the noise term $\mathbf{v}$. The second conditions is violated if $H^T H$ is rank deficient (i.e. contains zero Eigen values). In this situation the possibility of many solutions is huge; additional information is needed to choose the correct solution. Finally, because discontinuities cause instability in many algorithms, the solution must depend continuously on the data. In this section, Tikhonov-Miller regularization is introduced as a frame-work for making the restoration problem well-posed. This framework is then generalized so that it can be implemented using regularizers like as the total variation (TV) norm. Finally, common methods for choosing the regularization parameter are presented. Tikhonov-Miller regularization uses an explicit regularization term to incorporate information about the real image:

$$\text{Umin}=||g - Hu||_2^2 + \lambda||Ru||_2^2 \tag{2.7}$$

where $|| \, ||_2^2$ is the l_2 norm, λ is the regularization parameter and R is the regularization matrix. The regularization matrix R (also known as the Tikhonov matrix) can be a variational operator, a weighted Fourier operator or simply the identity matrix, depending on the chosen image model. The trade-off between preserving image fidelity and removing noise is controlled by the regularization parameter λ. Differentiating (2.7) with respect to $\mathbf{u}$ before setting the derivative equal to zero, it can easily be shown that the solution of this optimization issue can be written as

$$u^* = (H^T H + \lambda R^T R)^{-1} H \tag{2.8}$$

If $R = \Sigma^{1/2}\Sigma^{-1/2}$, where Σ and Σ being the covariance matrices of the real picture and the blur respectively, then Eq. (2.8) minimizes noise to signal ratio.

2.4.1 Regularizer design

The quality of the restored image will depend on how accurately the regularizer models the characteristics of the original image. Traditionally, the regularizer would be defined using the l_2 norm and a simple variational operator R, such as the Laplacian. This creates a more well-posed problem by introducing a smoothness constraint that penalizes variations caused by amplified noise. Natural images are only piecewise smooth, however, so traditional regularizers adversely affect the restoration of sharp edges, producing images that are over- smoothed. More advanced regularizers, such as the TV norm, use nonlinear penalty functions to represent the features of the the real image. There- fore, the majority of restoration procedures solve given generalized Tikhonov-Miller objective

$$U_{min} = ||g - Hu||_2^2 + \lambda R(u) \tag{2.9}$$

where R(**u**) is a general regularization term. In the following, we introduce TV and sparsity-based regularizers as effective choices for R.

2.4.2 Choosing the regularization parameter

Practically, a perfect balance ought to be created between regularization (to remove noise) and preserving data fidelity because no regularizer exactly represents the features of the original picture. For example image degraded by a 9 ×9 uniform blur and additive zero-mean Gaussian noise of variance $\sigma^2 = 25$. For a small regularization parameter $\lambda = 0.001$, the regularizer has little effect and the noise is amplified at the output, see Figure2. 6. In contrast, for $\lambda = 10$ the image is over-smoothed and edge details are lost, see Figure 2.6(d)

Many restoration methods, such as the Tikhonov-Miller method, do not provide a means to gauge the regularization parameter λ. Therefore, the regularization parameter ought to be estimated using some additional information or assumptions. In, the Miller regularization approach was used to estimate the regularization parameter λ for image restoration.

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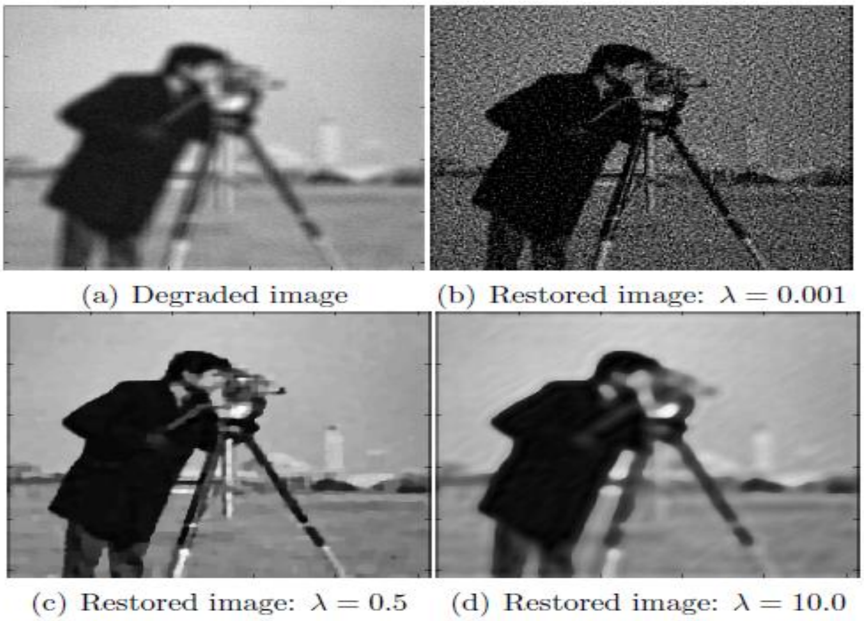

(a) Degraded image (b) Restored image: $\lambda = 0.001$

(c) Restored image: $\lambda = 0.5$ (d) Restored image: $\lambda = 10.0$

Fig. 2.7 Results using Tikhonov-Miller regularization, TV regularizer and different λ values. Cameraman degraded by 9 × 9 uniform blur and zero-mean Gaussian .

The noise bound estimate $\xi \approx \|\mathbf{g} - H\mathbf{u}^o\|^2_2$ and a regularizer bound estimate $s \approx \|R\mathbf{u}^o\|^2_2$, Miller regularization

$$\lambda = \frac{\sigma_v^2}{\|R\|^2_2(\sigma_u^2 + m^2)} \qquad (2.10)$$

where σ_{u2} and σv^2 - variances, respectively and **m** is the image mean .In practice, s is often not known, or cannot be accurately estimated, so λ cannot be calculated using this method. The following regularization parameter was proposed

$$\lambda = \frac{\|g - Hu\|^2_2}{1/\gamma - \|Ru\|^2_2} \qquad \textbf{(2.11)}$$

Here γ is a user selected control parameter that should be less than $1/\|R\mathbf{u}\|_2^2$. The formulation in Eq. (2.11) has a number of desirable qualities including:

1) It is inversely proportional to $1 - \gamma\|R\mathbf{u}\|_2^2$

2) It is proportional to $\|\mathbf{g} - H\mathbf{u}\|^2_2$,

3) $\lambda = 0$ in the absence of noise, i.e., for $\|\mathbf{g} - H\mathbf{u}\|_2^2 = \|\mathbf{v}\|2 = 0$ and

4) $\lambda \to \infty$ for $\|\mathbf{g} - H\mathbf{u}\|_2^2 \to \infty$.

2. 5 CONSTRAINED IMAGE RESTORATION

In this section, the restored image **u** and regularization parameter λ are calculated simultaneously by expressing the image restoration problem as a con-strained optimization problem with a linear or quadratic constraint.

2.5.1 Restoration using a linear constraint

The image restoration issue can be written like the given constrained optimization problem,

$$\text{Min } R(u) \quad \text{subject to} \quad Hu = g,$$

where $R : R^l \to R$ is a general regularizer. The solution of this optimization problem coincides with a stationary point of the Lagrangian:

$$L(u,\lambda) = R(u) + \lambda^T (Hu - g), \qquad (2.12)$$

Where $\lambda \in R^n$ is a vector of Lagrange multipliers (or dual variables). Often Equation (2.12) will have multiple stationary points; the Lagrange conditions provide necessary and sufficient conditions for optimality.

Directly applying the method of Lagrange multipliers to the image restoration problem in Eq. (2.12) does not produce a well-posed objective because the constraint does not account for noise. Instead, Eq. (2.12) is often expressed as the following augmented Lagrange equation:

$$L_\mu(u,\lambda) = R(u) + \lambda^T (Hu - g) + 1/2\mu\|g - Hu\|_2^2 \qquad (2.13)$$

where μ is a positive user defined constant. The additional least-squares penalty introduced by the augmented Lagrangian method makes it more well-posed than the Lagrange multiplier method. Furthermore, the Augmented Lagrangian converges under more general conditions. Equation (2.13) can be solved using the dual descent method, which alternates between minimizing $L_{\mu}(\mathbf{u}, \lambda)$ with respect to **u** (while keeping λ constant) and updating λ (while fixing **u**). Be- cause the augmented Lagrangian formulation is well-posed and easily solvable, it is the basis of many state-of-the-art image restoration methods.

2.6 BAYESIAN IMAGE RESTORATION

Quite opposite to the restoration methods talked earlier, Bayesian image restoration methods use probability theory to model the image restoration problem. This means the restored image and model parameters are represented by probability distributions rather than unique values. There are two distinct fields of statistics known as Classical statistics and Bayesian statistics. Each field defines the concept of probability differently. Classical statistics defines probability in terms of long term frequency of occurrence. In comparison, Bayesian statistics measures the plausibility or belief of a hypothesis when there is insufficient knowledge to establish certainty. The Bayesian definition is the most useful choice for modeling the image restoration problem and will be the focus of this section. To begin, the image restoration problem is modeled using Bayes law. Each of the components of the model will then be described in detail. In particular, the observation model and popular hyper-parameter priors will be presented. The importance of the image prior and its relation to regularization.

2.6.1 Bayes law and the observation model

In the ideal case where the blur matrix $H \in R^{n\times l}$, degraded image $\mathbf{g} \in R^{n}$ and hyper-parameters $\lambda \in R_{+}$ and $\mu \in R_{+}$ are known, the restored image $\mathbf{u} \in R^{l}$ is determined using the posterior law $P(\mathbf{u}|\mathbf{g},\lambda,\mu)$ In practical situations, however, the hyper-parameters λ and μ must be estimated. To estimate these values using Bayes law, the prior probability laws P $(\mathbf{g}|\mathbf{u},\lambda), P(\lambda), P(\mathbf{u}|\mu)$ and $P(\mu)$ must be assigned. Here $P(\mathbf{u}|\mu)$ is the image prior and P $(\mathbf{g}|\mathbf{u},\lambda)$ is the the observation model's PDF(Probability density function). Presuming that the prior probabilities are known and given data **g** the following joint probability follows from Bayes law:

$$P(u,g,\lambda,\mu) = P(g|u,\lambda)P(\lambda)P(u|\mu)P(\mu). \qquad (2.14)$$

In Bayesian image restoration, $P(\mathbf{g}|\mathbf{u},\lambda)$ being the conditional probability for seeing the degraded picture **g**, given **u** and λ. This probability distribution can be obtained directly from the observation model. Assuming a linear image degradation model and zero-mean AWGN, for example, the distribution is defined by the following Gaussian prior

$$P(g|u,\lambda) = \lambda^{n/2}\exp\{-\lambda/2||g-Hu||\} \qquad (2.15)$$

For which the number of elements in **g,**remains n.

2.7 Neural Network Method

It is the interconnection and interlinking of various parts of each information layer like a computer network interconnected gathering of hubs.

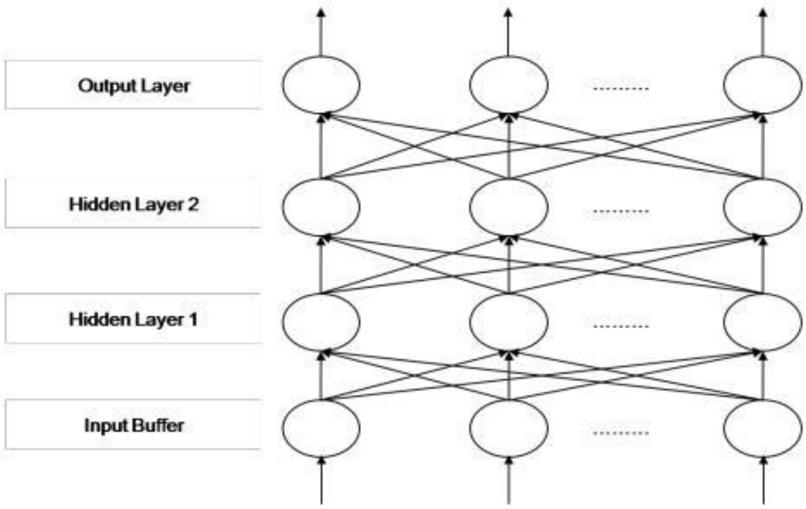

Fig.2. 8 Artificial neural network

These interconnected parts are known as neurons which send message to one another. On the off chance that a component of this system falls flat,that won't change or affect anything. Calculation like Back engendering and Perception utilize inclination plunge methods best fit a preparation set of information yield models.

The BPN(back propagation algorithm) contains 3 layers input layer which is first one, hidden layer as second layer and output layer as 3rd layer. In starting phase data is to be provided into first layer. In each layer weight is to be provided to each node, then that weight is summed up and given to next layer. O/p of a hidden layer functions as the i/p of the next layer. Once training phase is completed, it is easy to do the estimation about the amount of blur.

2.8 Iterative blind deconvolution

It is based on the fact that fourier changed causes very less calculation. It is having a quite nice noise cancellation power. In this reclamation of picture is troublesome piece picture recuperation is performed with less of no earlier learning of corrupting PSF. It has a higher goals and better quality. Assembly of this iterative procedure can not be ensured.

2.9 Deconvolution via use of regularised filter

It is another classification of non-dazzle deconvolution system. This is utilized when constrained data about the noise is known along with boundations like smoothness are attached on recouped picture. The debased pictures are reestablished by obliged slightest square reclamation by utilizing a regularized channel. In this less earlier data is required. Regularization can be a decent technique when factual information is

CHAPTER 3

BLIND DECONVOLUTION USING LUCY RICHARDSON

Blind convolution and non blind convolution- the two methods for image restoration. The deconvolution of non blind type is that which has the knowledge of PSF. This method has very popularity in astronomy and medical imaging fields. It was found by lucy and Richardson. It is a non-linear iterative method. This method performs the restoration of image better than linear methods. To restore the picture of good quality the quantity of cycles is to be resolved for the picture according to the PSF measure. The Richardson-Lucy method is an repeatitive method to recover the picture which was distorted by recognized (known) PSF. This method unlike Weiner method, is more robust to noise.

$$Z_{i=}n_{ij}t_j \qquad (3.1)$$

Where n_{ij} is point spread capacity, tj is pixel esteem at j area and Z_i the watched an incentive at pixel area I. The fundamental thought is to figure doubtlessly tj given watched Z_i and known n_{ij}. It is an iterative approach of image restoration.

3.1 PSF (POINT SPREAD FUNCTION)

How much a point of light is spread by an optical framework is PSF. The function of point spread is discovered to be the opposite Fourier change of OTF in the frequency domain. This reveals to us reaction for straight positioned non-variant framework to a drive. OTF is the Fourier transfer of PSF.

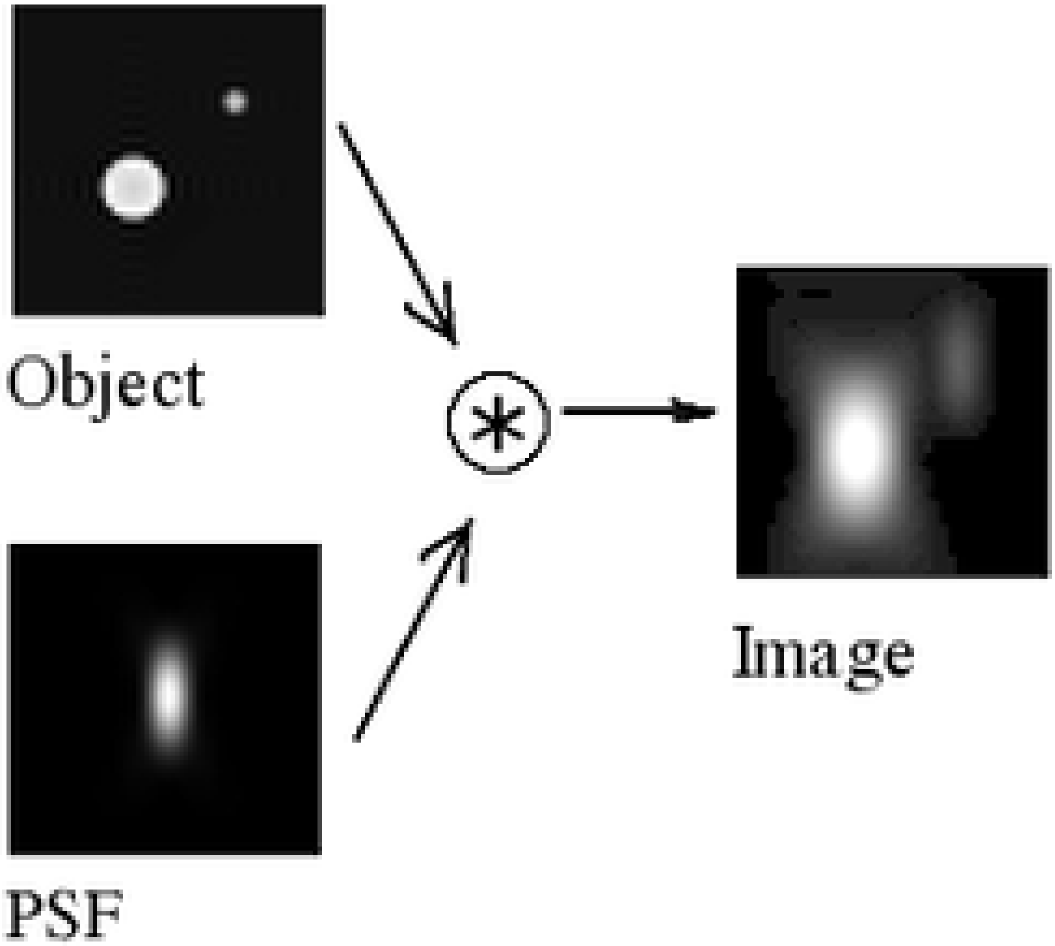

Figure 3.1 Point Spread Function(PSF)

3.2 FINDING THE ALGORITHM PARAMETERS

3.2.1 .Searching distorted regions in image

This approach is based on the search of motion vector for image fragments using the previous frame as a reference. If we denote current frame as I1 and previous reference frame as I0, then the divide the I1 in the non overlapping blocks of 8×8 pixel size. Next, for each block I1(x,y) of the current frame the most similar block I0(k,l) in the reference image I0 is searched. To define this block the following deviation function D = Dx,y(k, l) is minimized.

$$D=\Sigma\Sigma|I0(8k+n,8l+m)-I1(8x+n,8y+m)| \quad (3.2)$$

The search area is limited by the radius of six blocks. To select the blocks corresponding to moved fragments of the reference frame, we perform a threshold separation, taking only those blocks I1(x,y) which has a matching block in the reference frame I0(k,l) with deviation (6) $D<T$, where the threshold value T is set empirically. Otherwise the block I1(x,y) is not considered as a moved one. After the thresholding some morphological processing is performed to exclude isolated moved blocks which arose accidentally or as a result of insignificant movement (e.g., waving of tree leaves in wind). First, an auxiliary binary image *B* is formed, where we fix each value of pixel B(x,y)=1 if the corresponding 8×8-block I1(x,y) of the current frame is considered as a moved one; otherwise B(x,y)=0. Then image *B* is processed by two subsequent erosions followed by two dilations, each morphological procedure having the same bit mask representing a cross of 3×3 pixel size. After this morphological procedure the image *B* is considered as a bit mask defining those frame blocks which correspond to the regions of moving objects.

Lucy- Richardson method is an iterative procedure and has the following disadvantages: the restored image has artifacts looking like vertical and horizontal stripes appeared near the edges of objects and at the image borders. These distortions at the image borders can be reduced if the picture is extended beyond them, the brightness being gradually reduced to (or close to) zero level. We propose such extension with the values of boundary pixels, multiplied by a monotonically decreasing weight function. To reduce the brightness down to zero we chose a weighting capacity of Hamming window

$$W(x) = 00.540 - 0.460 \cos(2Sx / (2S - 1.00)), \quad (3.3)$$

where the value of *S* is selected proportionally to the length of the motion vector of the object. Diminished image distortion by greater than 50% in rms metric terms is caused by the use of the window.

3.2.2 Finding the parameters of blurring

To get better quality from Lucy-Richardson image restoration the IR defining distortion model should be given as an input parameter of the restoration algorithm. The more accurate is the initial estimation of the IR the better is the result. A good way to determine the parameters of blurring is using image cepstrum. The cepstrum of picture u(c,d) is characterized as

$$\hat{u}(c,d)=F^{-1}\{\log |U(u,v)|\}, \quad (3.4)$$

where F^{-1} denotes Fourier transform inverse.

Finding parameters of blur using image cepstrum has the following shortcoming: in case of small distortion (value of blur is less than 4 pixels) it is difficult to accurately determine the blur. Therefore, if the value of blur is small enough, it is impossible to reliably determine the parameters of distortion from the image cepstrum. We exclude such minimal blurring from our consideration as the corresponding distortion is almost invisible. Apart from that, to get better estimation of blur parameters one can use intra-frame information.

Taking these considerations into account, we suggest to utilize a hybrid method: to find the absolute value the blurring vector from picture cepstrum according to, and to find the angle of the vector from the intra-frame information on moving objects. Determining the angle of the blurring vector we stay with the hypothesis that the direction of the motion vector acc. object is equivalent with vector dir^n. As the blocks' motion vectors belonging to the same object may vary due to the influence of random factors, to determine the angle of blurring we apply median filter to block motion vectors. The experiments showed that the resulting angle of motion vector matches the angle of the blurring vector quite exactly.

3.2.3 Estimating the number of iteration

To determine the optimal number of iterations in Lucy-Richardson method an empirical algorithm was presented .It is based on the observation that when the restoration process has converged to the solution, the norm is calculated.

$$\left\| \hat{f}_k \;\; \hat{f}_{k1} \right\|$$

Obtained at the current and last iteration, stabilizes. Using that fact the following algorithm was proposed.

Step 0. Find normalization factor (rms) for an area `Ω :, comprising some central pixels of the image:

$$\sigma=[(1/\Omega)[\Sigma(g(i,j)-A)^2]^{1/2} \quad \text{where } A=(1/\Omega)\Sigma g(i,j)$$

Steps

Step 1 Perform 5 iteration method of Lucy-Richardson assume k=6.

Step 2. Go to the next (k-th) iteration and find the image estimate $\hat{f}k$ in accordance with.

Step 3. Find the norm of the difference $^{P}k = \left\| ^{f}k- \; ^{f}k1 \right\|$.

Step 4. To flatten changes of Pk do smoothing:

$$Pk \leftarrow \tfrac{1}{4}Pk–2 + \tfrac{1}{2} Pk–1 + \tfrac{1}{4} Pk.$$

Step 5. If max(Pk– 4, Pk– 3, Pk– 2, Pk– 1, Pk) < σ`Ω :·10^{-2}

If the value of blurring r < 15

We stop after k + 26 iterations.

Else

We stop after k + 1 iterations.

Else

Increase k by 1 and go to step 2.

3.3 FLOWCHART

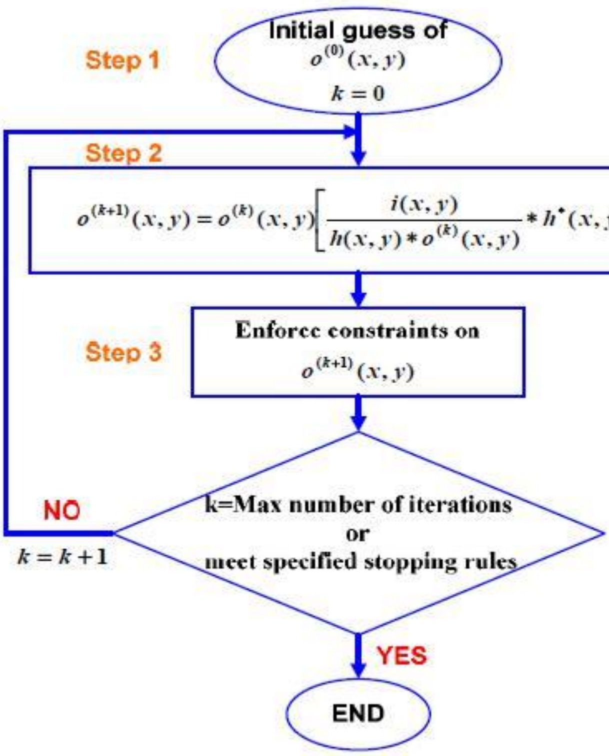

Fig. 3.2 flowchart of LR method

3.4 Results

METHOD	ITERATIONS	PSNR(dB)	MSE
Lucy Richardson (non blind)	100	30.5810386	57.33
	1000	30.8365493	50.59
	10000	31.1238417	47.30
	100000	31.6924103	44.39

Table 3.1 Restoration of the image in Fig.3.1 using Lucy Richardson method with different values of iterations and also showing values of PSNR and MSE according to the iterations.

Following figures show the process of application of Lucy Richardson method

Fig 3.3 original image

Fig 3.4 RGB to gray version of original image

Fig 3.5 blurred image

Fig 3.6 restored image after 100 iteration

Fig 3.7 Restored image after 10000 iterations

3.5 BLIND DECONVOLUTION

Till now we have seen that if we know how to estimate the PSF and if we can finally estimate this PSF. h(x,y,) which causes the degradation or blurring, its nearly possible to get back the then the actual image by deconvolution. But as we know its highly unlikely that we know the blur and we have a very little information about this true image. Hence, we have to recognize this true image f (x,,y) directly from g(x, y) even when we have partial or no information about the blurring or degradation process and the original true image. Therefore that issue of estimation, taking the linear degradation model formed blind deconvolution.

There exists a number of applications of blind deconvolution for image processing . Usually we observe that it is physically not possible and also dangerous and costly too to obtain an early information about that image. Also if we add to previous knowledge we can not precisely determine the degradation from hazing or blurring . We cannot accurately model the blurring as a random process in aerial imaging and astronomy type applications because it is very difficult to characterize the fluctuations in the PSF . In medical video-conferencing like real time image processing applications the PSF parameters can never be pre demonstrated to the deconvolved images. We observe that in different applications, the physical need for improving image quality are not feasible. For example , in x-ray imaging, as we increase the incident x-ray beam intensity, image quality gets improved, which is dangerous for the health of a patient. So as conclusion, blurring can not be avoided. In situations like this, the hardware which is available for the measurement of the PSF hard to use. But, the methods do perform satisfactorily in identifying the PSF.

3.6 METHODS TO APPROACH

It has 2 kinds of methods to approach.

From true image, recognize the PSF independently and then use it after with popular classical image methods for restoring the image. The methodology prompts basic calculations, joining the recognizable proof methodology with the restoring also. So both interpret that PSF and the true picture needs to be evaluated, which prompts the improvement in the algorithms.

3.7 CLASSIFICATION

These strategies be additionally partitioned into 5 general classifications. As every one of those classifications contain a few calculations for blind deconvolution. A portion of the calculations are in frequency domain and some are in spatial space and some of them utilize both information.

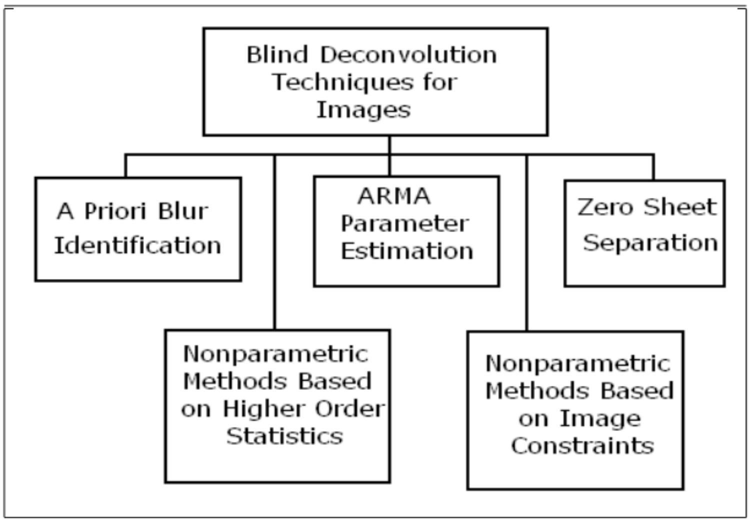

Fig. 3.8 classification for techniques of blind deconvolution

3.7.1 A PRIORI BLUR IDENTIFICATION

From the earlier, we know that noise recognizable proof techniques perform blind deconvolution by distinguishing the PSF preceding rebuilding. This group of methods makes presumptions for qualities of the PSF, for example, symmetry, and accessibility of noise. Well known parametric models incorporate PSFs coming about because of straight camera movement or an out-of-center focal point framework. In view of these presumptions, an effort is made to totally describe the PSF utilizing unique highlights of the genuine/obscured picture. Once we recognize the PSF completely, we use any of the classical restoration techniques using deconvolution. They have low requirements computation wise. When true image is having special features, then these methods are applicable.

3.7.2 Motion Blur Identification based on cepstrum

Strategy for distinguishing direct blur during motion is to register the 2-D cepstrum of the image l(i.,j). The cepstrum of l(i.,j) is given by

$$C(l(i., j)) = F^{-1}(\log(|F(l(i.,j))|) \quad (3.5)$$

, we have

$$C(l(i., j)) = C(f(i., j)) + C(h(i., j)) \quad (3.6)$$

$$C(h(i., j)) = F^{-1}(\log(|F(h(i., j))|)$$

at a distance L from the origin has big spikes. By the additivity property of the cepstrum, the negative peak is maintained in C(g(x, y)) ,from a distance L from the origin. We have to draw a straight line from origin to 1st negative peak to determine the angle of motion.

Fig. 3.9 (a)The original picture . (b) Blurred picture after blurring of 30 pixels length and 0^o angle (c) restored picture

3.7.3 Limitations

We found out that this method gives very good results for motion blur which is horizontal. And same goes with vertical motion blur too. We are getting perfect restoration because the length was estimated accurately. But in case of blur direction not horizontal or vertical, this length estimation shows error.

3.7.4 Image constraint based non- parametric method

This method does not need or take the parametric model to estimate blur or noise but this assumes deterministic constraints such as non negativity, known finite support, and existence of blur invariant edge. There are many methods of this kind like the Iterative Blind Deconvolution algorithm , (NAS-RIF)algorithm. These methods are iterative .The constraints which we apply on the true image and the psf(PSF) are fitted into an optimality criterion and then that criterion is minimized.

3.7.5 Deterministic image constraints

Non negativity and knowledge of finite support are included in determining the constraints. We can assume the Non negativity for both image pixel values and PSF coefficients. The 2nd constraint we can use is a known finite support. We can define the support as the littlest square shape which can provide envelope to the true image. But blurring and noising make the image to spread outside the support. Algorithms that we use to restore the image use this fact that true image pixels can not lie outside the support. One more spatial domain constraint we find good is that the sum of the PSF coefficients will always be equal to one. And we enforce this constraint may be in each and every cycle of the method.

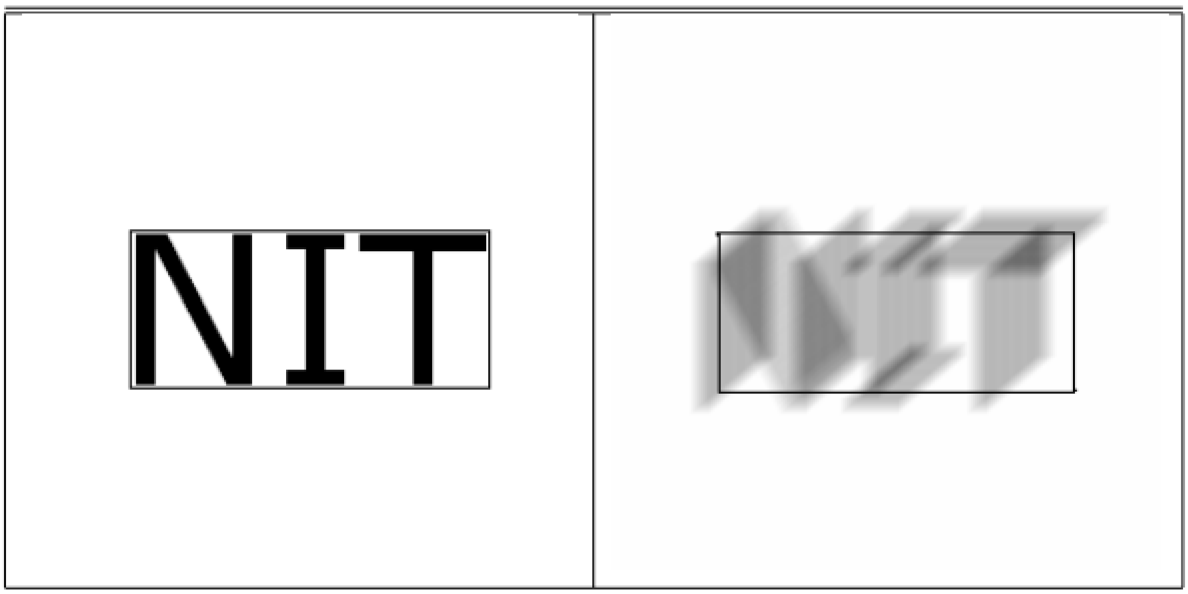

Fig 3.10 (a).Picture surrounding via a support. (b) Same picture spreading outside support after blurring.

3.8 (IBD) ITERATIVE BLIND DECONVOLUTION

Let us we have original image of f(i,j) then the degraded image will be obtained by convolving this image with the psf(PSF h(i,j)

$$g(x,,y) = f(x,,y)*h(x,,y) \quad (3.7)$$

and in frequency domain

$$G(u,,v) = F(u,,v)H(u,,v) \quad (3.8)$$

IBD method uses the information about the initial image and the psf which is earlier known to us. Then we made a random initial estimate of the psf(PSF),then this algo switches between the fourier domain and image ,applying the known constraints in each. The information which we have about the image and PSF serves as the constraints. Initial, a non negative-esteemed initial guess of the PSF ^h(x;, y) is contributed to the iterative plan. ^H(u;,v)is its fourier transform. which is then modified to frame an inverse filter and multiply with G(u; v) to shape a next spectrum estimate of the first image spectrum F(u;, v). This assessed Fourier spectrum is inversly transformed to give f(x;,,y). By putting to zero all pixels of the f(x; y) image domain constraint is applied which is having a negative value. ^ f(x;, y) is a positive constraint estimate that gives fourier transformed value of ^ F(u;, v). This is inverted to give another filter which is inverse type which then multiplied by G(u;,v) to give the next estimate H(u;, v). An iterative circle is completed by inverse Fourie transform of H(u;,v) to give h(x;,y) and by applying nonnegative constraints ,yielding ^h(x,y)).

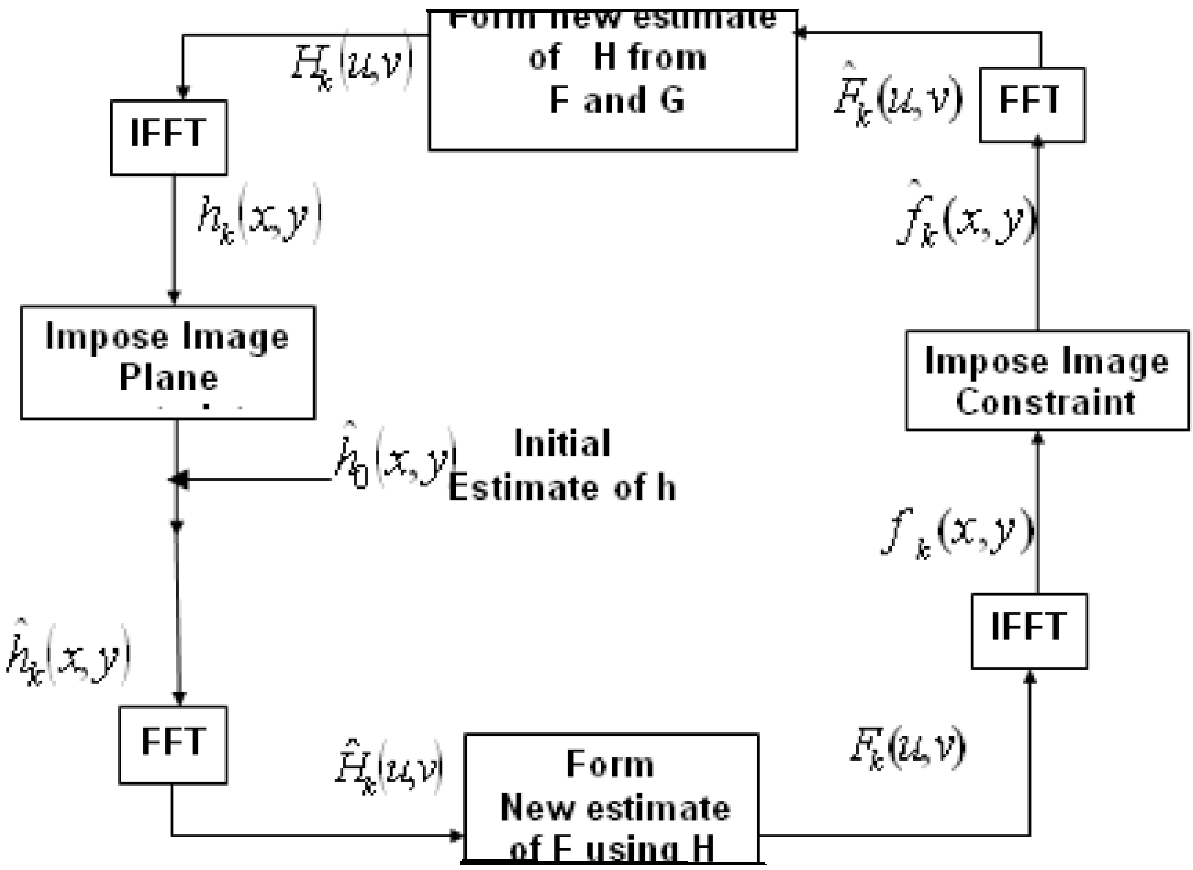

Fig.3.11 Operations in the IBD algorithm.

This constraint which we are using here not only forces the positivity but also it conserves energy at each cycle. The condition is realized by uniformly redistributing the sum of the function's negative values is redistributed uniformly over the function estimate. The problem here is if we perform the operation G(u; v)=H(u; v) then if H(u,v) contains very small value then F(u,v) will have very high values.

This constraint is described as the constraint over the product of the Fourier spectrum of f and h which make to be equal to the convolution spectrum. We should note that, at the kth iteration, we have two estimates for each Fourier spectrum means, $H_k(u; v)$ and $\hat{H}_k(u; v)$ These both have properties having some common properties with the desired deconvolved solution. $\hat{H}_k(u; v)$ has an inverse transform which is non negative and the second estimate $H_k(u; v)$ fulfills the constraint in Fourier domain. That's why after each iteration both the estimates are averaged and a composite new estimate is formed. This averaging we are doing is not essential for converging the procedure; however, this converging rate depends on β, and algorithm to found the optimum value of β is still unknown. Small, confined regions of very less or zero value which are present in G(u; v) we deal with them using only the estimate $\hat{}H_k(u; v)$.

if $|G(u;, v)| < Td$ $\quad\quad H_{k+1}(u;, v) = \hat{}H_k(u;, v)$ (3.9)

if $|\hat{}\ F_k(u;, v)| \geq |G(u,; v)|$

$$H_{k+1}(u;, v) = (1-\beta)\ \hat{}H_k(u;, v) + \beta G(u;, v) / \hat{}\ F_k(u; ,v) \quad (3.10)$$

,

if $|\ \hat{}\ F_k(u;, v)| < |G(u;, v|$;

$$1/H_{k+1}(u;, v)=(1-\beta)/\hat{}H_k(u,, v)+ \beta\hat{}\ F_k(u,,v)/G(u,; v) \quad (3.11)$$

β lies between 0 and 1. Here we are considering the problem of Hk(u,; v) (or equivalently of Fk(u; v)) which is having a small modulus. If it is having modulus of Hk(u; ,v) less than that of the convolution spectrum, then in rather performing the linear average, we perform average of the inverses of the two function spectrum estimates. We will now get this new estimate as the inverse of this average

3.8.1 Disadvantages

The main drawback of this method is the complexity in its computation. This method requires at least 300 to 500 iterations to get the moderately restored image. Also, there is no particular criteria to converge for this IBD method. We have to examine the deconvolved image visually to cease the iterative process. Another drawback is that the converge of the process depends on the initial estimate of the psf(PSF).

3.9 EFFICIENT BLIND DECONVOLUTION

This algorithm can perform well when no information about the psf is known. Here the Blind process is applied on the Lucy Richardson algorithm which itself is a non blind method. For restoring the blurred image, Lucy Richardson algorithm is studied above and blind process gets applied on that method to get the image restored by estimating the near true value of the point spread function (PSF)

3.9.1 SOBEL FILTER

Sober filter operator measures the 2D spatial gradient of the image. And the regions which have high spatial frequency corresponding to edges this filter highlights that region. It finds out the absolute value of the magnitude of that gradient.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

$$|G|=\sqrt{Gx^2+Gy^2} \quad (3.12)$$

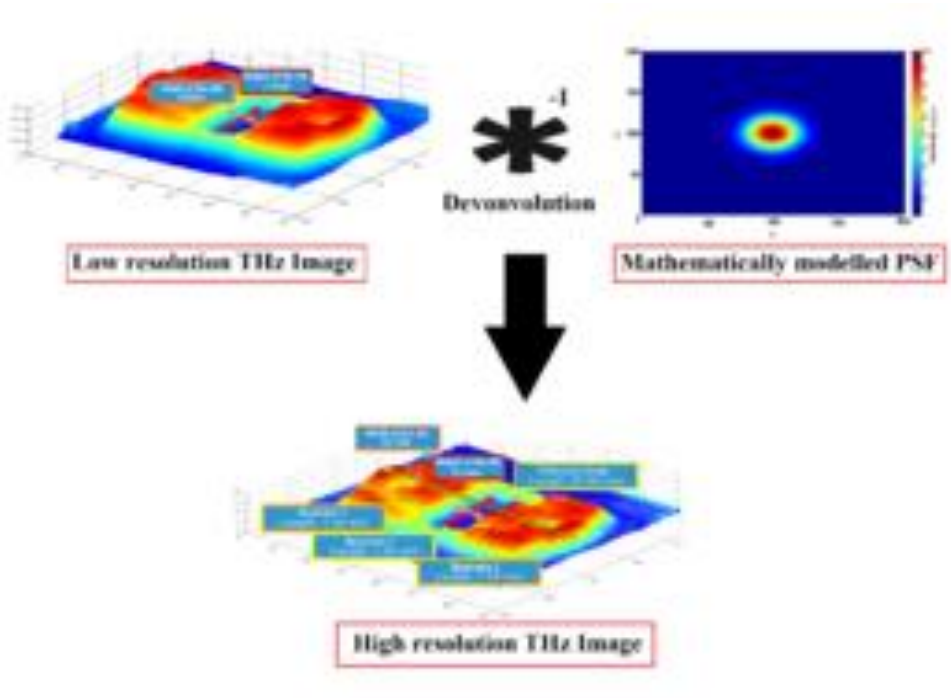

Fig.3.12 PSF

3.9.2 ALGORITHM

1 Select the image then simulate the blur by convolving the image with the gaussian filter.

2 Three restorations will be done to estimate the near true value of the psf.

3 Deconvolution is performed for under psf, over psf and initial psf.

4 To remove the ringing effect in the restored image which occurs along the sharp intensity contrast and the borders weight function is defined.

5 Using and passing the structuring element pixel desired and undesired will be given pixel value 1 and 0 simultaneously.

6 Then the deconvolution is performed for restoring the image with the help of structured psf.

3.9.3 Criteria To stop

To define, the power of the picture, squared sum of the every pixel in the is taken. In each cycle, calculation of standard deviation of the image power for last i-*n* cycles is done. If that value is less than a particular threshold value TD, then the algorithm can be terminated. The definition of stopping criteria can be summarized as follows:
Power at ith iteration as:

$$Pow_{i} = \Sigma_{x=1}\Sigma_{y=1} (fi(x; y)^{2}) \qquad (3.13)$$

• Standard deviation SD of the last i- n power values.
• If SD < TD halt the process.

3.10 Results

METHOD	PSNR WITH BLURRED IMAGE	PSNR WITH DEBLURRED OUTPUT	MSE WITH BLURRED IMAGE	MSE WITH DEBLURRED IMAGE
BLIND DECONVOLUTION FOR IMAGE 1	39.1999649	41.5244057	7.88	4.61
BLIND DECONVOLUTION FOR IMAGE 2	42.2094279	44.8633751	6.42	4.02

Table 3.2 Showing the results of Blind Deconvolution method with PSNR and MSE values

Following figures show the process of blind convolution method for image restoration

Fig 3.13 original image

Fig 3.14 RGB to grey image

Fig. 3.15 blurred image

Fig 3.16 deburring with undersized PSF

Fig 3.17 delurring with oversized PSF

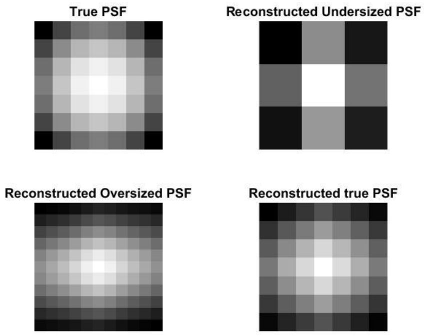

Fig 3.18 PSF

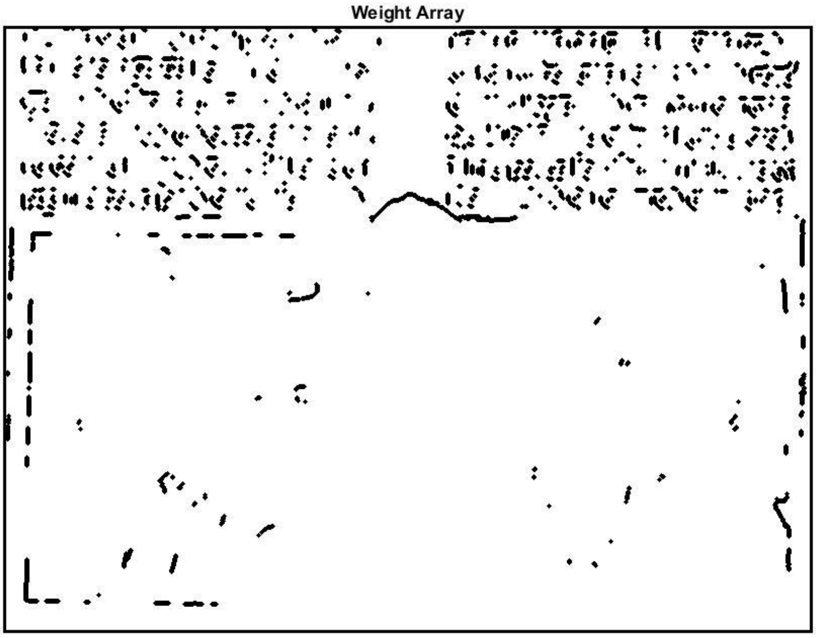

Fig 3.19 Weight Array of image

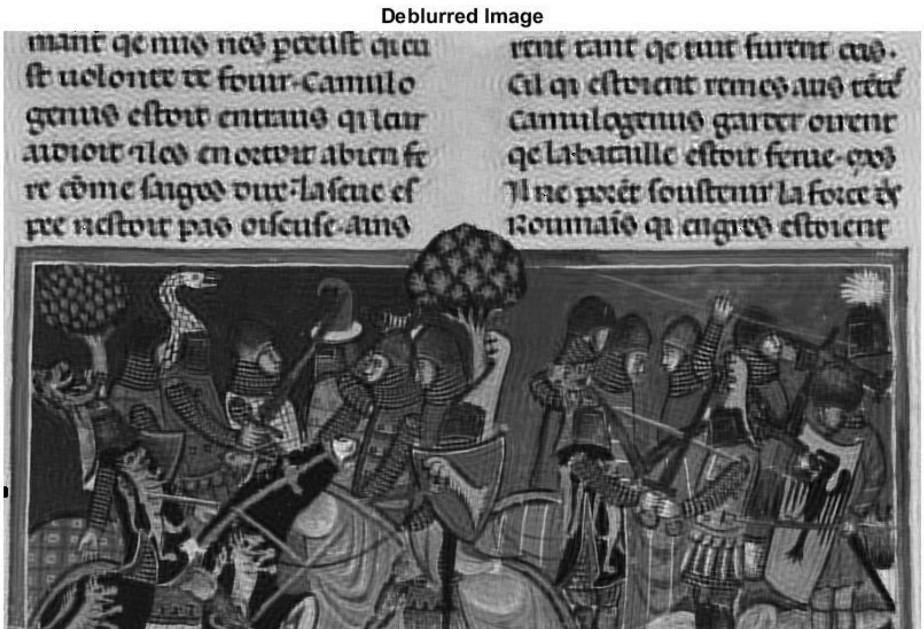

Fig 3.20 Final restored image

Example 2

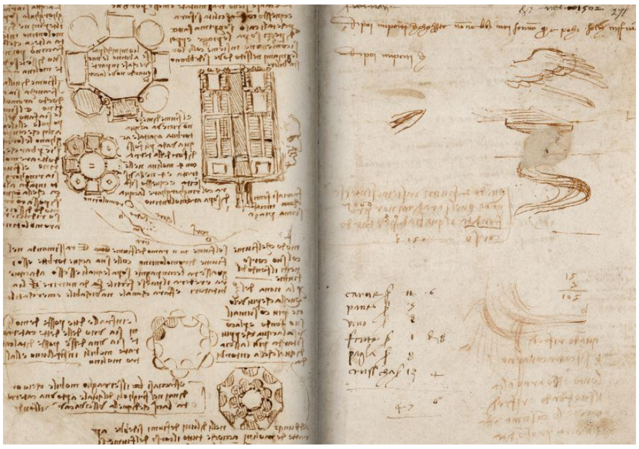

Fig 3.21 2nd original image

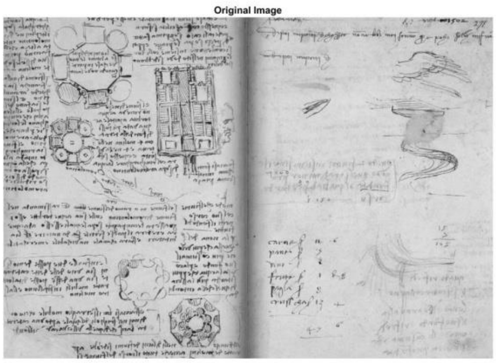

Fig 3.22 RGB to grey

Fig 3.23 blurred image

Fig 3.24 deblurring with underPSF

Fig 3.25 deblurring with oversized PSF for 2ng image

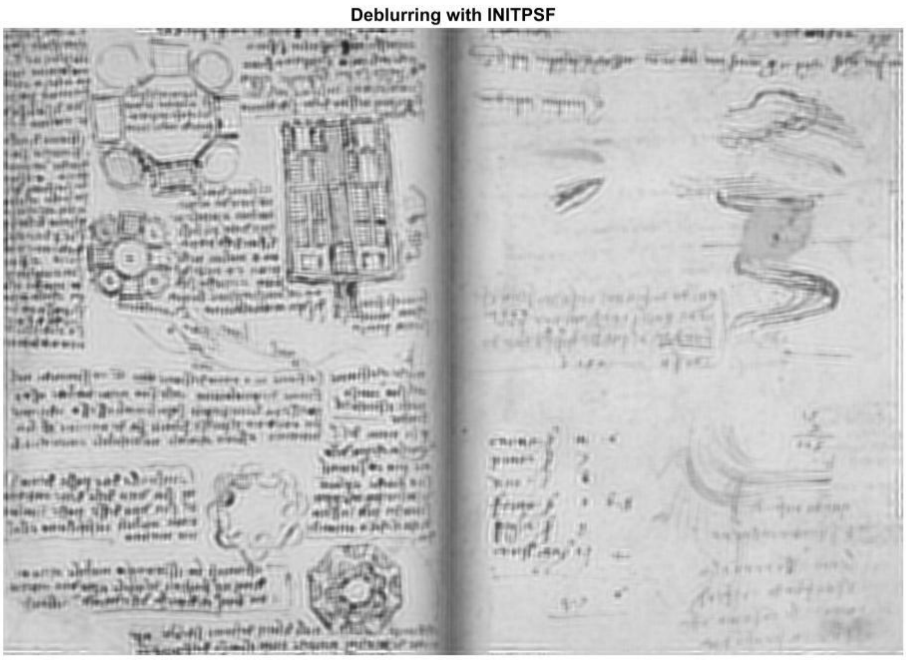

Fig 3.26 deblurring image 2 with INTPSF

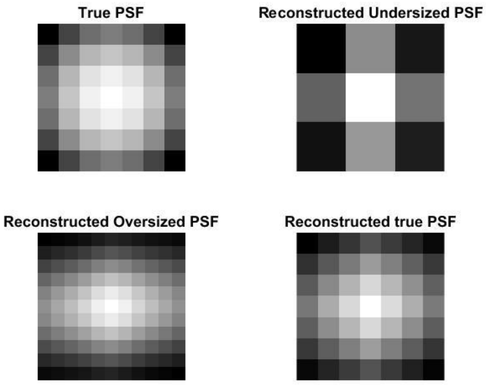

Fig 3.27 PSF

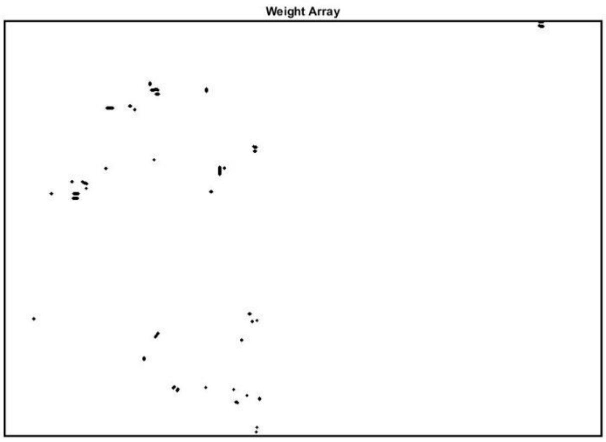

Fig 3.28 Weight Array for 2nd image

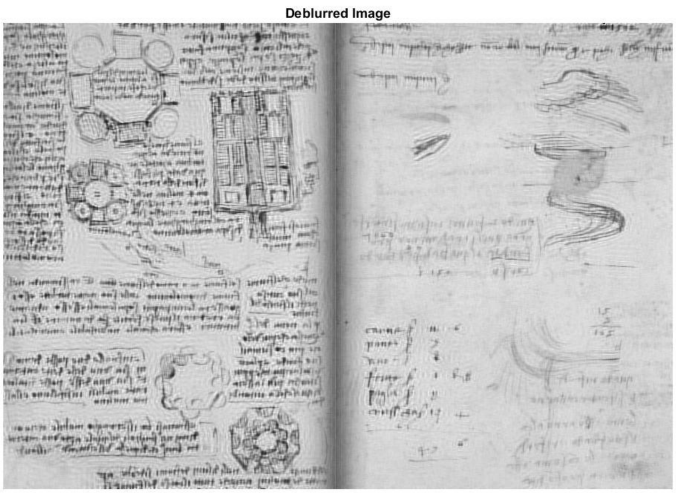

Fig 3.29 Final restored 2nd image

3.11 PERFORMANCE COMPARISON OF VARIOUS METHODS WITH PROPOSED METHOD

Methods	PSNR(dB)	MSE
Inverse filter	26.45	62.33
Weiner filter	30.12	50.12
Lucy Richardson	31.69	47.30
Blind deconvolution	44.86	4.02

Table 3.3 comparison of simulation results of different methods

S.No.	**METHOD**	**ADVANTAGE**	**DISADVANTAGE**
1	**ITERATIVE BLIND DECONVOLUTION**	HIGHER RESOLUTION BETTER QUALITY	CONVERGENCE RELATED, SENSITIVE TO NOISE
2	**WIENER FILTER**	OPTIMAL,CAN BE COMPUTED IN REAL TIME	NOT GOOD IN CASE OF MIXED DISTRIBUTIONS,ONLY PROVIDE A POINT ESTIMATE
3	**DECONVOLUTION USING REGULARIZED FILTER**	USEFUL TOOL WHEN STATISTICAL DATA IS UNAVAILABLE.	MORE USEFUL ONLY WHEN SMOOTHNESS CONSTRAINT APPLIED TO RECOVERED IMAGE

4	**LUCY-RICHARDSON METHOD**	BETTER RESTORED IMAGES THAN LINEAR METHODS. POPULAR IN MEDICAL IMAGING AND ASTRONOMY.	SMALL AMOUNT OF RINGING REMAINS
5	**LR METHOD WITH BLIND DECONVOLUTION**	CAN BE USED FOR NON LINEAR AND MOTION BLUR ALSO	IT IS HAVING HIGH PROCESSING TIME AND ESTIMATION OF PARAMETERS MUST BE ACCURATE

Table 3.4 Differentiating various techniques of image restoration

3.12 SUMMARY

In this report various approaches to image restoration were presented for example inverse filter, weiner filter ,Lucy Richardson and Blind deconvolution. Results of these methods were compared in the form of PSNR and MSE values. We observed that the blind deconvolution method is showing better results as compared to the others and inverse filtering method is showing least satisfying results.

CHAPTER 4

CONCLUSION WITH FUTURE WORK

4.1 CONCLUSION SUMMARISING FUTURE WORK

In this report we have dealt with various types of image deblurring processes. Some non- blind and some blind approaches are studied and also some parametric and non-parametric methods are also studied. As we talk about the non-parametric systems they give quite good outcomes in case of deconvolution. But, as we are using image constraint that alone is not appearing to yield an acceptable reestablished picture. Parametric type systems also have some limitations in terms of the minimization of the cost function because that minimization does not always mean a meaningful and good solution.

In case of non-blind approaches the (LR) Lucy-Richardson is studied which is nonlinear and therefore it has very slow convergence and but it is a non blind process where knowledge of PSF is present which is its advantage. In case of blind methods (IBD) Iterative Blind deconvolution method is studied which is showing some better results, we can't have the satisfaction in terms of restoration. IBD has its major drawback in its slow convergence rate. If we want to accelerate the converging rate we can limit the high magnitude values in the frequency domain of estimated image and also in frequency domain of the estimated PSF. Also we observe that if we force the sum of the PSF coefficients at the end of each cycle or iteration then that will improves the quality of the restored image to quite good extent. Original IBD algorithm is not having any stopping criteria. But, here we introduce a new stopping criteria which is based on the standard deviation of power of image for previous k iterations. The values which we obtain of the initial PSF can't affect the performance of the algorithm. But, we have to know the size of the PSF earlier to the start of the algorithm.

The motion blur estimation scheme is showing some excellent results for a limited motion blur domain. The new approach is giving better results but it needs accurate estimation of the psf and better limitations regarding the accuracy and precision of estimation of the parameters.

Future Aspects:

So finally we conclude by showing some points which need to be worked upon which are given as

- Convergence rate
- Ringing effects
- Limited motion blur domain
- High processing time
- Accurately estimation of parameters
- Sensitive to noise

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