Blind Deconvolution Algorithm based on Filter and PSF Estimation for Image Restoration

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ABSTRACT

Image restoration is the process of reconstruction of the original image from the observed degraded image. Blind image restoration, that restores a clear ideal image from a single blur image, is the ill-posed problem of finding two unknowns, the point spread function (PSF) and the ideal image. Different methods of blind image restoration, which iteratively approximate the PSF, their performance is sufficiently dependent on the precision of that estimate. When we restore a degraded image, if the blur function is unknown, it is necessary to estimate the PSF and the ideal image by using an input image. A method of alternately repeating PSF and ideal image estimations produces good results. In order to improve the quality of the restored image, a blind deconvolution method is proposed by estimating the blur function of the imaging model. This method is used for PSF estimation. In addition, we propose to use a filter for removing noise.

Keywords:- *Motion Blur Images, Image Restoration, Deblurring, Blind Deconvolution, PSF Estimation, Filtering.*

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1. INTRODUCTION

Image restoration is based on the concept to improve the quality of an image. The purpose of image restoration is to "undo" defects or damage which degrade an image. Degradation occurs due to different reasons such as motion blur, noise, and miss-focus of camera. There are various types of blur model. Motion blur is caused by the relative motion between camera and pictured objects[1]. Motion blur can be reduced by decreasing the exposure time[2]. The quality of the deblurred image depends upon the estimation accuracy of the hidden kernel[1].

The determination of Point Spread Function (PSF) is an important part in the process of restoration of motion-blurred image. The accurate estimation of motion parameters PSF can improve the effect of image restoration[3]. Generally, image blur degradation can be represented by the convolution of an ideal image and a point spread function (PSF). In blind deconvolution, we estimate the PSF by solving a minimization problem and restore the ideal image using the PSF. However, there are still several problems with respect to practical use such as restoration failure and the emphasis of noise generated from an error in the PSF estimation. Therefore, more accurate PSF estimation is required deconvolution[6].

In this paper, we propose an improvement to blind deconvolution algorithm for PSF estimation that alternates the repetition of a latent image estimation (x-step) and a PSF estimation (k-step). A blind deconvolution method is proposed by estimating the blur function of the imaging model to improve the quality of the restored image. Specifically, in the x-step, we improve the performance of the estimated PSF by restoration and using filter.

1.1 BASIC CONCEPT

Image restoration techniques are used to make the degraded or corrupted image as similar as that of the original image. Fig. 1 shows classification of restoration techniques. Basically, restoration techniques are classified into blind restoration techniques and non-blind restoration technique. Non-blind restoration techniques are further divided into linear restoration methods and nonlinear restoration method[9].

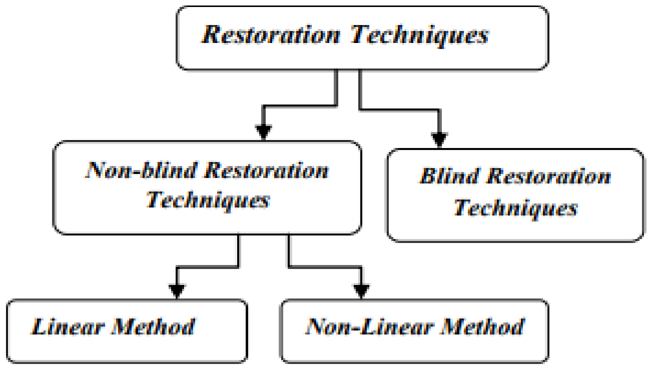

Fig-1: Classification of restoration techniques[9]

1.2 IMAGE RESTORATION MODEL

Image degradation/restoration process is as shown in Fig. 2. In degradation process, a degradation function H that, together with an additive noise η(x,y), operates on an input image f(x,y),to produce a degraded image g(x,y). The objective of a restoration is to obtain an estimate f^(x, y) of the original image.

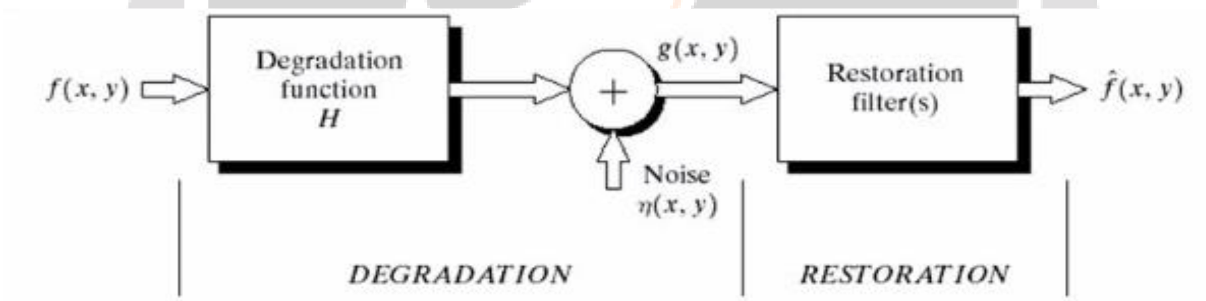

Fig-2: Image restoration model[9]

The blurred image is the result of the convolution of original latent image with a blur kernel with the addition of some noise. It is represented as follows:

$$g(x,y) = H[f(x,y)] + \eta(x,y) \qquad (1)$$

where, f(x,y) is the original image, g(x,y) is the degraded image and H is the blurring kernel (PSF), and n(x,y) is the noise and f^(x, y) is is the restored image after the restoration filter is applied.

Since, blurring is the result of convolution operation; deconvolution operation is performed to reverse the effect of convolution on blurred image to recover the original image. There are two types of deconvolution operation: Blind deconvolution and non blind deconvolution. In blind deconvolution, there is no prior knowledge about the kernel as well as the latent image. An algorithm is used to recover the kernel from given blurred image and the estimated kernel is then deconvolved with given blurred image in order to acquire the deblurred image. But, in non blind deconvolution technique, a blur kernel is specified apriori, which is used to recover the original image from the blurry version[1].

2. BLIND DECONVOLUTION ALGORITHM

Fig. 3 shows an overview of x-step and k-step in PSF estimation. We utilize a blind restoration process involving alternative minimization of evaluation functions for ideal image estimations and PSF estimations. However, prior to PSF estimation, an image is processed to remove texture components. After removing the texture components, the shock filter emphasizes edge components. This supports the convergence of the evaluation function, which improves convergence performance. In addition, to reduce processing time and improve image restoration performance, a deconvolution process, is applied to the deconvolution method[2].

Fig. 3 shows the block diagram for our blind deconvolution; it includes:

A. Latent image estimation
B. PSF estimation
C. Final deconvolution.

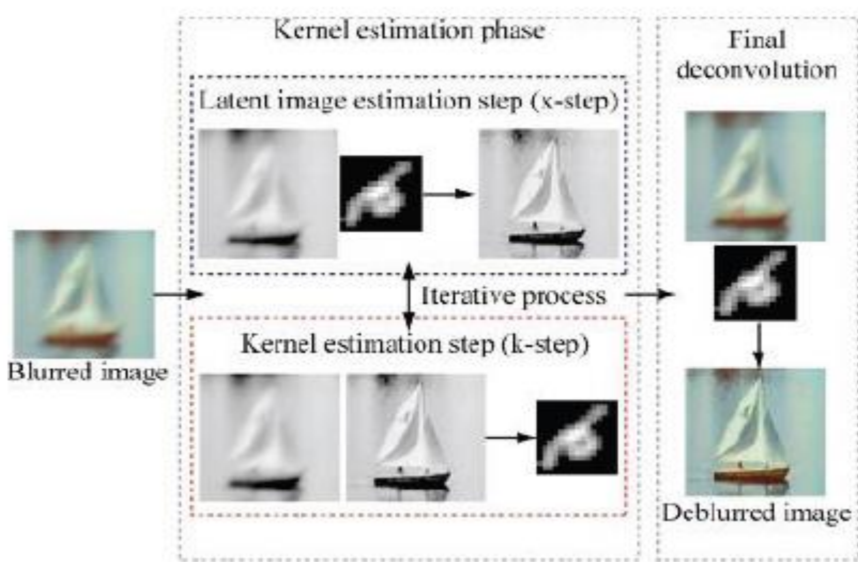

Fig-3: Processing flow of blind deconvolution[2]

The PSF estimation and the deconvolution process are performed only for grayscale images. The size of the PSF is increased as the iteration process advances, in order to ensure effective PSF estimation. Initially, it is set to 3 * 3 pixels, and finally, it is increased to the original PSF size. The final deconvolution image is obtained by utilizing the estimated PSF in the iterative processes[2].

A. Latent Image Estimation (x-step) [2]:

A temporal deconvolution image is obtained by utilizing the estimated PSF as shown in Equation (2). The Fast image deconvolution using hyperlaplacian prior approach is used to minimize Equation (2); this approach is based on heavy-tailed distributions, whose tails are not exponentially bounded in natural scene images.

Its distribution is modeled using Hyper-Laplacian, which is a non-convex optimization problem with substantial computational costs. Therefore, this optimization problem is divided into two stages, x-step and k- step, in which the latent image and the optimal PSF are obtained alternately. In addition, the processing time of the sub-problems is significantly reduced by utilizing a look-up table, and ringing artifacts are also reduced.

$$\min_{x} \sum_{i=1}^{N} \left(\frac{\lambda}{2}(x \otimes h - g)_i^2 + \sum_{j=1}^{J} |(x \otimes f_i)_i|^{\alpha}\right) \quad (2)$$

After the deconvolution, the texture components are removed from an initial image represented as shown in the Equation (3) and the algorithm for total variation minimization is used to minimize Equation (3). In addition, edges of the image are emphasized by utilizing the shock filter; this procedure is represented in Equation (4).

$$f_0 = \operatorname{argmin}_f\{\|f - g\|_2^2 + \lambda_r \mathrm{TV}(f)\} \tag{3}$$

$$f_{t+1} = f_t - \operatorname{sign}(\Delta f_t)\|\nabla f_t\| \tag{4}$$

B. PSF Estimation (k-step) [2]:

The PSF is estimated from the gradient distributions f in an image, and a thresholding process is used to reduce noise. The PSF is calculated as shown in Equation (4). The conjugate gradient method is used to minimize Equation (5).

$$h = \operatorname{argmin}_h\{\|\nabla f' * h - g\|_2^2 + \lambda_h\|h\|_1\} \tag{5}$$

C. Final Deconvolution[2]:

The final estimated PSF is obtained by iterative processes (A) and (B); the final deconvolution image is obtained by utilizing the final estimated PSF, as shown in Equation (5). The final deconvolution is processed in each RGB component.

3. FILTERING TECHNIQUES [9] [10]

Different types of filtering techniques can be used to improve the quality of images. For comparing the two different images, we can add different noises into the image. They are known as: salt & pepper noise, speckle noise, uniform noise, gaussian noise, defocus blur and motion blur.

The following list shows the description for different filter type:

A. **Direct Inverse Filtering:** Blurring can be considered as low pass filtering in inverse filtering approach and use high pass filtering action to reconstruct the blurred image without much effort[9].

B. **Wiener Filter:** This is a standard image restoration approach proposed by N. Wiener that incorporates both the degradation function and statistical characteristic of noise into the restoration function. It is the best deblurring linear method which reconstructs an image from degraded image by using known PSF. It works with high pass filter to perform Deconvolution and with low-pass filter to remove noise with compression opertaion[9].

C. **Arithmetic Mean Filters:** The Arithmetic mean filter is also called Linear Filter. It averages all the values of pixels within the window. It is used to remove Gaussian and Uniform noise[10].

D. **Midpoint Filter**: The Midpoint filter computes the midpoint between the maximum and minimum values of the image. The midpoint filter is widely used for noises like Gaussian noise and uniform noise. But it works well only for randomly distributed noise [9].

E. **Median Filter:** This filter first calculates the median of the intensity levels of the pixels. Then after calculating the median, it replaces the corrupted pixel value with the new value (median value).This filter is more robust and is much better at preserving sharp edges than another filter. But it is more expensive and complex to execute[9]. It helps in removing Gaussian and Impulse noise[10].

F. **Max and Min Filter:** These filters are used to find the brightest and darkest points in the image. The Max filter replaces the pixel value with the brightest point and the Min filter replaces the pixel with the darkest point. Max filter helps to find light colored pixels in an image while Min filter helps to find dark points in the image[9]. Max filter removes only Salt noise and Min filter removes only Pepper noise[10].

G. **Harmonic Mean filter:** It is used in a situation in which data values are so high. It cannot denoise the pepper noise[9]. This is the best filter for gaussian noise and salt noise. [10].

H. **Adaptive Mean Filter:** In Adaptive median filters, the size of the filter can be change. The other filters can mostly be used for the images where the density of the noise is less. [9]. But this filter is used especially to remove high-density noise from corrupted images, hence removes Impulse noise[10].

4. RELATED WORK

4.1 LITERATURE REVIEW

4.1.1 Adaptive Blind Deconvolution and Denoising of Motion Blurred Images

- In [1] Nelwin Raj N R and Athira S Vijay, proposes an effective approach for estimating the blur kernel from the blurred image, and is used to restore the original image, using the deconvolution operation. The overall process is of adaptive deblurring using piecewise linear model and denoising using wavelet multiframe decomposition. The proposed blind deconvolution algorithm using piecewise linear approximation along with denoising is very efficient in identifying the blur kernels present in the blurred images very accurately and can improve the quality of estimation process. Moreover, the proposed method can improve the PSNR values of the deblurred images.

4.1.2 Fast Blind Restoration of Blurred Images Based on Local Patches

- In [2] Tomio Goto, Hiroki Senshiki, Satoshi Hirano and Masaru Sakurai proposes a blind method that rapidly restores blurred images using local patches. In this method, a portion of the blurred image is used for PSF estimation. An automatic PSF size calculation algorithm is used that generates an autocorrelation map (automap). The proposed method significantly reduces computation time by selecting an optimal patch for PSF estimations and generates an edge map from the Laplacian filter and the Sobel filter, to select an optimal edge map for PSF estimations. In addition, it selects the patch based on the strength of the edge. Moreover, in the selected patch, it calculates the auto map and estimates the PSF size. It also estimates the PSF in the selected patch, and executes the final deconvolution at original blur image size.

4.1.3 Research on the blind restoration algorithm of motion-blurred image

- In [3] Yan Ge, proposed the blind restoration method for motion-blurred image based on estimated motion blur angle and length. First, the blur angle was estimated by Hough transform algorithm. Then the edge detection of the blurred image was done by Canny operator edge detection before detection of blur angle. Next, the blur length was estimated by differential-autocorrelation. Finally, motion-blurred license plate images were restored by Lucy-Richardson based on blur angle and length and the restored image were very clear. This method is useful and feasible with accurate parameters estimation.

4.1.4 Kernel Estimate for Image Restoration Using Blind Deconvolution

- In [4] Alexander Tselousov and Sergei Umnyashkin proposed a method for restoration of images distorted by “shake-like” blur kernel. The method is based on gradient field and cepstral analyses to approximate initial distortion kernel by line segment followed by iterative kernel search. As the method is combined with spectral estimation of noise power, it results in better performance of blind deconvolution image restoration. Both visual and measured quality of restored images becomes better and the computational load gets lower.

4.1.5 Bayesian Image Blind Restoration Based on Differential Evolution Optimization

- In [5] He Fuyun and Zhang Zhisheng, proposed the Bayesian image blind restoration method based on the differential evolution optimization to reduce the ringing effect of image restoration. Firstly, the Gauss model and Laplace model are introduced as the priori model of the original image and the point spread function. Secondly, the unknown parameters are described by Jeffrey prior distribution. Finally, the differential evolution optimization method is used to alternately estimate the original image; the point spread function and the optimal value of the parameter through iteration. The method also reaches better performance on two objective evaluation indexes of the mean structural similarity and PSNR.

4.2 COMPARATIVE TABLE

Table-1: Comparative Table

Sr. No.	Paper Title	Method Used	Advantages	Disadvantages
1	Adaptive Blind Deconvolution and Denoising of Motion Blurred Images [1]	Blind Deconvolution technique using piecewise linear model, Denoising technique	Improve the PSNR ratio, Efficient in identifying blur kernels accurately.	Processing time is high.
2	Fast Blind Restoration of Blurred Images Based on Local Patches[2]	Blind Image Restoration Method using Local Patches	Generates accurate de-blurred images. Processing time is significantly lower.	Only for grayscale images. Not suitable for moving pictures.
3	Research on the Blind Restoration Algorithm of Motion-Blurred Image[3]	Hough transform algorithm, Differential-autocorrelation	Gives clear restored image. Suitable for parameter estimation of motion-blurred image.	Feasible with Accurate parameter estimations.
4	Kernel Estimate for Image Restoration Using Blind Deconvolution[4]	Blind Deconvolution for kernel & PSF estimation.	Better quality of restored images. Computational load gets lower.	Mostly applicable for linear kernel.
5	Bayesian Image Blind Restoration Based on Differential Evolution Optimization[5]	Bayesian Image Blind Restoration, Differential Evolution Optimization Algorithm	Reduce the impact of ringing effect.	Choice of threshold is very crucial. No fixed threshold value will be optimum for different images.

4.3 PROPOSED MODEL

The proposed model is an improvement to blind deconvolution algorithm based on the filter used to remove texture components along with noise and PSF estimation. We can use the filter to get the restored deblurred image for further PSF estimation. The aim is to significantaly reduce the computation time and get better PSNR values to improve the quality of the image.

Fig. 5 shows the block diagram for the proposed method. The main steps of blind deconvolution and deblurring of blurred images can be summarized as follows:

Step 1: Initially, we can take the blurred image as an input.
Step 2: Apply degradation process to get the degradation function.
Step 3: Before kernel estimation, an ideal image is processed using the restoration filter in order to remove the noise. Then, we can use canny edge detector, to extract useful structural information.
Step 4: In feature extraction, we can identify the feature point using segmentation to get the shape and texture components by using the filter and the canny edge detector.
Step 5: Then kernel estimation is performed to get accurate PSF parameters.
Step 6: Then we can use classification method to get the deblurred image from the degraded image.

Step 7: Finally, we can get the deblurred image as similar to the original image by performing deconvolution process to get the output image.

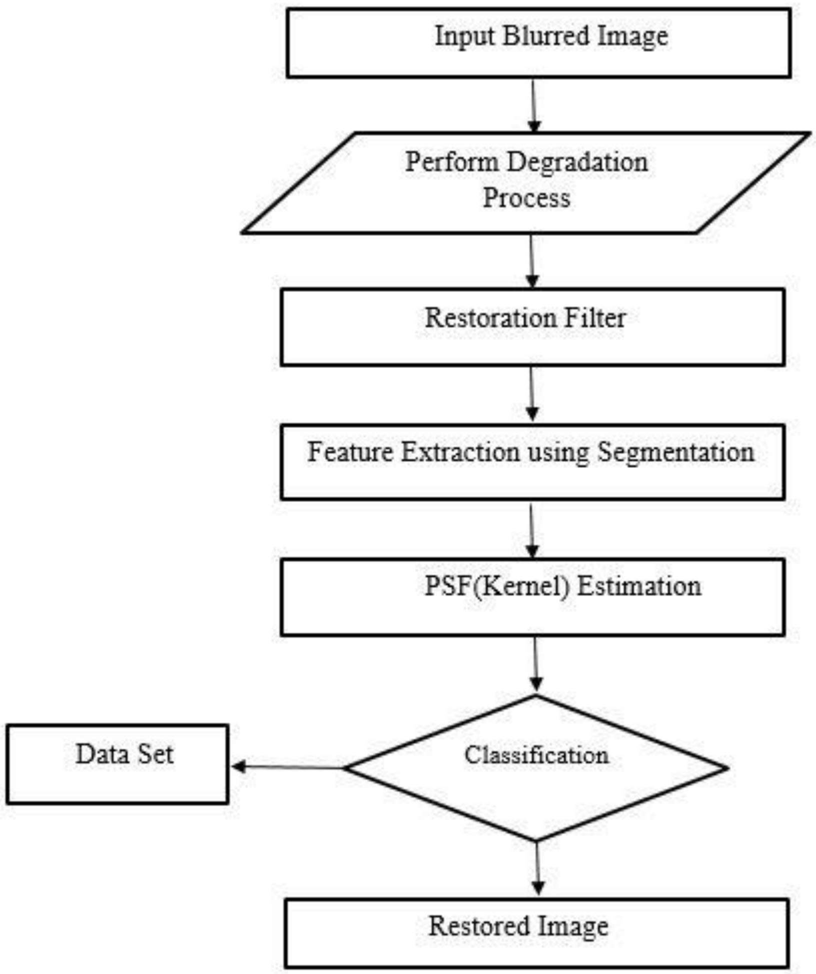

Fig-4: Proposed model for blind deconvolution image restoration

The proposed method can be used for the improvement of the blind deconvolution algorithm by using the filter to remove the noise and extract the feature matrix using segmentation and then accurately estimate the PSF parameters to get the deblurred image that is almost as similar to as our original input image. It gives better PSNR values and also reduces the computation time.

4.4 PERFORAMANCE PARAMETERS

Peak Signal to Noise Ratio (PSNR) [11]**:** One of the common reliable methods to measure the accuracy in the image restoration is the PSNR. It is used to measure the quality of reconstruction. The peak signal to noise ratio (PSNR) [5] for an image is computed using the Equation (6).

$$PSNR(x,y) = 10\log_{10}\left(\frac{(2^n-1)^2}{MSE}\right) \quad (6)$$

Where, MSE[11] is Mean Square Error between images x and y, n is the bit number of each sample.
The other performance parameters are: Structural Similarity (SSIM)[5] and Mean Structural Similarity (MSSIM)[5].

5. CONCLUSIONS

Image restoration is the process to recover the original image from degraded image, using the degradation function. In this paper, we proposed an algorithm for the effective restoration of blurred images using the filter and PSF estimation. Clear images can be reconstructed with considerably less noise and less ringing and hence, achieving more effective deconvolution. The filter is used to remove the texture components and we use the canny edge detector for edge detection of the blurred image. The accurate PSF estimation is essential for the restoration of image. Moreover. The proposed method will focus to improve the PSNR values of the deblurred image and hence improve the quality of the restored image.

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