IMPROVEMENT TO BLIND DECONVOLUTION ALGORITHM BASED ON FILTER AND PSF ESTIMATION

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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.

Index Terms - Motion Blur Images, Image Restoration, Deblurring, Blind Deconvolution, PSF Estimation, Filtering.

I. 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 Image Restoration Model

Image degradation/restoration process is as shown in Figure 1. 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.

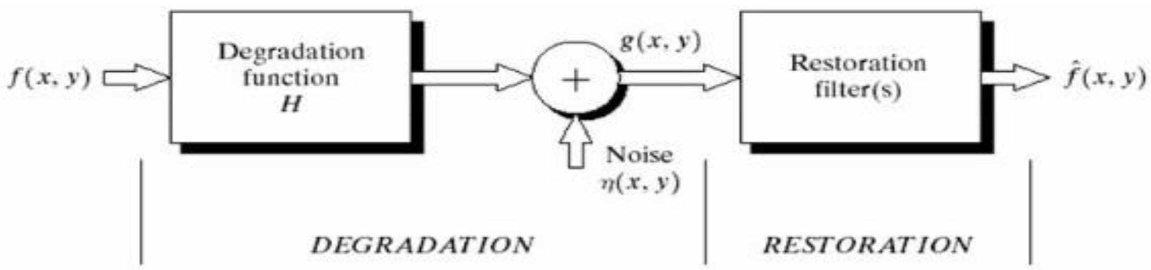


Figure 1: Image restoration model [9]

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:

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

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]

1.2 Blind Deconvolution Algorithm

Figure 2 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]

Figure 2 shows the block diagram for our blind deconvolution; it includes:

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

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]

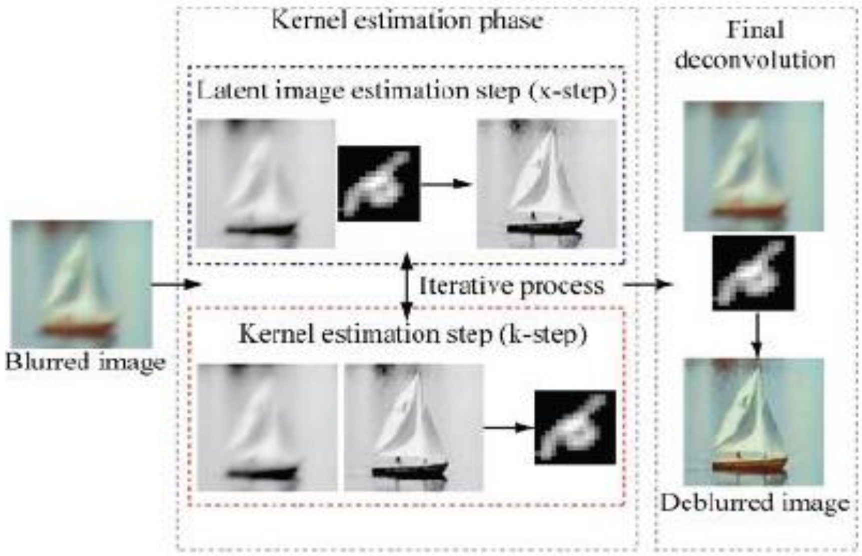


Figure 2: Processing flow of blind deconvolution [2]

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. 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.

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

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).

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

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

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).

$$h = \mathrm{argmin}_h\{\| \nabla f' * h - g\|_2^2 + \lambda_h\|h\|_1\} \quad (5)$$

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.

II. LITERATURE SURVEY

Nelwin Raj N R and Athira S Vijay, [1] the author 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.

Tomio Goto, Hiroki Senshiki, Satoshi Hirano and Masaru Sakurai, [2] 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.

Yan Ge, [3] 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.

Alexander Tselousov and Sergei Umnyashkin, [4] 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.

He Fuyun and Zhang Zhisheng, [5] 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.

Hiroki Senshiki, Satoshi Motohashi, Tomio Goto, Haifeng Chen and Reo Aoki, [6] proposed a novel PSF estimation using total variation regularization and the shock filter. The image is restored using blur degradation model. Generally, image blur degradation can be represented by the convolution of an ideal image and a point spread function (PSF). In blind deconvolution, they estimate the PSF by solving a minimization problem and restore the ideal image using the PSF. Hence, proposed a novel PSF estimation that alternates the repetition of a latent image estimation (x-step) and a PSF estimation (k-step).

III. PROPOSED METHOD

The proposed method can be used for the improvement of the blind deconvolution algorithm by using median filter to remove the texture components along with noise and extract the feature matrix using segmentation. Then, accurately estimate the PSF parameters to get the deblurred image that is almost as similar to as our original input image. The aim is to get better PSNR values to improve the quality of the image. Figure 3 shows the block diagram for the proposed method.

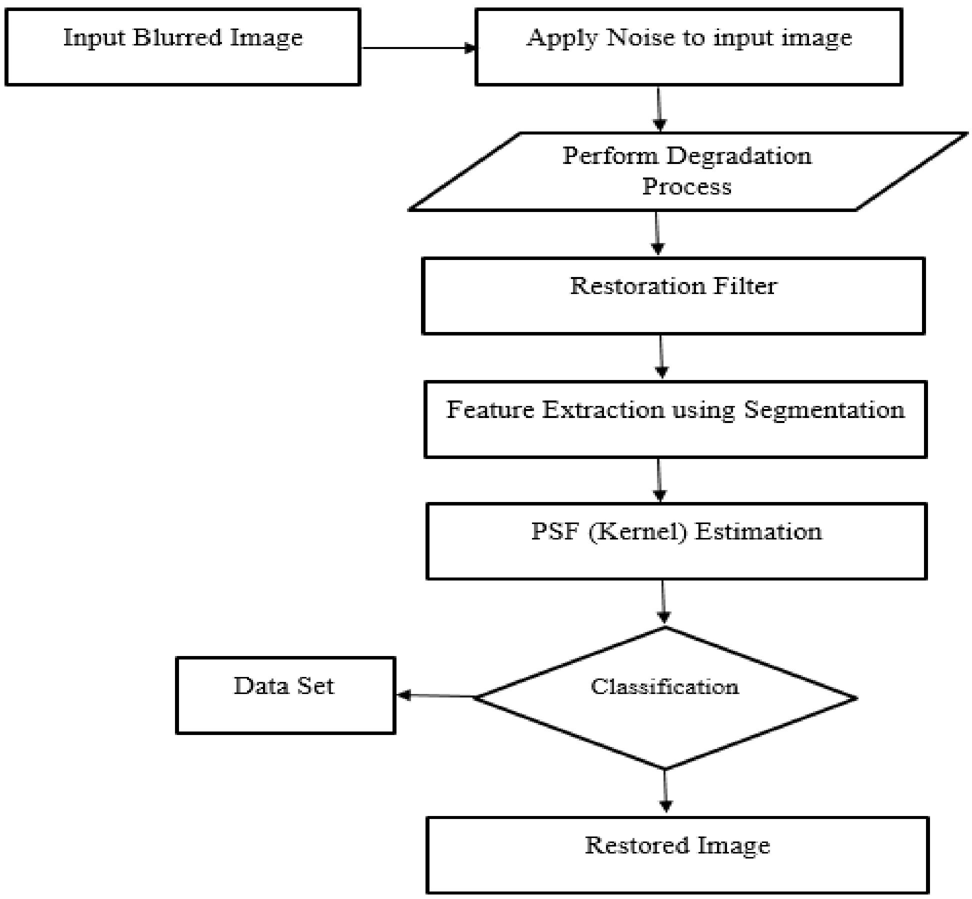


Figure 3: Proposed Method for Blind Image Restoration

The main steps of blind deconvolution and deblurring of blurred images can be summarized as follows:

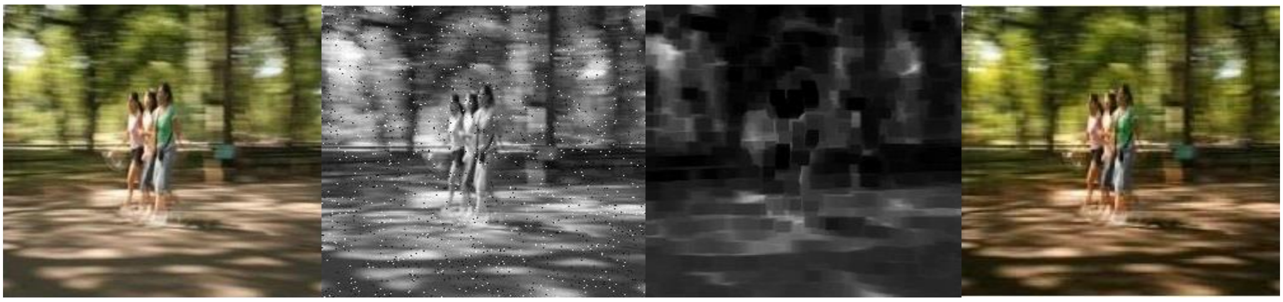
Step 1: Initially, we can take the blurred image as an input.
Step 2: Apply degradation process to get the degradation function.
Step 3: Before kernel estimation, an ideal image is processed using the restoration filter in order to remove the noise. Then, we can use canny edge detector, to extract useful 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.

IV. EXPERIMENTAL RESULTS

Peak Signal to Noise Ratio (PSNR): [5] One of the common reliable methods to measure the accuracy in the image restoration is the PSNR. It is used as a qualitative tool for analysis and also used to measure the quality of reconstruction. The PSNR[5] for an image is computed using the Equation (6).

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

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: SNR (Signal to Noise Ratio) and RMSE (Root Mean Square Error).



(a) (b) (c) (d)

Figure 4(Image 1): (a)Input Degraded Image (b) Salt & Pepper noise (c) Dark Channel Estimation (d) Output Image

(a) (b) (c) (d)

Figure 5(Image 2): (a)Input Degraded Image (b) Salt & Pepper noise (c) Dark Channel Estimation (d) Output Image

(a) (b) (c) (d)

Figure 6(Image 3): (a)Input Degraded Image (b) Salt & Pepper noise (c) Dark Channel Estimation (d) Output Image

Table 1: Parameters Estimated using blind Deconvolution + Denoising & Proposed Method

Method	Image	PSNR	MSE	RMSE	SNR
Blind Deconvolution + Denoising [1]	Image 1	59.00	0.082	0.317	-0.4
	Image 2	47.40	1.192	3.039	-0.9
	Image 3	45.91	1.630	2.30	-0.2
Proposed Method	Image 1	68.4735	0.0092	0.0961	1.7074
	Image 2	75.4088	0.0019	0.0433	0.6029
	Image 3	61.0750	0.508	0.2253	2.8548

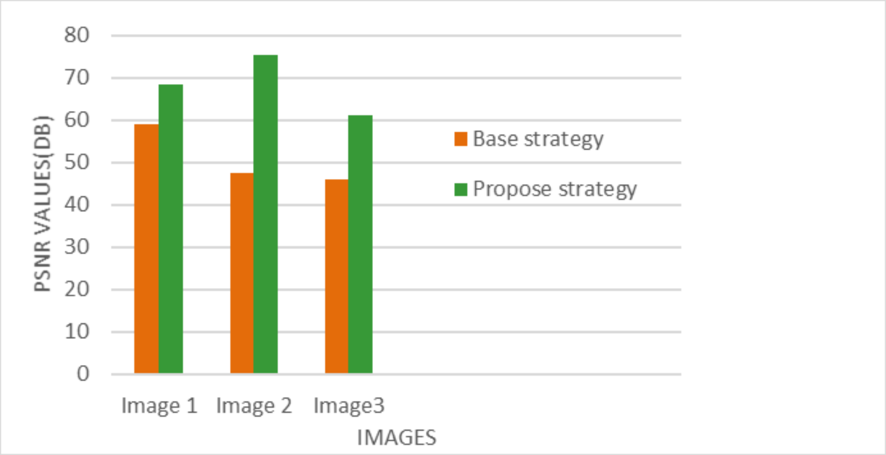


Figure 7: Performance analysis in terms of PSNR (dB) Values

The experimental result shown in Figure 7, PSNR values for proposed strategy is higher than the Blind deconvolution + Denoising algorithm. Hence, the performance of the proposed method gives better quality of restored image.

V. CONCLUSION

In this paper, we proposed an algorithm for the effective restoration of blurred images using the median filter and PSF estimation. Clear images can be reconstructed with considerably less noise and less ringing and hence, achieving more effective deconvolution. First, the filter is used to remove the noise from the blurred image. Then, the accurate PSF estimation is essential for the restoration of image. As per the experimental results, the proposed method improves the PSNR values of the deblurred images and hence gives better quality restored image.

VI. FUTURE SCOPE

In future work, we intend to reduce the computation and processing time of our proposed algorithm, so that it can be used for implementation in consumer devices such as digital cameras, cell phones and tablet PCs.

VII. ACKNOWLEDGEMENT

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