Vipul pathak, Deepali Kaushik, Pawan Verma, Rohit Pathak / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 3, Issue 3, May-Jun 2013, pp.1264-1270

An Efficient Algorithm For Deblurring A Natural Image

Vipul pathak, Deepali Kaushik[2], Pawan Verma[3] and Rohit Pathak[4]

[1] Department of Electronic Communication Engineering, Teerthanker Mahaveer University, Moradabad (U.P.), India

[2] Department of Computer Science & Engineering, Krishna College of Engineering and Technology Ghaziabad (U.P.), India

[3] Department of Master in Computer Application, Sharda University G.Noida (U.P.), India

[4] Department of Electronic Communication Engineering, Moradabad Institute of Engineering and Technology Moradabad (U. P.), India

1. Introduction

Blurred image has always been a bottleneck for investigating agencies. Deblurring from a single image has been an ill-posed and challenging problem due to the large number of unknowns in the estimation process. The unknowns are the type of blur, the extent of blur and the noise, which degrade the image further. There does not exist any efficient algorithm that can deblur any given image. This paper attempts to deblur blindly a given natural image with an assumption of uniform blur throughout the image. The algorithm uses the Variation Bayesian approach for optimizing the posterior probability and deriving the most probable Point Spread Function (PSF). Once the PSF is estimated, a modified Lucy Richardson algorithm is used to do the deconvolution operation and to get the deblurred image. The algorithm is found to be very effective for natural images and the results are quantified using the Cumulative Probability of Blur Detection (CPBD) values. Most of the natural images are acquired in neither controlled environments nor using professional camera. By a professional camera, we mean that it has the capabilities to detect, motion and rectifies it on capture. Although images are captured to record useful information, degraded version of the original image results in practical cases. Most of the on-field cameras are hand held and thus, acquiring a good quality image with the help of such a camera is challenging, especially when the lighting conditions and environment are not controlled. Many hardware techniques have been incorporated now days in cameras to stabilize the optical system. Optically stabilized lenses are used in both video and still cameras but are quite expensive in nature. They make use of gyroscopes and inertial sensor systems to stabilize the optical system.

Another hardware approach is to use customized CMOS image detectors that selectively can stop image integration more quickly in areas where movement is detected. However, these hardware techniques are effective only in removing small camera shakes at relatively short exposures. In many practical cases, long exposures are needed to capture low light images. The imperfections in capturing introduce blur and noise to the image

1.1 *PROBLEM STATEMENT*

Restoration of blurred images is a vital problem especially in tracking and identification of criminals. The available image can be used to identify a human face or a moving vehicle's number plate taken in hit and run situation or in a bomb blast site. To restore a blurred image successfully, blurring function needs to be estimated accurately. Blurring function is referred to as Point Spread Function (PSF) which is the response of an imaging system to a point source or it can be said as the impulse response of a focused optical system [1]. It is non-parametric and spatially varying. Deblurring is an ill-posed problem because of the number of unknown parameters is more than the available parameters. This paper discusses some of the available deblurring algorithms and proposes an efficient approach to deblur issue. The aim is to identify the PSF and to apply the restoring algorithm to get the latent image. Some of the reasons for these imperfections are as follows:-

- Relative motion between camera and the subject being captured: During the exposure time of the camera, this type of motion causes the pixels being spread over a distance in the direction of the motion. It can be said that the image gets integrated over time during the exposure; thus causing a single pixel recorded from each point of the scene contributing to several different pixels in the real image. This degradation of image can be termed as motion blur.
- Atmospheric turbulences: It can be caused due to temperature variations and wind that causes the light rays to refract and degraded the image received on the camera sensor.
- Imperfect focus: Wrong focal point of the camera lenses leads to blurred version of the image. Even after taking care of focal point adjustment, use of a shallow depth of field may cause blur to some parts of the image.
- Bad capturing device: Damaged camera sensor, shutter or lenses can induce blurring effect by scattering the light falling on the sensor.

Noise plays a major role in aggravating the degradation. It may be introduced by the following sources

- Measurement errors of the sensor/camera: Measurement errors of the camera are caused due to damages in the camera circuitry, sensor or lenses.
- Quantization noise while digital storage: Digital images are quantized while being stored in a storage device. This introduces a quantization noise depending upon the sampling rate selected by the system. The bit depth of the digitization process limits the Signal to Noise Ratio (SNR) of a digital system.
- Noise introduced by the medium: Noise is also introduced by the medium due to scattering effects and random absorption. This is very common in the case of distant photography.
- Electronic Noise: Even without incoming light, the electrical activity of the sensor itself generates some signal. For understanding, this can be compared with background humming sound of audio equipment, which is switched on without playing any music. This is caused by the electronic components like amplifiers in the circuit. This additional signal is noisy because it varies per pixel and increases with temperature and adds to the overall image noise.
- Photoelectric noise: Each pixel in a camera sensor contains one or more light sensitive photodiodes, which convert the incoming light (photons) into an electrical signal, which is processed into the color value of the pixel in the final image. If the same pixel would be exposed several times by the same amount of light, the resulting color values would not be identical but have small statistical variations and can be called as noise. Relative motion between camera and the subject is one of the prime player which causes blurring in an image. The real relative motions can take convoluted paths and thus making the restoration more complex. Restoring of blurred image involve two components, namely identification of blur and restoration of image using the obtained blurring parameters

1.2 GENERAL BLUR MODEL

Degradation of sharpness and contrast of an image, which cause loss to the higher frequencies, is called as blur. The observed image is a result of the convolution of the latent image with a point spread function and some added noise. Figure 1 shows the general model of blur which shows the blurred astronomical image. In the image, it is evident that the observed image is blurred and classification or identification of the object in it is difficult. The blurred image is formed as a result of the degradation caused by the Unknown Point Spread Function as shown in Figure 1. The unknown noise adds to the trouble by making the operation difficult to reverse.

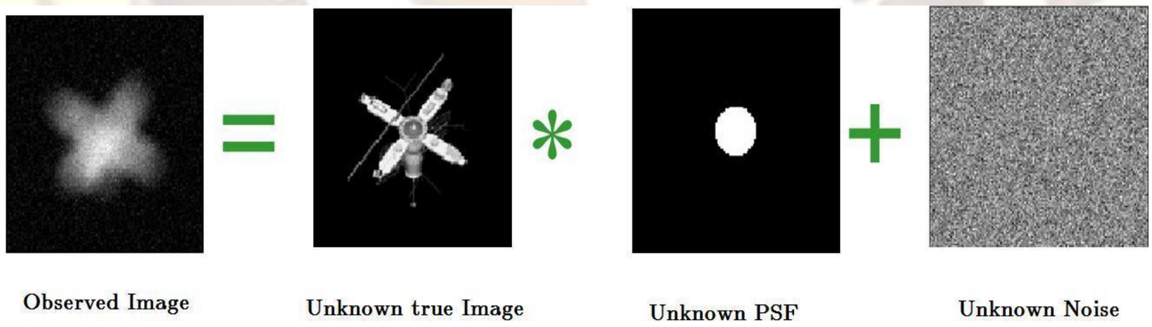

Figure 1 General Model of Blur

Let g(x,y), f(x,y) ,h(x,y) and n(x,y) be the measured image, the true image, the point spread function (PSF) and the additive random noise respectively where (x,y) represent the position of the pixels.

Then, (x,y) can be defined as

$$g(x,y) = f(x,y) * h(x,y) + n(x,y) \qquad (1.1)$$

$$= \sum_{m=0}^{m-1} \sum_{n=0}^{n-1} f\,(x,y) h(x-m, y-n) + n(x,y) \qquad (1.2)$$

Where * is convolution operation. Now if one considers in frequency domain, then one gets

$$G(u, v) = F(u, v)H(u, v) + N(u, v) \quad (1.3)$$

It can be seen that all the parameters on the right hand side of the Equation 1.3 are unknown. There are two types of deblurring approaches namely, non-blind deblurring and blind deblurring which are classified according to the context or application. In non-blind deblurring, knowledge of the Point Spread function (PSF) is available whereas in case of blind deblurring, any prior knowledge about the PSF or type of blur is not available. This paper addresses the blind deblurring operation. For a perfect motion blur, the parameters to be considered are the length and the direction of blur. In this case if it is assumed that there is no noise, it is easy to reconstruct the PSF using the length and the angle parameters and to do a non blind deblur operation. Some of the typical PSFs are shown in Figure 1.2. There are four different types of Point Spread Functions, namely Motion Blur, out of Focus Blur, Gaussian Blur and Scatter Blur that are very basic and generic in nature. Out of those four, two functions belong to the category of sharp edged PSFs and the other two belong to the category of smooth edged PSFs. These illustrations of these PSF models are in time domain. In practical cases, such estimated models might not be as perfect as shown in figure1.2.

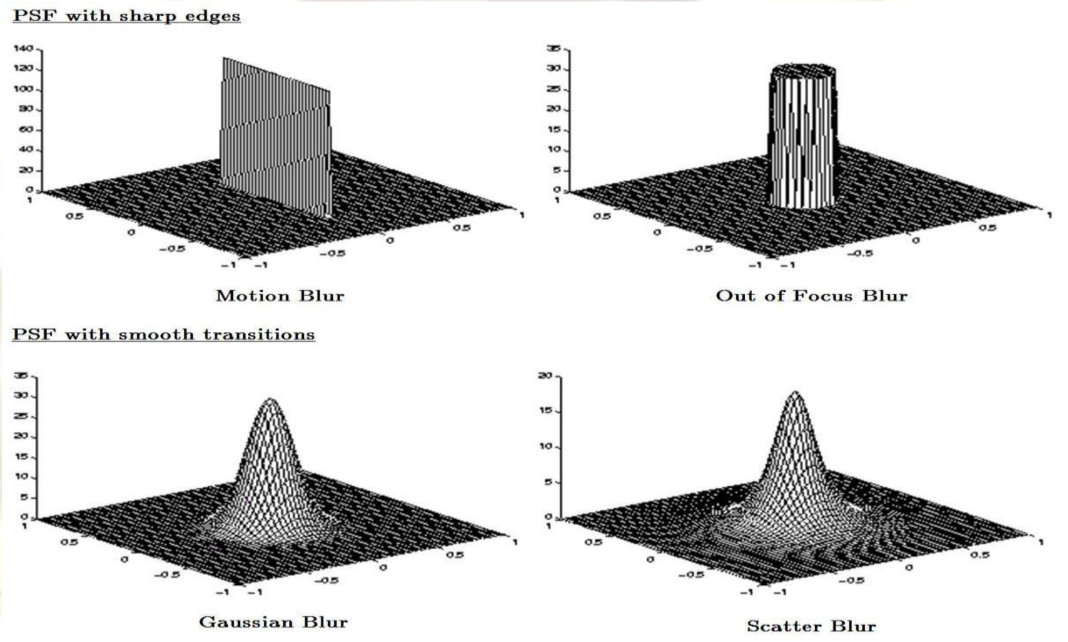

Figure 1.2 Graphical Interpretations of Different Types of Blurs

2. RELATED WORK

Attempts have been made to address the problem of blind deconvolution for deblurring of a natural image. Recent algorithms have achieved dramatic progress. However, there exist yet many aspects of the problem which are still challenging and hard to solve. Lokhande et. al. have worked on identification of motion blur parameters [2] using frequency domain analysis and tried to reconstruct the PSF using the length and angle information. This approach may not perform well for natural images because the algorithms assumes PSF to be perfectly box (linear) which is not the case in many natural images. The algorithm also does not cater for varying noise levels. Joshi et. al. have tried to estimate the PSF using sharp edge prediction [3]. They have tried to predict the ideal edge by finding the local maximum and minimum pixel values. This algorithm has given good results for smaller blurs but has not performed well for larger blurs. Levin et. al. have proposed an algorithm to deblur a blurred image using image statistics [4]. They have proved that the direction of motion blur is the direction with minimal derivative variation and the value which gives the maximum likelihood of the derivatives is the blur length. This algorithm has given good results only for box kernels. Box kernels are characteristics of perfect motion blurs. Blurs are not always motion blurs alone and most of the motion blurs do not have perfect box PSF. Fergus et. al. [5] have approached the problem using a variational Bayesian approach for PSF estimation. Shan et. al. [6] have used a semi maximum a-posteriori (MAP) algorithm which is used to get a point estimate of the unknown quantity based on empirical data. They have used a Gaussian prior for natural image and edge reweighting and iterative likelihood update for approximation of latent image. This algorithm does not work well for all images which is sparse or a bit away from Gaussian. Yuan et. al. have used of two sets of images (one blurry and one noisy) to recover the original image [7]. A comprehensive literature review to approach a deconvolution problem can be found in [8]. Miskin and Mackay have used ensemble learning algorithm to extract hidden images from a given image [9]. They have used Variational Bayesian approach to do ensemble learning.

2.1 CHALLENGES

The major challenge in deblurring a natural image is the determination of the unknown parameters like type of blur, extend of blur (PSF) and the approximation of noise. The number of unknowns is more than the number of known parameters making the problem ill posed. Even minor reduction in accuracies in PSF estimation leads to degradation of image quality while deblurring.

3. PROPOSED WORK

This paper work started with the approach of estimating the blur parameters using the algorithms discussed below. The algorithm aims at determining the Blur parameters such as length of blur in pixels and the angle of blur in degrees. This algorithm used for estimating the blur parameters, deblurring of the image using the estimated parameters, its limitations and the proposed Efficient Deblurring Algorithm for natural images. following is our proposed model figure 3.

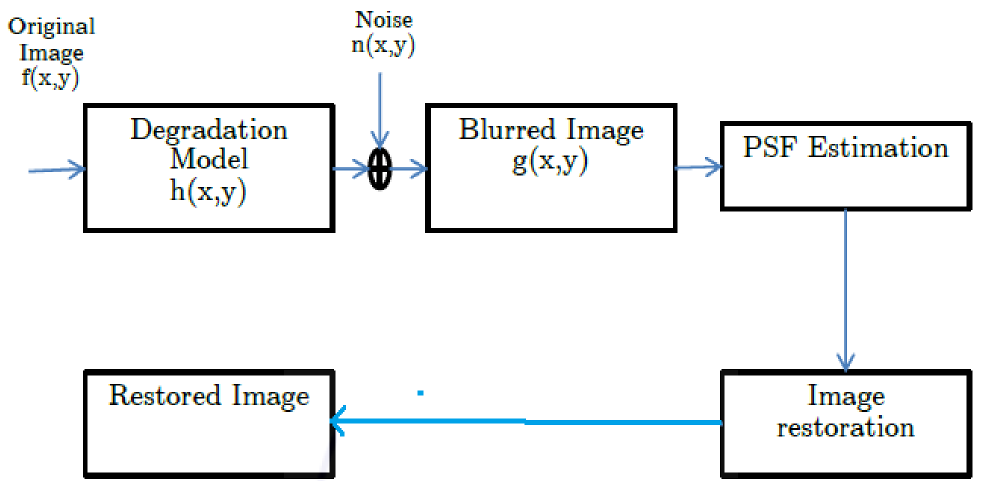

Figure:- Proposed model

3.1 DESIGNING

Lokhande et. al have introduced the use of frequency domain to estimate the blur parameters length and angle. The algorithm uses the spectrum of the image for analyzing the blur and Hough transform to determine the blur angle. Spectrum of an image does not reduce all the noise parameters introduced and hence display lines which are not representing the blur direction in the image. Hough transform also does not perform well in such a case and is computationally intensive. This paper uses the cestrum of the image instead of spectrum and radon transforms instead of Hough transforms. While taking radon transform, binary image of the spectrum is used to make computations easy. Radon transform gave accurate results and is easy to implement. Once the blur direction is obtained, the binary cepstrum image is rotated by the estimated angle and average of each column is taken. The distance between the zero-crossings represents the inverse of the length parameter. The algorithm is as follows:-

- Read the image
- Convert to grayscale
- Calculate Log and square of the image.
- Calculate Inverse Fast Fourier Transform to get the cepstrum.
- Convert to binary
- Apply radon transform for various angles.
- Find the angle at which the radon transform value is maximum to get θ.
- Calculate average along each column.
- Find the distance between the zero crossings to get the periodicity and hence L.

3.2 DEBLUR USING THE BLUR PARAMETERS

Using the parameters, blur length and angle, the PSF can be constructed. Once the approximate PSF is available, the latent image can be reconstructed using any of the deconvolution algorithms explained in above This paper uses the wiener filter, which is faster and computationally less expensive. Approximating the correct value of Noise to Signal Ratio dictates the quality of the output of the Wiener Filter. We have approximated Noise to Signal Ratio (NSR) as follows:-

NSR=1/ (2log base10 (max pixel value-min pixel value)/ standard derivation)

3.3 LIMITATION

This algorithm works well for synthetically generated blurs but fails for natural blurs. The main reason for this is the fact that most of the natural blurs are not perfect motion blurs which have an angle and length. These blurs are either out of focus blurs or non-linear motion blurs due to camera shake, or random blurs. The biggest challenge is to know the type of blur and then decide the way to obtain the PSF. Most of the naturally blurred images have Point Spread Functions which have random shape and estimating such a PSF is a big challenge. Image processing problems do not have fixed solutions. All problems are specific to the image and thus one need to look for a solution that can generalize some of the restrictions and come to a common conclusion or work individually on each input images. These results also suffer from the phenomenon of ringing artifacts.

4. EXPERIMENTAL RESULTS

Experiments have been carried out using the proposed algorithms in this paper. The User assisted deblurring algorithm using radon transform and cestrum gave excellent results for synthetically generated blurs. The results of the angle and length estimated are illustrated in Table 4.1 as well as in the images.

Image Name	Actual Theta	Estimated Theta	Actual Length	Estimated Length
Car1	30	34	60	62
Car2	30	33	50	50
Bike	45	48	65	66
Gate	30	32	45	45
Ground	10	11	55	55
Face	9	10	31	30
Peacock	2	3	50	49

TABLE 1

5. CONCLUSION & FUTURE WORK

It is difficult to generalize image-processing problems. Every image is different from each other and thus needs human intelligence and intervention to approach a problem. Therefore, it can be concluded that every image-processing problem is unique. This paper has improved upon the algorithm suggested by Lokhande et. al. [2] by increasing the accuracy of blur parameters detection and reduced the computational complexity by using radon transform and cestrum domain. It also proposes an efficient algorithm using machine-learning approach to come to an accurate estimation of PSF. The algorithm requires user intervention to select the Region of Interest (ROI) which does not have saturated pixels. The results depend largely on the area of interest selected and the degree of non-saturation in the image. It is difficult to incorporate all possible type of image degradation in a single model. However, this algorithm gives good results for natural blurs and it caters for most types of blurs. There is a scope for improvement in the deconvolution algorithm like Lucy-Richardson algorithm and wiener filter. Reduction of ringing artifacts has been a challenge while working in frequency domain. Modeling of noise is very important while approaching ill-posed problems. The algorithm can perform better if noise can be modeled in a better manner. Gaussian approximation is used for noise in this algorithm and that might not be ideal for camera noises. The algorithm assumes images to have linear tone scale. However, cameras generally have sigmoid shape to their tone response curve. The selection of ROI is done manually to avoid saturated regions and thus the consistency of the algorithm varies. If some statistical or heuristic approach can be implemented for the selection of ROI, better results can be obtained. Use of shallow depth of field in many cameras cause blur only to certain areas of the image. Using the same PSF to deblur the whole image may cause the unblurred parts to degrade further. It is possible to segment the image based on some energy function or blur measurement function and carry out deblurring for different segments using different PSFs. This may make the recovered image also look segmented. The algorithm has been implemented as a serial code and there is a scope of parallelizing it for larger images.

REFERENCES

[1] Wikipedia, Point spread function --- Wikipedia
[2] R. Lokhande, K. V. Arya, and P. Gupta, "Identification of parameters and restoration of motion blurred images," in Proc. of the 2006 ACM symposium on Applied computing, 2006, pp. 301-305.
[3] N. Joshi, R. Szeliski, and D. J. Kriegman, "PSF estimation using sharp edge prediction," in Proc. IEEE Conf. Computer Vision and Pattern Recognition CVPR 2008, 2008, pp. 1-8.
[4] Anat Levin, "Blind motion deblurring using image statistics," i Advances in Neural Information Processing Systems (NIPS), 2006.
[5] Rob Fergus, Barun Singh, Aaron Hertzmann, Sam T. Roweis, and William T.Freeman, "Removing camera shake from a single photograph," in SIGGRAPH '06, 2006, pp. 787-794.
[6] Qi Shan, Jiaya Jia, and Aseem Agarwala, "High-quality motion deblurring from a single image," in ACM SIGGRAPH 2008 papers, 2008, pp. 73:1--73:10.
[7] Lu Yuan, Jian Sun, Long Quan, and Heung-Yeung Shum, "Image deblurring with blurred/noisy image pairs," in ACM SIGGRAPH 2007 papers, 2007.
[8] D. Kundur and D. Hatzinakos, "Blind Image Deconvolution," IEEE Signal Processing Magazine, vol. 13, no. 3, pp. 43-64, 1996.
[9] James Miskin and J. C. David, "Ensemble Learning for Blind Image Separation and Deconvolution," inIndependent Component Analysis, M. Girolani, Ed.: Springer-Verlag, 2000.

Authors

Vipul Pathak

The author is pursuing Post Graduation in engineering from Teerthanker Mahaveer University, Moradabad (U.P.). He had completed engineering from Moradabad Institute of Technology; Moradabad(U. P.) affiliated to Gautam Buddha Technical University in 2011.

Deepali Kaushik

The author is pursuing Post Graduation in engineering from Krishna Institute of Engineering and Technology Ghaziabad (U.P.). She had completed engineering from Venkateshwara Institute of engineering & Technology; MEERUT (U.P.) affiliated to Gautam Buddha Technical University in 2011.

Pawan Verma

The author is pursuing Post Graduation in Master In computer Application from Sharda University, Greater Noida (U.P.).

Rohit Pathak

The author had completed engineering from Moradabad Institute of Technology; Moradabad(U. P.) affiliated to Gautam Buddha Technical University in 2011.