Image Restoration of Motion Blur Image using Alternating Direction Balanced Regularization Method

Manoj Kumar Rajput
Department of CSE & IT, MITS Gwalior 474005 India
manojrajput2012@gmail.com

Rajeev Kumar Singh
Department of CSE & IT, MITS Gwalior 474005 India
rajeev.mits1@gmail.com

Abstract**--**In this research, two different schemes are proposed to estimate the motion blur parameters. Two dimensional Gabor filter has been used to calculate the direction of the blur. Radial basis function neural network (RBFNN) has been utilized to find the length of the blur. Subsequently, Alternating Direction Balanced Regularization method has been used to restore the images. Noise robustness of the proposed scheme is tested with different noise strengths. The visual as well as the peak signal to noise ratio (PSNR in dB) of restored images are compared with competent recent schemes**.**

Keywords**—**Gabor Filter, RBFNN, ADBM, PSNR, MSE.

I. Introduction

During the formation, transmission and record of images, the quality of the images will be declined, such as image blurring, distortion, and becoming noisy because of various reasons. This process is called image de-gradation [1]. There are many causes of image degradation, for example atmospheric turbulence, the characteristic of sensor, the aberration of optical system, and the movement between object and imaging device. Image restoration is the process and method to obtain clear images from degraded images.Image restoration can be thought of as the inverse process of image degradation. So before we recover the images, we should build a degradation model, analyzing and estimating the process of image degradation and expressing it with a certain mathematical model. Input an image $f\,(x,y)$ through the degraded system $H(x,y)$, the output is the degraded image. The process of degradation is usually regarded as the noise pollution. Assuming that noise $n(x,y)$ is additive white noise, the degradation of image .

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

Where (x, y) is function of all reasons for degradation. The recovery process is on the basis of the degradation model and knowledge of the original image. g(x , y) is output image. The restoring image must be closest to the original image in some principles.Image degradation model can be described in mathematical expressions:

$$g(x,y) \; = \; f\,(x,y) \, * h(x,y) \; + \; n(x,y) \qquad (2)$$

In the formula (2): $h(x,y)$ represents time-domain description of degradation function. It's called point spread function,$*$ is convolution in time domain. The performance of time domain convolution is the frequency domain, so frequency domain expression of equation (1) is.

$$G(u,v) \; = \; F(u,v)H(u,v) \; + \; N(u,v) \qquad (3)$$

Image deblurring is a widely existing problem in image formation process. Due to the imperfection of the imaging devices, it still remains an active research area in image processing communities. The formation process of image blur is usually modeled as-

$$B \; = \; I * k \; + \; \epsilon \qquad (4)$$

Where$B$, I, k, and $\boldsymbol{\epsilon}$ represent the blurred image, latent image, blur kernel, and the additive noise, respectively and $*$ denotes the convolution operator. Because image deblurring is an ill-posed problem, most approaches introduce an image prior that favors natural images over degraded ones. By regularizing the problem in this fashion, a high quality result can be achieved [2]. There exists a variety of schemes, which describes the de-blurring techniques such as Wiener filter, Fourier wavelet regularized de-convolution, Expectation–Maximization algorithm for wavelet-based image de-convolution. All these techniques have some apriori knowledge about the nature of the degradation function. In most of the practical situations, the degradation function $h(x, y)$ is not known. This makes the restoration process difficult to recover the original image only from the observed image. Such restoration is commonly known as blind deconvolution. This paper deals with restoration of linear motion blurred images [3]. The motion blurred image restoration is an important branch in the image restoration technology. Motion blur is caused by the relative motion between the image system and the target. In the research of motion blurred image restoration, the point spread function in motion blur image degradation is an important parameter. Here Gabor filter have been employed to estimate the blur angle. Gabor filters are Gaussian filters modulated by a sinusoidal wave. A good number of researchers have used Gabor filter bankto extract image features in applications like pattern recognition, image segmentation, etc. The second parameter of motion blur is length of the blur (L).This describes how much of distance the object or camera has moved during the exposure time. To predict that length we employ RBFNN.

II. Literature Review

SinaFirouzi et al [5] In their paper, have introduced a novel algorithm to modify the phase correlation method for motion estimation in blurred images/frames. Unlike common motion estimation techniques such as block matching and regular phase correlation, our method is designed to estimate the motion in transitions from non-blurred to blurred frames and vice versa, and also in frames with different blurring values. We have compared our method against the blur-invariant motion estimation method which uses a $2n$ power of phase in the spectrum domain and we have shown that our method obtains lower errors in motion estimation. We have also shown the strong resilience of our method against noise.

Woo Jin Jeong et al [6] propose an efficient algorithm for motion deblurring withkernel estimation using consecutive images. First they estimate motion vectors between consecutive images using optical flow and RANSAC. Then they calculate the weights of motion vectors. The proposed method is similar to Ben-Ezra's method. The main difference is that they use a single camera for estimating a blur kernel and capturing a blurred image. Experimental results have shown that the proposed method produces better de-blurred images with less artifacts. Shamik Tiwari, et al [7] give an overview of some of the most widely used motion blur estimation methods with a quantitative evaluation. When noise is added to a degraded image, the sharpness of edges changes and the parallel dark lines in frequency spectrum of blurred image become fragile or disappear. Motion blur orientation estimation algorithms discussed in section IV shows that the presence of additive Gaussian noise mean absolute error increases from 0.2631 to 1.2632 ,1.2632 to 1.6316 and 2.9 to 3.3158 for Hough transform, Radon transform and steerable filter methods respectively. In existence of the same noise, the mean absolute error in length estimation for cepstral transform and Radon transform methods increases from 0.1875 to .5 and 0.8202 to 1.9616 respectively. Results of section VII shows that in case of inaccurate estimation of blur model, the image will be rather distorted much more than restored. This work encourages us to design a robust method for motion blur estimation.

III. Proposed Methodology

In this process, firstly we take an original grayscale image. Then take length and blur angle for point spread function generation. Degrade image with a motion blur and estimate blur angle using Gabor filter and estimate blur length using RBFNN of the blurred image. Using ADBM filter, restore the degraded image.

A. Motion Blur Model

Two parameters govern the motion blur length of blur L and angle of blur θ. The restoration performance depends on the estimation of PSF, which in turn dependent on L and θ. So challenge lies for accurate estimation of these parameters from a given motion blurred image.

The proposed algorithm estimates the parameters θ and L separately. The PSF is constructed from the parameters and the conventional Wiener filter is used for restoration of the blurred image.

Proposed Algorithm

1) Take an input original image.
2) Initialize original length and angle for an image.
3) Apply Motion Blur and add Gaussian noise with zero variance and 0.001 noise density.
4) Calculate blur angle (θ) using Gabor filter.

$$\mathrm{G(x,y)} = \frac{1}{2\pi sigma_{\mathrm{x}} sigma_{\mathrm{Y}}} \exp[-\frac{1}{2}(\frac{\mathrm{x}^2}{\mathrm{sigma}x} + \frac{\mathrm{y}^2}{\mathrm{sigmay}})] \times \exp[-j\omega(xcos\emptyset + ysin)]$$

Where $sigma_{\mathrm{x}}$, $sigma_{\mathrm{Y}}$ is the standard deviation in x and y direction respectively. $\emptyset$ And ω represents the orientation and frequency of theGabor filter.

5) Estimate the spectrum of the blurred image.
6) Logarithm of the spectrum of the blurred image i.e. Blurred image=log (G(u, v)) is used as input to the Gabor filter.
7) Gabor filter with different orientation ($\emptyset$) are convolved with Blurred_image to get different responses $R(\emptyset)$.
8) For every$\emptyset$, the L2 norm of the result of the convolution calculated. The blurring angle is then calculated as,

$$\hat{\theta}\text{Blur} = \arg\{\max R(\emptyset)\}$$

9) The blurred image is rotated in the direction opposite to the blur angle to obtain the equivalent horizontal blurred image.
10) Calculate blur length (L) using RBFNN.
11) PSF is created using the estimated blur parameters.
12) The image is restored using the alternating direction balanced regularization method.

A fast algorithm based on a variable splitting and the classical alternating direction method of multipliers (ADMM) was proposed for solving the analysis-based and synthesis-based approaches in image restoration [9]. The numerical experiments showed that the resulting algorithm was faster than the previous state-of-the-art methods in a set of standard image restoration problems such as image de-convolution,. The fast speed of this algorithm came from the fact that it used a regularized version of the Hessian of the $l_2$data-fidelity term, which can be computed efficiently for these standard image restorations, while the previously mentioned algorithms essentially only use the gradient information. This motivates us to adapt the alternating direction method to solve the balanced regularization problem in the frame-based image restoration [10].

IV. ANGLE ESTIMATION USING GABOR FILTER

One of the important observations in motion blurred images is that its frequency spectrum shows dominant parallel lines which correspond to the angle of blur. This can be observed from the Lena image blurred with an angle theta = 30◦ and L = 20 shown in Fig. 1. So, any of the line detection algorithms can be used to determine the orientation of the parallel lines.

A detail of the parameter estimation is described in sequel in the following sections-

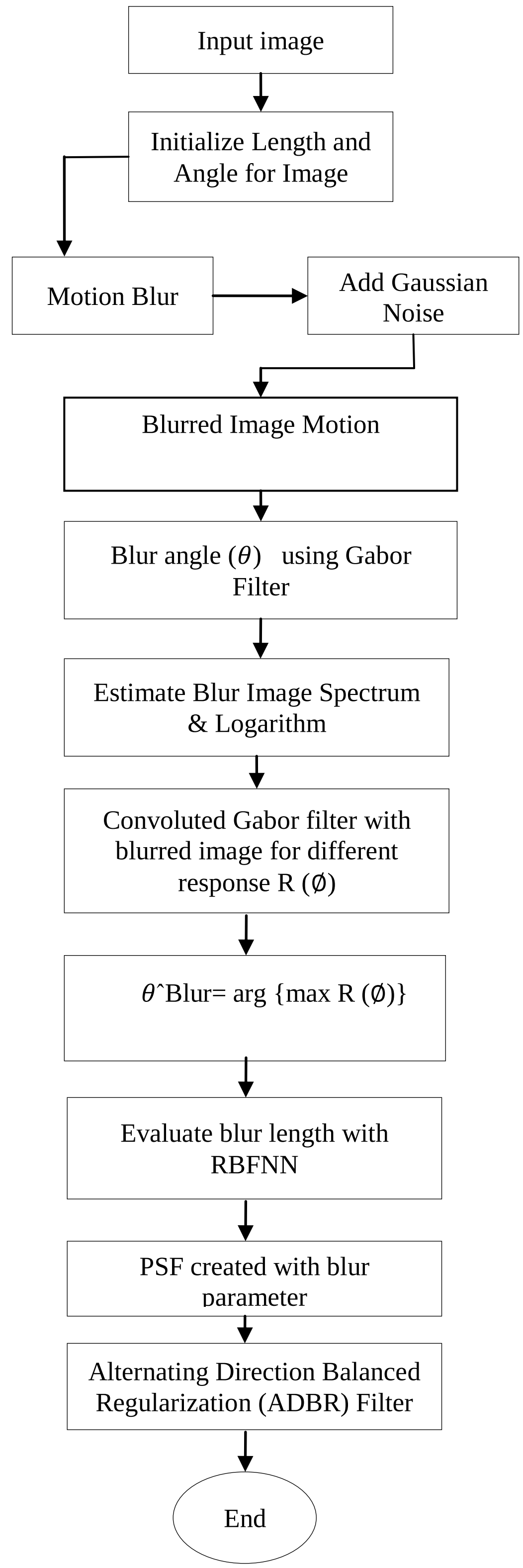


Fig 1: Flow Chart of Proposed Work

Gabor filters are Gaussian filters modulated by a sinusoidal wave [3]. A good number of researchers have used Gabor filter bankto extract image features in applications like pattern recognition, image segmentation, etc.

Modulated Gaussian filters can be used to find the orientation in the patterns. The two-dimensional Gabor filter masks for different orientation are shown in Fig. 2. In this plot, mask size of 7×7 has been used. The response of the Gabor filter varies with orientation parameter. This orientation parameter of a two dimensional Gabor filter has been utilized to calculate the blur angle. The two dimensional Gabor filter is convolved with the spectrum of the blurred image to get the response at different orientation by keeping other parameters fixed. The σ and ω values are chosen through experimentation and kept 3 and 1.75 respectively. The detail of theangle estimation strategy is described below. Pattern of the frequency response of the blurred image has been used to find the motion direction. Various line detection algorithms such as Hough transform, Radon transform can be used to detect the orientation of the line. However, Hough transform requires a threshold to identify points on the line [4]. This threshold is different for different images. Any small error in threshold could result to a large variation in estimation of the blur angle. To alleviate this problem, Gabor filter has been used to determine the blur angle.The response of the Gabor filter depends upon the frequency and orientation of the input image. In this method we apply a Gabor filter to power spectrum of the blurred image to detect the direction of motion. To detect the blur angle (θ), we search for the $\emptyset$ with the highest response value. The highest response of a filter cans be calculated using L2 norm [16]. For this, initially the parameters i.e. variances (σ_x and σ_Y), frequency (ω), and orientation ($\emptyset$) is chosen randomly and kept as $\sigma_x = \sigma_Y = 3$, and $\omega = 1.75$, and ($\emptyset$) = 0◦ respectively. Subsequently, the orientation is varied by keeping other parameters fixed. The filter with different orientation ($\emptyset$) is convolved with the Fourier transform of the blurred image. So for each $\emptyset$, $L2$ norm of the matrix resulting from the convolution is calculated. The $\emptyset$ with the largest $L2$ norm corresponds to the blur angle.

V. Length Estimation Using RBFNN

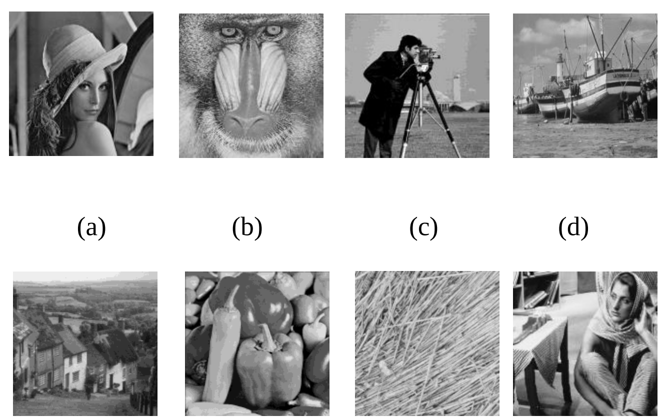
To predict the blur length of aparticular blurred image, we employ a RBFNN with Sum of the Magnitude of Fourier Coefficients (SUMFC) of the corresponding blurred image as its input. Following observations with respect to SUMFC versus the blur length of various blurred images motivated us toutilize a nonlinear predictor RBFNN.

Fourier feature of an image is one of the simplest feature infrequency domains and easy to determine using FFT algorithm.Standard images like Lena, Cameraman have been blurred horizon-tally using different blur lengths. The SUMFCs of different blurred images have been computed and normalized between 0 and 1. Fig. 3 depicts the relationship between SUMFCs and their corresponding blur lengths. It has been observed that there exists a nonlinear relation between these two parameters and true for all images. This non-linear behavior is exploited to predict the blur length from SUMFC as input through a RBFNN. Radial basis function neural network

Radial basis functional network has gained considerable attention as an alternate to Multilayer Perceptron trained by the back propagation algorithm. The basic functions are embedded in a two layer neural network, where each hidden unit implements a radial basis activation function. There are no weights connected between the input layer and hidden layer. The output unit implements a weighted sum of hidden unit outputs. The input into a RBF net-work is nonlinear while the output is linear. RBFNN is characterized by its localization (center) and activation hyperspace (activationfunction).

VI. Result Analysis

For proposed work evaluation consider the image dataset of different image such as Lena, Monkey, Cameraman, Boat, House etc. In the experiment, take eight images such as lena, cameraman, baboon, stick, peppers, boat, Barbara, house. In the simulation, estimate blur angle and blur length of a blurred image.

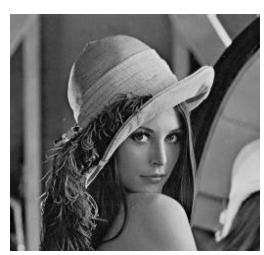


(a) (b) (c) (d)

(e) (f) (g) (h)

Fig2. Image Dataset

1) Read Original Image



DOI- 10.18486/ijcsnt.2015.4.3.03
ISSN-2053-6283

Fig3. Original Image

2) Degraded Image using Motion Blur

Fig4. Degraded Image

3) Restored Image using ADBR Filter

Fig5. Restored Image

The estimated blur angle is varies from 29 to 59. The estimated blur length is varies from 13 to 39. The image quality is measured with peak signal noise ratio which is reached up to 69%. And also find error of an image with mean square error which is reach up to 0.007. The execution time is better than previous method.

Length and Angle of image data set

Image	Original Blur Length	Original Blur Angle	Estimated Blur Length	Estimated Blur Angle
(a)	15	30	13.42	29
(b)	20	45	19.89	44
(c)	30	40	13.25	39
(d)	40	60	38.15	59
(e)	15	30	16.52	29
(f)	20	45	17.89	44
(g)	30	40	29.13	39
(h)	40	60	20.16	59

Table 1: Shows the values of Original & Estimated blur

Proposed result in terms of PSNR, MSE and Time

Image	Base PSNR	Proposed PSNR	Base MSE	Proposed MSE	Base Time	Proposed Time
(a)	66.16	68.60	0.0158	0.0090	11.16	1.43
(b)	68.74	69.08	0.0087	0.0080	13.78	5.10
(c)	66.16	69.93	0.0157	0.0066	12.47	5.83
(d)	67.36	68.42	0.0119	0.0093	10.42	0.95
(e)	66.38	68.94	0.0149	0.0083	26.71	6.31
(f)	68.49	73.84	0.0092	0.0027	15.70	4.82
(g)	69.50	69.67	0.0073	0.0070	20.16	1.25
(h)	63.79	65.54	0.0271	0.0181	8.68	7.17

Table 2: Shows the result of proposed methodology and comparison with existing method.

The figure 6 and 7 shows graph of result comparison between proposed methodology and existing method on the basis of MSE and TIME respectively given below

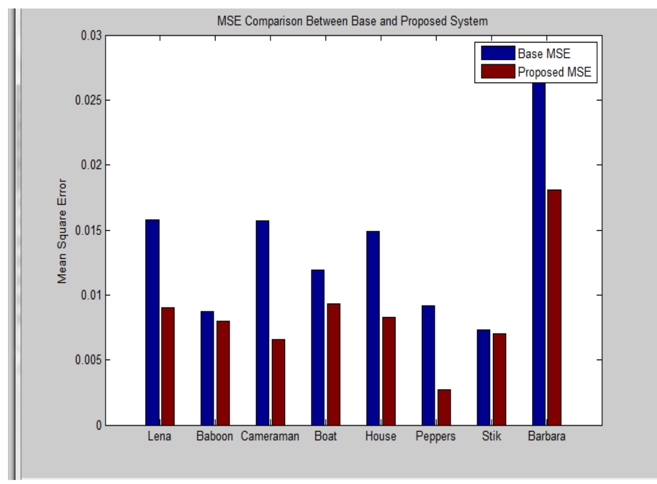


Figure 6: Comparison between existing Method and Proposed Method MSE on different images

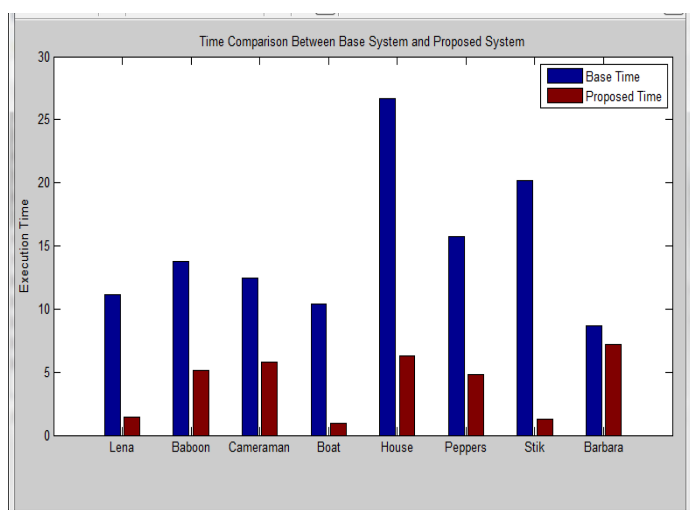


Figure 7: Comparison between existing and Proposed System Time on different images

Conclusion

In this study, Gabor filter and radial basis function network have been used to estimate blur angle and blur length respectively. Performance analysis has been made on only blurred images as well as noisy blurred images. The proposed scheme estimates the blur parameters close to the true value. Comparative analysis demonstrates the efficacy of the proposed scheme. This implicates the robustness of the proposed scheme. Both standard and real-time images have been included in experiment. It has been observed in all cases the proposed scheme has an upper hand in parameter estimation as well as restoration performance.Further, we will observe on one of the image restoration problems that can be modeled as multi-objective optimization problem for better approximation of blur parameters.

References

[1] ShuaiJia, Jie Wen, “Motion Blurred Image Restoration”, 2013 6th International Congress on Image and Signal Processing (CISP,2013),PP47-52.

[2] Jinshan Pan and Zhixun Su, “Fast -Regularized Kernel Estimation for Robust Motion Deblurring”, IEEE SIGNAL PROCESSING LETTERS, VOL. 20, NO. 9, SEPTEMBER 2013,PP132-137.

[3] Ratnakar Dash∗, BanshidharMajhi, “Motion blur parameters estimation for image restoration”, Optik 125 (2014), PP1634– 1640.

[4] R. Lokhande, K.V. Arya, P. Gupta, “ Identification of parameters and restorationof motion blurred images”, in: Proceedings of the 2006 ACM Sympo-sium on Applied Computing, vol. 9 of SAC 2006, Dijon, France, 2006, pp301–305.

[5] SinaFirouzi, Chris Joslin, “Motion Estimation in Blurred Frames Using Phase Correlation”, 2013 International Conference on Signal-Image Technology & Internet-Based Systems, PP230-235.

[6] Woo Jin Jeong1, Jin Wook Park1, Dong-Seok Lee2, Wonju Choi2, and Young Shik Moon1, “Weighted Linear Motion Deblurring with Blur Kernel Estimation using Consecutive Frames”, IEEE ISCE 2014 1569948611PP418-423.

[7] ShamikTiwari, V. P. Shukla, and A. K. Singh, “Review of Motion Blur Estimation Techniques”, Journal of Image and Graphics Vol. 1, No. 4, December 2013,PP126-131.

[8] Tom Goldstein, Brendan O’donoghue, Simon Setzer, And Richard Baraniuk “Fast Alternating Direction Optimization Methods” goldstein-cam12-35.pdf,PP332-338.

[9] M. Afonso, J. Bioucas-Dias, and M. Figueiredo, “Fast image recoveryusing variable splitting and constrained optimization”, IEEE Trans.Image Process., vol. 19, no. 9, Sep. 2010 pp. 2345–2356.

[10] ShoulieXie, SusantoRahardja “Alternating Direction Method For Balanced Image Restoration” IeeeTransactions On Image Processing, Vol. 21, No. 11, November 2012,PP667-671.

AUTHOR’S PROFILE

Manoj kumar rajput has received the B.E. degree in information technology, from IPS-CTM, Gwalior, India in 2011. Currently he is pursuing M.Tech (Computer Science & Engineering) from MITS, Gwalior. His research area includes Image Restoration.

Rajeev Kumar Singh is working as assistant professor, Department of Computer Science Engineering & Information Technology, MITS, Gwalior, India. His passion is to contribute in research activities of Science & Technology. His teaching and research include Image Processing and software engineering

DOI- 10.18486/ijcsnt.2015.4.3.03
ISSN-2053-6283