Estimation of Motion Blur Parameters and Restoration Techniques

Kishore R. Bhagat* and Puran Gour

Department of Digital Communication, NRI Institute of Information Sci. & Technology, Bhopal.

ABSTRACT

One of the most common problems in digital image restoration is motion blur caused by an image captured from a moving platform especially at low light condition having long exposure time of camera. Removing of blur is always challenging for image processing field because one has to estimate the motion blur which can spatially differ over image. Motion blur is simply an undesired effect. Restoration of blur image is very important in many of the cases like identification of number plates of moving vehicle and identification moving human beings. In restoration of motion blur the knowledge of the point spread function (PSF) is key factor. This paper presents the algorithm to estimate PSF parameters like motion blur angle and the motion blur length. Once PSF parameters are estimated then restoration of the blurred image can be achieved. Furthermore paper discusses the comparative study of different restoration techniques. The experimental result shows estimated blur angle and blur length are very close to theoretical value and the blur images with natural and artificial noise are successfully restored. The wavelet based fused image shows the best results.

Introduction

Motion blur is simply an undesired effect eventually causes degradation of image quality. The motion blur can be removed by minimizing the shutter exposure time but in case of low light situation this will causes unavoidable tradeoff of increased noise. One of the frequent reason of motion blur is camera shake. We can address this problem by using some mechanical means like camera can place on tripod stand. Secondly the object movement in the scene causes the motion blur. This type of blur is harder to control so it is often desirable to remove it by post synthesis of blur.

Images may be blur due to improper focusing of lens, atmospheric turbulence, undesirable working of optical systems, relative motion between the camera and scene. Hence in the restoration of noisy and blurred images knowledge of blurring system is important. Motion blur is defined with two essential parameters called motion blur angle and motion blur length. An Interactive Deblurring Technique for Motion Blur in which Segment based semi-automated restoration method is proposed using an error gradient descent iterative algorithm [1]. R. Lokhande, K. V. Aarya and P. Gupta [2] successfully proposed the algorithm to determine the motion blur PSF parameters. Numerous methods for estimation of blur parameters have been proposed in literature [3, 4, 5, 6, 7]. Fabian and Malah [4] discussed about the improvement in sensitivity of Cannon's method. Huiji & Chaoqiang Liu[5] introduce a hybrid Fourier-Radon transform to estimate the parameters of the blurring kernel with improved robustness to noise over available techniques. Gennery has discussed the parameters of blur function (PSF) in spectral domain [7]. Taeg Sang Cho has discussed about Blur Kernel Estimation using the Radon Transform [8]. Alex Rav-Acha, Shmuel Peleg [10] describes how different images, each degraded by a motion blur in a different direction, can be used to generate a restored image. Y. S. Chen and I. S. Choa describes transformation of the enhanced spectral magnitude function in cepstral domain [11] and the blurred image is pre-processed to remove the noise using Spectral Subtraction method [12], whereas Cannon [16] has identified the point spread function (PSF) parameters in the power cepstrum of the image by inspecting the negative peak.

In most of the blur kernel parameter identification methods the blur motion is consider along the horizontal direction, in practice which is not always the case. The method of detecting the blur angle by rotating the coordinate system following by computing its 1-D spectrum and inspecting the peaks and valleys in it is discussed by Li and Yoshida [9].

This paper suggest the approach to find out motion blur PSF parameters, i.e. blur angle and blur length, in frequency domain. After getting the approximated parameters those are used in restoration of image. The different types of filters are used for restoration of images and have been compared in this paper. Finally the wavelet based image fusion is used for betterment of results.
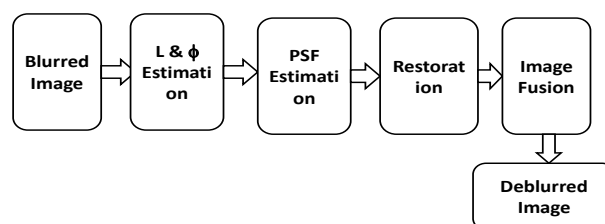

Figure1: Stages of proposed system

Further this paper is organized as, section II contains the Image acquisition Model. Algorithm for identification of motion blur parameters has been explained in Section III. The

comparison of restoration method is given in Section IV. Section V contains the wavelet based image fusion. The experimental results are given in section VI. Finally conclusion is given.

Following figure shows the propose stages to remove the motion blur.

Image acquisition Model

The technique for Image acquisition with linear space-invariant image system is depicted as shown in figure 2. Mathematically represented as,
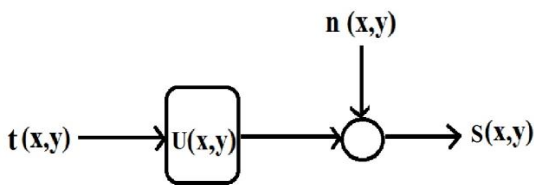
$$s(x, y) = t(x, y) * u(x, y) + n(x, y) \qquad (1)$$

Where t(x, y)is original image s(x, y)is the observed image u(x, y) is the point spread function of the imaging system n(x, y) is additive noise which is Gaussian white noise with zero mean in our case and (*) is the convolution operator.

If the u(x, y) point spread function is linear and space invariant function, then the blurred or noisy image is in spatial domain and it is given as,

$$U(x,y) = \begin{cases} \dfrac{1}{d}, & if\ 0 \leq |x| \leq d; \quad y = d\cos\phi \\ 0, & Otherwise \end{cases} \qquad (2)$$

Where d is blur length and it is proportional to relative velocity between camera and object to the exposure time.

Original Image   Motion Blur Kernel   Noise   Blurred Image
Figure2: Image Acquisition System

So s(x, y) also given as,

s(x, y) = t(x, y) * u(x, y) + n(x, y)

$$= \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} u(x - i, y - j)t(x, y) + n(x, y) \qquad (3)$$

Where ⊗indicates the 2-D convolution and s, u, t and n are observed image, degradation function, original image and noise respectively. All of these images are of size M×N, where M and N represent the image size in x and y axis respectively.

Above equation in the Fourier transform can be written as follows,

$$S(u, v) = T(u, v).U(u, v) + N(u, v) \qquad (4)$$

Since convolution in spatial domain is multiplication in frequency domain.Where (u, v) are the spatial frequency coordinates and S, U, T and N represent the Fourier transforms of the observed image s, degradation function u, original image t and noise n respectively.

This paper deals with images blurred by the uniform linear motion between the image and the sensor during image acquisition. Consider the scene to be acquired at constant relative velocity V between the scene and the camera with an angle of ϕdegrees along the horizontal axis during the exposure time [0, T] then the motion blur PSF u(x, y) for blur length L = V T [9,11] is given as in equation (2).For simplicity, let us assume that motion is along the horizontal direction i.e. $\phi = 0^o$, then (2) can be expressed.

$$u(x, y) = \begin{cases} \dfrac{1}{d}, & if\ 0 \leq |x| \leq d;\ \ y = 0 \\ 0, & Otherwise \end{cases} \qquad (5)$$

Using $\sin x = \dfrac{1}{2j}[e^{jx} - e^{-jx}]$ on the Fourier transform of(5) we will get,

$$U(k) = \sin c(\pi kL).e^{-j\pi kL} \qquad (6)$$

The magnitude transfer function of (5) is given by

$$|U(k)| = \sin c(\pi kL) \qquad (7)$$

Note that U(k) is independent of the l(vertical frequency Coordinate). Similarly, the expression for motion blur PSF of blur length L whose blur angle is ϕ^o with the horizontal axis is obtained in [14] and given by,

$$U(k, l) = \sin c(\pi Lt); where\ t = k\cos\phi + l\sin\phi \qquad (8)$$

Above equation can be taken as model of PSF for given parameter l and ϕ.

Estimation of blur kernel frameworks

In this section we discuss the line of action to find out the motion blur kernel parameters.

Blur Length Estimation

If noise is neglected, the Fourier transform of observed image is equal to the multiplication of Fourier transform of PSF (u(x, y)) and original image. The frequency response of the motion blur PSF(2) whose magnitude is given by (6), is characterized by periodic zeros on the k axis which occur at,

$$k = \pm\frac{1}{d}, \pm\frac{12}{d}, \pm\frac{3}{d}, \pm\frac{4}{d} \ldots\ldots. \qquad (9)$$

Line of Action for Estimation of Blur Length

● Step1: Determine the Fourier transform of the given blurred image as,

$$s(x,y) \xrightarrow{FT} S(k, l)$$

● Step2: The log spectrum of S(K, l) is calculated and converted to binary.

● Step3: System coordinate of binary structure is rotated in direction opposite to the of blur.

● Step4: Convert the 2D data in single dimension by taking average along the columns

● Step5: Take the IFT of 1-D data obtained in step 4.

● Step6: The real part of first negative value is found as blur length.

Above algorithm is proposed with consideration of no noise. If noise is present the same steps to be followed by applying average filtering of blurred image before computing its Fourier transform. With assumption that that zero mean white Gaussian noise and average filter effectively remove the Gaussian noise [14].

Blur Angle Estimation

The spectrum of non-blurred original image is isotropic, whereas that of motion blurred image is anisotropic based on this observation one can estimate the motion blur angle. u(x, y) is the convolution kernel that causes the motion blur so a blurred image due to motion is represented by a linear system of a convolution $s(x; y) = t(x,y)(\ u(x, y)$. The motion blur kernel low-passes the image in the direction of the blur. The anisotropy in the spectrum introduced by the motion blur is always perpendicular to the motion direction.

Therefore, to determine the blur direction, the spectrum is treated as an image and the Hough transform is then used to detect the orientation of the line in the spectrum.

Following algorithm is for finding motion LINE.

● Step 1: Consider ϕ_{min} and ϕ_{max} be the minimum and maximum values of ϕ.

● Step 2: Consider accumulator array A(r; ϕ) starting with zero.

● Step 3: find the max. value as A(r_m, ϕ_m)) in the accumulator array.

● Step 4: The max. value (say A(r_m, ϕ_m)) in the accumulator array corresponding line.

● Hence the corresponding line is rm = x cosϕ_m + y sinϕ_m..

The Hough transform divides the parameter space into accumulator array. For each point (x, y) in the image, the corresponding curve given by r = x_i cos ϕ + y_i sinϕ is entered in the accumulator by incrementing the count in each array along the curve. Thus, accumulator cell in the 2-D records the total number of curve is passing through it. The accumulator is searched to find cells having high counts when all the image point s have been recorded in accumulator array. If the count in a given cell (r; ϕ) is N, then N image points lie along the line whose normal parameters are (r; ϕ). Then Hough transform performed and provide the accumulator array in which the maximum value corresponds to blur direction. By transforming spectrum in to binary one can reduce the computation cost of the Hough transform.

following steps are perform to identify the blur angle.

● Step 1: Determine the FT S(k, l) of the blurred image s(x, y).

● Step 2: Calculate the log spectrum of S(k,l) of FT and convert it to binary.

● Step 3: The accumulator array is derived by using Hough transform.

● Step 4: The max. value in the A(r; ϕ) gives the blur angle.

Comparison of Image Restoration Techniques

In this section comparison of different image restoration techniques are discussed. This paper has used Wiener filter techniques, Lucy-Richardson techniques and blind de-convolution techniques to compare.

Wiener Filter Restoration Technique

Wiener filter [5] based algorithm considers images and noise as random process, and aims to find an estimate f of the ideal image f such that the mean square error between them is minimized. Transfer function for wiener filter is given by [5],

$$\hat{F}(k,l) = \left[\frac{H * (k,l)S_f(k,l)}{S_f(k,l)|H(k,l)|^2 + S_n(k,l)} \right] G(k,l) \quad (10)$$

where H(k, l) is the frequency response of PSF h(x, y), H*(k,l)is the complex conjugate of H(k, l), $|H(k, l)|^2$ = H*(k, l)H(k, l)and Sf (k; l) and Sn(k, l) are the power spectrum of the original image and noise respectively. The restored image in the spatial domain is given by the inverse Fourier transform of the frequency domain estimate F(k, l) If the noise is zero, then the noise power spectrum vanishes and the Wiener filter reduces to the inverse filter [11]. Equation (10) requires the knowledge of original images power spectrum, which is rarely known. Therefore, the equation (10) can be approximated by the following expression.

$$\hat{F}(k,l) = \left[\frac{H * (k,l)}{|H(k,l)|^2 + K} \right] G(k,l) \quad (11)$$

Where K is a constant and can be determined through experiments. The experiments reveal that a good estimate for the value of K is, K = 1/ω, where ω is the width of the image.

Lucy Richardson Restoration Method

The Lucy-Richardson deconvolution is an iterative algorithm optimized for Poisson distributed data. Poisson distribution can be assumed in the case that an image is recorded by a digital camera. In the absence of noise, a blurred image i(x) is formed from an unblurred image O(x) by the convolution. Lucy Richardson based filter algorithm posses iterative procedure that maximizes probability of restored image, when convolved with PSF, as part of original with Poisson noise statistics. If C_i is considered as observed value of location i then it can be given as

$$C_i = \sum_j P(i,j)u_i$$

Where $p_{(i,j)}$ is the PSF (the fraction of light coming from true location j that is observed at position i),U_j is the pixel value at

location j in the blurred image. The iterative procedure to calculate U_j mathematically can be given as,

$$u_j^{t+1} = u_j^t \sum_i \frac{C_i}{\hat{C}_i} p_{ij}$$

Where,

$$c_i = \sum_j u_j^t p_{ij}$$

$$\mathbf{p_{ij} = PointSpreadFunction.}$$

Blind De-convolution restoration method

Within this isoplanatic patch of the instrument (+ transmitting media), an observed image g(x) follow the image formation equation:

$$g(x) = (f * h)(x) + n(x) = \int f(y)h(x - y)dy + n(x) \quad (12)$$

where f(x) is the brightness distribution of the source, h(x) I the point spread function (PSF) and n(x) is the noise contribution. The discrete version of Eq. (12) is suitable for sampled data:

g = m + n

where the model m of the data g is:

$$m \equiv f * h = F^{-1}.(\hat{f} \times \hat{h}) \quad (13)$$

where * and × denote discrete convolution and element wise multiplication respectively,$\hat{f} == F$ f is the discrete

Fourier transform of f, and the inverse Fourier transform operator is.

$$F^{-1} = \frac{1}{N_{pixel}} F^H \left(in \; \mathbf{1}D: F_{u,x} = e^{\frac{-i2\pi ux}{N}} \right) \quad (14)$$

Under certain restrictions (constraints), it is possible to recover some approximation of both f and h from the data g alone. Such a process is an inverse problem known as blind deconvolution. The obvious advantage of blind deconvolution with respect to deconvolution is that it requires no knowledge of the PSF. This is very important in situations where calibration of the effective PSF is not possible, or very difficult, or time consuming, as it is the case, e.g., in high angular resolution astronomy or medical imaging. The drawback of the blind deconvolution is that it is far more difficult and, in practice, it takes much more time to be solved than conventional deconvolution.

Wavelet based image fusion

In this section paper has focused on the improvement of image quality by using wavelet based image fusion technique. The proposed system has shown in fig 3.
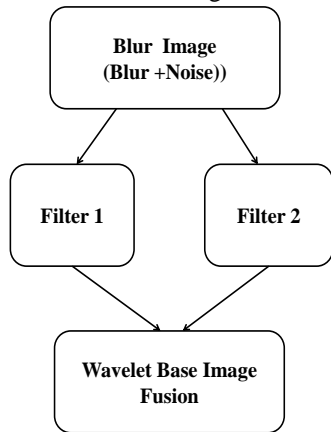

Figure 3: Proposed Method of Image Fusion

The input image is blurred and noisy. To remove the blur from the image it has to be restored with restoration algorithms. Finally the restored images are fused using fusion method to get deblurred image.

The wavelet based fusion technique for the fusion can be explained with the help of following fig4.
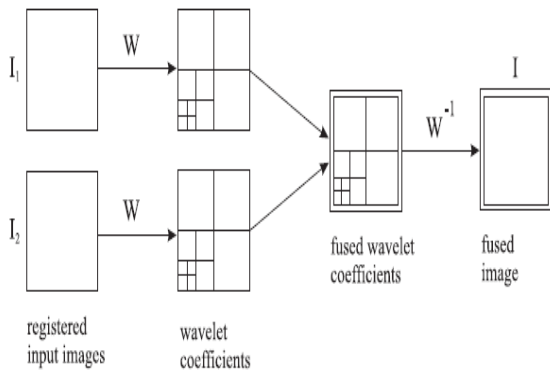

Figure 4: Fusion of wavelet transform of two images
Experimental Result

The experiments are performed on the gray scale images with both natural and artificial motion blur and noise. Artificial blurring is done using different values of blur lengths and blur angle.

The experimental results with natural blurred images are shown in Figure. Figure 5(a) shows the blurred image of baby and Figure 5(b) shows the corresponding restored image. The detected blur angle and blur length for baby image are 50 and 30 respectively. An example of artificially blurred images and corresponding restored images with different restoration technique are shown in Figure 6.

Fig.(5a)Real Blurred Image   **Fig.(5b) Restored Image**

Wiener filter   **Lucy Richardson**

Blind Deconvolution   **Wavelet Base fusion**

Figure 6: An example of artificially blurred image and corresponding restored images with different restoration technique.

Then different images are blurred artificially with different blur angles and lengths. In table 1 column number 2 shows noise variance, column number 3 and 4 shows the detected blur length and blur angle with noise.

Table1. Estimated Blur Angle and Blur Length with Noise

IMAGE USED	NOISE INVARIANCE	BLUR LENGTH	BLUR ANGLE	EST. BLUR LENGTH	EST. BLUR ANGLE
Lena. jpg	2.000	20	35	19	35
	45.230	42	54	34	54
	170.26	52	66	31	66
Aishwar ya. jpg	1.750	25	35	24	35
	25.560	40	52	35	52
	160.00	33	40	34	40

Table 2. Comparative Results of Different Restoration Techniques

Sadhna.tif with blur length 47 and Blur angle 60^0			
Parameter	**Entropy**	**PSNR**	**RMSE**
Wiener Filter	7.3617	66.6965	0.1180
Lucy Rich.	7.3638	67.8716	0.1030
Blind Deconv.	7.3604	67.8660	0.1021
Fused Image	7.3666	67.9510	0.1031

Table 2 shows the performance parameters like Entropy, RMSE, PSNR of the restored images for Wiener Filter restoration, Lucy-Richardson Filter and Blind de-convolution filter and the fused image.

Conclusion

This paper presented algorithm to estimate the PSF parameters. The parameters are blur length and blur angle which are used to restore images from the motion blurred images. Different restoration algorithms viz. Wiener, Lucy Richardson and Blind deconvolution are used to restore the images from motion blurred image. The comparative results for different restoration methods shows that Lucy Richardson method gives better result on increasing the iterations. The experimental results have shown that (i)In artificially blurred images the estimated blur length and blur angle are very close to theoretical value, and (ii)the proposed image restoration techniques effectively restores the images from natural motion blurred, artificial motion blurred and noisy images.(iii)Finally the fused image gives the best results .

References

[1] Yogesh K .meghrajani, Himanshu Mazumdar, An Interactive Deblurring Technique for Motion Blur, International Journal of Computer Applications (0975 – 8887) Volume 60–No.3, December 2012.

[2] R. Lokhande, K. V. Arya, and P. Gupta. 2006. Identification of parameters and restoration of motion blurred images. In Proceedings of the 2006 ACM symposium on Applied computing (SAC '06). ACM, New York, NY, USA, 301-305.

[3] M. M. Chang, A. M. Tekalp, and A. T. Erdem. Blur identification using the bispectrum. IEEE Trans. Signal Processing, 39(10):2323{2325, 1991.

[4] R. Fabian and D. Malah. Robust identification of motion and out-of-focus blur parameters from blurred and noisy images. CVGIP: Graphical, Models and Image Processing, 53:403{412, 1991.

[5] Hui Ji, Chaoqiang Liu, Motion Blur Identification from Image Gradients, IEEE-978-1-4244-2243-2/08,2008.

[6] R. C. Gonzalez and R. E. Woods. Digital Image Processing. Pearson Education, 2003.

[7] D. B. Gennery. Determination of optical transfer function by inspection of frequency domain plot. J. Opt. Soc. Amer., 63(12):1571{1577, 1973.

[8] Taeg Sang Cho, Blur Kernel Estimation using the Radon Transform, Massachusetts Institute of Technology,2010.

[9] Li and Y. Yoshida. Parameter estimation and restoration for motion blurred images. IEICE Trans .Fundamentals, E80-A(8), 1997.

[10] Alex Rav-Acha Shmuel Peleg, School of Computer Science and Engineering, Proceedings of the Fifth IEEE Workshop on Applications of Computer Vision (WACV'00), IEEE--7695-0813-8/00, 2000.

[11] Y. S. Chen and I. S. Choa. An approach to estimating the motion parameters for a linear motion blurred image. IEICE Trans. Inf. Syst., E83-D(7):1601{1603,2000.

[12] R. L. Lagendijk and J. Biemond. Hand Book of Image and Vedio Processing, chapter Basic Methods for Image Restoration and Identfication, pages 125{140. Academic Press, 2000.

[13] J. S. Lim. Image restoration by short space spectral subtraction. IEEE Trans. Acoust. Speech Signal Process., 28(2):191{197, 1980. .

[14] D. G. Childers. The cepstrum: A guide to processing. Proceedings Of The IEEE, 65(10):1428{1443, 1977.

[15] I. Rekleitis. Visual motion estimation based on motion blur interpretation. Master's thesis, School of Computer Science, McGill University, 1995.

[16] M. Cannon. Blind deconvolution of spatially invariant image blurs with phase. IEEE Trans. Acoust. Speech Signal Process., 24(1):56{63, 1976.