A Non-uniform Motion Blur Parameter Identification and Restoration using Frequency and Cepstral Domain

Ashwini M. Deshpande
Department of E &Tc. Engineering
SRES' College of Engineering, Kopargaon, India

Suprava Patnaik
Department of Electronics Engineering
S. V. National Institute of Technology, Surat, India

ABSTRACT
A near accurate method for extracting blur parameters from a non-uniformly motion blurred images; in a blind image deconvolution scheme is proposed. In case of a non-uniform motion blur, we should be able to extract both the blur parameters and the combination of their extent fairly accurate, in order to improve the quality of the restored image.

Initially, the parameters of the motion blur point spread function (PSF) of the observed blurry image are estimated. The blur parameters, which consist of two different directions and lengths of motion, can be extracted from the spectral and cepstral domain responses respectively, of that of the blurred image. Thereafter the morphological filtering is employed to enhance the precision of the directions and the lengths identification. Further, the estimated point spread functions (PSFs) of the motion blur are used to model the degradation function. A parametric Wiener filter performs deconvolution using the estimated PSF parameters and helps restoring these non-uniformly motion blurred images. The experimental results show that the performance of the algorithm proposed in this paper has higher PSF parameter estimation accuracy.

General Terms
Algorithms, Modeling, Performance, Estimation, Restoration.

Keywords
Non-uniform Motion blur, Spatial-variance, PSF, Spectrum, Cepstrum, Blind deconvolution.

1. INTRODUCTION
A motion blur is one of the major causes of image deterioration. Blurred images are often encountered either due to camera shaking or object motion. The motion blurred image is expressed by a convolution of a sharp image with the PSF [1, 2]. Having the input in the form of blurry image, reconstructing the original image by means of the PSF estimation is hence termed as the *deconvolution* or *inverse problem*.

A significant effort in recent years has been devoted to solving the so called *blind image deconvolution* problem, in which it is assumed that little or nothing is known about the underlying blurring process. In most practical applications, the point-spread function (PSF) that has caused the degradation is either unknown or not perfectly known. Although some partial information about the PSF is available, this information is never exact. Here the inverse problem becomes ill-posed, as usually very less we are aware of the actual form of PSF function.

There are two groups of blur, depending on how the blur affects different parts of the image, viz., *spatially-variant* and *invariant*. The latter affects the whole image in the same way whereas the former affects different parts of the image in different ways. Many approaches for motion blur identification dealt with the case of uniform linear motion or spatially-invariant type of blur that is described by a rectangular function PSF [1-8]. In this case, the motion blur is identified by extracting motion blur parameters such as the direction and the length.

Spatially variant or non-uniform blur does depend on position i.e., an object in an observed image may look different if its position is changed or two different parts of the same scene are affected by different amounts of blur [14]. This is more realistic and frequently occurring phenomenon. In such situations, the motion blur does not have a single direction but multiple directions and lengths; and the algorithms based on linear motion blur model usually fails to find the motion blur PSFs. The method proposed in this paper addresses this problem, for dual blur directions and lengths and tries to find the near accurate solution for multiple PSF parameters' identification.

The rest of the paper is arranged as follows. The related work done earlier by various researchers is discussed in Section 2. A non-uniform blur parameter attributes and their annotations are described in Section 3. Section 4 presents the proposed identification scheme of blur parameters in spectral and cepstral domains respectively, followed by briefings about the parametric-Wiener filter restoration. Section 5 provides the experimental evaluation and presents the stepwise results obtained based on our algorithm on various test images. Conclusions are drawn in Section 6.

2. RELATED WORK
Although blind motion deblurring of the degraded images has been researched for many years, it is still the challenging work in the field of digital image restoration. It is because the effective and accurate estimation of the amount of degradation that the original image has undergone in various imaging environment, imaging systems and the imaging processes cannot be recovered to the fullest. In general, for most of the classical image restoration algorithms or deblurring techniques, the PSF of imaging system, the imaging environments and the observation noise information are assumed to be known a priori [2, 7] i.e., most of the previous work assumes a space-invariant blur kernel, which seldom occurs in practice.

In reality, a number of problems need to be addressed typically in single image blind deconvolution, including spatially-varying blur, dim-light conditions, objects in motion and many more. Thus, removal of the blur caused by camera shake or hand shake and object motion is still a complex problem and needs more attention. Some of the recent works although attempt to overcome this limitation by using space-variant blur modeling and estimation [12, 14], majority of the existing work has been focused in the area of space-invariant deblurring. We have simulated the spatial-variant phenomenon by adding the multiple blur directions and blur lengths at arbitrary locations in the test images; it is as if, there are objects in the scene which are moving into different directions and with different velocities and hence termed it as *non-uniform* motion blur.

Uniform or spatial-invariant blur parameter estimation has been addressed by various researchers [3-6, 8-14] in past. One of the basic methods based on power spectral zeros was given by [1], which is being commonly experienced whenever frequency domain representation is used for blur parameter identification. But noisy conditions, image restoration part and thorough experimentation are lacking. Autocorrelation based parameter identification was introduced by [4], wherein power spectrum averaging to handle noise was performed in [5]. Many approaches for motion blur parameter identification dealt with the case of uniform linear motion blur that is described by a rectangular PSF are supported by [3, 6, 8, 9, 12]. In all these methods, the motion blur is identified by extracting motion blur parameters such as the direction and the length. However, these algorithms based on linear motion blur model fail to find the motion blur PSF with multiple directions and lengths. In order to cope up with such cases, [14] used multiple images whereas [12] presented the method to extract motion blur PSF that is a piecewise linear. For that they used forward ramp function to be applied on horizontal and vertical directions along with Radon transform and autocorrelation function as well. In spite of successful result, their algorithm is quite complicated and not able to find proper PSF when the number of components is large or the difference between two directions is small. In one case, [10] performed PSF estimation using Hough transform, whereas in other case, [Moghaddam] did it using a combination of radon transform and fuzzy logic, but both cases were meant for linear PSF. Recently, the cepstrum domain was also particularly addressed by [15, 16] and rather satisfactory results were produced, however they didn't consider multiple blur quantities or spatial-variant case in their methods.

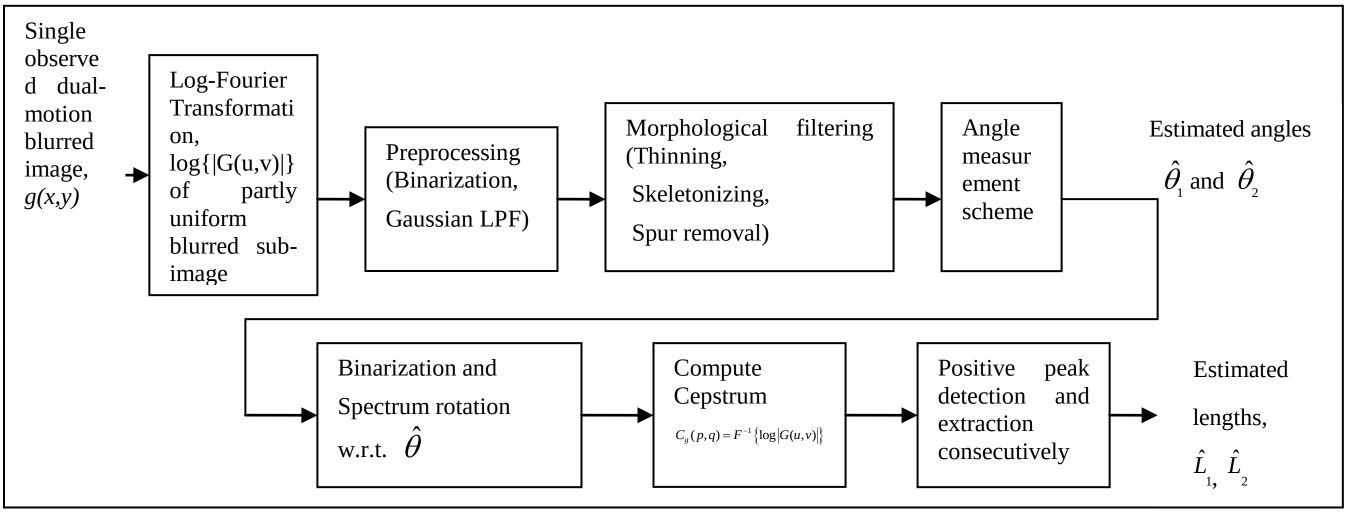


Figure 1: Proposed motion blur parameter estimation scheme

In this paper, we propose a new method to combine a log-spectral and cepstral domain representations of the single blurred input image to obtain a blur kernel estimation for non-uniform blur and using the same performed the restoration that is both noiseless and to much extent blur-free. The proposed algorithm selectively applies deconvolution to the image sub-sections and reconstructs the sharp features of the original image.

3. NON-UNIFORM MOTION BLUR ATTRIBUTES

In general, the process of degradation in optical imaging system can be assumed to be spatially invariant. Discrete model for a linear degradation caused by blurring can be given by the following equation [7]:

$$g(x,y) = f(x,y) \otimes h_s(x,y) + n(x,y)$$
$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(\alpha,\beta).h_s(x-\alpha, y-\beta)\,d\alpha\,d\beta + n(x,y)$$

(1)

where $\otimes$ is the convolution operator, $f(x,y)$ is the original image, $g(x,y)$ is the observed blurry image, $n(x,y)$ represents additive noise of any form. The quantity $h_s(x,y)$ characterizes a non-uniform PSF kernel where, $s = 1, 2....n$ denotes the image sub-sections and can be of any arbitrary size (rectangular, triangular, circular etc.) and *n* stands for number of subimages of the original image. This kernel function is assumed to be uniform over the specified section of the subimage for which the PSF is to be estimated.

As we have considered the noiseless non-uniform synthetically blurred test images, the additive noise is assumed to be zero-valued. Since we have simulated test images for dual motion blur case, the total non-uniform PSF kernel is a linear combination of two independent uniform PSF kernels. Each of such uniform motion blur PSF kernel is modeled by,

$$h_s(x_s, y_s; L_s, \theta_s) = \begin{cases} \dfrac{1}{L_s} & \text{if } \sqrt{x_s^{\,2} + y_s^{\,2}} \le \dfrac{L_s}{2} \text{ and } \dfrac{x_s}{y_s} = -\tan\theta_s \\ = 0 & \text{elsewhere} \end{cases}$$
(2)

where s=1, 2; L is the length of blur in pixels and θ is the direction of blur in degrees. Thus the deconvolution kernel is the function of both of these parameters. As the work is carried out for the blind deconvolution, the first step of the single image deblurring is to identify these motion blur parameters from the available single blurred input image that will be used to restore the sharp image by applying the deconvolution step.

4. PROPOSED PSF IDENTIFICATION METHOD

Given a single blurred input image to our algorithm, we first estimate PSF attributes from the log-spectrum and cepstrum of the blurred image, respectively. In this section we analyze and present the spectral and cepstral features of the blurry image under test. Fig. 1 depicts the proposed motion blur parameter estimation scheme in terms of block diagram representation which is elaborated in detail in the subsequent sections.

4.1 Blur direction identification in spectral domain

The convolutional relationship between the original image and the degradation or PSF kernel was introduced in Eq. 1. As the available form is the result of convolution, the recovery of the original image is possible if the estimation of PSF is as accurate as possible. As well this recovery is to be performed following deconvolution operation.

The deconvolution operation when performed into frequency domain, by applying the Fourier transform to Eq. 1, takes a more convenient multiplicative form, given as,

$$G(u,v) = F(u,v).H(u,v)$$
(3)

where $G(u,v), F(u,v)$ and $H(u,v)$ are the Fourier transforms of $g(x,y), f(x,y)$ and $h(x,y)$ respectively and (u,v) are the spatial frequency coordinates and capitals represent Fourier transforms.

Every time when we take log-Fourier transform of the blurred image, because the degradation that is underlying is a motion blur, which affects the sharpness and ultimately high frequency contents in the original image, the PSF kernel is assumed to take a rectangular form [9] in spatial domain. Hence the log-spectra of such motion blurred images are always sinc in nature and therefore contain spectral zeros periodically as shown in Fig. 2 below.

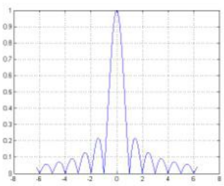


Figure 2: Spectral zeros observed in frequency domain of blurred image

The morphological filtering steps including Gaussian filtering, thinning, removal of spur pixels are further added to the spectral representation of blurred image, that refines the central directional lobes (as there will be two such lobes for dual blur case) and hence estimation angle identification can be performed with greater precision. With reference to the dual-blurred test image, the results obtained in Section 5 show the performance of the angle estimation part.

4.2 Blur length identification in cepstral domain

This section investigates the behavior of the cepstrum of blurred images and hence estimation of blur lengths in the cepstrum domain. Cepstrum analysis presents a standard pitch detection algorithm as in 1-D signal processing practice, which is being used to find valleys in cepstral domain. It is applicable to 2-D signals as well and being used largely in PSF estimation for the sake of detecting peaks and valleys.

Thus, the *cepstrum* is Fourier transformation or inverse Fourier transformation (IFFT) of the log-spectrum of an image that is given in Eq. 4. Thus it forms a tool for analyzing the frequency domain of an image.

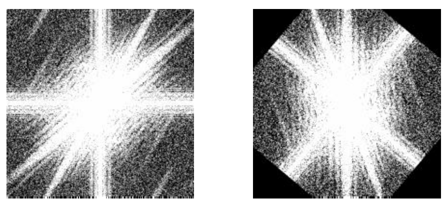
$$C_g(p,q) = F^{-1}\left\{\log\left|G(u,v)\right|\right\}$$
(4)

where $C_g(p,q)$ is the cepstral domain representation of blurred image which is input for our algorithm to successively estimate the blur lengths. Referring Eq. 3 and by taking the logarithm of the spectrum, the product of spectrums is converted to the sum of two cepstrums;

$$C_g(p,q) = C_f(p,q) + C_h(p,q)$$
(5)

According to Eq. 5, cepstrum of blurred image contain information about the PSF underlying and is exploited in this part.

In this step, taking reference from the angles being estimated in the earlier section, the binarized log-spectrum is rotated consecutively in two directions w. r. t. $\hat{\theta}$ as shown in Fig. 3.



(a) **(b)**

Figure 3: (a) Binarized spectrum, (b) Rotated binarized spectrum w.r.t. estimated angle

Taking the cepstrum of the rotated, binarized log-spectrum, result into 1-D representation, that shows two prominent positive peaks (two because of the symmetry in the nature of cepstrum). Out of two the first encountered positive peak points to the estimated blur length, another peak can be neglected. In this way, two different values of estimated lengths are resulted for two types of orientations i.e., estimated angles. A combination of two estimated blur lengths and blur angles constitute a non-uniform PSF kernel, which is used to deblur the test image.

4.3 Parametric-Wiener filter restoration

The Wiener filtering offers an optimal tradeoff between the basic inverse filtering and noise smoothing [7]. It removes the additive noise and inverts the blurring simultaneously. It minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering provides a linear estimation of the original image.

Basic Wiener filter requires the power spectra of noise and image to be known. As we have considered noiseless situation, the ratio is approximated in a form of factor K and is determined manually such as to minimize the error function. The corresponding frequency domain form is thus termed as ***parametric-Wiener filter*** and is given in Eq. 6 as follows

$$H_{wiener}(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + K} \tag{6}$$

where K has a small positive value and is usually selected in the range of $0 < K < 1$, by trial and error, so as to minimize the error function. Thus, at once the dual-blur PSF is being identified, it is deconvolved with the Wiener filter frequency form and deblurring is obtained.

5. EXPERIMENTAL EVALUATION

The simulation of dual motion blurring and deblurring on the test images was carried out in Matlab 7.0.1.

Initially, the test images were bifurcated into two different regions, either into two horizontal sections or two vertical sections or that of diagonally parted. Thereafter these two sections were motion blurred intentionally, but with dissimilar amount of blur directions and lengths. Thus, it results into a non-uniformly blurred test input (with 2 uniformly blurred subimages) for determination of a combined dual-blur PSF to be used for deblurring. Fig. 4 shows the original satellite-captured test image and its dual-blurred version. The lower and upper parts about the diagonal of complete image are motion blurred with the blur lengths = 40 and 30 pixels and blur angles= 150^0 and 130^0 respectively.

(a) **(b)**

Figure 4: (a) Original sharp test image, (b) Dual-motion blurred test image with true values of blur parameters set as -

$PSF1: L_1 = 30$ pixels and $\theta_1 = 130^0$, $PSF2: L_2 = 40$ pixels and $\theta_2 = 150^0$

The log-spectrum of the blurred input image is shown in Fig. 5 below, which shows two directional central lobes along with their respective parallel lines indicating the periodic nature of the sinc function, extended in 1st and 3rd quadrants. The blur angles to be estimated are determined from the spectral representation referring this figure.

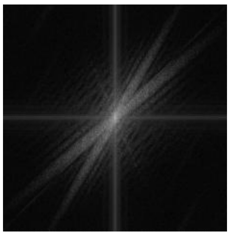
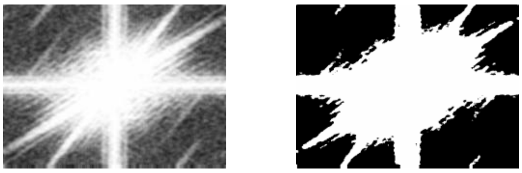


Figure 5: Log-FFT spectrum of the blurred test image

To improve the estimation accuracy the spectral characteristics are enhanced by initially applying Gaussian filtering followed by morphological skeletonizing, thinning and removing the spur pixels as depicted in Fig. 6 and 7. Ultimately it results into thin lined structure which we have used to characterize the angle measurement scheme.



(a) **(b)**

Figure 6: (a) Gaussian low pass filtered log-spectrum, (b) Binarized low-pass filtered log-spectrum

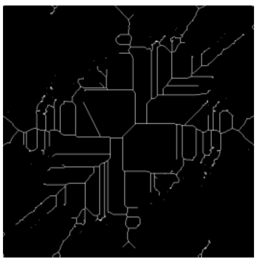


Figure 7: Skeletonized log-spectrum after removing spur pixels

The estimated angle is formulated considering the following angle estimation scheme,

- For the true values of the blur angle, $0^0 \le \theta \le 90^0$ calculate the estimated angle as modeled in Eq. 7:

$$\hat{\theta} = \tan^{-1}\left(\frac{u}{v}\right) \tag{7}$$

and for the true values of the blur angle, $90^0 \le \theta \le 180^0$, calculate the estimated angle as modeled in Eq. 8-

$$\hat{\theta} = \tan^{-1}\left(\frac{u}{v}\right) + 90^0 \tag{8}$$

where $\hat{\theta}$ is the estimated angle by our algorithm. Since the test images are blurred with two blur directions, there will be two values of estimated angles namely $\hat{\theta}_1$ and $\hat{\theta}_2$. The angle measurement scheme employed is described in Fig. 8. In order to identify these estimated angles, it is Fig. 7 which is mapped onto Fig. 8 to actually follow the angle measurement scheme.

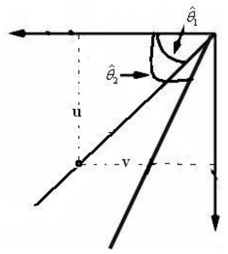


Figure 8: Proposed reference angle measurement scheme

Once the estimated angles are identified, the next step to perform is the identification of blur lengths. It is carried in the cepstrum domain as described in Section 4.2. The estimated angles are determined from combined plot of log-spectrum, wherein the cepstral domain evaluation of blur lengths is performed consecutively. Figures 9 and 10 show the resulting blur length in the cepstrum domain, marked as the prominent positive peaks.

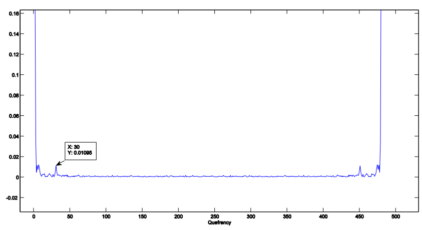


Figure 9: I^st Estimated length ($\hat{L}_1 = 30$) in cepstral domain

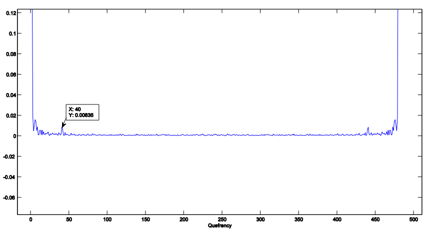
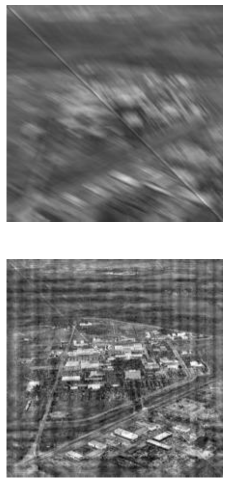


Figure 10: II^nd Estimated length ($\hat{L}_2 = 40$) in cepstral domain

The combined PSF including two estimated blur lengths and angles forms the estimated PSF. It is given to the parametric-Wiener filtering along with the blurry test image. The restoration results into the deblurred image as shown in Fig. 11 (b).

The result of deconvolution shows the accuracy of our PSF identification method. Incorrect PSF identification always results into further deterioration of restored image, which is definitely not happening in our case.

The ringing artifact occurring in the restored image is due to the inherent problem of the restoration algorithm which can be minimized by applying some post-processing techniques like zero-padding, proper boundary condition selection etc.



(a) **(b)**

Figure 11: (a) Dual-blurred test image, (b) Deblurred test image with estimated values of blur parameters by our algorithm as -

$PSF1: \hat{L}_1 = 30$ pixels and $\hat{\theta}_1 = 129.8055^0$ and

$PSF2: \hat{L}_2 = 40$ pixels and $\hat{\theta}_2 = 150.2254^0$

Table 1 presents additional simulation results for different dual-blurred test images by the true values of PSF parameters and deblurred images using the estimated PSFs.

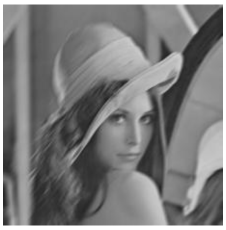
6. CONCLUSION

In this paper we proposed a non-uniform motion blur PSF identification method with improved accuracy in estimation. The blur parameters, which consist of two directions and lengths of motion, were estimated fairly accurately from the spectral and cepstral responses of the blurred image. The morphological filtering steps helped improving the accuracy of identification.

As presented in the experimental results, the estimation angles obtained are closer to the true values of blur directions. We obtain higher precision in blur lengths' estimation, as the values identified are exactly same as that of the set values of blurring lengths. Although noise component is not being modeled, the method attempts to address the noiseless, spatially-variant blur and effectively performs the non-uniform blind motion deblurring from a single image using the spectral and cepstral basics.

However, the proposed algorithm does not work satisfactorily when the blur angles and/or lengths are too small or strong noise is added. Work will be extended in future to deal with these problems.

Table 1. Additional PSF estimation and deblurring results

Dual-motion blurred test image (True blur parameters)	Deblurred image with estimated PSF by our algorithm (Estimated blur parameters)
 $PSF1: L_1 = 30$ pixels $\theta_1 = 40^0$ $PSF2: L_2 = 20$ pixels $\theta_2 = 60^0$	 $PSF1: \hat{L}_1 = 30$ pixels $\hat{\theta}_1 = 39.9662^0$ $PSF2: \hat{L}_2 = 20$ pixels $\hat{\theta}_2 = 60.5725^0$
 $PSF1: L_1 = 20$ pixels $\theta_1 = 50^0$ $PSF2: L_2 = 10$ pixels $\theta_2 = 30^0$	 $PSF1: \hat{L}_1 = 20$ pixels $\hat{\theta}_1 = 50.37^0$ $PSF2: \hat{L}_2 = 10$ pixels $\hat{\theta}_2 = 29.5^0$
 $PSF1: L_1 = 30$ pixels $\theta_1 = 40^0$ $PSF2: L_2 = 50$ pixels $\theta_2 = 60^0$	 $PSF1: \hat{L}_1 = 30$ pixels $\hat{\theta}_1 = 39.749^0$ $PSF2: \hat{L}_2 = 50$ pixels $\hat{\theta}_2 = 59.8349^0$

REFERENCES

[1] M. Cannon, "Blind deconvolution of spatially invariant image blurs with phase," *Acoustics, Speech, and Signal Processing of IEEE Transactions* on Vol. 24, pp.58 - 63, 1976.

[2] D. Kundur, D. Hatzinakos, "Blind image deconvolution," *Signal Processing Magazine, IEEE*, Vol.13, pp.43-64, 1996.

[3] M. M. Chang, A. M. Tekalp, and A. T. Erdem, "Blur identification using the bispectrum," J, IEEE Transactions on signal processing, vol. 39, no. 12, October, 2323-2325, 1991.

[4] Y. Yitzaky and N.S. Kopeika, "Identification of Blur Parameters from Motion Blurred Images," *Graphical Models and Image Processing* ,vol. 59, no. 5, pp. 310-320, 1997.

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

[6] Y. Chen and I. Choa, "An Approach to Estimating the Motion Parameters for a Linear Motion Blurred Image," *IEICE Trans. Inf.*, vol. E83-D, no. 7, pp. 1601-1603, July 2000.

[7] Gonzalez, R., Woods, R., and Eddins, S. Digital Image Processing Using MATLAB. Pearson Prentice-Hall, Upper Saddle River, NJ, 2004.

[8] R. Lokhande, K. V. Arya & P. Gupta, Identification of Parameters and Restoration of Motion Blur Images, Proceedings of The 2006 ACM Symposium on Applied Computing, pp. 301-305, Dijon, France, 2006.

[9] Mohsen Ebrahimi Moghaddam, Mansour Jamzad, "Linear Motion Blur Parameter Estimation in noisy images using Fuzzy sets and Power Spectrum," EURASIP Journal on Advances in Signal Processing, Article ID 68985, 2007. doi:10.1155/2007/68985

[10] M. Sakano, N. Suetake, E. Uchino, A PSF estimation based on Hough transform concerning gradient vector for noisy and motion blurred images, IEICE Trans. Inform. Syst. E90D (1) pp. 182–190, 2007.

[11] S. Q. Wu, Z. K. Lu, E. P. Ong, and W. S. Lin, "Blind image blur identification in cepstrum domain," *IEEE* Proceedings of 16th International conference on computer communications and networks, 10, August, 1166-1171, 2007.

[12] Karn Patanukhom and Akinori Nishihara, "Identification of Piecewise Linear Uniform Motion Blur", 2007 IEEE Region 10 Conference.

[13] Yuji Oyamada, Hideo Saito, Koji Ootagaki, and Mitsuo Eguchi, "Cepstrum based blind image deconvolution," in *International Workshop on Vision, Communications and Circuits*, pp. 197–201, 2008.

[14] M. Sorel, F. Sroubek, and J. Flusser, *Unexploded Ordnance Detection and Mitigation*, Springer Science+Business Media B.V., chap. Recent Advances in Space-Variant Deblurring and Image Stabilization, pp. 259-272, 2009.

[15] Zhizhong Fu, Haiying Xian, Jin Xu and Xiaoqi Ge, "Evaluation of motion blur parameter based on cepstrum domain of the intentional restored image," *IEEE ICCP 2010*, pp. 271-274, Dec. 2010.

[16] Haruka Asai, Yuji Oyamada, Julien Pilet, Hideo Saito, "Cepstral analysis based blind deconvolution for motion blur," in Proceedings of 2010 *IEEE 17th International Conference on Image Processing (ICIP2010)*, pp. 1153-1156, Sept. 2010.