Evaluation of Blind image Restoration

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Abstract- **Blind image restoration has many application in fields such as astronomical imaging, medical imaging of remote sensing, etc. The objective of the blind image restoration is to reconstruct the original image from a degraded observation without the knowledge of either the true image or the degradation process. A prior blur identification method is the class of methods that perform the blind deconvolution by identifying the PSF prior to the restoration. Motion blur is an inevitable trade-off between the amount of blur and the amount of noise in the acquired image. The effectiveness of any restoration algorithm typically depends on their amounts and it is difficult to find the best balance in order to ease of the restoration technique. This paper describes the concept of PSF identification, image restoration using various blind deconvolution algorithms.**

Keywords- **Image restoration, Image degradation, blind image deconvolution, PSF.**

I. INTRODUCTION

Some of the applications such as astronomical imaging, sonar imaging, remote sensing, medical imaging, microscopy imaging, and photography deblurring, the recorded image represents a noisy and blurred version of the original scene. The analysis of a picture using techniques that can identify shades, colours and relationships that cannot be perceived by the human eye. It deals with images in bitmapped graphics format that have been scanned in or captured with digital cameras. Restoration is a technique used to reconstruct or recover an image that has been degraded by using a priori knowledge of the degradation phenomenon.

Generally, the imaging system can be described as

$$g = Hf + n$$

where f and g represent the original image and degraded image. H is a matrix constructed from point-spread function. There are basically two types of image restoration methods namely non-blind restoration and blind restoration methods. A non-blind restoration method estimates the desired image 'f' from the given degraded image 'g'and PSF 'h'.Blind image restoration is the process of estimating both true image and blur from degraded image characteristics using partial information about the imaging systems. In many practical cases of interest H is not known. For example when taking the photograph of a moving object when the shutter speed and the speed of the object are unknowns. In this case we are faced with the very difficult problem of "blind" image restoration. In such cases we have to utilize prior knowledge in order to somehow recover simultaneously both f and H. There are many different ways to incorporate prior knowledge about the image f and the degradation H in the problem. One of them is using deterministic constraints in the form of convex sets. Another approach is using stochastic constraints in the form of prior distributions in a Bayesian framework. Various methods have been proposed in the literature to address the blind image restoration problem. These blind restoration methods can be divided into two main classes. The first class contains methods that separate blur identification as a disjoint procedure from restoration, such as zero sheet separation [6], general cross-validation [7] expectation maximization (EM) using ARMA modelling [8], maximum likelihood (ML) using ARMA modelling [9], and a priori blur identification [5] and [10] is used to estimate the blur kernel and then a standard deconvolution algorithm [11] is used for restoration. The second class consists of those methods that combine blur identification and restoration in one procedure. The method proposed in this paper belongs to the second class.

A marginal likelihood optimization method is used to estimate the PSF prior to the image and that is more robust than some joined method [1]. The main objective of this paper is to show that an approximation to MAP_k can, in fact, be optimized easily using a simple modification to $MAP_{x,k}$ algorithms. Similar to $MAP_{x,k}$ approaches, we alternate between solving for the kernel and solving for the image. The critical difference is that our kernel update system accounts for the covariance around the current latent image estimate, and not only for an image estimate itself. Furthermore, an efficient approximation to this covariance can be computed with no extra computational complexity. The algorithm is derived by casting the MAP_k problem in the Expectation- Minimization framework where the latent variable is the sharp image.

Ayers and dainty [2] proposed an iterative blind deconvolution algorithm to estimate the image and blur in the frequency domain. This technique is developed for blind deconvolution of two convolved functions. The maximum likelihood deconvolution (MLD) restoration method is presented in [4]. It is used to deconvolve an image with high quality and the processing time is low. Abd-Krim proposed KL divergence method to blind image restoration [15]. In this method ML blind image restoration is conceptualized as an alternating minimization of the Kullback–Leibler (KL) divergence between a parameter family and a desired family of probability distributions.Closed form solutions for these alternative projections are developed using the Gaussian assumption on the original image. These closed form solutions for the double minimization are very simple to implement and stable to converge. Filip and Jan developed MC blind image restoration [16] which uses MC alternating minimization algorithm (MC-AM) which incorporates the EVAM condition matrix into the anisotropic denoising technique. The combination of the anisotropic denoising technique provides both the numerical stability and the necessary robustness to noise

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The general system design describes the blind image restoration is represented in a block diagram given below in Fig.

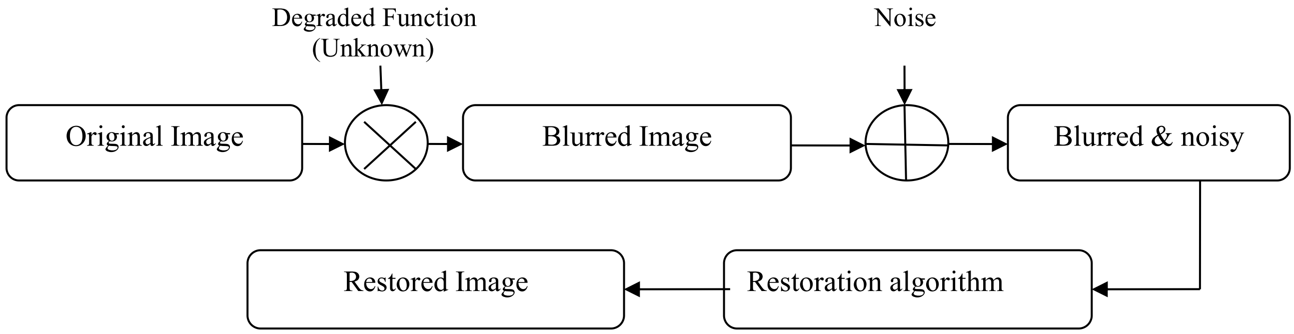

Fig 1. General Block diagram for blind image restoration

II METHODOLOGIES

This section describes the different methodologies used in the blind image restoration technique.

A. Iterative blind deconvolution

The image-domain constraint of non-negativity is commonly used in iterative algorithms. The complete image-domain constraint is not only forces the function estimate to positive but also conserves energy at each iteration.

The function estimate can be expressed as,

$$\tilde{f}_i(x) = f_i(x), \quad f_i(x) \geq 0$$

$$\tilde{f}_i(x) = 0, \quad \text{otherwise}$$

$$E = \int_{-\infty}^{+\infty} [f_i(x) - \tilde{f}_i(x)]\,dx$$

where E is the sum of the function's negative values. Energy redistribution is represented by,

$$\tilde{f}_i(x) = \tilde{f}_i(x) + E/N,$$

where N is the number of pixels in the image data array.

If the function estimate still contains negative regions, then the processing is repeated fourier domain contraints is described as constraining the fourier product of two function spectrum. The function $F_i\{u\}$ and the estimate $[C(u)/G_i(u)]$ are obtained on imposing the fourier -domain constraint. Fourier-domain constraint is summarized as,

$$|C(u)| < noise\ level, \quad F_{i+1}(u) = \tilde{F}_i(u)$$

$$|\tilde{G}_i(u)| \geq |C(u)|$$

$$F_{i+1}(u) = (1-\beta)\tilde{F}_i(u) + \beta \frac{C(u)}{\tilde{G}_i(u)}$$

$$|\tilde{G}_i(u)| < |C(u)|$$

$$\frac{1}{F_{i+1}(u)} = \frac{(1-\beta)}{\tilde{F}_i(u)} + \beta \frac{\tilde{G}_i(u}{C(u)}$$

General Flowchart for blind image deconvolution is given in Fig 2.

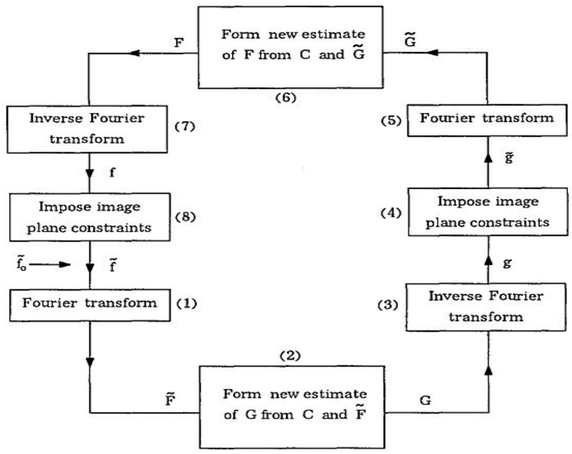

Fig 2. General Deconvolution Algorithm

The performance of restored result can be evaluated by PSNR, UIQI & Q-metric. The corresponding values 27.712, 0.984, 45.90 respectively.

B. Maximum Likelihood Deconvolution

Maximum likelihood estimation (MLE) is a mathematical optimization which is used for producing estimates of quantities corrupted by random noise. The image reconstruction is presented from three microscope modalities namely wide-field epifluorescence, brightfield fluorescence and confocal laser scanned fluorescence microscope.

The general flowchart for MLD shown in fig 3 is described as follows. In this flowchart $o^{(k)}$ is the estimate of the true image of the k-th iteration, $h^{(k)}$ is the restored PSF of the k-th iteration, $(\ )^*$ is the transpose operator. In step 1, initial guesses of the true image $o^{(0)}(x, y)$ and the PSF $h^{(0)}(x, y)$ are made. Step 2 is designed from the optimization strategy specified by the expectation maximization algorithm. Step3 enforces reasonable constrains on the solutions of the restored image and PSF.

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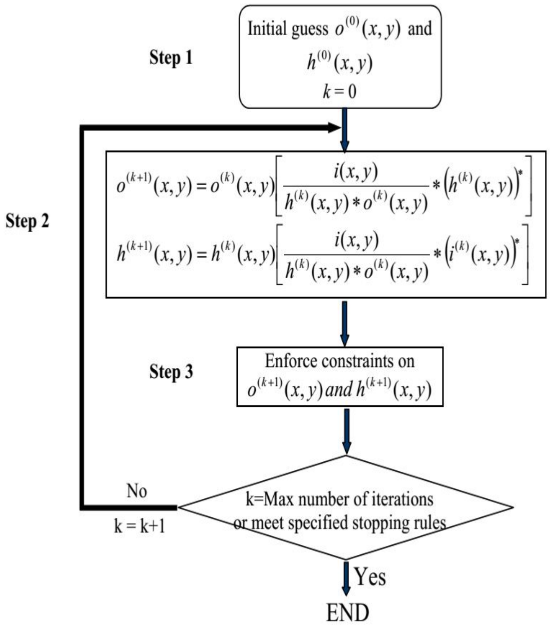

Fig 3. General flow chart for MLD algorithm

MLE is used in an automation of noise removal, cell counting, morphometric feature measurements and neuron tracing. As number of iteration increases the computational speed maximum possible array size and noise are increased. The PSNR, UIQI & Q-metric values of restored image obtained by this method are 26.742, 0.980, 45.33 respectively.

C. Multichannel Blind iterative image restoration

The MC alternating minimization algorithm uses Eigen-vector based method to restore a degraded image. In this method half-quadratic regularization together with a cell-centered finite difference discretization scheme is used .It provides a unified approach to the solution of total variation and Mumford-shah which are a denoising scheme. MC AM algorithm is stable for lower SNRs. Stability of their restoration process is high. Every iteration of the EM algorithm increases the likelihood function until a point of maximum is reached. When the number of iterations increases, the iteration first approaches the unknown object and then potentially goes away from it. The Energy functionis represented as,

$$E(u,h)=\frac{1}{2}\sum_{p=1}^{P}\left\|h*u-z\right\|^{2}+\lambda Q(u)+\gamma R(h)$$

Where ‘h’ is PSF, ‘u’ is an original image & ‘z’ is blurred image.

The following table describes the different values of PMSE for original restore image & blur.

S.No.	SNR	PMSE(h)	PMSE(u)
1.	50dB	3.12	2.29
2.	40dB	7.95	4.04
3.	30dB	15.25	7.03
4.	20dB	27.3	12.93
5.	10dB	44.88	21.86

Table 1. Performance of MC-AM

D. KL divergence approach

Original image and the blur are estimated by alternating minimization of the Kullback-Leibler divergence between a family of probability distributions defined using the linear image degradation model and a desired family of probability distributions of observed data. Using the Gaussian assumption on the original image, closed form solution for the parameters are developed. It is simple to implement and converge only after few iteration. A double minimization of the KL divergence is used to minimize the divergence between probability distribution of observed image and probability distribution of original image. In case of Blur identification the unknown parameter set θ is defined as a concatenation of three components: Image parameter set θ_x, Blur parameter set θ_d, and the regularisation parameter α. Thus the parameter set to be identified is denoted by $\theta = [\alpha\ \theta_d^T\ \theta_x^T]^T$. ML Parameter estimation problem can be obtained by

$$(\mathrm{p},\theta)_{\mathrm{ML}} = arg_{min}\, KL(p(y,x)\parallel q(y,x:\theta))$$

Camera man test image is taken as an input image and restored using KL-Divergence approach. The ISNR of restored result are given in the following table.

S.No.	Images with noise	ISNR
1.	Im1(30dB)	3.62
2.	Im2(50dB)	4.11

Table 2. ISNR of Restored Images

E. Marginal Likelihood Optimization:

Steps involved in reconstruction process are presented below.

Step 1: Getting the blurred image from an original test image.

Step 2: Adding Gaussian noise to the blurred image.

Step 3: Finding the PSF (Kernel) of blurred image

Step 4: Using MAP_k method to solve for the best ‘k’ from the given image.

Step 5: Using EM algorithm to estimate the mean image from the current kernel & to reconstruct original image.

Step 6: Evaluate the performance of restored image by calculating PSNR, Universal Image quality index (UIQI) & Quality factor (Q)

The PSNR, UIQI,Q metric values obtain for the restored result are 31.147,0.993,46.81 respectively. Fig 4 describes an evaluation result of the deconvolution error ratio across test examples.

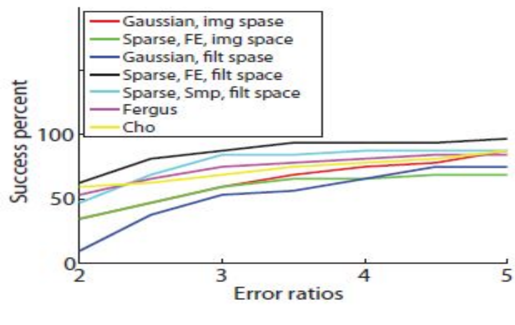

Fig 4. Cumulative histogram of the deconvolution error ratio

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F. MAP & HMRF Extractor

In this method deblurring of remote sensing images are performed by PSF support estimation method and joint estimation method to solve PSF co-efficients and restoration image. To regularize both the image of blur parameters. Huber Markov prior model is used.

i) PSF identification:

The PSF shape is considered to be rectangular .The horizontal and vertical measurements have to be estimated. The filtered image is obtained by convolving the degraded image with a filter. Two fixed filters have the characteristics of focusing image edge areas are used to identify the PSF support. From the filtered image PSF support can be determined.

The determination of the PSF support is given as follows:

$$v\_size = \arg_m \min(J(m,0))$$

$$h\_size = \arg_n \min(J(0,n))$$

where 'v_size' and 'h_size' are the estimated blur support in the vertical and horizontal directions, respectively.

J(m, n) is the autocorrelation of the image and it is defined by

$$J(m,n) = \frac{1}{(N-n)(M-m)} \sum_{x=n}^{N-1} \sum_{y=m}^{M-1} f(x,y) * f(x-n, y-m)$$

where N and M are the horizontal and vertical dimensions of the image.

f (x−n, y−m) is obtained by circularly shifting the image matrix n pixels in the horizontal direction and m pixels in the vertical direction.

ii) Estimation of restored Image:

To estimate the PSF coefficients and the restored image a MAP framework is used and the Huber–Markov random field (HMRF) prior model is used to regularize both the PSF & Restored image. The estimation of PSF co- efficient and the restored image contains two steps. First, the objective function is constructed and then optimization process is performed.

The MAP image restoration allows the posterior probability of the image and the blur to achieve the maximum, given a certain degraded image. The probability density function of image is given by,

$$p(f) = \frac{1}{Z_f} \exp\left\{ -\frac{1}{T_f} \sum_{c \in C} \rho_a (d_c^t f) \right\}$$

where Z_f is a normalization constant, T_f is the temperature parameter, c is the clique of image pixels, C is an assembly of c, and ρ(•) is the Huber function, which is defined as,

$$\rho_a(x) = \begin{cases} x^2, |x| \leq a \\ 2a|x| - a^2, |x| > a \end{cases}$$

where α is the threshold value which is used to define the separation for the quadratic and linear regions. It controls the scale and probability of the discontinuous area of the prior image.

$d_c^t f$ denotes the measures of the differences between pixels in neighbourhoods of the image field.

The probability density function of PSF is given by,

$$p(h) = \frac{1}{Z_h} \exp\left\{ -\frac{1}{T_h} \sum_{c \in C} \rho'_a (d_c^t h) \right\}$$

The minimum cost function is given by the equation

$$\hat{\boldsymbol{f}}, \hat{\boldsymbol{h}} = \arg\min_{\boldsymbol{f},\boldsymbol{h}} \left\{ \|\boldsymbol{g} - \boldsymbol{H}\boldsymbol{f}\|_2^2 + \lambda \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{i=1}^{4} \rho_a \left(d_{m,n,i}^t \boldsymbol{f} \right) + \gamma \sum_{m=1}^{P} \sum_{n=1}^{Q} \sum_{i=1}^{4} \rho_{a'} \left(d_{m,n,i}^t \boldsymbol{h} \right) \right\}$$

The first term represents the fidelity of the restored image 'f' with respect to the observation data 'g'. Excessive noise magnification due to the ill conditioning of the blur operator is minimized by this term. The second term narrows the solution space of 'f' and the λ is used to control the tradeoff between fidelity of the observation and smoothness of the restored image. The third term is used to ensure that h is solved steadily. An alternating minimization iterative scheme combined with a gradient descent algorithm is used to recover the image and identify the PSF simultaneously.

Let 's' be the gradient of the cost function with respect to image 'f' and 'q' be the corresponding conjugate vector. The steps involved in an optimization process are described as follows.

Step 1: Initialize the conjugate vector
Step 2: Calculate the step size to update the image f
Step 3: Update 'f' and the gradient of cost function
Step 4: Calculate the step size to update conjugate vector of the image
Step 5: Update the conjugate vector.
Step 6: The iteration is terminated when the calculated value is less than the predefined value.
Otherwise the iteration is continued.

III. PERFORMANCE ANALYSIS:

Peak signal-to-noise ratio (PSNR), the universal image quality index (UIQI) and the metric Q are calculated to evaluate the performance of the restored image. Ideal values of the PSNR and UIQI values are $+\infty$ and 1 respectively. The metric Q can reflect the amount of both blur and noise, without any prior knowledge. Image quality is high when it has larger Q value. The three metrics namely PSNR, UIQI, metric Q are calculated for both the noise free case and noisy case. Among all other methods MAP & HMRF method provides better result. In the noise free case-Input image is obtained by degrading original image by Gaussian

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blur with σ = 2.1.In the noisy case - Input image is obtained by adding Gaussian noise to the blurred image.

The following Table 3 describes the performance of restored image obtained by different types of blind image restoration techniques for noise free case. Overall performance of restored result for noise free case is described in fig 4.

Image	Noise free case		
	PSNR	UIQI	Q
Degraded image	22.719	0.943	41.76
IBD method	27.712	0.984	45.90
MLD method	26.742	0.980	45.33
MLO method	31.147	0.993	46.81
MAP & HMRF method	32.544	0.995	48.07

Table 3. Values of three metrics for different deconvolution methods (Noise free case).

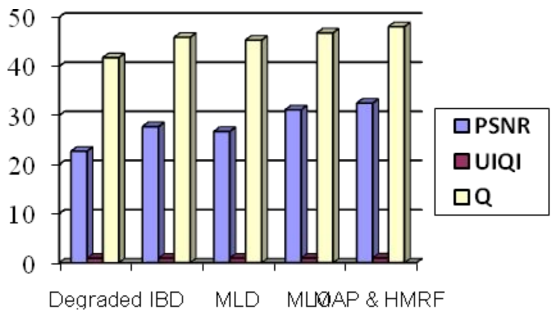

Fig 5. Overall performance in noise free case

The Table 4 describes the performance of restored image obtained by different types of blind image restoration techniques for noisy case. Overall performance of restored result for noise free case is described in fig 5

Image	Noisy case		
	PSNR	UIQI	Q
Degraded image	21.465	0.926	18.81
IBD method	22.559	0.944	30.86
MLD method	22.194	0.940	27.47
MLO method	23.342	0.955	39.32
MAP & HMRF method	23.782	0.959	46.14

Table 4. Values of three metrics for different deconvolution methods (Noisy case).

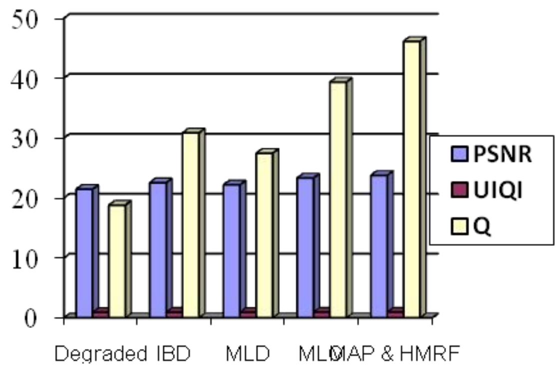

Fig 6. Overall performance in noisy case

IV. CONCLUSION:

This paper has presented the different algorithms used for the blind image restoration techniques. From the above discussion we can observe that the performance of MAP & HMRF method for restoring remote sensing image has better PSNR,UIQI & Q metric than any other methods. But the computational complexity is more than the IBD and MLD methods.

REFERENCES

[1] A. Levin, Y. Weiss, F.Durand, and W. T. Freeman, "Efficient marginal likelihood optimization in blind deconvolution", in *proc. IEEE CVPR*, 2011, pp.2657-2664.

[2] G. Ayers and J. Dainty, 'Iterative blind deconvolution method and its applications, *'Opt. LETT*., vol. 13, no. 7, pp. 547-549, Jul. 1988.

[3] D. Fish, A. Brinicombe, E. Pike, and J. Walker, "Blind deconvolution by means of the Richardson- Lucy algorithm", *J. Opt. Soc. Amer. A, Opt. Image Sci.,* vol. 12, no. 1, pp. 58-65, Jan. 1995.

[4] T.J. Holmes, S. Bhattacharyya, J. A. Cooper, D. Hanzel, V.Krishnamurthi, W. Lin, B. Roysam, D. H. Szarowski, ahd J. N. Turner, "Light microscopic images reconstructed by maximum likelihood deconvolution", in *Handbook of Biological confocal Microscopy*. Berlin, Germany: Springer-Verlag, 1955, pp. 389-402.

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[5] D. Kundur and D. Hatzinakos, "Blind image deconvolution," IEEE Signal Process. Mag., vol. 13, pp. 43–64, 1996.

[6] M. M. Chang, A. M. Tekalp, and A. T. Erden, "Blur identification using bi-spectrum," IEEE Trans. Signal Process., vol. 39, no. 10, pp. 2323–2325, Oct. 1991.

[7] S. J. Reeves and R. M. Mersereau, "Blur identification by the method of generalized cross-validation," IEEE Trans. Image Process., vol. 1,no. 3, pp. 301–311, Aug. 1992

[8] R. L. Lagendijk, J. Biemond, and B. E. Boekee, "Identification and restoration of noisy blurred images using the expectation-maximization algorithm," IEEE Trans. Acoust., Speech Signal Process., vol. 38, no. 7, pp. 1180–1191, Jul. 1990.

[9] G. Pavlovic and A. M. Tekalp, "Maximum likelihood parametric blur identification based on a continuous spatial domain model," in Proc. Int. Conf. Acoust., Speech, Signal Process., 1991, vol. 4, pp. 2489–2492.

[10] R. Fergus, B. Singh, A. Hertzman, S. T. Roweis, and W. Freeman, "Removing camera from a single photograph", ACM Trans. Graphics, vol. 25, pp. 787–794, 2006.

[11] L.Lucy,"Bayesian-based iterative method of image restoration," J. Astronomy,vol.79, pp. 745–754, 1974.

[12] L.Chen and K. Yap. "Efficient discrete spatial techniques for blur support identification in blind image deconvolution" ,*IEEE trans.signal process* .,vlo.54,no.4,pp.1557-1562,apr.2006.

[13] H.shen, L.zhang,B.Huang,and p.Li "A MAP approach for joint motion estimation, segmentation, and super resolution",*IEEE Trans.Image process*., vol.16,no.2,pp.479-490, Feb.2007.

[14]L.Zang,Q.Yuvan,H.Shen andP.LI, "Multiframe image super-resolution adapted with localspatial information",*J.,Opt.Soc.Amer.A,Opt.Image Sci*., vol.28,no.3,pp.381-390,Mar.2011.

[15] Abd-Krim Seghouane, "A kullback-Leibler Divergence Approach to blind image Restoration" IEEE Trans. Image Process., vol. 20, no. 7, July 2011

[16] Filip ˇSroubek and Jan Flusser, Senior Member, IEEE, "Multichannel blind iterative Image restoration", IEEE Trans on Image Processing ,vol:12,no:9,Sep 2003

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