

A REVIEW ON IMAGE RESTORATION TECHNIQUES

Manoj Kumar Rajput¹; Rajeev Kumar Singh²,
Department of CSE & IT, MITS, Gwalior (India)

Abstract

Image restoration is a process to improve the quality of image via estimating the amount of noises and blur involved in the image. The concept of restoration image that has been degraded using apriori knowledge of degradation phenomenon, in which most of part is an objective process. Image degradation may be occurred due to motion blur, blur due to camera mis-focus, atmospheric turbulence etc. Atmospheric turbulence blur depends on a variety of factors like temperature, wind speed and long-exposure time. Image deblurring process is used to deconvolute degraded image with point spread function (PSF) that exactly describe the distortion of the image. There is a wide spread application of image restoration in today's world. This paper gives a review of different image restoration techniques used.

Keywords:- Image restoration, Deblurring, Neural Network, Gaussian Blur.

I Introduction

The objective of restoration is to improve a given image into some predefined sense. Restoration is a low level technique of digital image processing in which an image is taken as an input and get restored image as an output the image. The degradation consists of two distinct processes. the deterministic blur and random noise. Image restoration is an estimation of image from blurred and noisy images. So, blur is the bandwidth reduction of an image at the time of capturing and it can be happened due to a number of reasons such as relative motion between camera and images, camera get focused from the object and due to atmospheric turbulence [1]. Noise may be occurred in an image at the transmission time and also at the time of image formation or combination of them. So, there is a different image restoration technique which deals with different degradation problem. For restoration process, it is nearly assumed the information i.e PSF (point spread function) required to restored image should be apriori. Here equation clearly shows image is degraded using degradation function and additive noise.

$$g(x, y) = h * f(x, y) + \eta(x, y) \quad (1)$$

Where $g(x, y)$ is degraded image and $f(x, y)$ is an original image which convolute with degradation function h and $\eta(x, y)$ is additive noise. Most of the restoration technique uses the degradation process and attempt to apply an inverse procedure to obtain an approximation of the original image [2][3]. Iterative image restoration techniques often attempt to restore an image linearly or non-linearly by minimizing

some measures of degradation such as maximum likelihood, constrained least square, etc. Blind restoration techniques attempt to solve restoration problem without knowing the blurring function which is used to blur image [4].

We use filters for restoration or deconvolution of an image. Inverse filter and wiener filter are used to filter image, but both of them have some limitation for restoring the image. Inverse filter provides a good result if we know exact point spread function (PSF) and ignore the noise effect present in an image. Wiener filter estimated image minimizing the mean square error between the original and restored image, it can be restored image if noise present in image but this filter requires a prior knowledge of power spectral density of original image which is generally unknown[7]. In constrained least square filtering the constraints have effect of adding information to an image which lost in degraded image to the restoration process. Constrained restoration refers to the process of obtaining meaningful restoration by biasing the solution toward the minimizer of some specified constraint functional. Constrained filter is a regularization technique which adds the langrange multiplier, λ , to control the balance between the noise artifacts and consistency with observed image.

The constrained least square filter is given

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

Here, $P(k, l)$ is the fourier transform of the laplacian filter. Where G, H , and \hat{F} denote the Fourier transform of g, h , and \hat{f} respectively, H^* is the conjugate of H .

II Types of Blur

In the digital camera there are four basic general kinds of blur effects:

A. Average Blur

Average blur is the one used to the remove noise and bits in a picture furthermore when noise is available over a complete picture. This sort of theblurring can be a conveyance in even and vertical heading and can be round about averaging by sweep R which is assessed through the formula[5].

$$R = \sqrt{g^2 + f^2} \quad (3)$$

where g - is the even size blurring heading f - vertical blurring size bearing and R - the range size of the roundabout

normal blurring



Fig 1: Average blur image

B. Gaussian Blur:

A Gaussian blur is the image blurring result through Gaussian function. It is an extensively used, which results in the graphics software, classically to reduce detail and reduce image noise. Gaussian blur is used as a preprocessing phase in the algorithms of computer vision in order to improve image structures at various levels. The Gaussian Blur filter effect that blends a particular numerous pixel incrementally, following a the bell-shaped curve. blurring is dense in the center and also edge feather. Using Gaussian Blur to an image when we want additional control over the effect of the Blur [7].

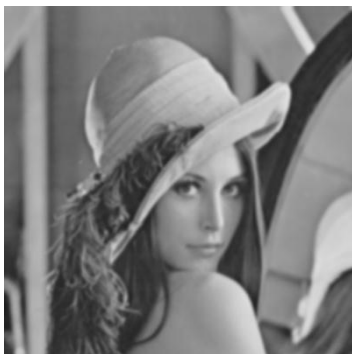


Fig2:Gaussian blur image

C. Motion Blur:

The Many sorts of movement obscure can be recognized each of which are because of relative movement between recording gadget and scene. This can be as an interpretation, a revolution, unexpected modification of scale, or a few blends of these. The Motion Blur impact is a channel that makes the picture seem, by all accounts, to be adding so as to move obscure in a particular heading. The movement can be measured by a point or bearing (0 to 360 degrees or -90 to +90) and/or through separation or power in the pixels (0 to 999), in light of the product used [6].



Fig 3: Motion blur image

D. Out-of-focus Blur:

At the point when a camera pictures a 3-D scene onto a 2-D imaging plane, a few scene sections are in the center while different parts are most certainly not. In the event that the gap of the camera is round, the picture of any point source is a little plate, called as a circle of perplexity (COC). The level of defocus (width of the COC) relies on upon the central length and the opening numerous lens, and the separation in the middle of camera and article. A precise model depicts the measurement of the COC, as well as the force conveyance inside of the COC[5].



Fig 4: Out-of-focus blur image

III Deblurring Techniques

A. Lucy- Richardson Algorithm Technique:

The Richardson-Lucy calculation, otherwise called Richardson-Lucy deconvolution is an iterative process for recouping the dormant picture that has been obscured through a called as PSF.[8].

B. Neural Network Approach:

Neural networks are types of the multiprocessor PC framework, with the components of basic preparing, a high level of interconnection, versatile communication between

the distinctive components, When a component of the comes up the short neural network, it can proceed with no issue through their parallel nature [9]. Manufactured Neural systems offer a strong instrument for approximating a point function give an accumulation data, yield sample furthermore for the recreationfunction from the class a picture. A calculation, for example, Back propagation and also Perceptron use gradient- decent methods to the tune system parameters to the best-fit a preparation gathering of information yield illustrations. Here we are applying Back propagation neural network strategy for image restoration. This system is equipped for the learning complex nonlinear capacities is relied upon to make the ideal structure particularly in the high recurrence areas of the picture. We utilized a 2-layer Back propagation network with the complete integration[5].

C. Blind Deconvolution Technique:

There are essentially two sorts of deconvolution routines. They are the projection based on the blind deconvolution and most extreme probability reclamation. In the first method at the same time restores the genuine picture and also function of the point spread. This starts through creating initial estimates of the genuine picture and PSF. The procedure is round and hollow in nature. Firstly we will discover the PSF assessment and it is trailed by the picture estimate. This cyclic procedure is rehashed until the predefined merging measure is met. The value of this strategy is that it seems robust to the support size impressions and also this type of technique is noise insensitive. The issue here is that it is not only unique, but this strategy can have slips connected with neighborhood minima. [10]

In the other method the most extreme probability assessment of the parameters like PSF and also covariance networks. As the PSF appraisal is not one of a kind different presumptions like symmetry, size and so forth of the PSF can be considered. The fundamentally favorable position is that it has got low complexity computation furthermore serves to discover blur, noise furthermore control spectra of the genuine picture. The disadvantage with this methodology is of calculation being joining to the nearby minima evaluated estimated function. [11]

D. Deblurring With Blurred/Noisy Image Pairs:

This type of approach deblurredpictures with the assistance of noisy picture. At the first stage, both the pictures are blurred and noisy picture are utilized to locate an exact blur bit. It is regularly extremely hard to get an obscure bit from one picture.

Taking after that a leftover deconvolution is done

and this will decrease artifacts that show up as spurious signs which are basic in picture deconvolution. As the third and last step the remaining relics which are available in the non-sharp pictures are stifled by an addition of controlled deconvolution process. The principle point of interest of this methodology is that it receipts both the noisy and blurred pictures and subsequently delivers brilliantly reproduced picture. With these two pictures an iterative algorithm has been expressed which will estimation a decent initial kernel and lessen deconvolution artifacts. There is no uncommon equipment is needed. There are additionally disservices with this methodology like there is the spatial point spread capacity that is invariant.[12]

E. Deblurring With Motion Density Function:

In this technique, picture deblurring is finished with the assistance of motion density function. A Unified model of the camera shake blur furthermore a system has been utilized to the recoup camera movement furthermore inactive picture from a single blurred picture. Camera movement is spoken to as an MDF (Motion Density Function) which records part of the time spent in every single discretized segment of the space of every conceivable camera postures. Spatially differing blur portions are gotten straightforwardly from the MDF. One constraint of this strategy is that it relies upon the defective spatially in statement invariant deblurring.[13]

F. Deblurring With Handling Outliers:

In this system different sorts of outliers, for example, pixels immersion and also non-Gaussian noise are broke down and after that a deconvolution technique has been suggested which holds an explicit segment for outlier modelling. Picture pixels are ordered into two principle classifications: Inlier pixels and Outlier pixels. After that an Expectation-Maximization system is utilized to iteratively refine the anomaly arrangement and the inert image.[14]

G. Deblurring by ASDS-AR:

In this methodology ASDS (Adaptive Sparse Domain Selection) plan is presented, which takes in a progression of minimal sub-lexicons and appoints adaptively every neighborhood fix a sub-word reference as the inadequate area. With ASDS, a weighted l1-standard scanty representation model will be the IR assignments suggested. Further, two versatile regularization terms has been brought into the system of the scanty representation. Initial, an accumulation of the AR (autoregressive) models are found out from the dataset of illustration picture patches. The best fitted models of AR to the patch assumed are adaptively chosen to be regularized picture nearby structures. Second, the picture nonlocal self-closeness is presented as an anotherregularization term [15].

IV Literature Review

In this paper [16] present that restoration of motion blurred images are a hot shot in the field of image processing. The degradation model of motion blurred images is clarified, and the estimation of the PSF parameter, as well as its algorithm is presented. Frequency spectrum and Radon transition are used for the length and angle calculation, then Wiener filtering and Inverse filtering are used for recovering the noisy and motion blurred images. The matrix conjugate gradient is used to process the images which are processed by Wiener filtering and Inverse filtering. These simulation results indicate that matrix conjugate gradient is effective and promising for their recovery.

Motion blurred image degradation model formula is as follows:

$$G(x, y) = f(x, y) * h(x, y) + n(x, y) \quad (4)$$

Make the Fourier transform for it and get the formula:

$$G(u, v) = F(u, v)H(u, v) + N(u, v) \quad (5)$$

From above formula, we can get inverse filtering formula:

$$\hat{F}(u, v) = \frac{G(u, v) + N(u, v)}{H(u, v)} \quad (6)$$

In the formula: $\hat{F}(u, v)$ is the restored image spectrum. Make the inverse Fourier transform for $\hat{F}(u, v)$, we can get the restoring image $F(x, y)$. $H(u, v)$ represents frequency-domain description of degradation and $G(u, v)$ is the degrade frequency.

In this paper [17] a powerful statistical image modeling technique, sparse representation has been successfully used in various image restoration applications. The success of sparse representation owes to the development of l_1 -norm optimization techniques, and the fact that natural images are intrinsically sparse in some domain. The image restoration quality largely depends on whether the employed sparse domain can represent well the underlying image. Considering that the contents can vary significantly across different images or different patches in a single image, we propose to learn various sets of bases from a pre-collected dataset of example image patches, and then for a given patch to be processed, one set of bases are adaptively selected to characterize the local sparse domain. We further introduce two adaptive regularization terms into the sparse representation framework. First, a set of autoregressive (AR) models is learned from the dataset of example image patches. The best-fitted AR models to a given patch are adaptively selected to regularize the image local structures. Second, the image of non-local self-similarity is introduced as another regularization term. In addition, the sparsity regularization parameter is adaptively estimated for better image restoration performance. Extensive experiments on image deblurring and super-resolution validate that by using adap-

tive sparse domain selection and adaptive regularization, the proposed method achieves much better results than many state-of-the-art algorithms in terms of both PSNR and visual perception.

The vector of AR model parameters, denoted by a_k , of the k^{th} sub-dataset S_k , can be easily computed by solving the following least square problem:

$$a_k = \operatorname{argmin} \sum_{s_i \in S_k} (s_i - a^T q_i)^2, \quad (7)$$

Where s_i is the central pixel of image patch s_i and q_i is the vector that consists of the neighboring pixels of s_i within the support of the AR model. By applying the AR model training process to each sub-dataset, we can obtain a set of AR models $\{a_1, a_2, \dots, a_k\}$ that will be used for adaptive regularization. And s_k is the matrix of dimension of image. a^T is a transpose of the matrix.

This paper [18] presents Images degraded by motion blur can be restored when several blurred images are given, and the direction of motion blur in each image is different. Given two motion blurred images, best restoration is obtained when the directions of motion blur in the two images are orthogonal. Motion blur at different directions is common, for example, in the case of small hand-held digital cameras due to fast hand trembling and the light weight of the camera. A simple and yet effective method for recovering this information is presented. This method does not require the knowledge of the blur kernel, and does not assume any relation between the image displacement and the motion blur. More investigations are needed regarding a possible use of more than two images. For example, it is logical to assume that three images of the same scene, blurred in directions that are in 60° one from another, can be better enhanced together.

The two input images g_1 and g_2 are observed by two systems modeled as:

$$g_1 = m_1 * f \quad (8)$$

$$g_2 = m_2 * f \quad (9)$$

Where g_1 and g_2 are images degraded by horizontal and vertical motion blur respectively and m_1 and m_2 are motion blur kernel and f is the original image.

This paper [19] present various blur detection methods along with proposed method. Digital photos are massively produced while digital cameras are becoming popular; however, not every photo has good quality. Blur is one of the conventional image quality degradation which is caused by various factors like limited contrast; inappropriate exposure time and improper device handling indeed, blurry images make up a significant percentage of anyone's picture collections. Consequently, an efficient tool to detect blurry images and label or separate them for automatic deletion in order to preserve storage capacity and the quality of image collections is needed. There are various methods to detect the blur from

the blurry images some of which requires transforms like DCT or Wavelet and some doesn't require transform.

In order to estimate images, first apply only one part of the SIFT algorithm, that is, detecting local key points of the images objects. Then, generate additional images from the given one through the linear diffusion process. And finally, analyze the variance values calculated for the local key points of the original and its filtered images generated in the scale space.

$$W = \sum_{i=1}^{n-1} \frac{|(\text{var}(i) - \text{var}(i+1))|}{\max |(\text{var}(i) - \text{var}(i+1))|} \quad i \in [1, n - 1] . \quad (10)$$

The variance value is calculated using the formula given above which is helpful in the description of input image, the key point of the image, for the curvature of the given plot.

In this paper [20] deals with the various image restoration and denoising techniques. We are recovering the original image from the degraded version by inverse filtering and wiener filtering techniques. Furthermore, we are denoising it by

average filtering and median filtering to remove the noise and maintaining the originality of the image as much as possible. Thus from this paper we could make comparisons regarding the techniques of restoration and denoising discussed above. This implies that an image could be degraded by many factors such as defocusing, malfunctioning of the camera, climatic disturbances, disturbances caused due to motion and many other factors and thus the true image could be regained by the above mentioned techniques.

This paper [21] demonstrate a superior performance of the variational Bayesian estimator and discuss suitability of automatic relevance determination distributions as image priors. Restoration of real photos blurred by out-of-focus and motion blur, and comparison with a state-of-the-art method is provided. In the discrete domain, convolution is equivalent to vector-matrix multiplication and its rewrite the model for every image pixel i as

$$gi = Hiu + ni = Uih + ni \quad (11)$$

where H and U are convolution matrices performing convolution with the blur and latent image, respectively, and h and u are now column vectors containing lexicographically ordered elements of the 2D random vector fields. Subscript i denotes the i -th element (row) of a vector (matrix) and n stand for noise. The goal was to provide better insight to image priors in blind deconvolution and understanding of superior performance of the family of ARD priors. We also show that the VB update procedure for the ARD prior is equivalent to the half-quadratic algorithm with the additional covariance term, which further emphasizes edges.

This paper presents [22] the motion blur is usually generated when people captures a picture in the daily life. This kind of blur is often non-linear motion and may cause the blurred contents seriously in this image. Hence, how to convert the blurred image into a clear image becomes a very important scheme. In this paper, the primary aim is to propose an efficient blurred image restoration method based on fast blur kernel estimation, which can quickly find the best kernel from a set of kernels. Many state-of-the-art methods for motion blur estimation usually use the recursive method to estimate motion blur kernel. However, it is quite time-consuming. In order to reduce the computational time, we use iterative phase retrieval algorithm and normalized sparsity measure to quickly obtain the best kernel and to achieve the deblurring. Experimental results verify that this approach can effectively speed up the execution time and obtain the best motion blur kernel and maintain the high quality of image deblurring.

$$N_{avg,k}(x,y) = \frac{1}{n_i} \sum_{i=1}^{n_i} N_{i,k}(x,y) \quad 0 \leq x,y \leq \text{kernel size} \quad (12)$$

Where k and n_i denote the number of clusters and the number of kernels belonging to the i th cluster, respectively. avg,k,N is the average kernel of the k th cluster. Second step is to refine avg,k,N , we calculate the probability of non-zero values in the coordinates for each blur kernel belonging to the same cluster.

Image restoration is a key research field in the digital image processing technology. Due to camera defocus, the relative movement and noise, the image quality declines. Because of the limitations of Wiener filtering method, the paper proposes a kind of improved Wiener filtering restoration method based on the partition. The method can not only enhance the edges and eliminate the noise, but also eliminate pseudo morph well. The PSNR of improved restoration method is higher than the original method.

$$F(u,v) = \frac{|H(u,v)|^2}{|H(u,v)|^2 + \frac{S_n(u,v)}{S_f(u,v)}} \cdot \frac{G(u,v)}{H(u,v)} \quad (13)$$

$H(u,v)$ is the degraded image data, $G(u,v)$ is the point spread function PSF, $S_f(u,v)$ is the original image power spectrum, $S_n(u,v)$ is the noise power spectrum. [23]

V Comparison Table

In the table below shows a comparison on Image blur or noise type and method for which PSNR value is evaluate.

Table 1: Comparative Study

Method name	Blur or Noise Type	Image Name	Psnr Value
Kurtosis minimization[1]	Atmospheric turbulence	Moon image	58.54
Anisotropic LPA-ICI deconvolution[2]	Motion blur	Balloons image	52.46
Neural network method[5]	Gaussian out-of-focus blur	Lena image	60.52
Conjugate gradient method[16]	Motion blur	Lena image	58.38
Adaptive sparse domain selection [17]	Gaussian blur	Cameraman	56.28
Low-pass Gaussian filter[19]	Gaussian blur	Lena image	61.49
Automatic relevance determination[21]	Motion blur	Lena image	58.32
Fast blur – kernel estimation [22]	Motion blur	Lena image	61.39

Conclusion

In this paper, we studied about the various techniques of image restoration at various phases. Image restoration applying image deblurring method. Few algorithm belongs to Gaussian blur which is the main and also few belong to the out of focus. Each method when seen independently it is good in its own criteria. Various filters and techniques are used in image restoration to restore the corrupted image to its original form. The restoration results in the improved quality of the image.

References

[1] Dalong Li and Steven Simske, “Atmospheric Turbulence Degraded Image by Kurtosis Minimization”, *IEEE Geoscience and Remote Sensing Letters*, Dec. 2008.
 [2] Giacomo Boracchi and Alessandro Foi, “Modeling the performance of Image Restoration from Motion Blur”,

IEEE Transactions on, vol.21, no.9, doi:10.1109/TIP.2012.2199324, pp. 3952 – 3966.
 [3] C. S. Vijay, P. Chandramouli, and A. N. Rajagopalan, “HDR imaging under non-uniform blurring”, in *Proc. ECCV Workshop Color Photometry Comput. Vis*, pp. 451–460 2012.
 [4] Dejee Singh, R. K. Sahu, “Analysis of Quality Measurement Parameters of Deblurred Images”, *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering* Vol. 3, Issue 10, pp: 12535-12541 October 2014.
 [5] Dejee Singh, Mr R. K. Sahu “A Survey on Various Image Deblurring Techniques”, *International Journal of Advanced Research in Computer and Communication Engineering* Vol. 2, Issue 12, December 2013.
 [6] J. Cai, H. Ji, C. Liu, and Z. Shen, “Framelet based blind motion deblurring from a single image”, *IEEE Trans. Image Process.*, vol. 21, no. 2, pp. 562–572 Feb 2012.,
 [7] Aizenberg I., Bregin T., Butakoff C., Karnaukhov V., Merzlyakov N. and Milukova O., “Type of Blur and Blur Parameters Identification Using Neural Network and Its Application to Image Restoration”, In: *J.R. Dorronsoro (ed.) Lecture Notes in Computer Science*, Vol. 2415, Springer-Verlag, Berlin, Heidelberg, New York, pp. 1231-1236 2002.
 [8] Y. Tai, P. Tan, and M. S. Brown, “Richardson-Lucy deblurring for scenes under projective motion path”, *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 8, pp. 1603–1618 Aug 2011.
 [9] Aizenberg I., Bregin T., Butakoff C., Karnaukhov V., Merzlyakov N. and Milukova O., “Type of Blur and Blur Parameters Identification Using Neural Network and Its Application to Image Restoration”, In: *J.R. Dorronsoro (ed.) Lecture Notes in Computer Science*, Vol. 2415, Springer-Verlag, Berlin, Heidelberg, New York, 1231-1236 2002,
 [10] D. Kundur and D. Hatzinakos, “A novel blind deconvolution scheme for image restoration using recursive filtering”, *IEEE Trans. Signal Process.*, vol. 46, no. 2, pp. 375-390 Feb. 1998.
 [11] A. Levin, Y. Weiss, F. Durand, and W. Freeman, “Understanding blind deconvolution algorithms”, *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2354–2367 Nov 2011.,
 [12] L. Yuan, J. Sun, L. Quan, and H. Shum, “Image deblurring with blurred/noisy image pairs”, *ACM Trans. Graph.*, vol. 26, no. 3, pp. 1–11 2007.
 [13] A. Gupta, N. Joshi, C. Lawrence Zitnick, M. Cohen, and B. Curless, “Single image deblurring using motion density functions”, in *Proc ECCV*, pp. 171–184 2010.
 [14] S. Cho, J. Wang, and S. Lee, “Handling outliers in non-blind image deconvolution”, in *Proc. ICCV*, pp. 495–502 2011,
 [15] W. Dong, L. Zhang, R. Lukac, G. Shi, “Image Deblurring and superresolution by adaptive sparse domain selection and adaptive regularization”, *IEEE*

Trans. On Image Processing, vol. 20, no. 7, pp. 1838-1857 July 2011.

- [16] ShuaiJia, Jie Wen “Motion Blurred Image Restoration” *,IEEE, 6th International Congress on Image and Signal Processing (CISP 2013)* 978-1-4799-2764-7/13/\$31.00 ©2013.
- [17] WeishengDong, Lei Zhang ,Guangming Shia, and XiaolinWuc, “ImageDeblurring and Super-resolution by Adaptive SparseDomain Selection and Adaptive Regularization”, This work is supported by the Hong Kong RGC General Research Fund (PolyU 5375/09E).
- [18] Alex Rav-AchaShmuelPeleg, “Restoration of Multiple Images with Motion Blur in Different Directions”, *IEEE, Proceedings of the Fifth IEEE Workshop on Applications of Computer Vision (WACV’00)* 0-7695-0813-8/00 2000. .
- [19] RupaliYashwantLande, Rakesh Sharma, “Blur Detection Methods for Digital Images-A Survey”, *International Journal of Computer Applications Technology and Research* Volume 2– Issue 4, 495 - 498, ISSN: 2319–8656 2013.
- [20] ShabnamSultana M.Varun Kumar N.Asha, “Comparison of Image Restoration and Denoising Techniques”, *Volume 3, Issue 11*, November 2013.
- [21] FilipSroubek, Vaclav Smdl, Jan Kotera, “UNDERSTANDING IMAGE PRIORS IN BLIND DECONVOLUTION”, *IEEE*, 978-1-4799-5751-4/14/\$31.00©2014.
- [22] Hui-Yu Huang Wei-Chang Tsai, “Blurred Image Restoration using Fast Blur-Kernel Estimation”, *Tenth International Conference on Intelligent Information Hiding and Multimedia Signal Processing 2014*.
- [23] Zhiqiang Wei¹, Caiyan Duan², Shuming Jiang¹, Yuanyuan Zhang¹, Jianfeng Zhang¹, Lianpeng Zhu¹, “The Improved Winner Filter Image Restoration Based on Partition”, *IEEE*, 978-0-7695-5079-4/13 2013.
- [24] **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 denoising.

Biographies



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.



Prof. **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