International Journal for Research in Engineering Application & Management (IJREAM)
Special Issue – ICRTET-2018 ISSN : 2454-9150

Low Rank Matrix Approximationbased On Wavelet Analysis To Deblur Image

[1]Shweta Gunjal, [2]Sushant Pawar
[1]PG Student, [2]Assisant Professor
[1,2]Department of Electronics and Telecommunication Engineering,
[1,2]Sandip Institute of Technology and Research Centre, Nashik,
[1,2]Savitribai Phule Pune University, Pune, India.

Abstract
In modern years, deblurring of image become necessity of photography applications. Basically blur is an unwanted change in photograph which lowers the quality of image significantly. It is challenging to avoid blur in the image, accurate reconstruction of image become difficult task. To address these issues the improvement of powerful image deblurring algorithm is critically required. In Image deblurring, most of existing methodologies relies on blind & non-blind deconvolution which has major limitation on reconstruction accuracy and quality of image. In the proposed work, a method created on low rank prior technique has been used to obtain deblur image from blurry and noisy observations. The blurred images are recreated using a discrete wavelet transform (DWT) technique. The low rank prior uses the low rank matrix approximation (LRMA) with weighted nuclear norm minimization (WNNM) technique for obtaining redundant matrix. The performance of the proposed methodology has been recorded in terms of measuring parameters such as PSNR, SSIM and KSIM which proven the robustness of proposed algorithm for deblurring of image.

***Index Terms* - Image deblurring, Discrete wavelet transform (DWT), Low Rank Matrix Approximation (LRMA), Weighted Nuclear Norm Minimization (WNNM), PSNR, Structural Similarity Index (SSIM) and Kernel Structural Similarity Index (KSIM).**

INTRODUCTION

In human life, photography is becomes trend of capturing valuable moments. In past decades, it is challenging task to recreate these precious moments without blur because of inadequate technology. In current eras capturing pictures without blur becomes possible due to advanced technology. Some common problems arises in photographs due to Object Movement, Out of focus Lenses, Camera shake & Vibration. Because of these problems photograph become blur. Camera shake very noticeable, when high-resolution of image is captured, these are long-lasting problem for photographers. Recovering deblurred image alone from blurred photograph are most popular research problem in image processing. Basically deblurring of picture or image is an old-fashioned inverse method used to get original image from the corresponding degraded image. Deblurring of image is a procedure used to minimize the blur quantity in a degraded image and create the deblur image. To obtain the deblur images, various image deconvolution method can be applied [1]. Out of these, blind image deconvolution & non-blind deconvolution [1, 2] are most popular method. In over past decades, several approaches are implemented to solve the non-blind deblurring and the blind deblurring deconvolution [3].

In non-blind deblurring, blur kernel is known and deblur image are brought from the blurry image. For non-blind deconvolution, the Richardson-Lucy method [3, 16] and Wiener filter [5, 16] methods are used. These methods required more time for execution of number of iteration therefore this creates the ringing artifacts. In contrast to the blind deconvolution, the blur kernel is undefined. Hence this method uses the approximation technique to get the deblur image from the degraded input image. For blind image deblurring, several approaches have been presented in literature. Fergus et.al [4], uses the Gaussian noise in image gradient which show that output image contain some artifacts. Wenqi et.al [10], utilized robust norms to detect outliers by an iterative approach. However, their fundamental disadvantage is that they utilize an image prior. The image prior are not capable of eliminating the existence of artifacts in the recreated images. For said problems, current research towards development of new prototypes and improving the efficiency of optimization methods.

To deal with these problems, Modified Low Rank Matrix Approximation (LRMA) [18] is one of the promising approach to remove artifacts. To accomplish this goal the system utilize weighted nuclear norm minimization to increase the efficiency [7]. With the help of ranking properties, it eliminates unwanted details and small edges from the input degraded image. The LRMA utilized for recover the basic low rank matrix from its basic degraded observation. However, proposed method to reduce the blur quantity from Input blur image via the LRMA. This operation, LRMA uses the image gradient & image intensity by keeping dominant edges of input image. The experimental results shows the superiority of the restored image.

The rest of the paper is organized into five sections. Section II describes the overview of literature survey. Section III demonstrates the proposed methodology. Section IV gives the details about experimental results and performance analysis while section V gives the conclusion of proposed methodology.

LITERATURE SURVEY

The equivalent work of deblurring of image are explained this section. There are several kinds of procedures for deblurring has been invented by authors. Some of the relevant to this proposed work are explained.

Outcome of Literature Survey

- The blur image is formed when pixels of image is scattered onto adjacent pixels due to blur. The blur is caused due to camera shake, out of focus lens, object movement. Because of blur, important information of image is get vanished or get hide somewhere in image. As per type of blur, noise like motion, average, Gaussian are generated in blurred image[1]-[4].
- The process to obtain or recover image in its original form known as deblurring of image.The principle of deblurring of image is to get the original image from blurry input image. Because of several pairs of latent image pixels and blur kernel gives similar result between blurry images & deblur image this will create the complexity.
- It becomes difficult to model more complex structures of images only using adjacent image pixels.Hence extra information like the statistics of ordinary images and blur kernels, gradient distributions normalized sparsity prior[6], sparsity constraints and L0-regularized gradient or arrangement of both the intensity and incline prior is required[4].
- To eliminate such type of problem, several approaches are developed for deblurring image such as blur kernel approximation by normalized color-line prior, matrix having low rank [7], deblurring using text-specific properties, L0gradient minimization and L0-regularized intensity.
- The proposed method uses low rank matrix approximation to deblur image. The important purpose of matrix calculation are used to acquire the low ranking matrix from corrupted observation. This matrix formation done by dissimilar patches in a normal image having low rank used for high performance image restoration jobs.

TABLE I.Summary of Literature Survey

Sr.no	Author Name	Title	Observations
1	Fagun et.al[1]	A Survey on different Image Deblurring Techniques	The overview of category of blur along with various deblurring methods. Richardson Lucy gives better result over other methods whereas Laplacian gives the poor result by comparing other techniques.
2	Praveen Ravichandran[2]	Literature Survey on Image Deblurring Techniques	The high quality of reconstructed image are obtained for robust flash deblurring & blurry noisy pair of image restoration method whereas blind image restoration for image statistics & fast image restoration gives the poor result for reconstructed image.
3	Sudha Yadav[3]	Evaluation of Image Deblurring Techniques	By comparing method of non-blind image deblurring. Weiner filter gives the poor result over Lucy algorithm for PSNR parameter. The blind image deblurring gives better result as compared with non-blind image deblurring technique with the help of motion segmentation &estimation method.
4	Rob Fergus et.al[4]	Removing Camera Shake from a Single Photograph	The image gradients for Gaussian noise & Bayesian approach of standard deconvolution techniques are used. This is not said as good model when image sensor noise occurred also this method required some manual involvement.
5	Qi Shan et.al[5]	High-quality Motion Deblurring from a Single Image	Uses the MAP method along with iterative optimization for blind & non-blind blur kernel refinement. This system is fails when blur image is not shift-invariant.
6	Anat Levin et.al[6]	Understanding and evaluating blind deconvolution algorithms	This method uses the MAP approximation method with Gaussian & sparse prior of 1D & 2D images. This method is useful for blind image deblurring technique. The method is fails for natural image.
7	Shuhang Gu et.al[7]	Weighted Nuclear Norm Minimization with Application to Image	This methods give denoising of image with matrix approximation for low rank with its classification. The WNNM method provides the less artifacts also improves the PSNR.

		Denoising	
8	Jinsha Pan et.al[8]	Blind Image Deblurring Using Dark Channel Prior	This is effective technique of blind image deblurring. The algorithm based on lookup table& half quadratic splitting approach. This technique furthermore enhanced for image deblurring non-uniform blur.
9	Libin Sun et.al[9]	Edge-based Blur Kernel Estimation Using Patch Priors	The kernel approximation is done through patch priors by modeling image edge primitives. In future the system is enhanced for handling more severe noise & outliner of other image to make system more robust.
10	Wenqi Ren et.al[10]	Image Deblurring via Enhanced Low Rank Prior	The unique advanced prior of rank matrix calculation is used for blind image deblurring. For this, WNNM approach to maximize the utility of low ranking properties. When input image contain natural scene the system fails to recreate clear image.

PROPOSED METHODOLOGY

In proposed work, a novel method based on low rank prior technique has been used to obtain deblur image from blurry and noisy observations. The blurred images are restored using a discrete wavelet transform (DWT) technique**.** The proposed method for using low rank prior with the help of WNNM as well as discrete wavelet transform for image deblurring purpose. The LRMA is used to obtain the basic low rank structure matrix x from degraded observation y. LRMA are used with respect to the Frobenius norm in which it minimizes the sum square differences of the target matrix with the help of Singular Value Decomposition (SVD). The nuclear norm minimization (NNM) used to find rank r from data matrix y which is given by [14].

$$\acute{\hat{X}} = argmin_x \frac{1}{2}||Y - X||_F^2 + \lambda||X||*(3.1)$$

Where, $||X||* = \Sigma i\ \sigma i(X)$ is the i-th singular value of matrix & λ is positive constant

In matrix approximation, nuclear norm minimization (NNM) treats the dissimilar rank components in the similar manner & compressed the rank components due to this capability and flexibility of matrix are tends to limited. To avoid his problem WNNM method is used. The WNNM is used to regularize the X & Eq.1 is rewritten as

$$\acute{\hat{X}} = argmin_x \frac{1}{2}||Y - X||_F^2 + ||X||w,*(3.2)$$

Where, $||X||w,*$ =sum of singular values and corresponding non-negative weights

The proposed structure having a novel strategy for utilizing prior of low rank with the help of WNNM is explained below with the help of block diagram as shown in figure 3.1.

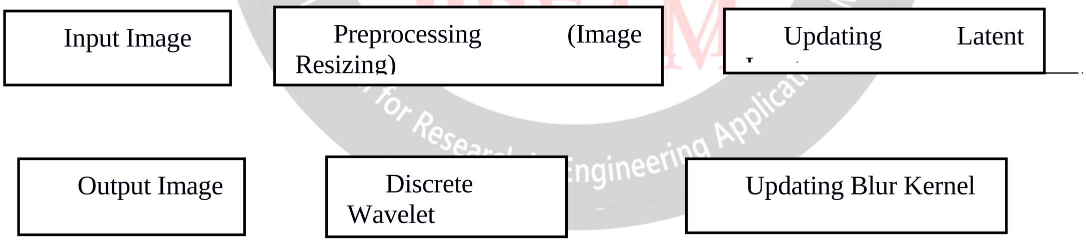


Fig.1 Block diagram of Proposed System

- Input Image: The blurred image is given as an input. The blur image consist of original image convolved with blur kernel addition with noise. The blurs can be of type Gaussian blur, camera motion blur, average blur etc. The proposed method uses camera motion blur. The input image is of the following form :

$$B = L \otimes K + N(3.3)$$

  Where, B= Blur image, L= Latent image or original image, N= Noise
- Preprocessing: After the input is given, the image undergo preprocessing in which the blur image will get resized into the image with the specified number of columns and rows. Also calculates the number of columns & rows sequence in order to maintain the image aspect ratio. Here the blur image gets resized into 512x512 image size.
- Kernel Estimation: In this section the estimation of kernel consists of two parts i.e. updating latent image & updating blur kernel. For this analysis, variables kernel size k = 5, sparsity gradient λ=0.05, the noise variance σ =0.08, the positive parameter variables like η = 1,βmax = 2 and τmax = 8 are used to solve Eq.3.5 For formation of kernel estimation the Eq.3.1 becomes the mixture of term of fidelity data, kernel prior & image prior [10]. For solving Eq.3.5

the deblurring by enhanced prior having low rank algorithm [10] with help of WNNM method [7] For updating latent image, the blur kernel K is fixed & evaluation of latent image l is carried out hence Eq.3.4 becomes

$$\{\hat{l}, \hat{k}\} = argmin_{l,k} ||\, l \otimes k - b \,||_1 + \gamma ||\, k \,||_2^2 + \lambda \sum_i ||li||w,* + \sigma \sum_i ||\nabla li||w,* \ (3.4)$$

For solving Eq.3.5 the deblurring by enhanced prior having low rank algorithm [10] with help of WNNM method [7] For updating latent image, the blur kernel K is fixed & evaluation of latent image l is carried out hence Eq.3.4 becomes

$$\hat{l} = argmin_{l,k} ||\, l \otimes k - b \,||_1 + \lambda \sum_i ||li||w,* + \sigma \sum_i ||\nabla li||w,* \ (3.5)$$

For solving Eq.3.5 the deblurring by enhanced prior having low rank algorithm [10] with help of WNNM method [7] are used. For updating blur kernel the, the latent image L is fixed & evaluation of the blur kernels are done Eq.3.5 becomes

$$\hat{k} = argmin_k |k \otimes \nabla l - b| \vee \ {}_2^2 + \gamma |k| \vee \ {}_2^2 (3.6)$$

For efficiency and stability, the fast deblurring method is to evaluate the blur kernel depend on the gradient images and l2-norm of data fidelity term [10], Eq.3.6 becomesBy using deblurring algorithm, the estimation of latent image & blur image are solved.

$$\hat{k} = argmin_k |k \otimes \nabla l - \nabla b| \vee \ {}_2^2 + \gamma |k| \vee \ {}_2^2 (3.7)$$

- Discrete Wavelet Transform: In this technique, the resultant image undergoes into Discrete Wavelet Transformation. The image are get decomposed into two level decomposition. For decomposition of level the symlet & coiflet wavelet are used.Becuase the symlet coefficients the gradually changing intensity value & increase the smoothness of image. Also it gives the perfect reconstruction of image after decomposition. The coiflet are used because it calculated the difference & average of adjacent pixels at time of reconstruction of image by using thresholding technique. After this inverse DWTused to reconstruct the image. By using this technique the deblur image is get produced. The resultant output of the system is the deblurred original image.

Following figure 3.2 shows the flowchart for proposed method. First initialize the input image which blur image then image get resized into 512x512 image format. After that kernel is get initialized. The kernel estimation are executed into two part i.e.fisrtly the latent image are updated keeping kernel constant as per Eq.3.4-3.5. In this procedure the WNNM technique is used with kernel prior & image prior by using auxiliary variables [10]. After this by keeping latent image constant, the kernel estimation are performed for updating kernel with the help of Eq.3.4,3.6,3.7 by utilizing algorithm for deblurring mentioned in Wenqi Ren et.al[10]. For both kernel estimation iteration are carried out till restored image is become satisfactory deblur image. The maximum iteration in proposed system are four. Once iteration are done that recreated image are undergoes to DWT Analysis to remove the maximum ringing artifacts & outliers. After this output image are obtained by measuring performance parameter mentioned in section 4.

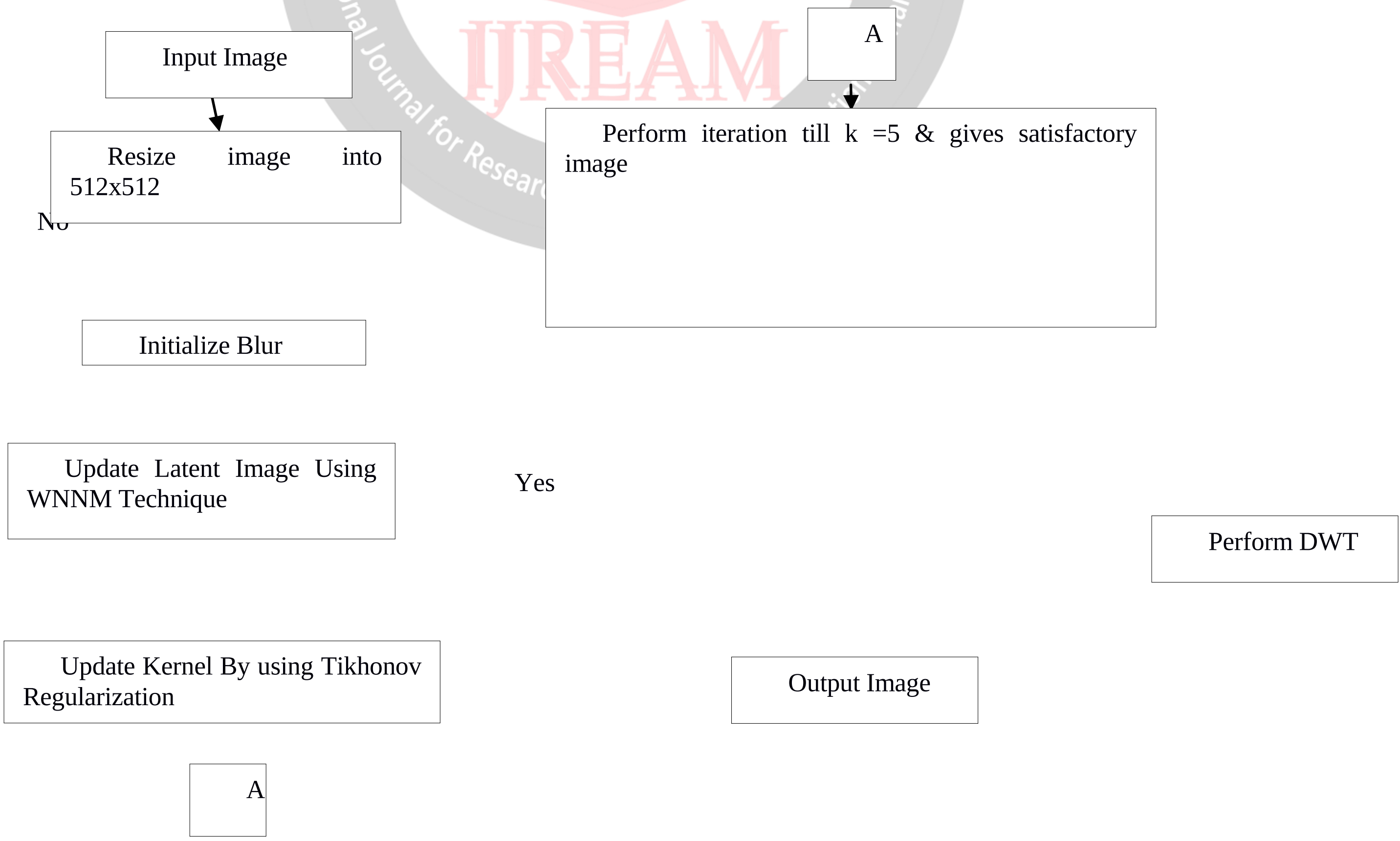


Fig2. Flowchart for Proposed Method

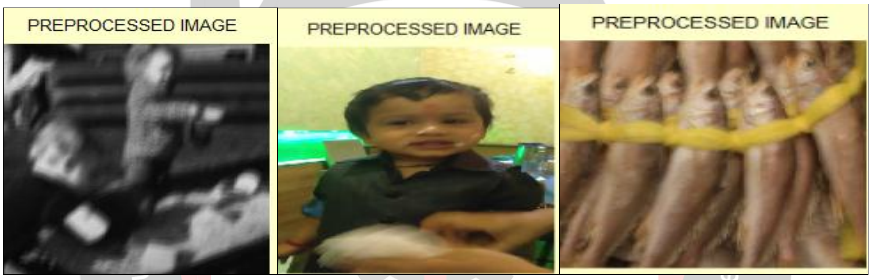
EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

Hardware Software Requirement for experimental results are follows: User Interface will be developed using Mat lab. The proposed system is implemented using processor I i.e. Intel P-3/P-5 based system with Processing Speed: 250 MHz to 833 MHz Software Interface required the Operating System: XP, Window 7 : Mat lab R2014a. In the following fig 4.1, in which fig (a) shows input image for Levin Dataset, fig (b) shows input image the result for real time dataset & fig(c) shows input image for the raw dataset. In all dataset, blur image caused by the camera shake used.

(a) (b) (c)

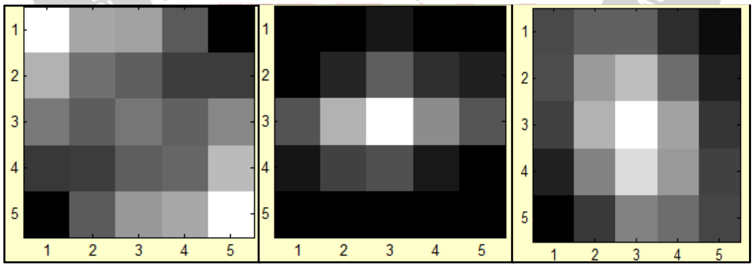
Fig3. Original Images of three dataset

In the following fig 4.2, fig (a) shows the result of pre-processed image for Levin Dataset, fig (b) shows the result of pre-processed image for real time dataset & fig (c) result of pre-processed image for the raw dataset. In all dataset the blur image is get resized into 512x512 format.



(a) (b) (c)

Fig4. Pre-processed Image of three dataset



(a) (b) (c)

Fig5.Estimation of kernel of Image of three dataset

In the above figure 4.3, figure (a) shows the result of kernel estimation for Levin Dataset, figure (b) shows the result for real time dataset & figure(c) result for the raw dataset. These results are obtained using WNNM by solving Eq.3,5 for updating latent image & kernel prior.

(a) (b) (c)

Fig6. Latent Image after kernel estimation of three dataset

In the above fig 4.4, fig (a) shows the deblur image for Levin Dataset, fig (b) shows the deblur result for real time dataset & fig(c) deblur image for the raw dataset. Latent Image after kernel estimation of three dataset.

(a) (b) (c)

Fig7. Discrete Wavelet Transform Image of three dataset

In the above fig 4.5, fig (a) shows the deblur image for Levin Dataset, fig (b) shows the deblur result for real time dataset & fig(c) deblur image for the raw dataset. These results are obtained by DWT method.

Performance Parameter

The Peak Signal to Noise Ratio (PSNR) represent the significance of the noisy image to the original image. Whereas Structural Similarity Index (SSIM) shows the Structural Similarity based on luminance, contrast & structural pixels of images.

$$PSNR = 10.log_{10}\left(\frac{Nx255x255}{\sum_i (x_i - \acute{x}_i)^2}\right) (4.1)$$

$$SSIM = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \cdot \frac{2\sigma_{xy} + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} (4.2)$$

TABLE II. Experimental Result for Average Matrices of Performance Parameter for Five Set of Image

Sr no.	Dataset(Type Of blur)	PSNR1	PSNR2	SSIM1	SSIM2	KSIM1	KSIM2
1	Levin Dataset (Object Movement)	26.080	39.4456	0.5009	0.9832	0.4777	0.9898
2	Real Time Dataset (Camera motion)	27.5464	36.7234	0.7139	0.9880	0.71870	0.9977
3	Raw Image Dataset (Out of focus)	29.2229	35.3259	0.9669	0.9545	0.96692	0.9782

The above results shows performance parameter like PSNR and SSIM KSIM. The each dataset having 5 images & the result are carried out average for each dataset. The above result table show the comparison between c. In table, PSNR1, SSSIM1, KSIM1 are the result for latent image after kernel estimation & PSNR2, SSSIM2, KSIM2 for after dwt implementation.

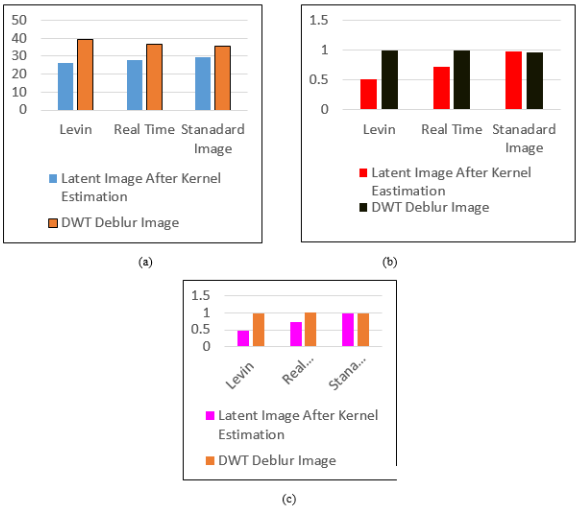


Fig8. Graph for PSNR and SSIM, KSIM for three dataset compared with latent image after kernel estimation & after dwt implementation.

From above graph shows that real time dataset gives higher PSNR value over remaining two dataset. The SSIM & KSIM of three dataset are having almost equal values.

CONCLUSION

In the proposed system, the implementation of DWT with improved low rank matrix approximation. For finding low rank matrix approximation, the WNNM method is used The DWT removes the fine blur texture which remaining while kernel estimation. By comparing these three dataset real time image gives higher PSNR value. This technique don't require special hardware circuitry. The future work would be to develop stronger statistical model for kernel estimation which would result into improved time complexity results.

REFERENCES

[1] Fagun Vankawala Amit Ganatra, Amit Patel, 2015.A Survey on different Image Deblurring Techniques.International Journal of Computer Applications (0975 – 8887) Volume 116 – No.

[2] Praveen Ravichandran,2016.Literature Survey on Image Deblurring Techniques.International Journal of Science and Research (IJSR),Volume 5 Issue 3.

[3] Kiran Kale, Sushant Pawar and Pravin Dhulekar, "Moving Object Tracking Using Optical Flow and Motion Vector Estimation" Published in IEEE 4th International conference on reliability, Infocom technologies and optimization (ICRITO 2015), 2-4 Sept 2015

[4] Sudha Yadav,Charu jain ,Aarti chugh,2016.Evaluation of Image Deblurring Techniques. International Journal of Computer Applications (0975 – 8887) Volume 139 – No.12

[5] Rob Fergus,Barun Singh,Aaron Hertzmann,Sam T. Roweis, William T. Freeman,2006.Removing Camera Shake from a Single Photograph.Association for Computing Machinery, ACM 0730-0301/06/0700-0787.

[6] Ganesh Kale, Sanjay Gandhe, Pravin Dhulekar, Sushant Pawar, "Designing a Quadruped with Stair Parameter Analyzing and Climbing Capability", International Conference on Computing Communication Control and Automation (ICCUBEA), 2015, Pages 546-550.

[7] Qi Shan ,Jiaya Jia,Aseem Agarwala2008.High-quality Motion Deblurring from a Single Image.ACM Transactions on Graphics, Vol. 27, No. 3, Article 73.

[8] Anat Levin, Yair Weiss, Fredo Durand, William T. Freeman,2009.Understanding and evaluating blind deconvolution algorithms.Computer Vision and Pattern Recognition IEEE Conference.

[9] Shuhang Gu, Lei Zhang, Wangmeng Zuo, Xiangchu Feng.2014.Weighted Nuclear Norm Minimization with Application to Image Denoising.IEEE Conference on Computer Vision and Pattern Recognition.

[10] Vicent Talens, Valero Laparra, Jesus Malo & Gustavo Camp-Valls.2013.Kernel Structural Similarity on Hyper spectral Images. IEEE International conference on Geoscience & Remote Sensing Symposium(IGARSS).

[11] Libin Sun_,Sunghyun Cho,Jue Wang,James Hays.2013.Edge-based Blur Kernel Estimation Using Patch Prior. IEEE International Conference on Computational Photography.

