IMAGE DEBLURRING BY ADAPTIVE SPARSE DOMAIN SELECTION

Mr. A. Hazarathaiah, Professor, Department of E.C.E, Narayana Engineering College, Gudur, SPSR Nellore, AP,India
N. Priyanka, G. Durga Prasad, A. Lokesh, N. Akhil, Department of E.C.E, Narayana Engineering College, Gudur, SPSR Nellore, AP,India :: priyankanoora2000@gmail.com

Abstract *Image recovery entails extraction of excessive nice photograph out of a degraded model of the equal photograph. The area entails the similarity degree of the enter degraded photograph with a hard and fast of photograph patches. These photograph patches may be notion of because the atoms of particle constituting a entire bodily object. This area is called sparse representation. In this paper, the sparse area scheme can be used to carry out photograph deblurring Two forms of blurs can be considered, Uniform and Gaussian. PSNR and SSIM values can be calculated to examine the overall performance of the proposed scheme with that of current methods.*

Keywords: - Patches, spares Representation, Uniform blur, Gaussian Blur, PSNR and SSIM

I. INTRODUCTION

Acquired images are commonly affected by blur. This kind of degradation happens in various physical processes and is usually reasonably modeled by a mathematical convolution. An example of this type of degradation is the well-known case of a blurred photo. Blurring degradations lead us to the inverse problem of Blind Image Deconvolution (BID) or blind deblurring.

Shift-variant image deblurring is an extension of the shift-invariant deblurring problem, in which the characteristics of the blurring degradation change across the observed image. Shift variant deblurring has applications in several engineering problems.Two typical degradations of this kind occur when: (1) the closer object has motion blur and the background scene is static and in focus (or vice-versa); (2) the closer object and the farther background are both stationary, but have different focus blurs. We are calculating the values from the below Equation 1,2,3,4.

Mean Squared Error (MSE):

$$\frac{1}{w \cdot h}\sum_i \sum_j (x_{i,j} - \hat{x}_{i,j})^2 \qquad (1)$$

Peak Signal to Noise Ratio (PSNR), measured in dB:

$$20\log_{10}\frac{2^B - 1}{\sqrt{\text{MSE}}} \ \text{(dB)} \qquad (2)$$

Maximum Absolute Error (MAE)

$$\max_{i,j}\left|x_{i,j} - \hat{x}_{i,j}\right| \qquad (3)$$

Structural Similarity

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (4)$$

II. LITERATURE SURVEY

The blurring is characterized by the point spread function (PSF) and blurred image is the result of convolution of original image with PSF. Then the captured image is formed after some noise addition. These steps are represented by the following equation.

$$f = h \otimes g + n \qquad (1)$$

where f is the blurred image, h is PSF, g is the original image and n is the additive noise

1. GENERAL LINEAR MODEL

The linear model is the basic model where the process by which the sharp image is converted into blurred image is assumed to be linear. In this case, the blurring of columns is assumed to be done independently that of rows. The process of blurring is represented by the following matrix operation

$$B = A_c I A_r^T \qquad (1.1)$$

where B is the blurred image, I is the original image, A_c and A_r are the column and row blurring matrices respectively. The solution of the above model is given below.

$$I = A_c^{-1} B \left(A_r^T\right)^{-1} \qquad (1.2)$$

The above equations ignored the noise that may be added to the image during image capturing. When the noise is taken into consideration the blurred image and deblurred image are given by

$$B = A_c I A_r^T + n \qquad (1.3)$$

2. RICHARDSON – LUCY DECONVOLUTION

This technique is used when the blurring is caused by known point spread function (PSF). The concert of this method is to denote the pixels of blurred image in terms of original image and PSF. When an image is recorded on a detector it is generally slightly blurred, with an ideal point source not appearing as a point but being spread out, into what is known as the point spread function.

3. WIENER FILTERING

The most commonly used technique in image deblurring is Weiner filtering. The performance of this technique is good when the blurring is resulted from focused optic, linear motion and poor sampling. Each pixel in an image represents the intensity value of stationary point. If the shutter time is relatively long or if the capturing device is in motion, the pixel will represent mix intensities of pixels along the camera motion. A number of variations of Wiener filtering can be found in the literature. The blurring model considered in Wiener filtering is given below.

$$b(x, y) = h(x, y) * s(x, y) + n(x, y).$$

III. EXISTING METHOD

IMAGE RESTORATION

Image Restoration is the operation of taking a corrupt/noisy photo and estimating the clean, unique photo. Corruption can also additionally are available many paperwork including movement blur, noise and digital digicam mis-focus. Image recuperation is executed with the aid of using reversing the technique that blurred the photo and such is executed with the aid of using imaging a factor supply and use the factor supply photo, that's referred to as the Point Spread Function (PSF) to repair the photo records misplaced to the blurring Image recuperation isn't like photo enhancement in that the latter is designed to emphasise functions of the photo that make the photo greater desirable to the observer, however now no longer always to supply sensible information from a systematic factor of view.

1. Geometric Correction
2. Radiometric Correction
3. Noise Removal

IV. PROPOSED METHOD

An **adaptive sparse area selection** (ASDS) scheme, which learns a sequence of compact sub-dictionaries and assigns adaptively everyneighbourhood patch a sub-dictionary because the sparse area, k=1, 2… K, is a fixed of Korthonormal sub-dictionaries. Let x be aphoto vector,and xi=Rix, i= 1, 2… N, be the ith patch (size: root (n) × root (n)) vector of x, wherein Ri is a matrix extracting patch xi from x.

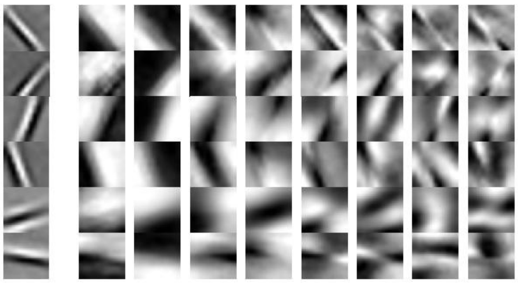


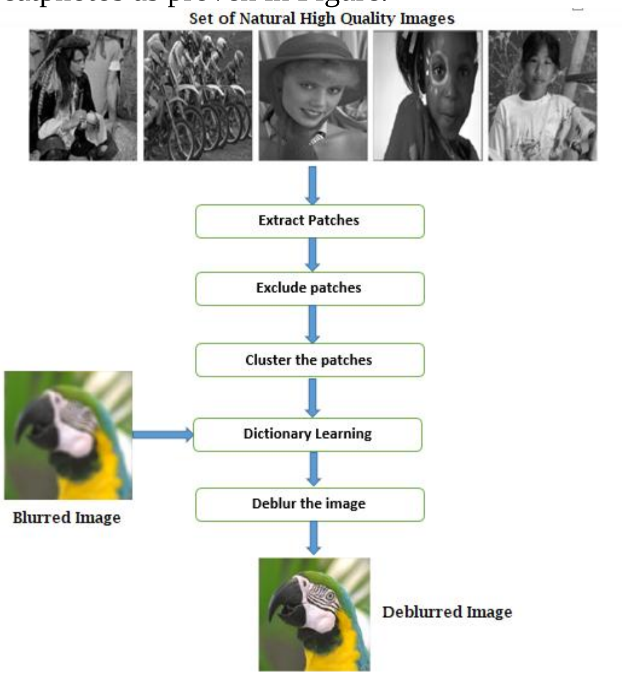
Fig 1: Different Patches formation

DICTIONARIES

Photograph contents can rangeloads from photograph to photograph, it's beendiscovered that the micro-systems of picturesmay be represented with the aid of using a small wide variety of structural primitives (e.g., edges, line segments and differentstandard features), and those primitives are qualitatively comparable in shape to easymolecular receptive fields. The human visibledevice employs a sparse coding approachto symbolizepictures, i.e., coding aherbalphotographthe usage of a small wide variety of foundationfeaturesselected out of an over-whole code set.

Fig 2: Dictionaries

The units of excessivegreatphotos used for education sub-dictionaries and AR models. The photoswithinside the first row encompasses the education dataset 1 and peoplewithinside the2nd row encompasses the education dataset 2. To illustrate the robustness of the proposed approach to the education dataset, we use one-of-a-kindunits of educationphotoswithinside the experiments, every set having fiveexcessivegreatphotos as proven in Figure.



Block diagram for ADSD

Extract Patches: - Splitting the snap shots into patches and extracting the photograph at precise region

Exclude patches: - Higher similarity patches and exclude from the photograph and it used for to cut backthe scale and patches

Cluster in Patches:- Dissimilar patches are reopened inside thephotograph deblurring. there will be the finite set of the patches inside thephotograph

Dictionary learning: The photographtraits of the deblurred pics generated through the DL-primarily based totallyset of ruleshad been quantitatively evaluated in phrases of depth profile, universal-pleasant index, and noise electricity spectrum.

Deblurring the photograph: - it is the approach of eliminating blurring artifacts from pics. get better Sharp Image S from blurred photographthat's B. Mathematically we constitute B = S*K in which B is blurred enterphotograph.

Deblurring Techniques

1. Wiener Filtering
2.Richardson – Lucy Deblurring
3. Blind Deconvolution

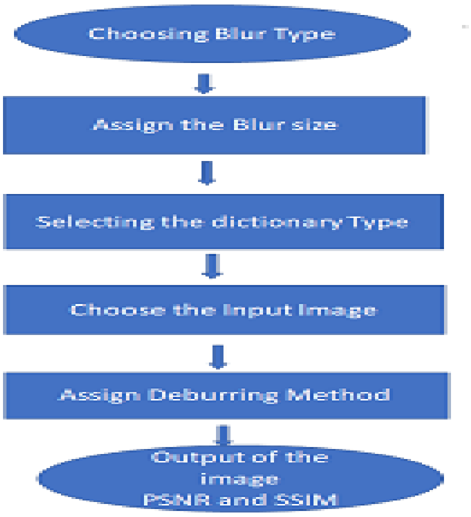
	Image-1		Image-2	
	PSNR(dB)	SSIM	PSNR(dB)	SSIM
PSF: Average Filtering with size [8X8]				
Wiener	72.83001	0.99994	69.55610	0.99977
Richardson-Lucy	73.26486	0.99997	69.31995	0.99979
Blind-Deconvolution	69.73941	0.99995	68.33532	0.99975
PSF: Average Filtering with size [16X16]				
Wiener	73.51449	0.99990	68.42871	0.99950
Richardson-Lucy	71.83786	0.99992	67.50461	0.99943
Blind-Deconvolution	71.53076	0.99993	67.86480	0.99954
PSF: Average Filtering with size [32X32]				
Wiener	71.04509	0.99967	66.64179	0.99888
Richardson-Lucy	69.41469	0.99963	65.63224	0.99862
Blind-Deconvolution	70.06579	0.99973	66.25602	0.99894
PSF: Average Filtering with size [64X64]				
Wiener	68.11707	0.99906	65.04106	0.99800
Richardson-Lucy	66.94935	0.99891	64.43943	0.99780
Blind-Deconvolution	67.75410	0.99919	64.77456	0.99805

Tabular column: Deblurring Technique

Sparse dictionary gaining knowledge of is a illustration gaining knowledge of approach which ambitions at locating a sparse illustration of the enter data (additionallycalled sparse coding) withinside theshape of a linear aggregate of simplefactorsin addition tothe onessimplefactors themselves. These factors are referred to as atoms and that they compose a dictionary.

Atoms withinside the dictionary aren't required to be orthogonal, and they will be an over-entire spanning set. This trouble setup additionallylets in the dimensionality of the indicators being represented to be better than the one of theindicators being observed. The above residencesresult in having apparently redundant atoms that permita couple of representations of the equalsignhoweveradditionallyoffer a development in sparsity and versatility of the illustration.

FLOW CHART of ADSD



Basically, there are two types of the blur in the spare's representation.

1. **Uniform Blur**

The phenomenon that explains how long or how the blur is spread over an image. Always a blur has a unit mass.

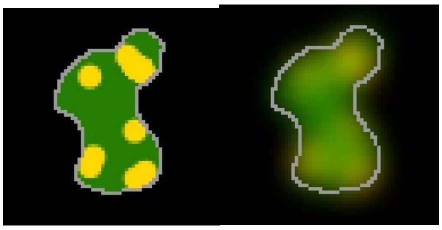


Fig 1.1: Uniform Blur

2. **Gaussian Blur**

A Gaussian blur is implemented by convolving an image by a Gaussian distribution. Other blurs are generally implemented by convolving the image by other distributions.

Fig 1.2:Gaussian Blur

In this the spares representation the blur Image is consider as two types.

1.**Kernel size**

A Kernel is simply a 2-dimensional matrix of numbers. While this matrix can range in dimensions, for simplicity this article will stick to 3x3 dimensional kernel

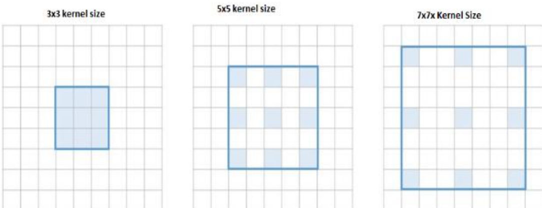


Fig 2.1: Kernel Size

2.Standard Variance Gaussian kernel size

In this the dictionary is important role in the spare's representation. The image is splitted into the patches and removing the unwanted patches in the image and restoring the original image after blurring.

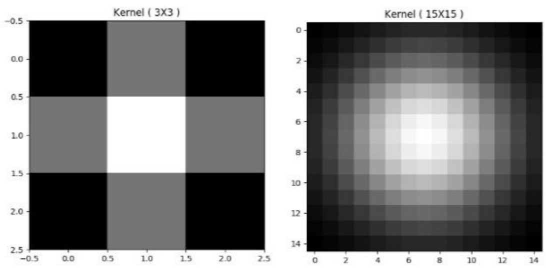


Fig 2.2: Standard Variance Gaussian Kernel size

Finally, we are calculating in the Image blurring there are two types.

1. **PSNR (peak to signal noise ratio)**

It the ratio between the maximum possible power of an image and the power of corrupting noise that affects the quality of its representation.

$$20\log_{10}\frac{2^B-1}{\sqrt{\text{MSE}}}\ \text{(dB)}$$

2. **SSIM (Structural similarity index measure)**

SSIM is used for measuring the similarity between two images.

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

GRAPHICALLY USER INTEREFACE(GUI)

In this the spares representation for the image deblurring technique were are using the GUI (graphically user Interface). This just like some protocol required to the GUI process.

```
:lassdef app1 < matlab.apps.AppBase

    % Properties that correspond to app components
    properties (Access = public)
        UIFigure                        matlab.ui.Figure
        SelectTypeofBlurDropDownLabel   matlab.ui.control.Label
        SelectTypeofBlurDropDown        matlab.ui.control.DropDown
        KernelSizeincaseofUniformDropDownLabel  matlab.ui.control.Label
        KernelSizeincaseofUniformDropDown  matlab.ui.control.DropDown
        SDincaseofGaussianDropDownLabel  matlab.ui.control.Label
        SDincaseofGaussianDropDown      matlab.ui.control.DropDown
        SelectDictionaryDropDownLabel   matlab.ui.control.Label
        SelectDictionaryDropDown        matlab.ui.control.DropDown
        RUNButton                       matlab.ui.control.Button
        SPARSEBASEDIMAGEDEBLURRINGLabel  matlab.ui.control.Label
        DeptofECENARAYANAENGINEERINGCOLLEGEGudurLabel  matlab.ui.control.Label
    end
```

Fig 1: Protocol for GUI

Above figure shows the protocol required for the image Deburring using spares representation using the GUI method.

They're required components for GUI process is

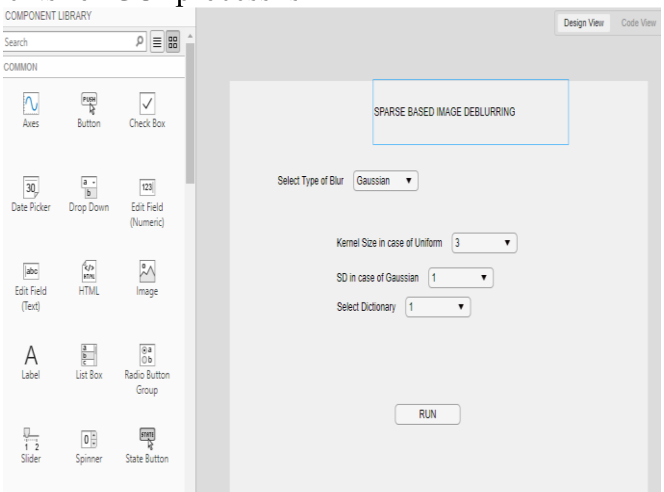


Fig 2: GUI input Components

There is a component required by the Axes, HTML, image, label etc. There will be some process in the above figure.

1. Directly selecting the selecting the Blur type
2. Kernel size
3. Selecting the Dictionary

V. SIMULATION AND RESULT

1.Unifrom Blur

blur type

% When blur type, blur par denotes the kernel size;

blur par = input ('Enter kernel size:');

% method = input ('Enter deblurring scheme');

dict = input ('Enter dictionary number');

'%s: PSNR = %3.2f SSIM = %f\n',

ISSN : 2347-7180
Vol-08 Issue-14 No. 01 : 2021

Fig 1: Uniform Blur

	PSNR (dB)			
	Uniform Blur, Kernel Size 9x9		Uniform Blur, Kernel Size 3x3	
Iteration	Dictionary - 1	Dictionary – 2	Dictionary – 1	Dictionary - 2
0	**23.87**	**23.87**	**30.71**	**30.71**
80	28.63	28.62	35.38	35.38
160	29.32	29.31	35.12	35.13
240	29.84	29.83	35.04	35.06
320	30.15	30.14	35.00	35.02
400	30.36	30.35	34.98	35.00
480	30.51	30.50	34.97	34.98
560	30.61	30.60	34.96	34.97
640	30.68	30.68	34.95	34.96
720	30.74	30.73	34.95	34.96
800	31.12	31.11	37.09	37.10
880	31.26	31.24	37.23	37.23
920	31.23	31.19	37.99	37.98
1000	**31.27**	**31.23**	**38.03**	**38.04**
SSIM	**0.90**	**0.90**	**0.965**	**0.965**

Tabular Column 1 : Uniform Blur

2.Guassain Blur

blur_type
% When blur_type, blur_par denotes the standard Deviation of Gaussian blur kernel size;
blur_par = input ('Enter kernel size:');
% method = input('Enter deblurring scheme');
dict = input('Enter dictionary number');
'%s: PSNR = %3.2f   SSIM = %f\n',

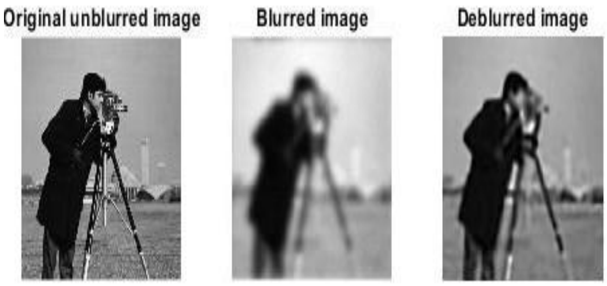


Fig 2: Gaussian Blur

	PSNR (dB)			
	Gaussian Blur, Standard Deviation 1		Gaussian Blur, Standard Deviation 3	
Iteration	Dictionary – 1	Dictionary - 2	Dictionary - 1	Dictionary - 2
0	30.16	30.16	24.07	24.07
80	36.06	36.04	26.84	26.84
160	36.05	36.03	27.15	27.15
240	36.07	36.06	27.35	27.34
320	36.03	36.02	27.48	27.47
400	35.97	35.97	27.58	27.57
480	35.95	35.95	27.65	27.64
560	35.94	35.95	27.70	27.69
640	35.94	35.94	27.74	27.73
720	35.93	35.94	27.77	27.77
800	37.52	37.47	27.80	27.78
880	37.59	37.53	27.82	27.80
960	37.89	37.83	27.83	27.80
1000	37.89	37.83	27.84	**27.81**
SSIM	**0.965**	**0.965**	**0.863**	**0.862**

Tabular Column: Gaussian Blur

Conclusion: -

In this project, a sparse representation has been proposed to be used in image restoration problems. In addition to the proposal of sparse representation, an adaptive selection scheme to select sub-dictionaries is presented. The choice of sub-dictionaries is so central to the whole sparse representation.

Two dictionaries are formed by considering a set of five images containing different kinds of edges, line segments and other elementary features. The proposed sparse representation has been used on the restoration problem image deblurring. Gaussian and Uniform blurs with different quantities are considered. PSNR and SSIM are calculated and these metrics highlight the significance of the proposed sparse representation.

REFERENCE

1. D. Donoho, "Compressed sensing," IEEE Trans. on Information Theory, vol. 52, no. 4, pp. 1289-1306, April 2006.
2. E. Candès and T. Tao, "Near ultimatesignrestoration from random projections: Universal encoding strategies?" IEEE Trans. on Information Theory, vol. 52, no. 12, pp. 5406 - 5425, December 2006.
3. E. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles: Exact sign reconstruction from rather incomplete frequency information," IEEE Trans. on Information Theory, vol. 52, no. 2, pp. 489 - 509, February 2006.
4. Jaya Krishna Sunkara, Kuruma Purnima, Suresh Muchakala, Ravishankar Y, "Super-Resolution Based Image Reconstruction", International Journal of Computer Science and Technology (e-ISSN: 0976-8491, p-ISSN: 2229-4333, GIF: 0.478), Vol. 2, Issue 3, pp. 272-281, September 2011.
5. Jaya Krishna Sunkara, Sundeep Eswarawaka, Kiranmai Darisi, Santhi Dara, Pushpa Kumar Dasari, Prudhviraj Dara, "Intensity Non-uniformity Correction for Image Segmentation", IOSR Journal of VLSI and Signal Processing (e-ISSN: 2319-4200, p-ISSN: 2319-4197), Volume 1, Issue 5, PP 49-57, Jan. -Feb 2013
6. Jaya Krishna Sunkara, Uday Kumar Panta, Nagarjuna Pemmasani, Chandra Sekhar Paricherla, Pramadeesa Pattasani, Venkataiah Pattem, "Region Based Active Contour Model for Intensity Non-uniformity Correction for Image Segmentation", International Journal of Engineering Research and Technology (RIP) (p-ISSN: 0974-3154) , Volume 6, Number 1, pp. 61-73, 2013.
7. J. Oliveira, J. M. Bioucas-Dia, M. Figueiredo, and, "Adaptive generalversionphotograph deblurring: a majorization-minimization approach," Signal Processing, vol. 89, no. 9, pp. 1683-1693, Sep. 2009.
8. P.Rajasekar, H Mangalam, "Design and implementation of power and area optimized AES architecture on FPGA for IoT application", Circuit World, ISSN 0305-6120, 2021, Vol. 47 No. 2, pp. 153-163 https://doi.org/10.1108/CW-04-2019-0039
9. V. V. Satyanarayana Tallapragada, G. V. Pradeep Kumar and Jaya Krishna Sunkara, "Wavelet Packet: A Multirate Adaptive Filter for De-noising of TDM Signal", International Conference on Electrical, Electronics, Computers, Communication, Mechanical and Computing (EECCMC), Jan 2018, Vellore.
10. P.Rajasekar, CS SubashKumar, "Implementation of Low Power Null Conventional Logic Function for Configuration Logic Block", Wireless personal communication, Springer, ISSN 0929-6212
11. L. Rudin, S. Osher, and E. Fatemi, "Nonlinear generalversionprimarily based totally noise elimination algorithms," Phys. D, vol. 60, pp. 259–268, 1992.
12. S. D. Babacan, R. Molina, and A. K. Katsaggelos, "Total versionexquisitedecisionthe use of a variational approach," in Proc. Int. Conf. Image Proc, pp. 641-644, Oct. 2008.