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A Method for Blind Deblurring of Natural Images

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Abstract

Image de blurring is an inverse problem whose aim to recover an image from a version of that image which has suffered a linear degradation and noise. A method for blind image de blurring is presented. The method only makes weak assumptions about the blurring filter and is able to undo wide variety of de blurring degradations .But effective ness of this approach under presence of noise is still confused. To overcome this an approach is investigated where, in presence of asymmetric noise, a preprocessing of image, i.e. denoising the image. To denoising the image we used two techniques, bilateral filtering and singular value decomposition de noising. We comparing the performance using these two methods to restore the image. To overcome the ill-posedness of the blind image de blurring problem, the method includes a learning technique which initially focuses on the main edges of the image and gradually takes details into account. A new image prior, which includes a new edge detector, is used. The method is able to handle unconstrained blurs, but also allows the use of constraints or of prior information on the blurring filter, as well as the use of filters defined in a parametric manner. Furthermore, it works in both single-frame and multiform scenarios. The use of constrained blur models appropriate to the problem at hand, and/or of multiform scenarios, generally improves the de blurring results. Tests performed on monochrome and colour images.
Keywords: Filter, Image, Deblurring, Frame, Optics

I. Introduction

In electrical engineering and computer science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or, a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing also are possible [1]. In particular, digital image processing is the only practical technology for Classification, Feature extraction, Pattern recognition ,Projection, Multi-scale signal analysis[2], Some techniques which are used in digital image processing include, Pixelization, Linear filtering, Principal components analysis, Independent component analysis, Hidden Markov models, Anisotropic diffusion, Partial differential equations, Self-organizing maps, Neural networks, Wavelets. To be suitable for computer processing, an image f (x,y) must be digitalized both spatially and in amplitude, Digitization of the spatial coordinates (x,y) is called image sampling, Amplitude digitization is called gray-level quantization ,the storage and processing requirements increase rapidly with the spatial resolution and the number of gray levels[3]. The number of pixels in the image is called the resolution of the image. If the number of pixels is too small, individual pixels can be seen and other undesired effects may be evident.

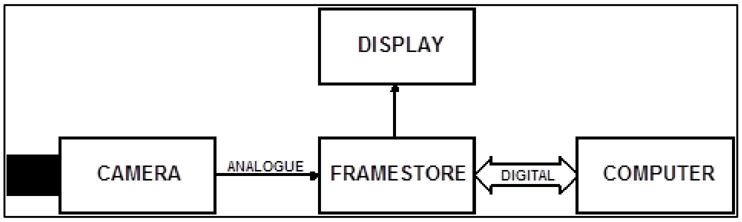

Fig. 1: Storage of image in computer

An image refers to a 2D light intensity function f(x,y), where (x,y) denote spatial coordinates and the value of f at any point (x,y) is proportional to the brightness or gray levels of the image at that point. A digital image is an image f(x,y) that has been discretized both in spatial coordinates and brightness[4]. The elements of such a digital array are called image elements or pixels. Fundamental steps are Image acquisition, Enhancement, Restoration, Color processing, Compression, Morphological processing, Segmentation, Representation and description.

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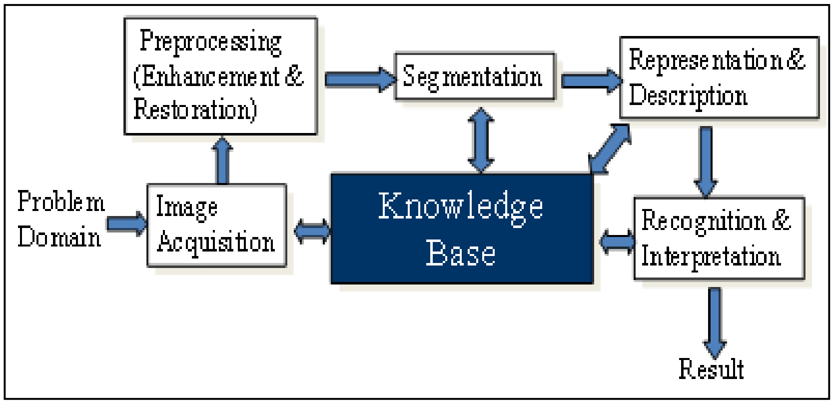

Fig. 2: Fundamental steps

Image restoration methods are used to improve the appearance of an image by applications of a restoration process that uses a mathematical model for image degradation. Examples of the types of degradation include, geometric distortion caused by imperfect lenses, - superimposed interference patterns caused by mechanical systems, noise from electronic sources[5]. In practice the degradation process model is often not known and must be experimentally determined or estimated. Any available information regarding the images and the systems used to acquire and process them is helpful [6]. This information, combined with the developer's experience, can be applied to solve the specific application. A general block diagram for the image restoration process is provided in Figure 3.

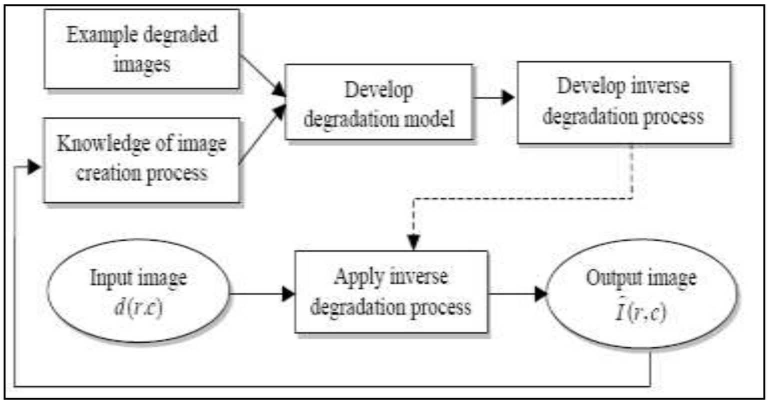

Fig. 3: Image restoration process

II. METHODOLOGY

The degradation that we aim to recover from, is modeled by

$$g = h*f + n$$

in which g, f and n are images which represent, respectively, the degraded image, the original image and additive noise; is the PSF of the blurring operator, and * denotes the mathematical operation of convolution. The blurring, or degradation, of an image can be caused by many factors, Movement during the image capture process, by the camera or, when long exposure times are used, by the subject ,Out-of-focus optics, use of a wide-angle lens, atmospheric turbulence, or a short exposure time, which reduces the number of photons captured, Scattered light distortion in co-focal microscopy.

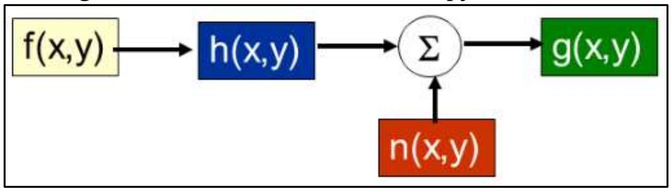

Fig. 4: Degradation model

In blind image deblurring (BID), not only the degradation operator is ill-conditioned, but the problem also is, inherently, severely ill-posed: there is an infinite number of solutions (original image + blurring filter) that are compatible with the degraded image. Read an image into the MATLAB workspace.

```
I = imread('board.tif');
I = I(50+[1:256],2+[1:256],:);
figure; imshow(I);title('Original Image');
```

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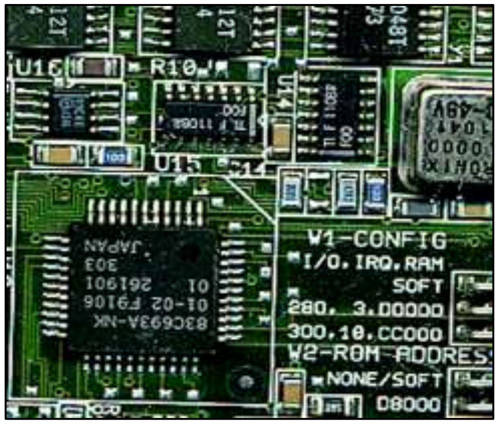

Fig. 5: Original image

Create the PSF.

```
PSF = fspecial('gaussian',5,5);
```

Create a simulated blur in the image and add noise.

```
Blurred = imfilter(I,PSF,'symmetric','conv');
V = .002;
BlurredNoisy = imnoise(Blurred,'gaussian',0,V);
figure;imshow(BlurredNoisy);title('Blurred and Noisy Image');
```

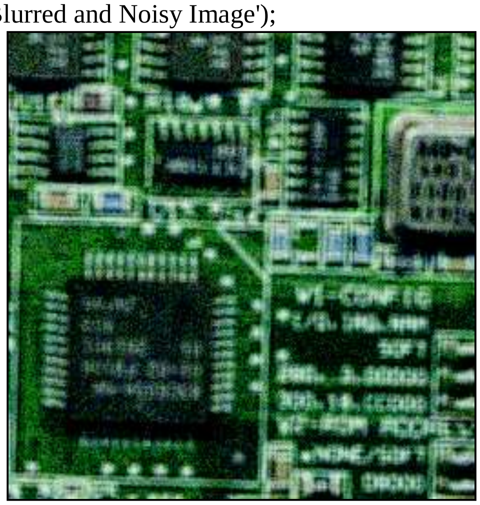

Fig. 6: 'Blurred and Noisy Image'

Use deconvlucy to restore the blurred and noisy image, specifying the PSF used to create the blur, and limiting the number of iterations to 5 (the default is 10)

```
luc1 = deconvlucy(BlurredNoisy,PSF,5);
figure; imshow(luc1);
title('Restored Image');
```

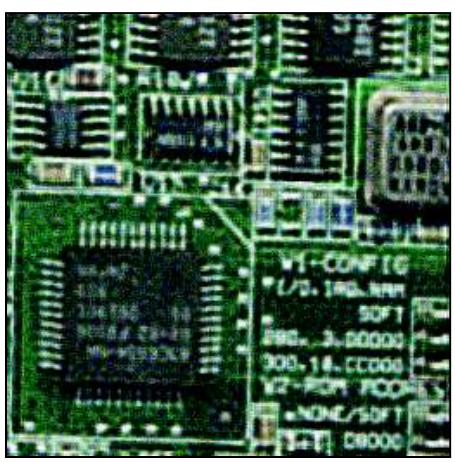

Fig. 7: Restored image

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The PSF reconstructed in the first restoration, P1, obviously does not fit into the constrained size. It has a strong signal variation at the borders. The corresponding image, J1, does not show any improved clarity vs. the blurred image, Blurred. The PSF reconstructed in the second restoration, P2, becomes very smooth at the edges. This implies that the restoration can handle a PSF of a smaller size. The corresponding image, J2, shows some de blurring but it is strongly corrupted by the ringing. Finally, the PSF reconstructed in the third restoration, P3, is somewhat intermediate between P1 and P2. The array, P3, resembles the true PSF very well. The corresponding image, J3, shows significant improvement; however it is still corrupted by the ringing. The measure that we used for evaluating the quality of the results of blind de blurring tests was the increase in signal to noise ratio (ISNR), similarly to what is commonly done in non-blind de blurring. However, the computation of a meaningful ISNR in blind de blurring situations raises some special issues that we now address. We start by recalling the basic concept of ISNR. Assume that is an original image y, is a degraded version of that image and is a recovered (enhanced) image, obtained from y.We start by defining the “signal” as image, the “noise” of y as $y - x_0$, and the “noise” of x as $x - x_0$. The ISNR of the recovered image relative to the degraded image is y, then, the difference between the SNR of yand the SNR of. It can be computed, in decibels, as

$$\boxed{\mathrm{ISNR} = 10 \log_{10} \frac{\sum_i \left(y^i - x_0^i\right)^2}{\sum_i \left(x^i - x_0^i\right)^2}}$$

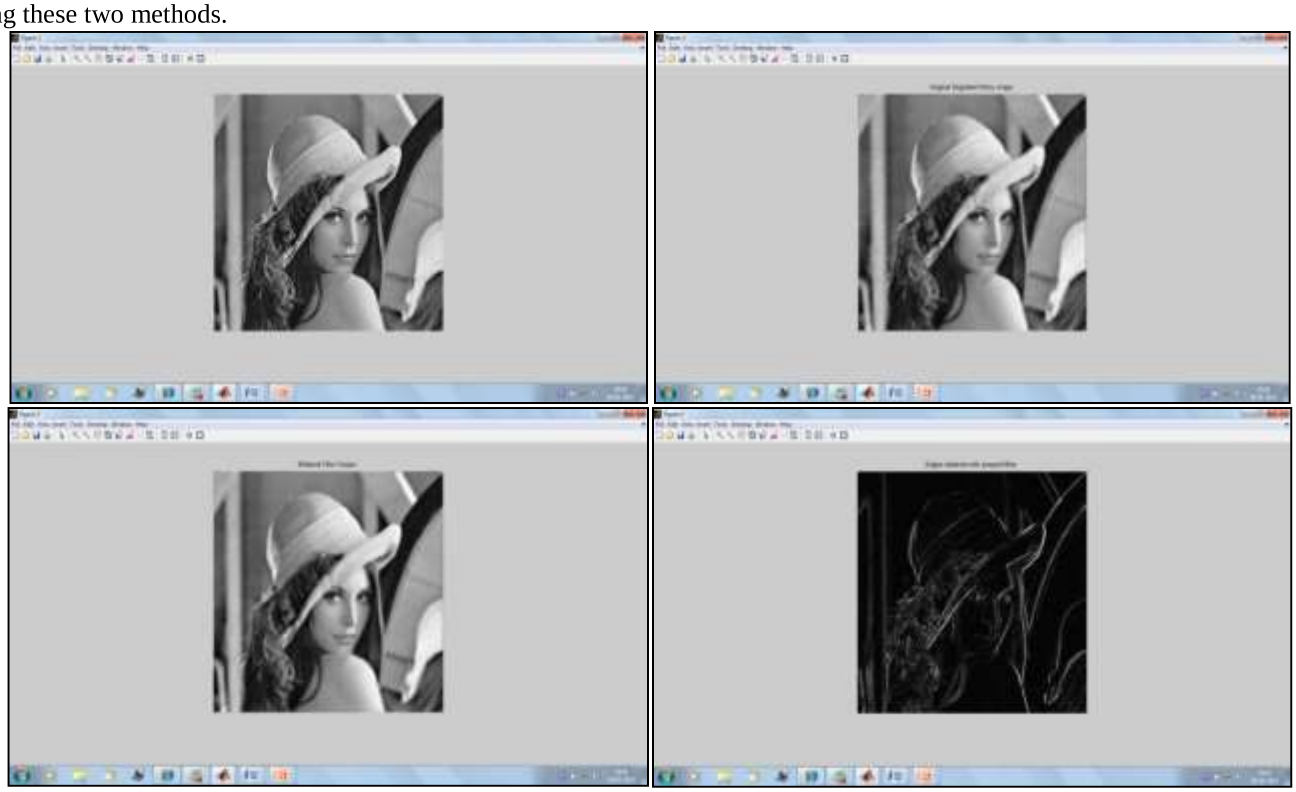
Where the superscript i indexes the images’ pixels, and the sums run through all pixels. The special issues that arise in the computation of this measure in blind de blurring situations are due to the following. The blind de blurring problem is strongly ill-posed. This means that non regularized solutions have a large variability. There are two different kinds of variability that we need to distinguish here.

III. Results

We tested the proposed method both on synthetic blurs and on actual blurred photos. The PSF of the base filter that was used to generate these edge detection filters in which each matrix entry gives the value of a pixel of the PSF, and the arrangement of the matrix entries corresponds to the spatial arrangement of the corresponding pixels in the PSF.

$$\boxed{d_0 = \begin{bmatrix} 1 & 2 & 2 & 1 \\ -1 & -2 & -2 & -1, \end{bmatrix} /12}$$

The other filters were obtained by rotating this base filter, with bi cubic interpolation, by angles multiple of 45. In the figures that we show ahead, the estimated image was first subjected to the affine transformation, and was then saturated to the maximum and minimum values of the blurred image. The blurred images were normalized so that black corresponded to 0.5 and white (or maximum intensity, in the case of color channels of a color image) corresponded to 0.5. Parameter was set to 0.002.The sequence of values of λ was a geometric progression $(\lambda_{n+1} = \lambda_n / r)$, initialized at $\lambda_1 = 2$. The values that were used for are given ahead for each specific case. We are using two de noising methods SVD and bilateral filtering. We comparing the performance of restored image using these two methods.



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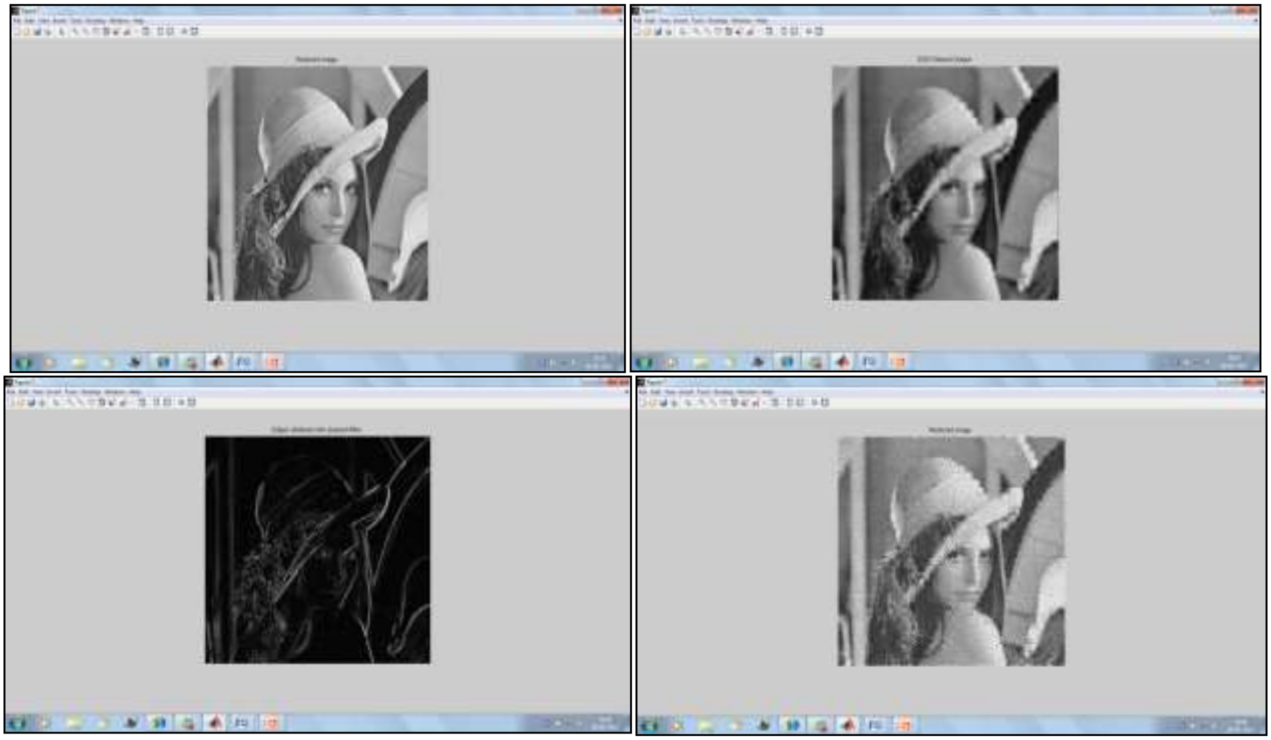

Fig. 8: Original image ‘Leana’, Blurred Noisy image, Denoised image using bilateral filter, Edge detector output, Restored image NEXT: using SVD, outputs.

Table – 1
Result

Image		*(using bilateral denoising)*		*(using SVD denoising)*	
	Blurs	*ISNR value*	*PSNR value*	*ISNR value*	*PSNR value*
Leana	*3*	*3.65*	*37.76*	*3.65*	*35.2*
	5	*8.40*	*36.62*	*8.22*	*31.30*
	7	*11.34*	*36.73*	*10.89*	*29.46*

IV. CONCLUSION

We have presented a method for blind image de blurring. The method differs from most other existing methods by only imposing weak restrictions on the blurring filter, being able to recover images which have suffered a wide range of degradations. Good estimates of both the image and the blurring operator are reached by initially considering the main image edges, and progressively handling smaller and/or fainter ones. The method uses an image prior that favors images with sparse edges, and which incorporates an edge detector that was specially developed for this application. The method can handle both unconstrained blurs and constrained or parametric ones, and it can deal with both single-frame and multiform scenarios. Experimental tests showed good results on a variety of images, both grayscale and color, with a variety of synthetic blurs, without and with noise, with real-life blurs, and both in single and in multiform situations. The use of information on the blurring filter and/or of multiform data, when available, typically led to improvements in the quality of the results. We have adapted the ISNR measure to the evaluation of the restoration performance of BID methods. The restoration quality of our method was visually and quantitatively better than those of the other methods with which it was compared. So far, whenever the blurred image has noise, the processing has to be manually stopped, by choosing the iteration which yields the best compromise between image detail and noise or artifacts. An automatic stopping criterion will obviously be useful. This is a direction in which further research will be done. The method can be extended in other directions: For example, 1) to address problems in which we aim at super-resolution, possibly combined with deblurring, and 2) to deblur images containing space-variant blur.

V. FUTURE WORK

Finally, on a more theoretical level, but with possible practical implications, is the problem that we mentioned above, that the best de blurring solutions generally do not correspond to the global minimum of the cost function. This apparently means that a more appropriate cost function should exist. If it were found, it would probably lead to a better de blurring technique, both in terms of speed and of the quality of the results. This clearly is an important research direction.

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