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Enhancement of Debased Images Using Guided Bilateral Filter

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ABSTRACT:Blurring of an image is a common problem that occurs when recording digital images due to long exposure time, or movement of objects, camera shakes. Clarity of picture assumes an imperative part in the picture handling without clear picture we can't encourage to use it for feature extraction or picture combination and so on. So principle focus of this paper is to upgrade the corrupted pictures. We are performing relative study between wiener filter, SURE-LET deconvolution algorithm and guided bilateral filter and we are demonstrating that the guided bilateral filter is proficient among these in terms of PSNR etc. The guided bilateral filter as an additional point of interest is that it can likewise be utilized for upgrade of colour pictures, as it is 3D filter.

KEYWORDS: Wiener filter, SURE-LET deconvolution, PSNR, guided bilateral filter.

I.INTRODUCTION

Adigital image is composed of picture elements called pixels. Each pixel is assigned an intensity, meant to characterize the colour of a small rectangular segment of the scene. A smallimage typically has around 2562 = 65536 pixels while a high-resolution image often has 5 to 10 million pixels. Some blurring always arises in the recording of a digital image, because it is unavoidable that scene information "spills over" to neighbouring pixels. For example, the optical system in a camera lens may be out of focus, so that the incoming light is smeared out. The same problem arises, for example, in astronomical imaging where the incoming light in the telescope has been slightly bent by turbulence in the atmosphere. In these and similar situations, the inevitable result is that we record a blurred image in image deblurring, we seek to recover the original, sharp image by using a mathematicalmodel of the blurring process. The key issue is that some information on the lost details is indeed present in the blurred image but this information is "hidden" and can only be recovered if we know the details of the blurring process. The degraded of image mainly takes place due to noise addition and blurring .so we must perform denoising and deblurring to recover back the original image.

Image denoising plays a vital role in digital image processing. There are many schemes for removing noise from images. The good denoising scheme must able to retrieve as much of image details even though the image is highly affected by noise. The noise pixels cannot be determined in spatial domain so we use FFT to convert it to frequency domain and convert back to time domain during restoration using IFFT. In common there are two types of image denoising model, linear model and nonlinear model. Generally linear model are being considered for image denoising, the main benefits of using linear noise removing models is the speed and the limitations of the linear models is the models are not able to preserve edges of the images in an efficient manner Non-linear models can preserve edges in a much better way than linear models but very slow.

Image deblurring is also one of the important task in image processing. If we know the function that is causing the blur then modest and easiest way to restore a original image is by reverse filtering .If we don't know the function that is causing blurring then we must obtain PSF (point spread function) and perform deconvolution to restore image. Blurring is mainly formed due to spreading of signal over its neighbor pixels.

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Degradation model:
The degradation process can be imagined with the following system.

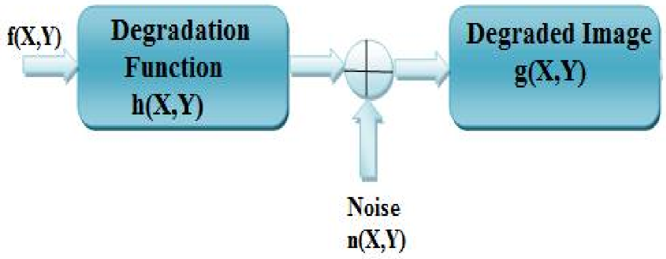

Figure.1.Degradation model

The original input is a two-dimensional (2D) image f(x, y).
This image is operated on by the system h (x, y) and after the addition of noise n(x, y) .One can obtain the degraded image g(x,y). Digital image rebuilding may be viewed as a process in which we try to obtain an approximation to f(x, y). The blurred image can be described with the following equation.

$$g(x, y) = h(x, y) * f(x, y) + n(x, y) \qquad (1)$$

We may write the above equation in an equivalent frequency domain representation:

$$G (u, v) = H (u, v) F (u, v) + N (u, v) \qquad (2)$$

II.PROPOSED METHODOLOGY

We are performing the comparative study between wiener filter, SURE-LET deconvolution algorithm and bilateral filter and we are showing that bilateral filter is proficient among all and we can also use this bilateral filter for colour image.

A. Wiener filter

If we know the function that is causing blurring of an image the simple and fast way to recover back the image is by inverse filtering but the disadvantage with the inverse filtering is that it acts as a high pass filter as noise components are present in high frequency they can easily pass through and even amplify .so the case become even worse. In order to avoid this we use a threshold based model it is called adaptive inverse filter, which is also called as wiener filter.

Wiener filters are characterized by the following:
1. Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross correlation.
2. Requirement: the filter must be physically realizable, i.e. causal (this requirement can be dropped, resulting in a non-causal solution).
3. Performance criteria: minimum mean-square error.

Wiener filter can remove the additive noise and blurring simultaneously.The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. That is the recovered image will almost be similar to that of the original image. The Wiener filter in Fourier domain can be expressed as follows:

$$R_w(u,v) = \frac{H^*(u,v)S_{im}(u,v)}{|H(u,v)|^2 S_{im}(u,v)+S_n(u,v)} \qquad (3)$$

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Where, H (u, v) =blurring function
S_{im}= Power spectra of image, S_n= Power spectra of noise.
The power spectra of noise is determined by the variance of noise and the power spectra of image by using periodogram estimate.

B. SURE-LET Deconvolution Algorithm

Degradation of image mainly takes due to two things they are noise addition and blurring. In order to restore back the original image we perform denoising and deblurring sequentially in this proposed algorithm. We perform denoising in the beginning and then we perform deblurring operation on the denoised image.
Denoising of an image is done in following steps wavelet decomposition, wavelet threshold and wavelet reconstruction

1. Wavelet decomposition

In wavelet decomposition the original image is transformed into four pieces which is normally labelled as LL, LH, HL and HH as in the figure 2.
The LH indicates that low pass in the horizontal direction and a high pass filter in the vertical direction, similarly for HL we will have a high pass filter in horizontal direction and low pass filter in vertical direction, HH we will have high pass filter in both the directions and for LL we will have low pass filter in both the directions.

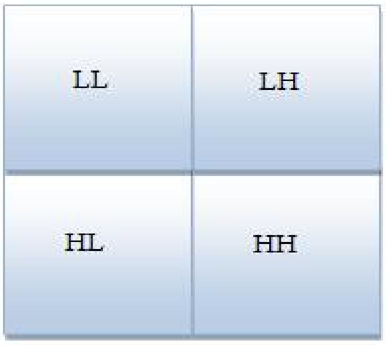

Figure.2. First level of wavelet decomposition

Noise is present in the high frequency not in the low frequency the filter bank associated with first level of decomposition is as show in figure 3.

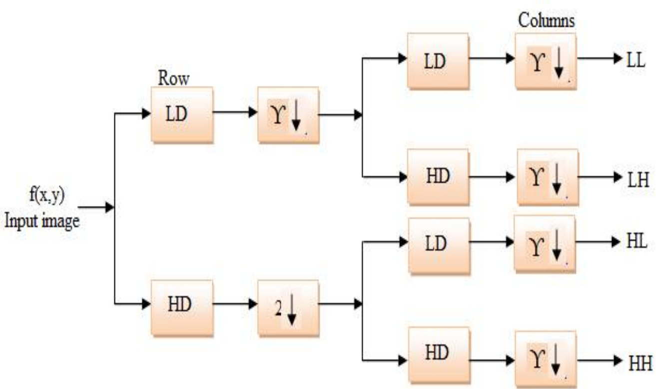

Figure.3. Filter bank associated with first level decomposition

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The LL1 section can be further divided to get LL2, LH2, HL2, HH2.which leads us to second level of decomposition

2. Wavelet threshold

Once we obtain the decomposed image we will compare them with the threshold to check whether to keep or discard/replace pixel with the threshold if it is noisier pixel.

These are two types of threshold:

a) Hard threshold

$$D(U,\lambda) = \begin{cases} U \; for \; all \left| U \right| \rangle \lambda \\ 0 \quad otherwise \end{cases} \quad (4)$$

b) Soft threshold

$$D(U,\lambda) = sgn(U)^{*}\max(0, \left| U \right| - \lambda) \quad (5)$$

Hard decision it is like a do or die .If it is greater than threshold it is retained and if it is less than threshold it is replaced by zero, some amount of information may be lost in denoising .So we prefer soft threshold over hard threshold.

3. Wavelet Reconstruction

Once we compare pixels with threshold we will replace or retain it based on the decision. As noise pixels cannot be determined in time domain we have converted it to frequency domain using FFT initially. In reconstruction we will convert them back to time domain using IFFT and reconstruction of the image is done.

Once we obtain the denoised image we perform deblurring on it by using the linear modelA. x=b
Where 'A' indicates the blurring, which causes transfer from original image x to degraded image b. In this proposed method we will find PSF (point spread function) and we deconvolve to restore back the original image.

C. Guided Bilateral Filter

It is a proposed system which is a combination of guided filter and a bilateral filter. It is a 3D filter so it can also be used to enhance the colour images also.

1. Guided filter

This filter works by keeping a guided image as a reference .the reference image can be input image or any other image. A filtering input image p, a guidance image I, and an output image q. Both I and p are given beforehand according to the application, and they can be identical. The filtering output at a pixel i is expressed as a weighted average.

$$q_i = \sum_j W_{ij}(I) p_j \quad (6)$$

Where, i and j are pixel indices. The filter kernel Wij is a function of the guidance image I and independent of p. This filter is linear with respect to p.

2. Bilateral filter:

A bilateral filter is a non-linear, edge-preserving and noise-reducing smoothing filter for images. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. It is given by:

$$W_{ij}^{\mathrm{bf}}(I) = \frac{1}{K_i} \exp\left(-\frac{|\mathrm{x}_i - \mathrm{x}_j|^2}{\sigma_s^2}\right) \exp\left(-\frac{|I_i - I_j|^2}{\sigma_r^2}\right) \quad (7)$$

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Where the pixel coordinate, and Ki is is a normalizing parameter to ensure that $\sum_j W_{ij}^{bj} = 1$. The parameters σ_s andσ_r adjust the spatial similarity and the range (intensity/colour) similarity respectively.

Bilateral filter is having the following characters
1. Its formulation is simple: Each pixel is replaced by a weighted average of its neighbours. This aspect is important because it makes it easy to acquire intuition about its behaviour, to adapt it to application-specific requirements, and to implement it.
2. It depends only on two parameters that indicate the size and contrast of the features to preserve.
3. It can be used in a non-iterative manner. This makes the parameters easy to set since their effect is not cumulative over several iterations.

Bilateral filters, on the other hand, can operate on the three bands at once.so it can also be used for enhancement of coloured images also.

III.RESULTS

The below figure shows the comparative results of all the three wiener filter ,SURE-LET algorithm and guided bilateralfilter and we can clearly see that the guided bilateral filter gives us the clear image which is almost similar to the original image.

Figure 4: comparative results of all the three in one window

The first subplot in the above figure is input image, second is blurred image, third is output of wiener filter, fourth is output of SURE-LET algorithm and fifth is the output of guided bilateral filter.

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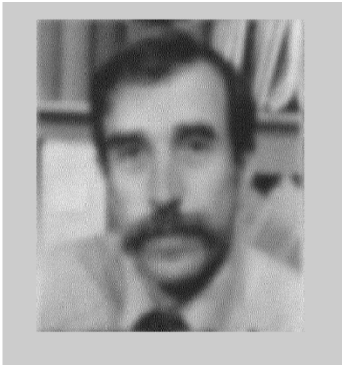

Figure.5.wiener filter output

Figure 5 shows,the output of wiener's filter individually and we can clearly observe from it that it is more noisy when compared to other filter and it also have less PSNR when related to other filter in term of restoration and it cannot be used for enhancement of colour images as it is 2D filter.

Figure 6: Guided bilateral filter output

The individual output of a guided bilateral filter is as shown in the above figure 6. In that the first subplot is input image, second is noisy image and the third is output of guided bilateral filter which is almost same as input image.

IV.CONCLUSION

We have obtained a novel method for enhancement of degraded images. That is the guided bilateral filter is efficient filter for enhancement of degraded images. As we can clearly see in the output show above clarity of image in guided bilateral is more and it is in close resemblance with input image We performed the relative study between wiener filter, SURE-LET deconvolution algorithm and bilateral filter and we have showed that bilateral filter is efficient among all these. In wiener filter both denoising and deblurring is done simultaneously. In SURE-LET deconvolution we first denoise image using wavelet transform and then deblur using linear model. Guided bilateral filter it is a edge preserving denoising filter this is efficient in term PSNR etc, this filter can also we used for enhancement of colour image.

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