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Image Sharpening & De-Noising Using An Adaptive Bilateral Filter

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Abstract:
The scope of this project is to deal with images that are appropriate for digital photography. The problem we are interested in is twofold. First to develop a sharpening method that increases the slope of edges without producing overshoot and undershoot, which renders clean, crisp, and artefact-free edges, thereby improving the overall appearance of the image. The second aspect of the problem is to address noise removal. In most applications, the degraded image contains both noise and blur. A sharpening algorithm that works well only for noise-free images will not be applicable in these situations. Hence a unified solution to both sharpness enhancement and noise removal is proposed.

Key words: *Image denoising, image restoration, adaptive bilateral filter*

1.Introduction

Image restoration refers to the genre of techniques that aim to recover a high quality original image from a degraded version of that image given a specific model for degradation process. Thus restoration techniques are oriented towards modelling the degradation and applying the inverse process in order to recover the original image. As Fig.1 shows the degradation function that, together with an additive noise term, operates on an input image $f(x,y)$ to produce a degraded image $g(x,y)$. Given $g(x,y)$, some knowledge about the additive noise term $\eta(x,y)$, the objective of restoration is to obtain an estimate $\hat{f}(x,y)$ of the original image. We want the estimate to be as close as possible to the original input image and, in general, the more we know about H and η , the closer $\hat{f}(x,y)$ will be to $f(x,y)$.

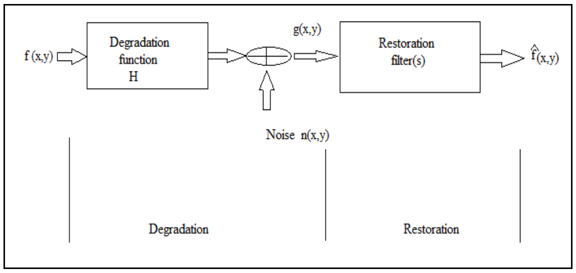


Figure 1: Model Of Image Degradation / Restoration Process

A new approach to image restoration is been proposed which is based on restoration in the presence of noise only that is spatial filtering is the method of choice in situations when only additive noise is present. The success of this broader application of the restoration algorithm will depend on how general is the degradation model under which the algorithm will be developed, as well as on how robust is the overall structure of the algorithm to deviations from the assumed degradation model. The scope of this project is to deal with images that are appropriate for digital photography. A unified solution to both sharpness enhancement and noise removal is proposed.

2.Algorithm

- Start.
- Read input image.
- Verify image exists and is valid.
- Differentiate between grey scale and color image.
- Obtain the data window of size $\Omega(m, n)$ on the image.
- Set the bilateral filter parameter
- Compute Gaussian distance weights of the image.
- Extract the local region of the image.
- Compute Gaussian intensity weights.
- Calculate the response of bilateral filter.
- Display input grey image and filtered output.
- If color image
- Convert RGB image to CIELab image.
- Repeat steps 5 to 10.
- Convert back CIELab image to RGB image.
- Display input color image and filtered output.

3.Adaptive Bilateral Filtering

The adaptive bilateral filter is the framework for our proposed algorithm. The idea underlying bilateral filtering is to do in the range of an image what traditional filters do in its domain. Two pixels can be close to one another, that is, occupy nearby spatial location, or they can be similar to one another, that is, have nearby values, possibly in a perceptually meaningful fashion. Closeness refers to vicinity in the domain, similarity to vicinity in the range. Traditional filtering is domain filtering, and enforces closeness by weighing pixel values with coefficients that fall off with distance. Similarly, range filtering, averages image values with weights that decay with dissimilarity. Range filters are nonlinear because their weights depend on image intensity or color. Computationally, they are no more complex than standard nonseparable filters. Most importantly, they preserve edges.

In order to increase the sharpness of the image some modifications to the bilateral filter is to be done, a new method for both sharpening and smoothing the image is been proposed here. The response at $[m0, n0]$ of the proposed shift-variant ABF to an impulse at $[m, n]$ is given by

$$h[m_0,n_0;m,n] = \begin{cases} r_{m_0,n_0}^{-1} \exp\left(-\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^2}\right) \exp\left(-\frac{(g[m,n]-g[m_0,n_0]-\zeta[m_0,n_0])^2}{2\sigma_r^2}\right), & [m,n] \in \Omega_{m_0,n_0} \\ 0, & \text{else} \end{cases}$$

Where $[m0, n0]$ is the center pixel of the window $\Omega m0, n0 = \{ [m, n]: [m, n] \in [m0 - N], [m0 + N] \; X \; [n0 - N] \; X \; [n0 + N] \}$ and σd and σr are the standard deviations of the domain and range Gaussian filters, respectively, and the normalization factor is given by:

$$r_{m_0,n_0} = \sum_{m=m_0-N}^{m_0+N} \sum_{n=n_0-N}^{n_0+N} \exp\left(-\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^2}\right) \times \exp\left(-\frac{(g[m,n]-g[m_0,n_0]-\zeta[m_0,n_0])^2}{2\sigma_r^2[m_0,n_0]}\right).$$

The ABF retains the general form of a bilateral filter, but contains two important modifications. First, an offset ζ is introduced to the range filter in the ABF. Second, both ζ and the width of the range filter σr in the ABF are locally adaptive. If ζ = 0 and σr is fixed, the ABF will degenerate into a conventional bilateral filter. For the domain filter, a fixed low-pass Gaussian filter with σd = 1.0 is adopted in the ABF. The combination of a locally adaptive ζ and σr transforms the bilateral filter into a much more powerful filter that is capable of both smoothing and sharpening. Moreover, it sharpens an image by increasing the slope of the edges.

The pixel dependent offset ζ in the ABF is the key to slope restoration. With ζ, we are able to restore the slope by transforming the local histogram of the image, thus circumventing the cumbersome process of locating edge normals and detecting edge profiles. Since

at any pixel $[m0, n0]$ in the image, the ABF output is bounded between $MIN(\Omega m0, n0)$ and $MAX(\Omega m0, n0)$, the ABF, in general, does not produce overshoot and undershoot.
By making ζ and σr adaptive and jointly optimizing both parameters, we transform the bilateral filter into a much more powerful and versatile filter. To smooth the image at a given pixel, we can shift the range filter towards $MEAN(\Omega mo, no)$, and/or use a large σr which enables the spatial Gaussian filter to take charge of the bilateral filtering. To sharpen the image at a given pixel, we can shift the range filter away from the midpoint of the edge slope which will be approximately equal to $MEAN(\Omega mo, no)$, towards $MAX(\Omega mo, no)$ or $MIN(\Omega mo, no)$, depending on the position of the edge pixel on the edge slope. At the same time, we would reduce σr accordingly. With a small σr, the range filter dominates the bilateral filter and effectively pulls up or pushes down the pixels on the edge slope.

4.Design & Implementation

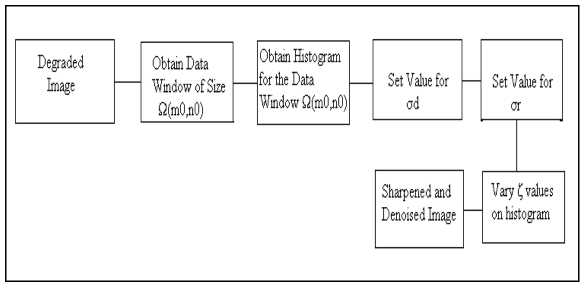


Figure 2:Block diagram

In the fig.2. A degraded image with the unknown degradation function is taken as the input.
A data window with pixel values $\Omega(m0, n0)$ fromobtained for the given image.
Obtain Histogram for the data window with values$\Omega(m0, n0)$. The histogram is used to classify pixels into smooth regions, soft edges and hard edges, which are subsequently processed with different sharpening strengths.
A constant value for Domain filter *σd* is being set, which acts as a fixed low pass Gaussian filter.
Select a value for the width of the range filter *σr.* It determines how selective the range filter is in choosing pixels that are similar in grey values to include in averaging operation. If *σr* value is too small bilateral filter is overdriven by Range filter and if the value of *σr* is too high bilateral filter acts as a domain filter.
A locally adaptive offset of the range filter ζ is shifted or varied on the histogram with following effects :
Shifting towards MEAN will blur the image.
Shifting away from the MEAN will sharpen the image.
Shifting away from MEAN towards MIN or MAX will over sharpen the image.

5.Result & Analysis
The project has been designed using MATLAB Image processing tool box. The performance of the ABF is evaluated with a grey scale image. The first test image is “Einsten,” as shown in Fig.3.

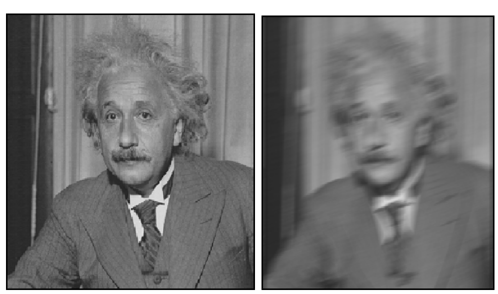


Figure 3: Input & Degraded Image

The ABF removes the noise & renders clean and sharp edges without the halo artifacts.
The Fig.4. shows the AB filtered image.

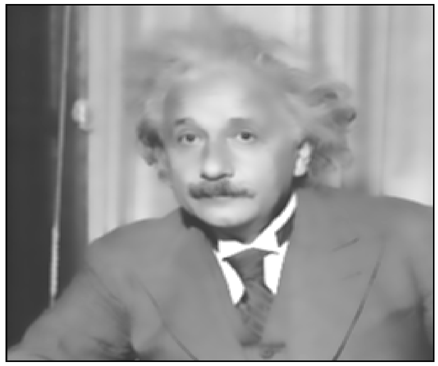
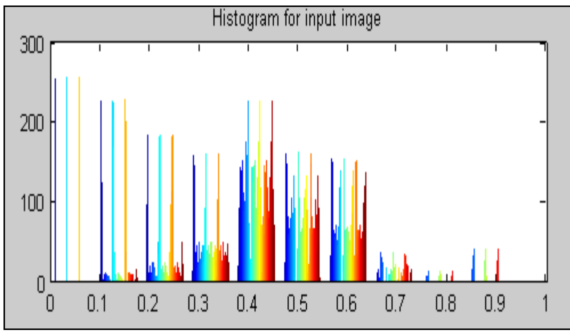


Figure 4: Adaptive Bilateral Filtered Image

The Fig.5.a.& Fig.5.b.below shows the histogram for input image and adaptive bilateral filtered image respectively.



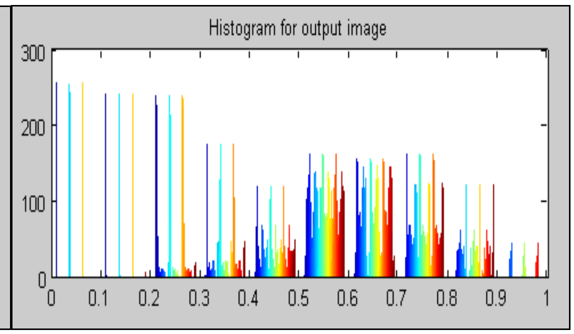


Figure 5a: Histogram for Input Image
Figure 5b: Histogram for AB filtered image

A variety of performance parameters like PSNR, MSE, hue, saturation, entropy, energy, contrast & homogeneity have been analyzed. The Fig.6.below shows different parameters extracted from the Adaptive Bilateral filtered image.

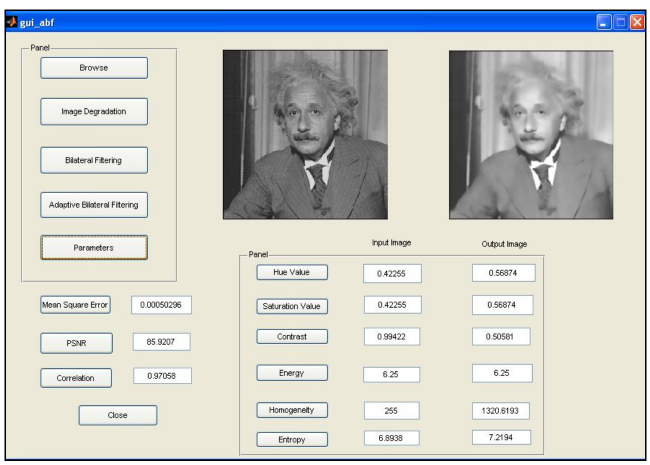


Figure 6: Parameters Obtained After Adaptive Bilateral Filtering

6.Conclusion

The proposed implementation of adaptive bilateral filter (ABF) outperforms the bilateral filter in noise removal. At the same time, it renders much sharper images than the bilateral filter does. As a result, the overall quality of the restored image is significantly improved. The ABF is efficient to implement, and provides a more reliable and more robust solution to slope restoration. It is been demonstrated that the ABF works well for both grey scale and color images.

7.Future Work

For future development of the ABF, we would suggest that the following issues be addressed. First, the ABF tends to posterize the image, due to its fundamental mechanism of sharpening an image by pulling up or pushing down pixels along the edge slope. Second, the ABF does not perform as well at corners as it does on lines and spatially slow-varying curves, since the ABF is primarily based on transforming the histogram of the local data, which cannot effectively represent 2-D structures. Finally, in the current design of the ABF, a fixed domain Gaussian filter is used. It would be interesting to see what can be gained by jointly optimizing both the domain and the range filters.

8.References

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