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Image sharpening & de-noising using bilateral & adaptive bilateral filters-A comparative analysis

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Abstract*:*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. The two most common forms of degradation, an image suffers are loss of sharpness or blur, and noise. In this paper, an attempt has been made to first develop a sharpening method that increases the slope of edges without producing overshoot and undershoot, which renders clean, crisp, and artifact-free edges, thereby improving the overall appearance of the image. The second aspect of the problem is to address noise removal. A unified solution to both sharpness enhancement and noise removal is proposed using adaptive bilateral filter. The paper compares the result of bilateral & adaptive bilateral filter for image sharpening and de-noising.

Index terms*:* Bilateral filter, ABF, image sharpening, image denoising

I. 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 modeling the degradation and applying the inverse process in order to recover the original image. As Figure 1.1 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 $f(x,y)$.

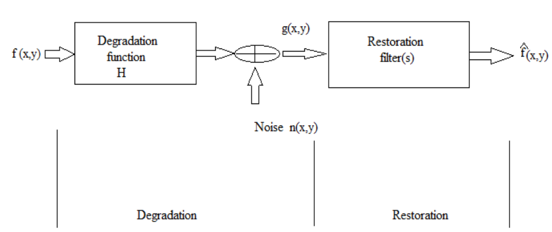

Fig1**.** Model of image degradation / restoration process.

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II. BILATERAL FILTER

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. Spatial locality is still an essential notion. In fact, it is shown that range filtering by itself merely distorts an image's color map. Then the combination of range and domain filtering is done, and shown that the combination is much more interesting. The combined filtering is known as bilateral filtering. Since bilateral filters assume an explicit notion of distance in the domain and in the range of the image function, they can be applied to any function for which these two distances can be defined. In particular, bilateral filters can be applied to color images just as easily as they are applied to black-and-white ones. The CIE-Lab color space endows the space of colors with a perceptually meaningful measure of color similarity, in which short Euclidean distances correlate strongly with human color discrimination performance. Thus, if we use this metric in our bilateral filter, images are smoothed and edges are preserved in a way that is tuned to human performance. Only perceptually similar colors are averaged together, and only perceptually visible edges are preserved.

A low-pass domain filter applied to image **f**(**x**) produces an output image defined as follows:

$$\mathbf{h}(\mathbf{x}) = k_d^{-1}(\mathbf{x}) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathbf{f}(\xi) c(\xi, \mathbf{x})\, d\xi \qquad (1)$$

Where $c(\xi, X)$ measures the geometric closeness between the neighborhood center **x** and a nearby point ξ. The bold font for **f** and **h** emphasizes the fact that both input and output images may be multiband. If low-pass filtering is to preserve the dc component of low-pass signals we obtain

$$k_d(\mathbf{x}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, \mathbf{x})\, d\xi \; . \qquad (2)$$

Range filtering is similarly defined as:

$$\mathbf{h}(\mathbf{x}) = k_r^{-1}(\mathbf{x}) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathbf{f}(\xi) s(\mathbf{f}(\xi), \mathbf{f}(\mathbf{x}))\, d\xi \qquad (3)$$

now $s(f(\xi), f(x))$ measures the Photometric similarity between the pixel at the neighborhood center **x** and that of a nearby point ξ. Thus, the similarity function s operates in the range of the image function **f**, while the closeness function c operates in the domain of **f**. The normalization constant (2) is replaced by

$$k_r(\mathbf{x}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} s(\mathbf{f}(\xi), \mathbf{f}(\mathbf{x}))\, d\xi \; . \qquad (4)$$

The appropriate solution is to combine domain and range filtering

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thereby enforcing both geometric and Where $[m0, n0]$ is the center pixel of the windo $\Omega m0, n0 = \{ [m, n]: [m, n] \in [m0 - N], [m0 + N] X [n0 - N] X [n0 + N]\}$ and σd and σr are the standard deviations of the domain and range Gaussian filters, respectively, and the normalization factor is given by photometric locality. Combined filtering can be described as follows:

$$\mathbf{h}(\mathbf{x}) = k^{-1}(\mathbf{x}) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathbf{f}(\xi) c(\xi, \mathbf{x}) s(\mathbf{f}(\xi), \mathbf{f}(\mathbf{x}))\, d\xi \quad (5)$$

With the normalization

$$k(\mathbf{x}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, \mathbf{x}) s(\mathbf{f}(\xi), \mathbf{f}(\mathbf{x}))\, d\xi \,. \qquad (6)$$

Combined domain and range filtering will be denoted as bilateral filtering.As a consequence, the bilateral filter acts essentially as a standard domain filter, and averages away the small, weakly correlated differences between pixel values caused by noise.

III. ADAPTIVE BILATERAL FILTER

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 $\Omega m0, n0\{ [m, n]: [m, n] \in [m0N], [m0 + N] X [n0 - N] X [n0 + N]\}$ 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. 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. By adding an offset ζ to the range filter, it is now able to shift the range filter on the histogram. The parameter σr of the range filter

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controls the width of the range filter. It determines how selective the range filter is in choosing the pixels that are similar enough in gray value to be included in the averaging operation.

IV. RESULTS and ANALYSIS

The performance of the ABF is evaluated with one grey scale image. The performance of ABF is compared with bilateral filter.

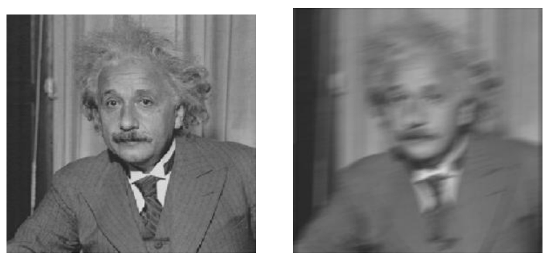

Fig 2.a&b: Input Image & degraded image

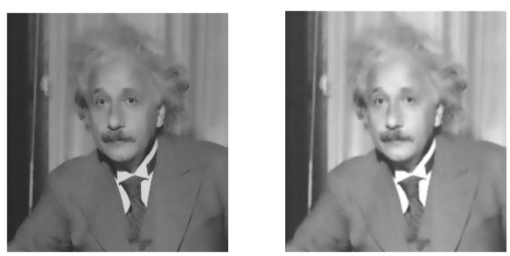

Fig 3.a&b: Bilateral Filtered Image &ABF filtered image

The bilateral filter removes the noise in the degraded image; but the edges are a bit blurred as those in the degraded image. The ABF removes the noise better than the bilateral filter do. At the same time, it renders clean and sharp edges without the halo artifacts.

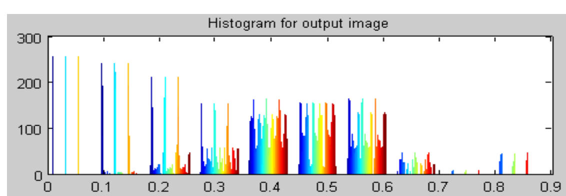

Fig4.a: Histogram for Bilateral Filtered Image

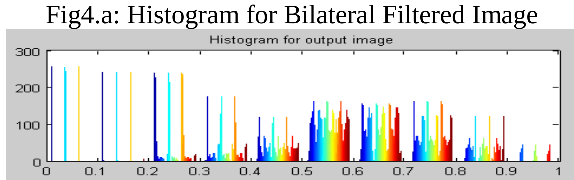

Fig 4.b: Histogram for Adaptive Bilateral Filtered Image

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From the histogram it can be seen that much of the noise present in the image is been removed after applying bilateral filter, ABF even shows the further reduction in the noise.

Different features of the bilateral filtered image and ABF filtered image are graphically represented below.

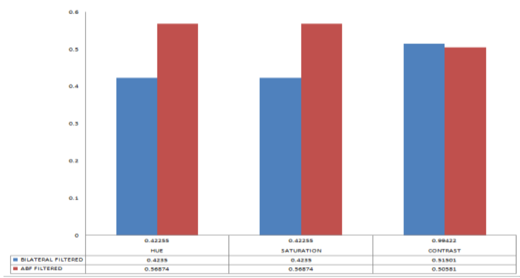

Fig.5: Graph indicating hue, saturation and contrast values for "Einsten"

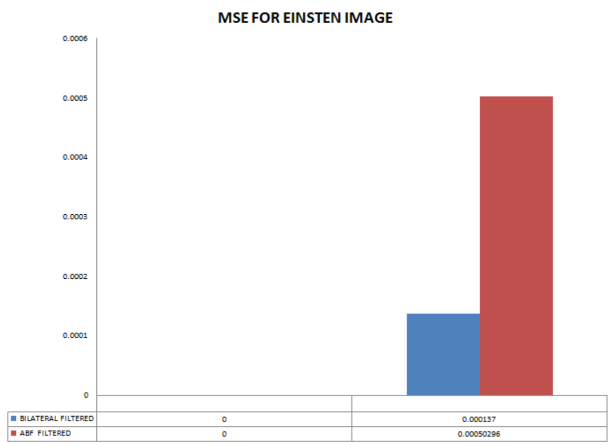

Fig.6: MSE graph for Einstein

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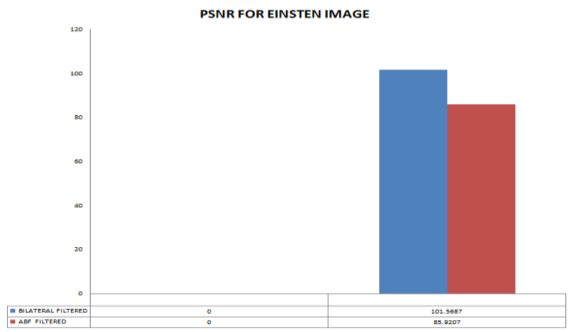

Fig.7 : PSNR graph for Einstein

Fig 8. shows the different parameters or the features of both the input image and bilateral filtered image.

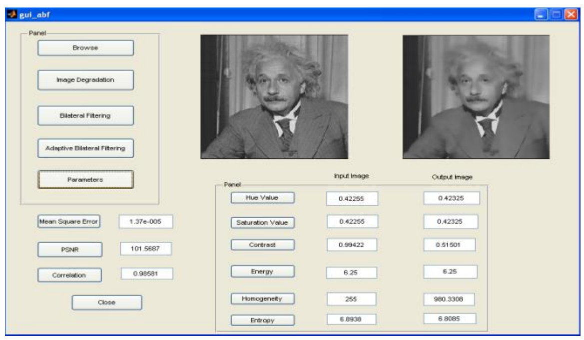

Fig.8:.Parameters obtained after bilateral filtering

Fig.9 shows the result of applying Adaptive Bilateral Filter to the input image.

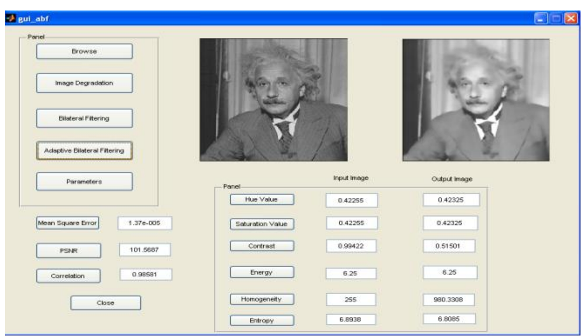

Fig.9 :Adaptive Bilateral Filtered Image

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V . 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.

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