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Comparative Analysis in Medical Imaging

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Abstract
Filtering is always the root process in many medical image processing applications. It is aimed at reducing noise in images. Any post-processing tasks, e.g., visualization, segmentation may benefit from the reduction of noise. Bilateral filtering smoothes images while preserving edges, by means of a nonlinear combination of nearby image values. This method is noniterative and simple. It combines gray levels based on both their two properties i.e. geometric closeness and their photometric similarity, and prefers the near values to distant values in both domain and range. In this paper we have made comparison between Bilateral, Bilateral Median and Gaussian filter. Bilateral filter combines both the domain and range filtering and combination is much more interesting. The bilateral filter shows good results in comparison to Gaussian however the Bilateral Median shows the best results in comparison to all. The comparison is based on the basis of MSE, PSNR, and CNR.

Keywords
Image Enhancement, Spatial Filtering, Bilateral Filter, Bilateral Median Filter, Gaussian Filter, Medical Images.

1. Introduction

Filtering is always the most fundamental operation of image processing and computer vision. In the right sense of the term "filtering," the value of the filtered image at a given location is a function of the values of the input image in a small neighborhood of the same location. Gaussian low pass filtering shows no ringing effect and computes a weighted average of pixel values in the neighborhood, in which, the weights decrease with distance from the neighborhood center which shows good results for medical imaging. Images typically vary over space, so near pixels are likely to have the similar values and it is therefore appropriate to average them together. The noise values that corrupt these nearby pixels are mutually less correlated than the signal values, so noise is averaged away while signal is preserved [3].

We assume that there is slow spatial variation at edges but it fails which are consequently blurred by low-pass filtering. To reduce this undesired effect many efforts have been made. How can we prevent averaging across edges, while still averaging within smooth regions?

In this paper, we used a non iterative scheme for edge preserving smoothing that is noniterative and simple. Earlier we have shown the relationship between bilateral filter and Gaussian filter [7]. The idea is there to use bilateral filtering which works in the range of an image what traditional filters do in the domain. There are two conditions either the pixels can be close to one another, that is, can have nearby spatial location, or they can be similar to one another, that is, have nearby values, possibly in a perceptually meaningful fashion. Closeness here refers to the vicinity in the domain, similar to vicinity in the range. Traditional filtering is domain filtering, which enforces closeness by weighing pixel values with coefficients that fall off with distance. Similarly, we define range filtering, which averages image values with weights that decay with dissimilarity. Since range filters weights depend on the image intensity so these are nonlinear.

When both domain and range filtering is combined then it is known as *bilateral* filtering. Since bilateral filters assume that an explicit notion of distance in the domain and in the range of the image function that can be applied to any function for which there two distances can be defined. The different results of the bilateral filters are compared with the Gaussian filter and the variations are compared in terms of mean square error (MSE), peak signal to noise ratio (PSNR) and contrast to noise ratio (CNR).

2. Filters for medical imaging

2.1 Bilateral Filter:

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

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

where $c(\xi, x)$ measures the geometric closeness between the neighborhood center x and a nearby point ξ. The f and h are the input and output images which may be multiband. If low-pass filtering is to preserve the DC component of low-pass signals we obtain

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

If the filter is shift-invariant, *c(ξ, x)* is only a function of the vector difference (*ξ*- *x*), and k_d is constant.

Range filtering is similarly defined:

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

Here *s(f(ξ),f(x))* measures the photometric similarity between the pixel at the neighborhood center *x* and that of a nearby point *ξ***.** It means 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 normalized constant for range filter is given by

$$k_r(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} s(f(\xi), f(x)) d\xi \quad (4)$$

The similarity function *s* depends on the image *f* and is equal to the difference f*(ξ) - f(x)*.

The appropriate solution is to combine domain and range filtering, thereby enforcing both geometric and photometric locality [3]. Combined filtering can be described as follows:

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

With the normalization

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

Combined domain and range filtering will be denoted as bilateral filtering [3]. It replaces the pixel value at *x* with an average of similar and nearby pixel values. In smooth regions, pixel values in a small neighborhood are similar to each other, and the normalized similarity function $k^{-1}s$ is close to one. As a consequence, the bilateral filter acts essentially as a standard domain filter, and averages away the small the small, weakly correlated differences between pixel values caused by noise.

Example

A simple and important case of bilateral filtering is shift-invariant Gaussian filtering, in which both the closeness function *c(ξ,x)* and the similarity function *s(φ,f)* are Gaussian functions of the Euclidean distance between their arguments [3].

More specifically, *c* is radially symmetric.

where

$$c(\xi, x) = e^{\frac{-1}{2}\left(\frac{d(\xi, x)}{\sigma d}\right)^2} \quad (7)$$

$$d(\xi, x) = d(\xi - x) = \|\xi - x\| \quad (8)$$

The similarity function s is perfectly analogous to *c*.

$$s(\xi, x) = e^{\frac{-1}{2}\left(\frac{\delta(f(\xi), f(x))}{\sigma r}\right)^2} \quad (9)$$

where

$$\delta(\phi, x) = \delta(\phi - x) = \|\phi - x\| \quad (10)$$

is a suitable measure of distance between the two intensity values *φ* and *f*.

2.2 Bilateral Median Filter:

The traditional bilateral filter performs a weighted averaging of a neighborhood. Noise influencing the centre pixel has a disproportionate influence on the range filtering. This suggests the following modification

i. Replacing the summation. In this approach, the pixels are combined using a weighted median.

ii. Exploring the alternative kernels for both domain and range filtering.

Potential Kernels:

The following robust kernel is used:

El Fallah ford:

$$g(x, \sigma) = \frac{1}{\sqrt{1 + (x/\sigma)^2}} \quad (11)$$

Gaussian

$$g(x, \sigma) = e^{\frac{-x^2}{2\sigma^2}} \quad (12)$$

Here for the domain and range filters either we can use the same kernel or the different kernels.

3. Experiments with black and white images

In this section we analyze performance of bilateral filter on black- and- white images. Figure 2 shows the effect of different values of the parameters that is domain parameter (σ_d) and range parameter (σ_r) on the resulting image after applying bilateral filter on Fig. 1. Rows correspond to different amounts of domain filtering, columns to different amounts of range filtering.

When the value of the range filtering constant σ_r is large (100 to 300) with respect to the overall range of values in the image the range component of the filter has little effect for small σ_d: all pixel values in any given neighborhood have about the same weight from range filtering, and domain filter acts as a standard Gaussian filter. This effect can be seen in the last two columns of figure (2).

For smaller values of the range filter parameter σ_r (10 or 30), range filtering dominates perceptually because it preserve images.

However, for σ_d =10, image detail that was removed by smaller values of σ_d appears.

In fact, σ_d = 10 is a very broad Gaussian, and the bilateral filter becomes essentially a range filter. Table 1 and Table 2 show the relation between different image parameters for the various domain and range parameters. Mean Square Error (rms) is the ratio of the square of difference between the input and output image to the size of the image. Peak Signal to Noise ratio is the logarithmic value of the ratio of size of the image and the mean square error of the image. Contrast to Noise ratio is the difference between the input and output signal to noise ratio.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(f_1(i,j) - f_2(i,j)\right)^2 \quad (13)$$

$$PSNR = 10LOG\left(255^2/MSE\right) \quad (14)$$

$$CNR_{AB} = (SNR_A - SNR_B) = \left(\frac{(S_A - S_B)}{\sigma_0}\right)^2 \quad (15)$$

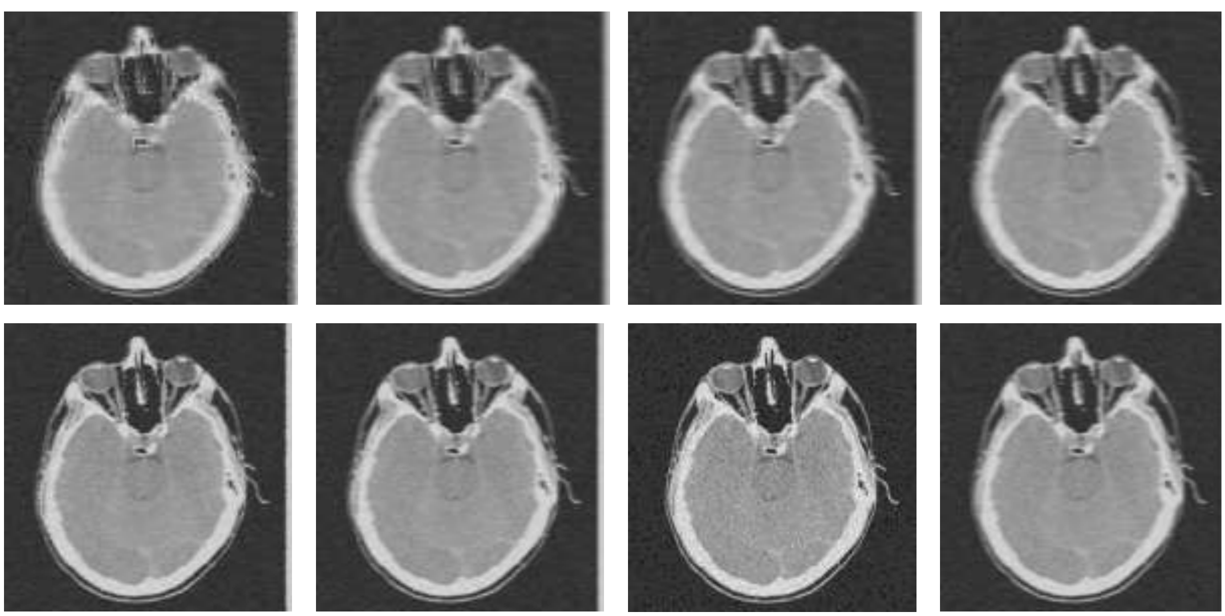
$$SNR = \frac{S_A}{\sigma_0} \quad (16)$$

Here f_1, f_2 are the input and output images respectively. CNR is the contrast to noise ratio between two tissues A and B. Here σ_0 is noise in the image. It is assumed that the noise is same for everyone. M and N are the sizes of the images. Here S_A, S_B are the mean intensity value of the image and the background respectively.

Fig 1: Original MRI Computed Tomography scan image

σ_d= 4

σ_d= 10



$\sigma_r = 10$ $\sigma_r = 30$ $\sigma_r = 100$ $\sigma_r = 300$

Fig 2: A detail from the figure 1 is processed with bilateral filters with various range and domain values.

TABLE 1 TABLE 2

Different image parameters applied on the bilateral filtered images.

σ_d=10	σ_r=10	σ_r= 30	σ_r= 100	σ_r=300
MSE	24.29	23.51	23.06	23.02
PSNR	20.45	20.72	20.89	20.90
CNR	10.21	11.31	11.65	11.94

Different image parameters applied on the bilateral filtered images.

σ_d= 4	σ_r=10	σ_r=30	σ_r=100	σ_r= 300
MSE	42.88	41.27	39.41	32.29
PSNR	15.44	15.60	16.23	16.24
CNR	7.99	8.34	9.11	9.21

The figure below shows the original image, and the bilateral or the Gaussian filtered images. Different image parameters show that for different values of range and domain parameters σ_r = 300 and σ_d = 10, the root mean square error is minimum in bilateral filtered image. The Gaussian filter has highest root mean square error for the same value of σ_d.

Fig. 3(a) Original image	Fig. 3(b) BF image	Fig. 3(c) BF image	Fig. 3(d) BF image	Fig. 3(e) Gaussian image

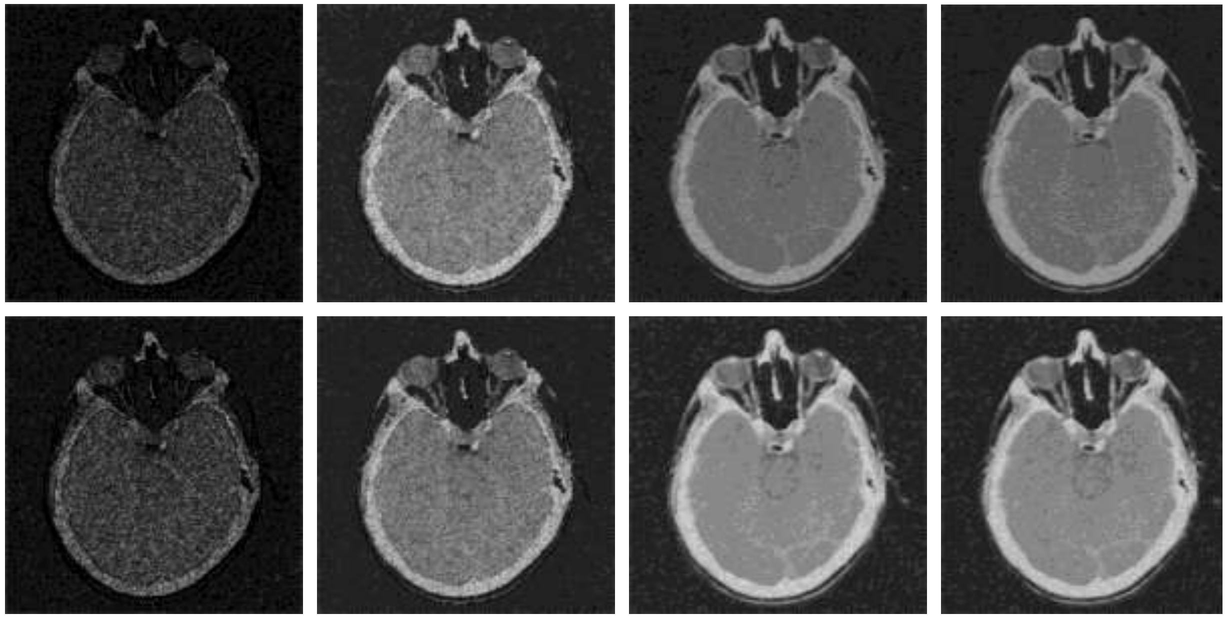
Table 3: Different image parameters applied on the bilateral filtered and Gaussian images

Parameters	Fig. 3(b) σ_r = 10, σ_d = 4	Fig. 3(c) σ_r = 30, σ_d = 10	Fig. 3(d) σ_r = 300, σ_d = 10	Fig. 3(e)
MSE	42.88	23.51	23.02	84.00
PSNR	15.44	20.72	20.90	9.54
CNR	7.99	11.31	11.94	9.24

Fig4:Original knee image σ_d = 4	Fig 4(a): Bilateral Filtered image of original image σ_r = 10	Fig 4(b): Bilateral Filtered image of original image σ_r = 30	Fig 4(c): Gaussian image of original image
MSE	42.88	41.27	83.91

σ_d= 4

σ_d= 10



$\sigma_r = 10$ $\sigma_r = 30$ $\sigma_r = 100$ $\sigma_r = 300$

Fig. 5: A detail from the figure 1 is processed with bilateral median filters with various range and domain values.

TABLE 4
Different image parameters applied
on the bilateral median filtered images.

σ_d=4	σ_r=10	σ_r= 30	σ_r= 100	σ_r=300
MSE	82.68	56.31	41.27	37.30
PSNR	9.54	13.01	15.76	16.72
CNR	7.21	9.15	10.01	10.84

TABLE 5
Different image parameters applied
on the bilateral median filtered images.

σ_d= 10	σ_r=10	σ_r=30	σ_r=100	σ_r= 300
MSE	76.95	41.80	20.60	17.00
PSNR	10.41	10.41	21.90	23.22
CNR	9.19	11.37	12.11	13.91

In the Table, the bilateral median filter is compared on the basis of various image parameters. From the table, it is clear that, in case of bilateral median filter for range parameter σ_r= 300, whether domain parameter σ_d is 4 or 10 the mean square error (MSE) is minimum and the peak signal to noise ratio (PSNR) is maximum. Also the contrast to noise ratio (CNR) is maximum.

4. Graph of Comparison of parameters for various Techniques

Now we have shown the results of our implementation through the graphs.

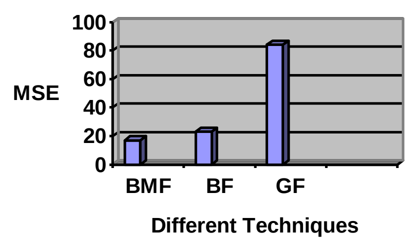


Fig. 6: Comparison of MSE for various techniques

The above graph shows the Mean Square Error for bilateral Median Filter is minimum.

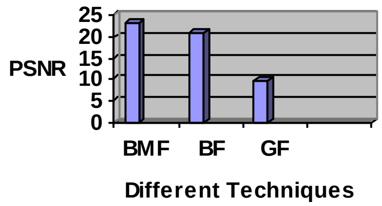


Fig.7: Comparison of PSNR for various techniques

The graph shows the value of peak signal to noise ratio to different techniques. The bilateral median filter shows the best results while the gaussian filter shows the worst result.

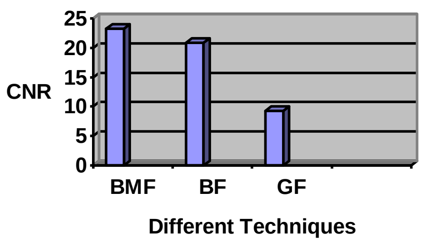


Fig. 8: Comparison of CNR for various techniques

The graph shows the value of Contrast to Noise Ratio for different techniques. The CNR value is maximum for the bilateral median filter and less for bilateral filter and least for gaussian filter.

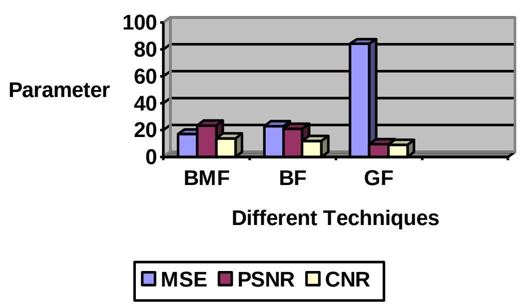


Fig. 8: Comparison of image parameters for various image enhancement techniques

5. Conclusions

In this paper we have implemented the concept of bilateral filtering for edge-preserving smoothing in medical images or bilateral median filtering. The filtered images are compared on the basis of different range and domain parameters that define the closeness and photometric properties. The bilateral median filter shows the best results of all the filters. Gaussian doesn't provide the desired results for medical images because MSE is very high for the output images.

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