

Methodology Article

Evaluation of Spatial Filtering Techniques in Retinal Fundus Images

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Abstract: The denoising of the fundus images is an essential pre-processing step in glaucoma diagnosis to ensure sufficient quality for the Computer Aided Diagnosing (CAD) system. In this paper, we present an evaluation approach for different denoising filters of eye fundus images that suffer from two different types of noises (Gaussian noise and Salt & Pepper noise), which had been applied to the retinal images and then various Spatial filtering techniques like linear (Gaussian, mean), nonlinear filtering (median) and adaptive filtering have been implemented to three types of images (original images, images with salt and pepper noise and images with Gaussian noise) and their performance are compared to each other based on evaluation parameters: Mean Squared Error (MSE), Peak Signal Noise Ratio (PSNR) and Structural Similarity (SSIM). The results showed that the adaptive median filter has the best performance in salt & paper noise and the adaptive filter has the best performance for Gaussian noise, but their performance is close to each other. In conclusion, six spatial filters applied to RIM-ONE fundus image database and found that, the adaptive median filter has the best performance compared to other filters to remove these noises and increase the quality of the resulting images, which can be implemented to the CAD system.

Keywords: Fundus Images, Spatial Filtering, MSE, PSNR, SSIM

1. Introduction

Early diagnosis is crucial in many sight-threatening diseases like glaucoma, hypertension and diabetic retinopathy which cause blindness among working age people. Therefore retinal image analysis has become one major diagnosis method in modern ophthalmology. Retinal image analysis typically involves in blood vessel segmentation, optical disc segmentation and fovea segmentation for detecting and analyzing any abnormalities. The restoration of noisy fundus images is an essential pre-processing step in any of the related image analysis approaches [1].

Retinal imaging has become a significant tool in medical imaging technology, due to its capability to extract many data can be used in various eye diseases diagnosis.

Digital images like fundus image are often corrupted by different types of noise during its acquisition and transmission

phase. Such degradation negatively influences the performance of many image processing techniques and CAD system performance based on this images, for that a preprocessing module to filter the

images is often required [2, 3]. That accuracy of disease detection depends on the quality of acquired retinal fundus image as some times it contains uneven illumination, blurry and noisy areas. So, Illumination equalization and noise removal are required to enhance the image quality and increase CAD system accuracy.

Noise in an image is undesirable to us as it disrupts and degrades the quality of the image. Noise removal is always a difficult task so as edge preservation when the intensity of the disrupted noise in the original image is high [4], as authors in [5] represents a comparison of different methods used for

pre-processing in retinal fundus images and discussed principles, advantages and disadvantages, Here adaptive median filter is found to be better compared to other preprocessing methods, because it have higher PSNR value and lower MSE value in 3 diabetic retinopathy retinal images, and authors in [6], [7] at HRT database and [8] used the median filter for noise removed in fundus retinal images. But the authors at [9] proposed denoising method based on image sequences and an adaptive frame averaging approach.

Filtering is a technique for modifying or enhancing an image via smoothing, sharpening and deblurring. For example, you can filter an image to emphasize certain features or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge enhancement. Noise removal is one of the major concerns in the field of computer vision and image processing. Images are often contaminated by impulsive noise due to noisy sensors or channel transmission errors or faulty storage hardware. The goal of removing impulsive noise is primarily to suppress the noise as well as to preserve the integrity of edges and detailed information see section (3.1.1). In digital image processing field, two applications of great importance are noise filtering and image enhancement.

Noise sources:

Image acquisition.

Image transmission

Noise models:

Spatially independent noise models

Gaussian noise

Rayleigh noise

Erlang (Gamma) noise

Exponential noise

Impulse (salt-and-pepper) noise

Spatially dependent noise model

Periodic noise [10].

In fundus image first step was to evaluate the noise in the image, then to estimate noise type.

Salt and pepper noise, Gaussian noises are the main noises effects in retinal image. In salt and pepper noise random occurrence of black and white pixel and in gaussian noise variation of intensity value with the gaussian normal distribution occur [5].

The rest of this paper is organized as follows. In Section 2, the material and method is introduced in detail. In Section 3, experimental results and discussion. Finally, in Section 4, the conclusion is presented.

2. Materials and Methods

The database used is from An Open Retinal Image Database for Optic Nerve Evaluation (RIM-ONE) is a fundus image database that is related to glaucoma disease. It consists of 169 ONH images, where the images are divided into five classes as follows: normal 118 images, early glaucoma 12 images, moderate glaucoma 14 images, deep glaucoma 14 images and ocular hypertension (OHT) 11 images [11].

2.1. Different Types of Filters Used to Remove Noises

2.1.1. Median Filter

Median Filtering Seems Almost Tailor-Made for Removal of Salt and Pepper Noise. Recall that the Median of a Set is the Middle Value When They are Sorted. If There are an Even Number of Values, the Median is the Mean of the Middle two. A median Filter is an Example of a Non-Linear Spatial Filter [12].

$$(x,y)=\{g(s,t)\},s,t\in S_{xy} \quad (1)$$

Let S_{xy} represents a set of rectangular sub image with window size $(m \times n)$ centered at (x, y) .

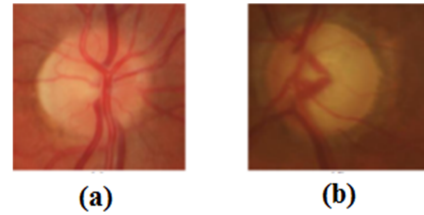


Figure 1. Eye RIM-ONE database images: (a) Normal image, (b) Glaucoma image (abnormal).

2.1.2. Adaptive Filter

Adaptive Filters Are a Class of Filters Which Change Their Characteristics According to the Values of the Greyscales Under the Mask, Is Implemented by Applying a Function to the Grey Values Under the Mask.

2.1.3. Mean Filter

The Mean Filter is a Simple Sliding-Window Spatial Filter that Replaces the Center Value in the Window with the Average (Mean) of All the Pixel Values in the Window. The Window, Or kernel, Is Usually Square But Can be Any Shape [13].

$$(x,y)=1/mn \sum (s,) \quad (2)$$

2.1.4. Guided Filter

The guided filter function performs edge-preserving smoothing on desired image, based on the content of a second image, called a guidance image, to influence the filtering. The guidance image can be the image itself, a different version of the image, or a completely different image, but the operation takes into account the statistics of a region in the guidance image when calculating the value of the output pixel. If the guidance and image to be filtered is the same the structures are the same an edge in the original image is the same in the guidance image. If the guidance is different, structures in the guidance image will affect the filtered image, in effect, imprinting these structures on the original image his effect is called structure transference.

2.1.5. Gaussian Filter

The Gaussian filters are ideal to start experimenting with filtering because their design can be controlled by manipulating just one variable- the variance, the Gaussian filter function is defined as

$$G(x, y) = \frac{1}{2\pi\sigma^2 e} - \frac{x^2 + y^2}{2\sigma^2} \quad (3)$$

The value of the sigma or the variance affect inversely to the filtering, smaller values of sigma means more frequencies are suppressed and vice versa.

2.1.6. Adaptive Median Filter

The Adaptive Median Filter performs spatial filtering to preserve detail and smooth non-impulsive noise. The main advantage to this adaptive against the median filtering is that repeated applications of this Adaptive Median Filter do not erode away edges or other small structure in the image.

2.2. Performance Evaluation

To evaluate the performance of these five filters, four measures are computed from the original image and filtered image, these measures are:

2.2.1. Mean-Squared Error (MSE):

$$MSE(x, y) = \frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2 \quad (4)$$

The error signal $ei = xi - yi$ is the difference between the original and distorted image [14].

2.2.2. Mean Peak Signal to Noise Ratio (PSNR)

$$PSNR = 10 \log_{10} \frac{L^2}{MSE} \quad (5)$$

Where L is the dynamic range of allowable pixel intensities. For example, for an 8-bit per pixel image, $L = 2^8 - 1 = 255$. L is the dynamic range of allowable image pixel intensities [15].

2.2.3. Structural Similarity Index (SSIM)

$$SSIM(x, y) = [l(x, y)]^\alpha \cdot [c(x, y)]^\beta \cdot [s(x, y)]^\gamma \quad (6)$$

Where it combination of the luminance, contrast and structure similarity functions [16].

Luminance function:

$$l(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \quad (7)$$

Contrast function:

$$c(x, y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \quad (8)$$

Structure function:

$$s(x, y) = \frac{2\sigma_{xy} + c_3}{\sigma_x^2 + \sigma_y^2 + c_3} \quad (9)$$

Standard deviation (σ_x):

$$\sigma_x = \left(\frac{1}{N-1} \sum_{i=1}^N (x_i - \mu_x)^2 \right)^{\frac{1}{2}} \quad (10)$$

Mean intensity (μ_x):

$$\mu_x = \bar{x} = \frac{1}{N} \sum_{i=1}^N x_i \quad (11)$$

2.2.4. Signal-to-Noise Ratio (SNR)

$$SNR = \frac{P_s}{P_N} = \frac{[(Asignal)]^2}{[(Anoise)]^2} \quad (12)$$

Where *Asignal* is the signal amplitude and *Anoise* the noise amplitude.

3. Results and Discussions

In this paper, two different types of noises (Gaussian noise and Salt & Pepper noise) had been applied to the retinal images and then various filtering techniques like linear (Gaussian, mean), nonlinear filtering (median) and adaptive filtering have been implemented to three types of images (original image without noise, image with salt and pepper noise, image with Gaussian noise). Finally, we used MSE, PSNR, SNR, and SSIM parameters to measure performance of the filters.

Figures (3, 4 & 5) show results of applying the filters to the fundus images with Gaussian noise and salt & pepper noise.

Tables (1, 2, & 3) show results of the performance evaluation after applying Adaptive filter, Guided filter, Gaussian filter, Mean filter & Median filter to retinal image with Gaussian noise (density = 0.05), retinal image without noise, retinal image with salt & pepper noise (Density = 0.02) respectively.

Tables (4 & 5) show results of PSNR after applying spatial filters to retinal images with different densities of salt and pepper noise and Gaussian noise respectively (10% to 50 %).

Figures (6 to 9) show results of performance evaluation using a bar chart.

The results showed that the adaptive median filter has the best performance in salt & paper noise and the adaptive filter has the best performance for Gaussian noise, but their performance is close to each other, based on our fundus image database noise. The results showed that the adaptive median filter has the best performance compared to other filters.

From the results, we can notice that the best performance to impulse noise is median filter and the best for Gaussian noise is an adaptive filter, but for retinal image without noise the Gaussian filter is superior, to get more accurate results the performance of five filtering methods was tested using retinal images with different noises level (Tables 4 & 5).

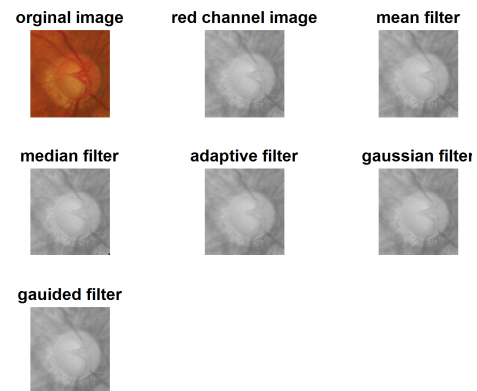


Figure 2. Different filters applied in glaucoma image show: the original image, mean, median, adaptive, Gaussian and guided filters..

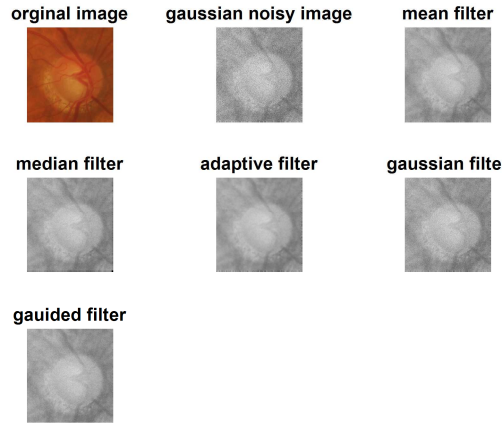


Figure 3. Different filters applied in Gaussian noisy glaucoma image show: the original image, mean, median, adaptive, Gaussian and guided filters..

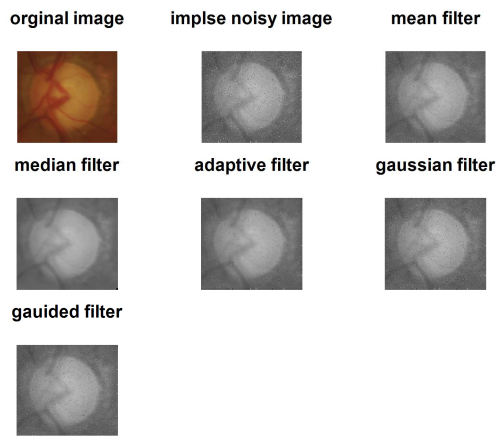


Figure 4. Different filters applied in (salt& paper) noisy glaucoma image show: the original image, mean, median, adaptive, Gaussian and guided filters.

Table 1. Performance evaluation of retinal image with Gaussian noise (density = 0.05) using spatial filters.

| Filters Name | MSE | PSNR | SNR | SSIM |
|-----------------|---------|-------|-------|------|
| Adaptive filter | 0.00026 | 36.16 | 31.42 | 0.90 |
| Guided filter | 0.00073 | 31.36 | 26.62 | 0.62 |
| Gaussian filter | 0.0021 | 26.87 | 22.13 | 0.36 |
| Mean filter | 0.00058 | 32.38 | 27.65 | 0.70 |
| Median filter | 0.00040 | 33.96 | 29.23 | 0.81 |

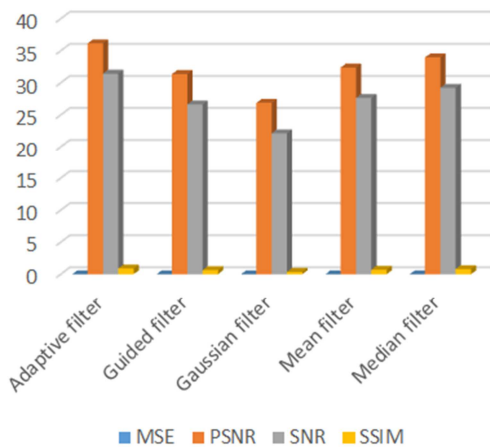


Figure 5. Bar chart show the comparison between the different filters types applied to image corrupted by Gaussian noise.

Table 2. Performance evaluation of retinal image using spatial filters.

| Filters Name | MSE | PSNR | SNR | SSIM |
|-----------------|---------|-------|-------|------|
| Adaptive filter | 6.7E-05 | 42.60 | 37.87 | 0.95 |
| Guided filter | 4.4E-05 | 44.18 | 39.45 | 0.96 |
| Gaussian filter | 3.0E-06 | 56.17 | 51.44 | 1.00 |
| Mean filter | 2.2E-05 | 47.57 | 42.83 | 0.98 |
| Median filter | 4.9E-05 | 43.58 | 38.84 | 0.97 |
| Adaptive median | 0.90 | 50.04 | 45.31 | 0.99 |

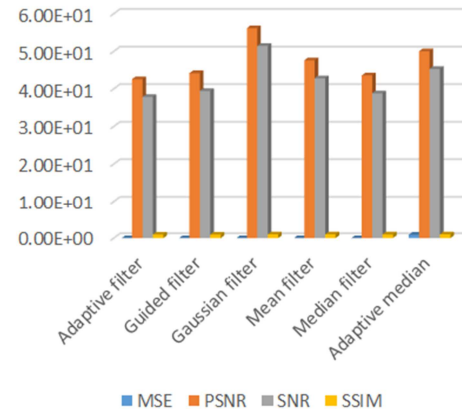


Figure 6. Bar chart shows the comparison between the different filters types applied to the original image.

Table 3. Performance evaluation of retinal image with salt & pepper noise (Density = 0.02) using spatial filters.

| Filters Name | MSE | PSNR | SNR | SSIM |
|-----------------|----------|-------|-------|------|
| Adaptive filter | 0.00093 | 30.36 | 25.63 | 0.80 |
| Guided filter | 0.0024 | 26.24 | 21.51 | 0.61 |
| Gaussian filter | 0.0023 | 26.35 | 21.62 | 0.59 |
| Mean filter | 0.00066 | 31.84 | 27.11 | 0.75 |
| Median filter | 4.96E-05 | 43.48 | 38.75 | 0.97 |

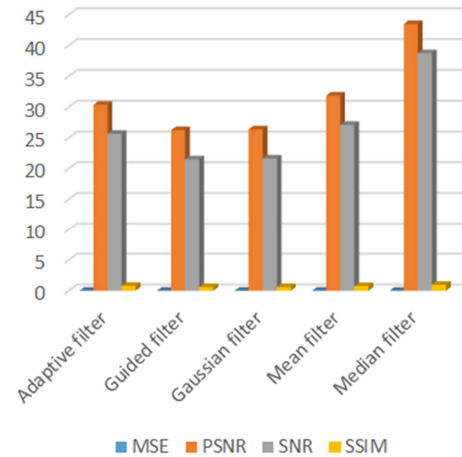


Figure 7. Bar chart shows the comparison between the different filters types applied to the original image corrupted by salt & pepper noise.

Table 4. PSNR of retinal image with different densities of salt & pepper noise using spatial filters.

| Salt & pepper Noise | 10% | 20% | 30% | 40% | 50% |
|------------------------|-------|-------|-------|-------|-------|
| Adaptive median filter | 50.05 | 49.08 | 47.77 | 46.41 | 44.97 |
| adaptive filter | 26.57 | 24.50 | 22.86 | 21.42 | 20.14 |
| Guided Filter | 17.70 | 13.87 | 11.73 | 10.26 | 9.15 |
| Gaussian filter | 19.32 | 16.25 | 14.43 | 13.12 | 12.10 |
| Mean filter | 24.70 | 21.40 | 19.37 | 17.85 | 16.64 |
| Median Filter | 39.51 | 34.16 | 31.08 | 28.52 | 24.55 |

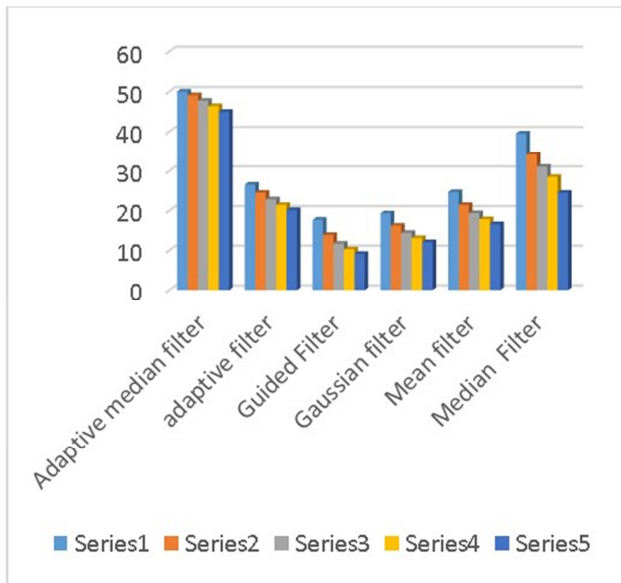


Figure 8. Bar chart shows results of fundus images filtration at different level of (Salt & Pepper) Noises.

Table 5. PSNR of retinal image with A different densities of Gaussian noise using spatial filters.

| Gaussian Noise | 10% | 20% | 30% | 40% | 50% |
|------------------------|-------|-------|-------|------|------|
| Adaptive median filter | 18.53 | 13.89 | 10.99 | 9.17 | 8.09 |
| adaptive filter | 20.08 | 14.36 | 11.23 | 9.34 | 8.22 |
| Guided filter | 19.17 | 14.13 | 11.15 | 9.30 | 8.21 |
| Gaussian filter | 18.71 | 13.99 | 11.08 | 9.27 | 8.19 |
| Mean filter | 19.73 | 14.27 | 11.19 | 9.32 | 8.21 |
| Median filter | 19.79 | 14.13 | 10.98 | 9.07 | 7.99 |

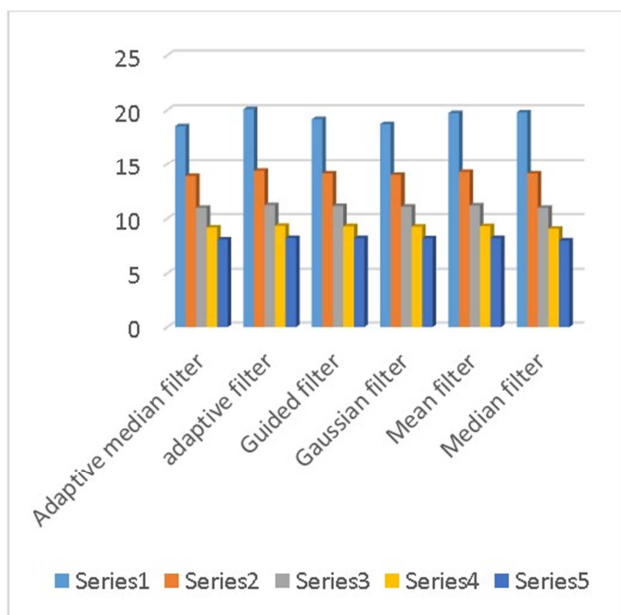


Figure 9. Bar chart shows results of fundus images filtration at the different level of (Gaussian) Noises.

4. Conclusion

In conclusion, six spatial filters applied to (RIM-ONE) fundus images database which, contain 169 images and their

performance are compared to each other based on three parameters: mean squared error (mse), peak signal noise ratio (psnr) and structural similarity (ssim), our experiments have shown that the best performance founded for impulse noise is an adaptive median filter and for Gaussian noise is an adaptive filter. The novelty of this paper discussed two types of noises present in the fundus images and also discussed different types of filters which are used to remove these noises to increase the quality of the resulting images, which can be implemented to the CAD system.

Future work will be to evaluate other image filters or combinations of them to make the image filtering assessment more robust and accurate.

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