A COMPARISON STUDY FOR IMAGE DENOISING

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Image denoising is the detection and removal of outliers in a image. A measured analog signal is affected by both the device from which the measurement is performed and the noise from the environment. Various types of noise are available. With the developed noise reduction methods, it is tried to eliminate the existing noise. In this study, Bandelet Transform and Bilateral Filter denoising methods are compared. Both methods have been used to eliminate noise of different types and different rates added to the benchmark and retina images. Bandelet transform is performed for both hard and soft threshold. Peak Signal-to-Noise Ratio, Mean Squared Error, Mean Structural Similarity and Feature Similarity Index are used as a comparison method.

Key words: Bandelet transform, Bilateral filter, Image denoising

1. Introduction

Today digital images are used in many areas such as intelligent traffic surveillance, medicine, astronomy, satellite television systems, etc. With the increasing need for digital images, denoising has gained importance. Noises cause distortion of spatial resolution in an image and reduce its contrast. Therefore, it negatively affects the edge properties of the image. Processes on noisy images can cause erroneous results. For example, the noise makes difficult to detect tumors and lesions. Thus, denoising must be applied before image analysis.

The images taken with sensors or cameras are usually exposure to noise. No matter how good the cameras are, there is always a need for image enhancement to improve their performance. Noises can result from the device, a data collection process, transmission, compression, environment conditions, etc. [1, 2].

The types of noise occurring in the image are varied. Gaussian Noise, Random Noise, Salt and Pepper Noise, Poisson Noise, Speckle Noise, etc. are general noise types [3]. Different types of noise occur in different imaging applications. For example, in the stages of image acquisition or transmission, quantum noise in X-rays and nuclear imaging, speckle noise in ultrasound imaging, and Rician noise in magnetic resonance imaging occur [4]. The structure of the noises is completely different from each other. Therefore, denoising methods can give good results in some filters and bad results in others. In this study, two denoising methods are compared by using three different noise types.

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Although there are many studies [4-11] that have been developed to denoising, most algorithms are not yet at the desired level [12]. Wavelet-based methods have good results in image denoising due to their sparseness and multiple resolution structure. Therefore, many wavelet based algorithms have been developed [13].

Image denoising is the common problem in image processing. Therefore, so much work has been done for image denoising. Zhang, et al. [14] investigated how a high-quality image can be reconstructed from a high-resolution and high-noise astronomical image. For this purpose 2G-bandelet denoising compressed sensing is proposed. As a result, a fast algorithm that preserves more image details and textures is created. Wang and Gao [15] used the second-generation Bandelet Transform (BT) and non-subsampled contourlet transform as a hybrid. The new denoising method performed better performance than the other two transform. Hazavei and Shahdoosti [16] proposed new multiresolution image denoising method using Bilateral Filter (BF) and complex wavelet thresholding. The advantages of both filters are combined. Experiments on real images showed the effectiveness. He, et al. [17] presented a new retinal image denoising approach that could preserve the details of the retinal vessels while removing image noise. The filter technique used combines the advantages of both BF and matched filter which employs the Gaussian-shape of the cross-section of the vessel. The results showed that this hybrid method was very successful. Finally, in another study by Ceylan and Ozturk [18] a similar performance comparison study was carried out using different denoising methods such as ridgelet, tetrolet, wavelet and curvelet. Deoising methods were evaluated according to the comparison results.

In this study, denoising was applied to the retina and five benchmark images. BT, which is one of the multiple resolution methods, was used with hard and soft thresholding methods which are the most popular threshold methods. Besides this transform, a BF was used to protect the edges and perform a non-linear transformation. The performances of the two methods were compared on three different types of noise.

2. Methodology

2.1. Bandelet Transform

BT proposed by Pennec and Mallat [19] is a transformation adapted to the geometric content of the image. In wavelet-based methods, the same texture values in the image have different directions. To solve this problem, geometric regularity is achieved by using Bandeletization.

BT uses the anisotropic regularity of natural images by creating orthogonal vectors with the direction in which the function has the maximum regularity. BT is a self-adapting multidimensional geometry analysis method that takes advantage of the recognized geometric information of images compared to non-adaptive algorithms such as curvelet and contourlet transformations. The geometric redundancy of an image is removed by bandeletization. In this way, the wavelet transform coefficients are adapted to the image geometry to capture the singularities of the image edges. [20, 21].

2.2. Bilateral Filter

BF, an alternative to wavelet-based denoising methods, was proposed by Tomasi and Manduchi [22]. Unlike other conventional filters, in BF, both spatial and density information between a point and adjacent points are considered. BF takes the weighted totals of local neighborhood pixels. Each pixel is replaced by the weighted average of its neighbors. The weights are determined to depend on both the
Spatial distance and the intensity distance. Thus, the edges are protected during noise cancellation [23, 24].

3. Application and Results

In this study, five benchmark images and 40 fundus images taken from the DRIVE dataset [25] were used. The used benchmark images and some fundus images are shown in Figure 1. First, Random, Gaussian and Rician noises were added to these images respectively (sigma = 5, 10, 15 for Random noise; signal-to-ratio (SNR) = 3, 5, 10 for Gaussian and Rician noise). Then, these noises were removed by BT and BF.

A thresholding process was applied to the detail coefficients obtained by BT. In this study, hard and soft thresholding methods were used. After the threshold value was applied, reconstruction was performed. The threshold $T$ is calculated as follows:

$$T = \sigma \sqrt{2 \log(M)}$$ (1)

### Table 1. Denoising performance results of fundus images

| Type of Noise | Noise Ratio | Evaluation Criteria | Bandelet-Hard | Bandelet-Soft | Bilateral Filter |
|---------------|-------------|---------------------|---------------|---------------|----------------|
| Random        | Sigma=5     | PSNR | 38.9224 | 34.4843 | 35.7433 |
|               |             | MSE 8.3338 | 23.1562 | 17.5101 |
|               |             | MSSIM 0.6696 | 0.4798 | 0.3567 |
|               |             | FSIM 0.9883 | 0.9248 | 0.9148 |
|               | Sigma=10    | PSNR 32.9028 | 28.2764 | 32.5224 |
|               |             | MSE 33.3276 | 96.7056 | 36.4667 |
|               |             | MSSIM 0.4799 | 0.2752 | 0.3615 |
|               |             | FSIM 0.9549 | 0.7915 | 0.9166 |
|               | Sigma=15    | PSNR 29.3756 | 24.6809 | 29.8126 |
|               |             | MSE 75.0805 | 221.3092 | 67.9410 |
|               |             | MSSIM 0.3630 | 0.1839 | 0.3696 |
|               |             | FSIM 0.9085 | 0.6764 | 0.9198 |
| Gaussian      | Snr=3       | PSNR 17.3931 | 15.2594 | 19.6052 |
|               |             | MSE 1247.3080 | 2038.7836 | 769.5456 |
|               |             | MSSIM 0.3919 | 0.3262 | 0.4860 |
|               |             | FSIM 0.0400 | 0.0301 | 0.0481 |
|               | Snr=5       | PSNR 19.3243 | 17.1597 | 22.5609 |
|               |             | MSE 800.4200 | 1316.5242 | 394.6266 |
|               |             | MSSIM 0.0532 | 0.0393 | 0.0709 |
|               |             | FSIM 0.4526 | 0.3799 | 0.5932 |
|               | Snr=10      | PSNR 259.5216 | 434.9683 | 57.1614 |
|               |             | MSE 10006 | 0.0775 | 0.1816 |
|               |             | MSSIM 0.6157 | 0.5327 | 0.8604 |
|               |             | FSIM 0.6157 | 0.5327 | 0.8604 |
| Rician        | Snr=3       | PSNR 38.6165 | 26.6154 | 37.6522 |
|               |             | MSE 8.9420 | 147.1538 | 11.4536 |
|               |             | MSSIM 0.4774 | 0.1643 | 0.3648 |
|               |             | FSIM 0.9562 | 0.6947 | 0.9177 |
|               | Snr=5       | PSNR 34.2520 | 25.8929 | 37.0590 |
|               |             | MSE 24.4282 | 172.4614 | 13.0325 |
|               |             | MSSIM 0.3288 | 0.1405 | 0.3723 |
|               |             | FSIM 0.9018 | 0.6703 | 0.9233 |
|               | Snr=10      | PSNR 28.0683 | 23.9843 | 33.3060 |
|               |             | MSE 101.4507 | 263.6581 | 30.4246 |
|               |             | MSSIM 0.1743 | 0.1022 | 0.3263 |
|               |             | FSIM 0.7629 | 0.6080 | 0.9362 |

Performance was compared with both methods after the noise was removed. Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Mean Structural Similarity (MSSIM) and Feature Similarity
Index (FSIM) metrics were used as comparison criteria. The results of Retina and Benchmark images are shown in Table 1 and Table 2.

![Image](https://example.com/image.jpg)

**Figure 1. The images used in the application**

| Type of Noise | Noise Ratio | Evaluation Criteria | Bandelet-Hard | Bandelet-Soft | Bilateral Filter |
|---------------|-------------|---------------------|---------------|--------------|-----------------|
| Sigma=5       |             | PSNR                | 38,9197       | 34,8545      | 31,4374         |
|               |             | MSE                 | 8,3390        | 21,2700      | 48,1022         |
|               |             | MSSIM               | 0,9394        | 0,8588       | 0,7156          |
|               |             | FSIM                | 0,9960        | 0,9778       | 0,9073          |
| Sigma=10      |             | PSNR                | 32,9062       | 28,6082      | 29,8290         |
|               |             | MSE                 | 33,3014       | 89,6368      | 68,7643         |
|               |             | MSSIM               | 0,8593        | 0,7227       | 0,7119          |
|               |             | FSIM                | 0,9851        | 0,9248       | 0,9067          |
| Sigma=15      |             | PSNR                | 29,3811       | 24,9829      | 28,0706         |
|               |             | MSE                 | 74,9854       | 206,5270     | 102,2293        |
|               |             | MSSIM               | 0,7935        | 0,6233       | 0,7105          |
|               |             | FSIM                | 0,9694        | 0,8696       | 0,9076          |
| Sigma=10      | Snr=3       | PSNR                | 17,3997       | 14,8921      | 19,4050         |
|               |             | MSE                 | 228,4930      | 2173,6538    | 784,7663        |
|               |             | MSSIM               | 0,2675        | 0,1881       | 0,3044          |
|               |             | FSIM                | 0,6415        | 0,5648       | 0,7055          |
| Sigma=15      | Snr=3       | PSNR                | 19,2674       | 16,7403      | 21,9790         |
|               |             | MSE                 | 800,9177      | 1423,5575    | 432,6751        |
|               |             | MSSIM               | 0,3257        | 0,2480       | 0,3767          |
|               |             | FSIM                | 0,6943        | 0,6192       | 0,7744          |
| Sigma=10      | Snr=5       | PSNR                | 24,1006       | 21,5181      | 27,9438         |
|               |             | MSE                 | 263,5003      | 475,8568     | 105,6665        |
|               |             | MSSIM               | 0,4874        | 0,4105       | 0,5881          |
|               |             | FSIM                | 0,8121        | 0,7496       | 0,8987          |
| Sigma=15      | Snr=5       | PSNR                | 38,5874       | 25,7080      | 31,9966         |
|               |             | MSE                 | 9,0021        | 178,5469     | 42,5126         |
|               |             | MSSIM               | 0,8617        | 0,5664       | 0,7191          |
|               |             | FSIM                | 0,9844        | 0,8435       | 0,9086          |
| Sigma=10      | Snr=5       | PSNR                | 34,1621       | 25,1344      | 31,6675         |
|               |             | MSE                 | 24,9396       | 203,2743     | 45,8304         |
|               |             | MSSIM               | 0,7735        | 0,5310       | 0,7194          |
|               |             | FSIM                | 0,9623        | 0,8323       | 0,9091          |
| Sigma=15      | Snr=10      | PSNR                | 34,1621       | 25,1344      | 31,6675         |
|               |             | MSE                 | 24,9396       | 203,2743     | 45,8304         |
|               |             | MSSIM               | 0,7735        | 0,5310       | 0,7194          |
|               |             | FSIM                | 0,9623        | 0,8323       | 0,9091          |
| Sigma=10      | Snr=10      | PSNR                | 28,1726       | 23,4804      | 30,3140         |
|               |             | MSE                 | 99,0426       | 295,1275     | 62,1657         |
|               |             | MSSIM               | 0,6165        | 0,4734       | 0,6862          |
|               |             | FSIM                | 0,8964        | 0,7988       | 0,9136          |
4. Conclusion

In this study, an image denoising application was performed comparing the performance of BT and BF. As shown in Table 1 and Table 2, the performance of denoising methods varies at different noise types and different images. In terms of image difference, BF showed better results in fundus images. In the denoising application performed with BT, similar results were obtained in both image types. When examined in terms of noise type, BF was better in both image types in Gaussian noise. BT was generally better in case of random and rician noise. However, as the noise ratio increases, the BF has performed better image denoising.

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