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A COMPARISON STUDY FOR IMAGE DENOISING

Muhammet Fatih ASLAN[1*], Akif DURDU[2], Kadir SABANCI[3]

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.

[1]Department of Electrical&Electronics Engineering, Karamanoglu Mehmetbey University, Karaman, Turkey, (mfatihaslan@kmu.edu.tr) http://orcid.org/0000-0001-7549-0137

[2]Department of Electrical&Electronics Engineering, Konya Techical University, Konya, Turkey, (adurdu@ktun.edu.tr) http://orcid.org/0000-0002-5611-2322

[3]Department of Electrical&Electronics Engineering, Karamanoglu Mehmetbey University, Karaman, Turkey, (kadirsabanci@kmu.edu.tr) http://orcid.org/0000-0003-0238-9606

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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 Flter (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:

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

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	0,0400	0,0301	0,0481
		FSIM	0,3919	0,3262	0,4860
	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	24,2172	21,9646	30,9685
		MSE	259,5216	434,9683	57,1614
		MSSIM	0,1006	0,0775	0,1816
		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.

Figure 1. The images used in the application

Table 2. Denoising performance results of benchmark images

Type of Noise	Noise Ratio	Evaluation Criteria	Bandelet-Hard	Bandelet-Soft	Bilateral Filter
Random	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
Gaussian	Snr=3	PSNR	17,3997	14,8921	19,4050
		MSE	1228,4930	2173,6538	784,7663
		MSSIM	0,2675	0,1881	0,3044
		FSIM	0,6415	0,5648	0,7055
	Snr=5	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
	Snr=10	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
Rician	Snr=3	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
	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
	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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