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Optimum Image Filters for Various Types of Noise

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Abstract

In this paper, the quality performance of several filters in restoration of images corrupted with various types of noise has been examined extensively. In particular, Wiener filter, Gaussian filter, median filter and averaging (mean) filter have been used to reduce Gaussian noise, speckle noise, salt and pepper noise and Poisson noise. Many images have been tested, two of which are shown in this paper. Several percentages of noise corrupting the images have been examined in the simulations. The size of the sliding window is the same in the four filters used, namely 5x5 for all the indicated noise percentages. For image quality measurement, two performance measuring indices are used: peak signal-to-noise ratio (PSNR) and structural similarity (SSIM). The simulation results show that the performance of some specific filters in reducing some types of noise are much better than others. It has been illustrated that median filter is more appropriate for eliminating salt and pepper noise. Averaging filter still works well for such type of noise, but of less performance quality than the median filter. Gaussian and Wiener filters outperform other filters in restoring mages corrupted with Poisson and speckle noise.

Keywords: *gaussian noise, speckle noise, poisson noise, salt & pepper noise, image filtering*

1. Introduction

Image processing is concerned of changing characteristics of images to improve their qualities. This includes various areas such as noise reduction, image enhancement and object recognition. In image restoration in particular, images are usually corrupted by noise during image acquisition and transmission. For example, images captured by today's cameras typically include some kind of noise or blur. There are several types of noise such as Poisson noise (also known as photon noise), salt and pepper noise (also known as impulse noise or spike noise), Gaussian noise (also known as electronic noise) and speckle noise (also known as multiplicative noise). In reducing these types of noise, numerous filters have been proposed by researchers such as Wiener filter, Gaussian filter, median filter and averaging filter.

In [1], the proposed model to recover images corrupted by Poisson noise is based on sparse representations of images where an alternating minimization scheme together with variable splitting have been used to solve the resulted optimization problem. In [2], properties of variance stabilization have been used in images to estimate unknown Poisson noise parameters.

The proposed algorithm in [3] for Poisson noise reduction is based on alternating direction optimization method. A fast and effective method is proposed in [4] to solve a Poisson-modified total variation model in which a large time step is used in discretizing the gradient descent flow. In [5], the Poisson-distributed measurement noise components are included in the proposed filter that is based on minimum-variance. In [6], the proposed work for recovering images corrupted by Poisson noise is based on confocal microscopy typically used for 3-D imaging of biological living specimens which produce images with high resolution. The Poisson noise is reduced through the method proposed in [7] using the Anscombe variance stabilizing transform.

A new quaternion filter for restoring color images corrupted with Gaussian noise is introduced in [8] based on a tight bound optimization of the quaternion mean square error (MSE) between the resultant (restored) image and the noise-free one. A fuzzy method based on weighted averaging is proposed in [9] to reduce mixed impulsive and Gaussian noise in color images. The method introduced in [10] is based on singular values to estimate the noise level of

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images corrupted with Gaussian noise. In [11], the proposed method for restoring images corrupted with Gaussian-impulse mixed noise is based on minimizing an objective function that includes a content-dependent fidelity term. In [12], a method is proposed to reduce Poisson-Gaussian noise mixture based on optimization of a linear expansion of thresholds. The introduced method in [13] works for mages corrupted with impulse noise as well as for those corrupted by impulse-Gaussian mixed noise. This method is based on both a modified total variation minimization scheme and median filtering.

In [14], the proposed method is based on image subspaces to reduce speckle noise from synthetic aperture radar (SAR) images. Various multiscale nonlinear thresholding methods for elimination of ultrasound speckle noise is proposed in [15]. The method introduced in [16] uses an adaptive data-driven exponential operator that is based on wavelet coefficients of the ultra sound images to reduce the effects of speckle noise. A generalized framework based on Bayesian nonlocal means is proposed in [17] to reduce speckle noise from synthetic aperture radar images corrupted with multiplicative speckle noise. The proposed scheme in [18] is based on Gamma distribution to improve quality of ultrasound images corrupted with speckle noise.

An iterative algorithm in which two decisions are required in each iteration to detect impulsive noisy pixels is proposed in [19]. Many two-stage algorithms for filtering of images corrupted particularly with impulse noise are proposed [20-25] where detection of noisy pixels is carried out in the first stage and reduction of this noise is accomplished in the second. A comprehensive overview of image filtering schemes and algorithms is introduced in [26]. This paper is mainly concerned with measuring the quality of performance of these filters in removing some types of noise, and finding the most optimum imaging filter, in terms of eliminating each type of such noises, using two performance measuring indices.

2. Research Method

The typical two dimensional (2-D) filters that are commonly used in image filtering techniques are the median filter, averaging (mean) filter, Gaussian filter and Wiener filter. In the median filter, the processed pixel is replaced by the median value of its mxn neighborhood (mxn is the size of the sliding window or kernel). In contrast, the averaging filter replaces each pixel at the center of the sliding window by the average (mean) value of its mxn neighborhood.

On the other hand, the Gaussian filter replaces each processed pixel at the center of the kernel by another value based on the Gaussian (normal) distribution with more weights for pixels close to the center of the kernel and less weights in the outward direction from the center of the sliding window. The Wiener filter is an adaptive filter that replaces each processed pixel at the center of the kernel by a computed value based on statistical approach (estimates of local mean and variance around).

2.1. Image Quality Metrics

Numerous performance measuring indices are typically used by researchers to evaluate the quality of the image filtering techniques, i.e., the similarity or closeness between the filtered (de-noised) image and the original uncorrupted image, and the capability of preserving image edges and details. In this paper, peak signal to noise ratio (PSNR) and the structural similarity (SSIM) are used. These performance measuring quality metrics are defined as follows.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M} \sum_{j=1}^{N}\left(R_{i,j} - G_{i,j}\right)^2 \tag{1}$$

$$PSNR = 10\, log_{10}\left(\frac{(L-1)^2}{MSE}\right) \text{ dB} \tag{2}$$

where MSE is the mean squared error between the restored resultant image (R) and the original image(G), $L = 2^n$ and n is the bit depth or the number of bits in each pixel (for 8-bit images, for example, n=8 and L=256), *M* and *N* are the total number of pixels in the horizontal and vertical dimensions of the image (rows and columns of the matrix representing the image), and $R_{i,j}$ and $G_{i,j}$ are the pixel values in the $(i,j)th$ locations of the filtered image and the original clean image, respectively.

The structural similarity (SSIM) index is a full reference metric that is commonly used to measure the similarity between two images. In other words, it is used for measuring the quality of the restored image with the original clean image used as a reference. Unlike peak signal-to-noise ratio (PSNR), the SSIM metric is based on visible structures in the image. It is claimed to be an improvement over other traditional metrics such as PSNR and MSE, which might not be consistent with human eye perception. It combines the luminance, contrast, and structure of the images into one single performance metric. In particular, the SSIM quality metric between two image signals x and y is a function of three components: luminance (*l*), contrast (*c*), and structure (*s*), where the luminance is a function of the mean intensities of these two images, the contrast is a function of their standard deviations, and the structure is a function of their covariance. The SSIM quality index can be defined as follows [27].

$$SSIM(x,y) = [l(\mathrm{x},\mathrm{y})]^{\propto}.[c(\mathrm{x},\mathrm{y})]^{\beta}.[s(\mathrm{x},\mathrm{y})]^{\gamma}$$

where; $l(\mathrm{x},\mathrm{y})$ is the luminance comparison function defined as

$$l(\mathrm{x},\mathrm{y}) = \frac{2\mu_x\mu_y+C_1}{{\mu_x}^2+{\mu_y}^2+C_1} \quad (4)$$

μ_x and μ_y are the mean values of the x and y images, respectively, and C_1 is a constant included to avoid instability when $({\mu_x}^2 + {\mu_y}^2)$ is very close to zero.
$c(\mathrm{x},\mathrm{y})$ is the contrast comparison function defined as

$$c(\mathrm{x},\mathrm{y}) = \frac{2\sigma_x\sigma_y+C_2}{{\sigma_x}^2+{\sigma_y}^2+C_2} \quad (5)$$

σ_x and σ_y are the standard deviation values of the x and y images, respectively, and C_2 is a constant included to avoid instability when $({\sigma_x}^2 + {\sigma_y}^2)$ is very close to zero.
$s(\mathrm{x},\mathrm{y})$ is the structure comparison function defined as

$$s(\mathrm{x},\mathrm{y}) = \frac{\sigma_{xy}+C_3}{\sigma_x.\sigma_y+C_3} \quad (6)$$

σ_{xy} is the covariance of the x and y images, and C_3 is a constant included to avoid instability when the product $(\sigma_x.\sigma_y)$ is very close to zero. The parameters α,β,γ are chosen to adjust the relative importance of the three components indicated above. If we choose $\alpha=\beta=\gamma=1$, and $C_3 = C_2/2$, the SSIM is simplified to

$$SSIM(\mathrm{x},\mathrm{y}) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{({\mu_x}^2+{\mu_y}^2+C_1)({\sigma_x}^2+{\sigma_y}^2+C_2)} \quad (7)$$

3. Results and Analysis

Simulations in this paper were performed in MATLAB using many images two of which are shown in the results in this section, namely Jet Plane image (512x512) and Walk Bridge image (512x512) as shown in Figure 1 and Figure 2, respectively. Wiener, Gaussian, median and averaging filters have been used to reduce Gaussian, Poisson, speckle and impulse noise. PSNR in decibels (dB) and SSIM were used to measure the quality of the filtered image after being corrupted by numerous types of noise with different densities (percentages). The size of the sliding window was chosen to be 5x5 for all filters being used. This size in particular has been chosen because it results in better performance for the maximum level of noise used in this paper (better performance with minimum blur).

In Tables 1 and 2, the Jet Plane and Walk Bridge images, respectively, are corrupted with Gaussian noise of zero mean and different noise variances that range from 0.05 to 0.25. The two tables show that the four filters have comparable results in removing Gaussian noise with a little better performance quality of the averaging filter.

Figure 1. Jet plane image

Figure 2. Walk bridge image

Table 1. PSNR in dB and SSIM of restored Jet Plane Image after being Corrupted with Gaussian Noise of Zero Mean and different values of variances Using Several Filters (V=noise variance)

Jet Plane image corrupted with Gaussian noise			Wiener Filter (5x5)		Gaussian Filter (5x5)		Median Filter (5x5)		Averaging Filter (5x5)	
V	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
0.05	14.15	0.1194	23.41	0.5310	23.71	0.4736	23.05	0.4541	23.38	0.5674
0.10	11.78	0.0778	20.77	0.4120	20.84	0.3642	20.67	0.3383	21.21	0.4671
0.15	10.53	0.0596	19.30	0.3558	19.18	0.3067	19.29	0.2780	19.76	0.4102
0.20	9.75	0.0499	18.32	0.3235	18.07	0.2740	18.26	0.2428	18.69	0.3741
0.25	9.22	0.0442	17.63	0.3026	17.31	0.2516	17.52	0.2195	17.96	0.3484

Table 2. PSNR in dB and SSIM of restored Walk Bridge Image after being corrupted with Gaussian Noise of Zero Mean and different values of Variances Using Several Filters (V=noise variance)

Walk Bridge image corrupted with Gaussian noise			Wiener Filter (5x5)		Gaussian Filter (5x5)		Median Filter (5x5)		Averaging Filter (5x5)	
V	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
0.05	13.80	0.2082	21.77	0.4754	22.17	0.5259	21.13	0.4120	21.72	0.4554
0.10	11.44	0.1309	20.08	0.3877	20.13	0.4195	19.56	0.3353	20.46	0.3910
0.15	10.31	0.0996	19.06	0.3409	18.90	0.3617	18.42	0.2880	19.52	0.3513
0.20	9.60	0.0826	18.47	0.3159	18.09	0.3218	17.59	0.2533	18.82	0.3196
0.25	9.08	0.0697	17.85	0.2880	17.45	0.2947	16.85	0.2246	18.20	0.2987

In Tables 3 and 4, the Jet Plane and Walk Bridge images, respectively, are corrupted with speckle noise of zero mean and different noise variances ranging from 0.05 to 0.25. As shown in these two tables, the Gaussian and Wiener filters, in order, have the best performance in removing the speckle noise while the median filter has the worst results in removing such type of noise. It is worth mentioning that the Wiener filter adaptively restores the original image based on the local image variance by performing little smoothing when the variance is large and more smoothing when the variance is small. On the other hand, the Gaussian filter works by convolving the 2-D Gaussian distribution function with the noisy image. It is somewhat similar to the averaging filter, however, central pixels in the Gaussian filter have a higher weighting than those on the periphery.

In Tables 5 and 6, the Jet Plane and Walk Bridge images, respectively, are corrupted with Poisson noise of different scales ranging from 1×10^{9} to 1×10^{11}. These two tables show that for lower quantities of noise, the Wiener and Gaussian filters have the best performance. For higher values of this noise, the median filter has the worst performance and the other filters have almost comparable results.

Table 3. PSNR in dB and SSIM of restored Jet Plane Image After being Corrupted with Speckle Noise of Zero Mean and Different Values of Noise Variance Using Several Filters (V=noise variance)

Jet Plane image corrupted with speckle noise			Wiener Filter (5x5)		Gaussian Filter (5x5)		Median Filter (5x5)		Averaging Filter (5x5)	
V	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
0 .05	16.53	0.2068	25.75	0.6177	25.92	0.5715	23.40	0.4692	24.49	0.6318
0.10	14.10	0.1465	23.13	0.4996	23.16	0.4670	21.14	0.3688	22.84	0.5505
0 .15	12.65	0.1167	21.29	0.4302	21.29	0.4081	19.71	0.3151	21.46	0.4975
0.20	11.60	0.0966	19.92	0.3879	19.91	0.3644	18.71	0.2788	20.22	0.4566
0.25	10.77	0.0835	18.81	0.3528	18.75	0.3322	17.91	0.2521	19.21	0.4203

Table 4. PSNR in dB and SSIM of Restored Walk Bridge Image after being Corrupted with Speckle Noise of Zero Mean and Different Values of Noise Variance Using Several Filters (V=noise variance)

Walk Bridge image corrupted with speckle noise			Wiener Filter (5x5)		Gaussian Filter (5x5)		Median Filter (5x5)		Averaging Filter (5x5)	
V	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
0.05	19.53	0.5231	23.72	0.5829	25.03	0.7025	22.65	0.5075	22.85	0.5370
0.10	16.70	0.3910	22.06	0.5128	23.65	0.6395	21.53	0.4543	22.28	0.5068
0.15	15.07	0.3176	20.93	0.4684	22.57	0.5944	20.76	0.4156	21.72	0.4829
0.20	13.92	0.2691	20.05	0.4379	21.72	0.5587	20.10	0.3893	21.22	0.4621
0.25	13.05	0.2325	19.43	0.4138	20.98	0.5257	19.53	0.3674	20.72	0.4439

Table 5. PSNR in dB and SSIM of Restored Jet Plane Image after being Corrupted with Poisson Noise of Different Scales Using Several Filters

Jet Plane image corrupted with Poisson noise			Wiener Filter (5x5)		Gaussian Filter (5x5)		Median Filter (5x5)		Averaging Filter (5x5)	
Scale	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
1×10^{9}	31.55	0.7330	33.03	0.8949	32.21	0.9185	29.31	0.8663	26.13	0.8281
5×10^{9}	24.58	0.4473	30.84	0.8432	30.78	0.8336	28.45	0.8002	25.94	0.7929
1×10^{10}	21.57	0.3379	29.33	0.7945	29.51	0.7572	27.61	0.7367	25.71	0.7548
5×10^{10}	14.57	0.1520	24.05	0.5123	24.61	0.4963	23.81	0.4867	24.18	0.5762
1×10^{11}	11.54	0.1000	21.32	0.3824	21.96	0.3816	21.21	0.3562	22.85	0.4669

Table 6. PSNR in dB and SSIM of Restored Walk Bridge Image after being corrupted with Poisson noise of Different Scales Using Several Filters

Walk Bridge image corrupted with Poisson noise			Wiener Filter (5x5)		Gaussian Filter (5x5)		Median Filter (3x3)		Averaging Filter (3x3)	
Scale	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
1×10^{9}	33.48	0.8537	29.58	0.8537	26.90	0.7956	27.07	0.8016	26.31	0.7801
5×10^{9}	26.51	0.7755	28.23	0.8164	26.59	0.7762	26.26	0.7534	25.962	0.7547
1×10^{10}	23.52	0.6643	27.00	0.7747	26.23	0.7543	25.49	0.7099	25.55	0.7279
5×10^{10}	16.51	0.3508	21.97	0.5676	24.14	0.6408	22.01	0.5262	23.22	0.5909
1×10^{11}	13.50	0.2329	19.25	0.4516	22.44	0.5531	19.62	0.4033	21.45	0.4976

In Tables 7 and 8, the Jet Plane and Walk Bridge images, respectively, are corrupted with salt and pepper noise of different percentages varying from 5% to 40%. As depicted in these two tables, the median filter has the superior performance over the other filters in removing this type of noise. It should be noted that the median filter has a better performance in removing salt and pepper noise than the averaging filter since the median value, in general, is much less sensitive to outliers than the average (mean) value.

Table 7. PSNR in dB and SSIM of Restored Jet Plane Image After being Corrupted with Salt & Pepper Noise of Different Densities Using Several Filters (D=noise density)

Jet Plane image corrupted with salt & pepper noise			Wiener Filter (5x5)		Gaussian Filter (5x5)		Median Filter (5x5)		Averaging Filter (5x5)	
D	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
5%	17.94	0.3479	23.33	0.5711	26.72	0.6712	29.31	0.8864	24.66	0.6868
10%	14.93	0.1887	21.41	0.4720	23.96	0.5285	28.51	0.8807	23.30	0.5895
15%	13.13	0.1286	20.36	0.4140	22.09	0.4412	27.73	0.8734	21.99	0.5240
20%	11.91	0.0973	19.51	0.3709	20.55	0.3772	26.58	0.8643	20.84	0.4716
25%	10.95	0.0771	18.73	0.3392	19.37	0.3317	25.44	0.8549	19.77	0.4249
30%	10.17	0.0640	17.98	0.3117	18.28	0.2950	24.63	0.8448	18.82	0.3898
35%	9.45	0.0522	17.21	0.2898	17.41	0.2668	23.83	0.8334	17.99	0.3561
40%	8.90	0.0430	16.61	0.2674	16.53	0.2371	23.08	0.8165	17.11	0.3289

Table 8. PSNR in dB and SSIM of restored Walk Bridge Image After being Corrupted with salt and Pepper Noise of Different Densities Using Several Filters (D=noise density)

Walk Bridge image corrupted with salt & pepper noise			Wiener Filter (5x5)		Gaussian Filter (5x5)		Median Filter (5x5)		Averaging Filter (5x5)	
D	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
5%	18.26	0.5118	22.26	0.5329	24.59	0.6755	24.22	0.6212	22.73	0.5222
10%	15.25	0.3216	20.91	0.4603	22.90	0.5834	24.04	0.6161	22.00	0.4799
15%	13.55	0.2300	20.11	0.4121	21.59	0.5132	23.70	0.6088	21.19	0.4364
20%	12.27	0.1731	19.38	0.3733	20.42	0.4519	23.51	0.6034	20.46	0.4013
25%	11.27	0.1341	18.78	0.3410	19.43	0.4011	23.15	0.5945	19.76	0.3713
30%	10.48	0.1082	18.28	0.3199	18.59	0.3587	22.79	0.5854	19.09	0.3447
35%	9.81	0.0897	17.70	0.2910	17.83	0.3215	22.38	0.5737	18.44	0.3189
40%	9.23	0.0738	17.22	0.2649	17.12	0.2906	21.88	0.5581	17.79	0.2915

4. Conclusion

This paper is mainly focused on measuring the quality of some filters in removing some types of noise and which filter better suits eliminating each type of such noises using some common performance measuring indices. Several filters have been used to restore images corrupted with various types of noise. In particular, Wiener, Gaussian, median and averaging filters have been used to eliminate Gaussian noise, speckle noise, salt and pepper noise and Poisson noise. Simulation results for images corrupted with a wide range of noise quantities have been examined using both peak signal to noise ratio and structure similarity as performance measuring indices using the same size of sliding window. The results show that the four filters have almost comparable performance in eliminating Gaussian noise. The median filter has a superior performance in comparison with other filters in reducing salt and pepper noise, and has the worst performance for other types of noise. Wiener and Gaussian filters show good performance in restoring images corrupted with speckle and Poisson noise.

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