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Salt and Pepper Noise Removal Algorithm by Novel Morpho Filter

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Abstract: In this study, a new decision based morpho filter is proposed for denoising images that are highly corrupted images by salt and pepper noise. The main problem of de-noising is how to keep the poise between degrading image noise and preserving image edge information. Hence, the main aim is to construct a de-noising algorithm which not only eliminate the noises but also preserves image edge information. The algorithm replaces the noisy pixels by morphological operations. Experiments are carried out on benchmark images such as Lena, Barbara, Baboon and peppers. A competitive denoising is achieved in comparison with Standard Median Filter (SMF), Adaptive Median Filter (AMF) and Decision Based Algorithm (DBA).

Key words: Image denoising, salt and pepper, mathematical morphology, impulse noise, median filter

INTRODUCTION

Image de-noising refers to the recovery of a digital image that has been affected by noises. The digital image can be affected by different types of noises. They are salt and pepper noise (Impulse noise), Poisson noise and Additive White Gaussian Noise (AWGN). The Standard Median Filter (SMF) is a non linear digital filter widely used in image processing. SMF is able to remove impulse noise as well as preserve the edges. However, the main drawback is it works only for low noise densities. At high noise densities, the image gets blurred and insufficient noise suppression for small window sizes (Pitas and Venetsanopoulos, 1990; Pomalaza-Racz and Macgillem, 1984). To overcome this, noise detection process is introduced in Adaptive Median Filter (AMF) (Zhang and Karim, 2002), Decision Based Algorithm (DBA) (Florencio and Schafer, 1994) and switching median filters (Eng and Ma, 2001).

A novel Open-Close Sequence (OCS) filter to remove impulse noise in highly corrupted images based on mathematical morphology is presented (Deng *et al*., 2007). The morphological residue detector powerfully determinates the impulse noise with a low percentage error. The OCS filters effectively remove high probability impulse noises. A new concept in impulse noise detection and elimination through primary implicant elimination is developed (Agaian *et al*., 2008). The filtering algorithms are implemented based on logical transform to detect and eliminate the impulse noise.

A highly effective switching-based adaptive weighted mean filter for removing impulse noise from the corrupted image is implemented (Zhang and Xiong, 2009). The directional difference based noise detector can realize accurate noise detection, thus facilitating the prevention of image degradation resulting from the undetected noise pixels and misidentified noise-free pixels. A modified decision based un-symmetric trimmed median filter for high density salt and pepper noise removal is implemented (Esakkirajan *et al*., 2011) that replaces the noisy pixel by trimmed median value when other pixel values, 0'sand 255's are present in the selected window and when all the pixel values are 0'and 255'sec then the noise pixel is replaced by mean value of all the elements present in the selected window.

A new Fuzzy Switching Median filter (FSM) employing fuzzy techniques to de-noise the corrupted image is developed (Toh and Isa, 2010). This mechanism is an extension to the classical switching median filter by employing fuzzy inference mechanism. This filter is able to remove salt-and pepper noise in digital images while preserving image details and textures very well. By incorporating fuzzy reasoning in correcting the detected noisy pixel, the low complexity FSM filter is able to outperform some well known existing salt-and pepper noise fuzzy and classical filters.

A novel two-stage noise adaptive fuzzy switching median filter for salt-and-pepper noise detection and removal is presented (Toh *et al*., 2008). This filter does not

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require any further tuning or training of parameters once optimized. It is able to yield good filtering results with efficient processing time. An effective and accurate algorithm for impulse noise detection is presented (Duan and Zhang, 2010), which consists of two iterations to make the decision as accurate as possible. Two-robust and reliable decision criteria are used for each iteration.

PROPOSED ALGORITHM

The groundwork in the proposed morpho filter is the detection of noisy pixels. The impulse corrupted pixels can take minimum (0) or maximum (255) intensity value. Hence the noisy pixels are identified by checking the pixel intensity values. If the processed pixel has 0 or 255, then the proposed morpho filter is applied to de-noise the processed pixel.

The proposed algorithm replace the noisy pixels by using the morphological dilation filtering technique in which 3×3 structure element is used. Each dilation eight neighbors of the Noisy Pixel (NP) are scanned and tested. If all the neighbor pixels are uncorrupted pixels, then the median value of the neighbor pixel is used to remove the NP. If any neighbor pixels that are found noisy pixels then later dilation are applied to remove the NP. The median value of the uncorrupted neighbor pixel and the uncorrupted pixels from the later dilation is used to remove the NP. Figure 1 shows the position of the dilation pattern applied for the corrupted pixel and Fig. 2 shows the later dilation applied for neighboring pixels.

The proposed algorithm keeps track of noisy pixels in the scan order of left to right and top to bottom. The proposed algorithm is as follows:

Step 1: If the processed pixel N(X, Y) is noisy pixel, then the noisy pixel is replaced by following Step 2. Otherwise the next pixel is considered for the test

Step 2: The dilation pattern for the corrupted pixel is identified by comparing a 3×3 window centered on the noisy pixel with dilation pattern shown in Fig. 1. The numerals in Fig. 1 denote the corresponding later dilation pattern

Case 1: If all the pixels values corresponding to their later dilation pattern are uncorrupted, then the noisy center pixel N (X, Y) is replaced by the median value of the pixels considered

Case 2: If any pixel found noisy, then later dilation is applied based on their corresponding numerals in Fig. 1. Except the black shaded portions in Fig. 2 are the expansion pixels of specific later dilation. The expansion pixels are found for all noisy pixels. The processed pixel N (X, Y) is replaced by the median of all expansion pixels with uncorrupted pixels in the 3×3 window

Step 3: Steps 1 to 2 are repeated until all noisy pixels are de-noised

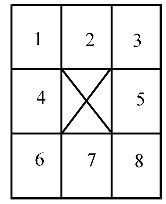

Fig. 1: Dilation pattern for corrupted pixel

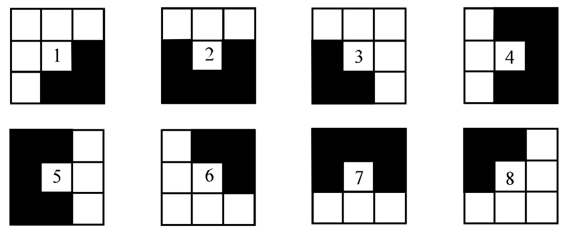

Fig. 2: Later dilation pattern for neighbor pixels

EXPERIMENTAL RESULTS

The de-noising performance of the proposed system is quantitatively evaluated by using Peak Signal to Noise Ratio (PSNR), Image Enhancement Factor (IEF) and Mean Squared Error (MSE). First, salt and pepper noise of variance from 0.1-0.9 is added to the standard benchmark image. Then theses images are filtered by using the proposed decision based morpho filter and the performance measures are calculated. Also the performance of the proposed method is compared with other methods such as Standard Median Filter (SMF), AMF and DBA.

The PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR is most commonly used as a measure of quality of reconstruction in image enhancement. It is most easily defined via the root mean squared error (RMSE) which for two images f (x, y) and $\hat{f}(x,y)$ considering one of images as a noisy approximation of the other. It is defined as:

$$RMSE = \sqrt{\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left[\hat{f}(x,y) - f(x,y)\right]^2} = \sigma_e$$

The PSNR is defined as:

$$PSNR = 10.\log_{10}\frac{(\text{peak} - \text{to} - \text{peak value of the referenced image})^2}{\sigma_e^2}$$

Table 1: PSNR, IEF and MSE for various algorithms for Lena image

	PSNR				IEF				MSE			
Noise (%)	Median filter	AMF	DBA	Proposed approach	Median filter	AMF	DBA	Proposed approach	Median filter	AMF	DBA	Proposed approach
10	36.68	41.63	44.16	44.31	0.94	2.63	5.91	4.80	13.98	4.47	2.49	2.41
20	35.72	39.90	40.68	41.22	1.55	3.80	5.83	4.99	17.42	6.66	5.56	4.91
30	34.65	37.83	38.38	39.29	1.97	3.78	5.48	4.73	22.29	10.72	9.44	7.66
40	33.70	35.95	36.96	38.06	1.97	3.07	4.81	4.65	27.76	16.53	13.08	10.16
50	32.56	33.97	35.64	36.77	1.86	2.45	4.47	4.44	36.10	26.04	17.75	13.69
60	31.38	32.23	34.50	35.84	1.67	1.92	4.10	4.18	47.29	38.93	23.07	16.94
70	30.21	30.66	33.57	34.98	1.42	1.52	3.63	3.94	62.02	55.91	28.60	20.65
80	28.89	29.10	32.11	33.65	1.27	1.29	3.27	3.67	84.02	79.97	40.00	28.04
90	27.80	27.90	30.46	31.13	1.14	1.13	2.52	3.60	107.88	105.50	58.45	50.11

Table 2: PSNR, IEF and MSE for various algorithms for pepper image

	PSNR				IEF				MSE			
Noise (%)	Median filter	AMF	DBA	Proposed approach	Median filter	AMF	DBA	Proposed approach	Median filter	AMF	DBA	Proposed approach
10	38.56	43.89	44.36	45.16	1.49	4.40	3.82	3.47	9.05	2.66	2.39	1.98
20	37.25	41.70	41.84	42.34	2.28	5.36	5.22	4.69	12.25	4.40	4.26	4.25
30	35.89	39.12	39.53	40.22	2.60	4.73	5.34	4.97	16.75	7.96	7.24	6.17
40	34.60	36.70	37.71	38.55	2.53	3.70	5.27	5.07	22.52	13.89	11.02	9.08
50	33.16	34.49	36.53	37.55	2.20	2.75	5.08	5.08	31.39	23.10	14.46	11.42
60	31.71	32.51	35.27	36.66	1.85	2.08	4.61	4.84	43.88	36.50	19.32	14.04
70	30.31	30.70	33.88	35.46	1.52	1.59	4.25	4.61	60.61	55.34	26.64	18.50
80	29.19	29.41	32.63	34.29	1.31	1.32	3.62	4.15	78.27	74.52	35.45	24.22
90	28.08	28.18	30.64	31.51	1.12	1.11	2.87	4.06	101.12	98.90	56.09	45.95

Fig. 3(a-b): Simulation results of different algorithms for 30% noise added to (a) Lena image: Noisy image, median filter, AMF, DBA, proposed approach and (b) Pepper image, noisy image median filter, AMF, DBA, proposed approach

Here, peak to peak value of the referenced image is the maximum pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. The peak signal to noise ratio is calculated from the error using the above equation. The higher the value of the PSNR, the better is the performance of that particular local operator for the noise added. The image enhancement factor is defined by:

$$\text{IEF}=\frac{\left(\sum_{xy}\text{noisy}(x,y)-f(x,y)\right)}{\left(\sum_{xy}\hat{f}(x,y)-f(x,y)\right)}$$

where, noisy is the corrupted image, f is the input image and $\hat{f}$ is the de-noised image. The PSNR, IEF and MSE values for different methods are shown in Table 1 and 2 for Lena and pepper image, respectively. From the table, it is observed that the PSNR of the proposed decision based morpho filter is higher than other methods. Figure 3 and 4 shows the simulation results of different algorithms for 30 and 70% noise added to Lena and pepper image, respectively. Figure 5 shows the simulation results of noise density vs. PSNR for different algorithms. Also the simulation results of noise density vs. IEF and noise density vs. MSE for different algorithms is shown in Fig. 6 and 7, respectively. From the

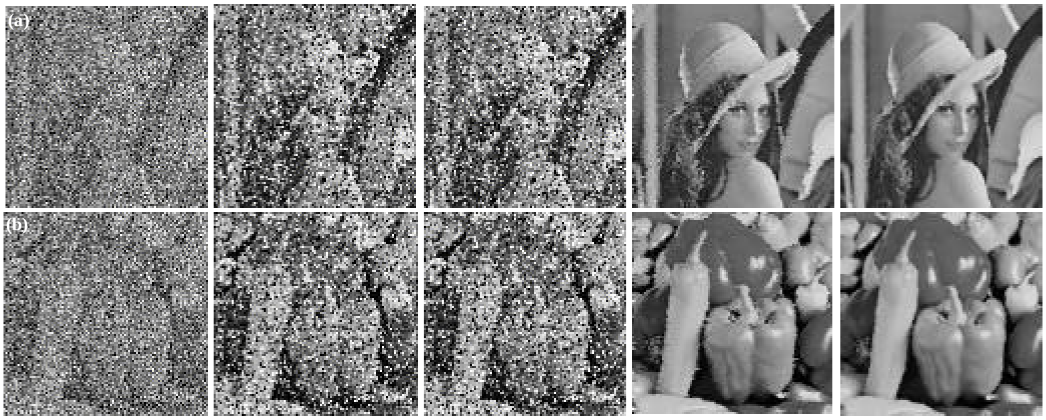

Fig. 4(a-b): Simulation results of different algorithms for 70% noise added to (a) Lena image: Noisy image, median filter, AMF, DBA, proposed approach and (b) Pepper image, noisy image, median filter, AMF, DBA, proposed approach

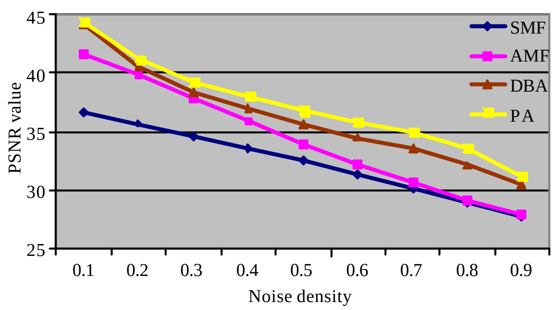

Fig. 5: Simulation results of noise density versus PSNR of Lena for different algorithms

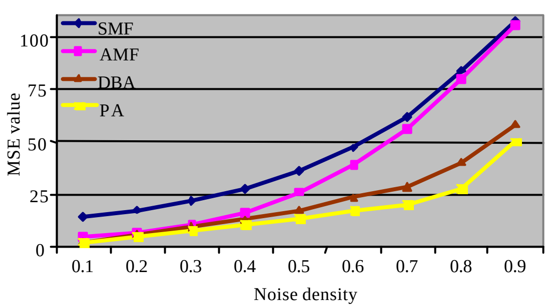

Fig. 6: Simulation results of noise density versus MSE of Lena for different algorithms

Fig. 6, it is noted that IEF of the proposed morpho filter is in between 4 and 5 irrespective of noise density and the IEF of others are decreases as noise density increases.

It is observed from the Table 1 and 2, the performance of the proposed approach is better than SMF, AMF and DBA methods. The PSNR of the proposed approach is approximately minimum 4dB higher than SMF, AMF and DBA methods irrespective of the density of noise present in the given image. Also, the MSE of the proposed approach is lower compared to others. The IEF of the proposed approach is higher than AMF and DBA based approach for those images corrupted by higher density salt and pepper noise.

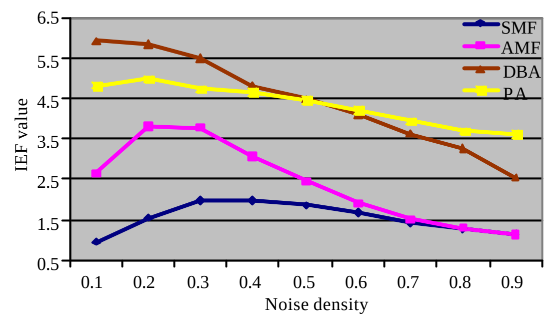

Fig. 7: Simulation results of noise density versus IEF of Lena for different algorithms

CONCLUSION

In this study, a decision based morpho filter is developed for de-noising images that are corrupted by salt and pepper noise. This approach uses morphological dilation to de-noise the noisy pixels. The salt and pepper noise with densities 10-90% is added to the input image and then the noisy pixels are removed by the proposed approach. The proposed filter is tested with benchmark images such as Lena, pepper images. To demonstrate the performance of the proposed approach, three performance metrics PSNR, MSE and IEF of the proposed approach is compared with other state-of-art techniques such as SMF, AMF and DBA. The simulations result shows that the proposed filtering scheme has a very satisfactory denoising property as well as edge and detail preserving at very high noise densities.

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