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Conference Paper in IOP Conference Series Materials Science and Engineering · November 2020

DOI: 10.1088/1757-899X/928/3/032001

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A New Adaptive Filter for Eliminating Salt and Pepper Noise

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Abstract: Salt-and-pepper noise can substantially degrade the appearance of images and make further processing difficult. This paper develops a new filter for eliminating different levels of salt-and-pepper noise efficiently without degrading important image details. The filter uses a variable window size. After identifying distorted pixels, if there is at least one or more undistorted pixels are encountered in the processing window, the updated value of the distorted pixel is calculated by the weighted mean of undistorted pixels when a window size is 3×3 and replaced by the mean value of the undistorted pixels with the highest frequency distribution when a window size is larger. This filter is applied twice in order to sufficiently remove high noise levels. The comparison results with other denoising filters indicate that the developed filter has superior or comparable denoising capability in terms of visual appearance and objective measures.

Keywords: weighted-mean; denoising capability; salt-and-pepper noise; high frequency.

1. INTRODUCTION

Different types of noise can distort images in the acquisition and/or transmission operation. One of the most popular types is the impulse noise. This kind of noise could occur due to camera sensor malfunctions and memory location faults [1]. The impulse noise causes the values of image pixels to be significantly different than those of their neighbors. The well-known categories of impulse noise are fixed-valued (salt-and-pepper) and random-valued. The former noise takes only two values: the maximum and minimum intensity levels. For 8-bit images, the noisy pixels have a minimum value of 0 which like dark spots (pepper) and a maximum value of 255 which like white spots (salt). Several filters have been developed for dealing with impulse



noise in digital images. The standard median filter (MF) is the most common one for this type of noise, which is simple, nonlinear and works well for low noise levels. Because the MF works within a fixed-size window and changes all pixels in the image, it gives unsatisfactory results for high noise levels [2].

Several modifications have been suggested to improve the performance of the MF. A switching operator is used with the median filter to preserve undistorted pixels in images [3]. The idea of switching operator is to detect impulse noise according to a specific condition in order to decide which pixels should be modified. Wang and Zhang [4] applied median filtering with a switching operator progressively over several iterations. This filter is denoted as PSMF. Srinivasan and Ebenezer [5] developed a two-stage decision-based algorithm (DBA). First, the pixels with salt-and-pepper noise are marked. Then, these distorted pixels are updated by a median value within a window of size 3×3 . This algorithm yields artefacts when noise levels are very high. To mitigate this drawback, Esakkirajan et al. [6] introduced a modified decision-based unsymmetric trimmed median filter (MDBUTMF). In this filter, the noisy pixels are replaced by either a trimmed median value of noise-free pixels or by mean value when all pixels in the processing window are noisy. The main weakness of this filter is that it does not give satisfactory results when all pixels inside the window are noisy. Recently, Zhang et al. [7] designed a new impulse noise detection using evidential reasoning and a new adaptive median filter.

The denoising capability of the MF is also improved by adapting the processing window size in accordance with the noise level. Hwang and Haddad [8] developed an adaptive median filter (AMF) in which the processing window size is modified with regards to noise levels. The results of this filter indicate that a window size of 5×5 gave a good result when a noise level was 30% and a window size of 11×11 gave a satisfactory result when a noise level was 70%. Although this filter works adequately for low and medium noise levels, it cannot cope with high noise levels. The center-weighted median filter (CWM) filter [9] and its modified version [10] are also developed. The CWM filter introduced weights to each median filter component such that the central weight is greater than other weights. In [10], the difference between the CWM filter output and the central pixel is used in the detection of noise. Based on a simple threshold operator, the final filter output is selected as either the median value or the central pixel. Kalyoncu et al. [11] proposed an interpolation-based impulse noise removal technique in which a weighted mean value is calculated as a final filter output for each noisy pixel. The weights are computed according to the distance between the surrounding pixels and the primary pixel in adaptive window size. Zhang and Li [12] introduced an adaptive weighted mean filter (AWMF) where the adaptive window is used in order to detect distorted pixels. After that, the distorted pixels are restored using the weighted mean value. Kandemir et al. [13] eliminated the spatial tendency to the center of undistorted pixels via first detecting distorted pixels, then recalibrating the weights for the undistorted pixels and finally replacing the distorted pixels with the weighted mean value. Erkan et al. [14] adopted a new filter (DAMF) for restoring salt-and-pepper noise. First, the distorted image is padded symmetrically. Three window sizes are used and the proper size is chosen depending on local image content. Then, the distorted pixels are modified using the median value of undistorted pixels.

Many filters have been developed using fuzzy set theory [15,16,17,18,19]. Eng and Ma [15] incorporated a novel switching mechanism with a weighted median filter using fuzzy set theory to deal with the weakness of the traditional switching-based median filters. This mechanism has been tested on noise levels, ranging from 10% to 70%. Toh and Isa [16] combined a switching median filter and fuzzy reasoning into a hybrid filtering scheme, which is denoted as NAFSM. In this scheme, the histogram is employed to identify distorted pixels. Ahmed and Das [17] developed an iterative adaptive fuzzy filter. First, a new detector using a fuzzy set scheme is designed to detect distorted pixels. Then, the detected pixels are modified via a weighted mean filter. Wang et al. [18] developed a fuzzy switching based weighted mean filter for recovering pixels distorted by impulse noise. In this filter, the distorted pixels are detected using the maximum value of an absolute luminance difference in a processing window. In [19], the distorted pixels are determined by tuning two Gaussian membership functions. The final filter output is calculated using weighted mean filtering based on a fuzzy approach.

The evaluation results from different filters in the literature demonstrate that (1) mean filtering outperforms median filtering for restoring salt-and-pepper noise, (2) an adaptive (dynamic) window size gives a superior performance over a fixed window size particularly when noise levels are high, (3) modifying only distorted pixels can better preserve image details. Therefore, this work proposes a new filter for dealing with salt-and-pepper noise in which the distorted pixels are firstly determined, and then a denoising operation is performed on these pixels. For each distorted pixel, the filter output is calculated as the weighted mean of undistorted pixels when the window size is 3×3 and calculated as the mean value of undistorted pixels which have the highest frequencies in accordance to their histogram distribution when the window size is larger.

2. THE PROPOSED FILTER DESCRIPTION

This section gives a detailed description of the proposed filter. Let I represent the original image with a size $G \times H$. G_{max} and G_{min} represent the highest and lowest grayscale values in I respectively. When I contains salt and pepper noise, some values of I 's pixels will be set as G_{max} or G_{min} . Therefore, the pixel $b_{x,y}$ at position (x,y) in the distorted image B can be expressed as

$$b_{x,y} = \begin{cases} G_{max} & \text{with probability } Z, \\ G_{min} & \text{with probability } R, \\ I_{x,y} & \text{with probability } 1 - L \end{cases} \quad (1)$$

The proposed filter only restores the distorted pixels using their neighboring undistorted pixels. The values of undistorted pixels are kept without alteration. The binary mask S is created to detect the position of distorted pixels in the matrix B . The set of identified distorted pixels is denoted as B_{noisy} .

In the filtering process, the window size is varied in order to deal with different noise levels. For each identified pixel $b_{x,y}$ in the B_{noisy} , the size of the window is adapted in accordance to the noise level. If none of undistorted pixels is encountered in the processing window, the size of this window is continuously enlarged. If at least one or more undistorted pixels is detected, the weight

$\vartheta_{p,q}$ is calculated for each one according to the Manhattan distance of the undistorted pixel to the center of the window. After that, the weighted mean value of undistorted pixels is calculated as the filter output when the window size is 3×3 . For larger window size, the undistorted pixels with the highest frequency are extracted and the mean value of these pixels is used as the new output. The frequencies of the pixels can give an indication of the main intensity value that is dominated in the window. The mean value of the highest frequency pixels could better preserve image details than the mean values of all undistorted pixels when the window size is greater than 3×3 . Finally, if the largest window size is reached to a predetermined maximum value and none of the local pixels is noise-free, the pixel with the highest frequency in the window is selected as the new output value. This filter is applied twice in order to deal with high noise levels. Several preliminary analyses have been conducted and shown that the weighted mean value gives better results when the window size is set at 3×3 while the mean value of only the highest frequency pixels give superior results when the window size is greater than 3×3 . Let $W_{x,y}^{C \times C}$ is the processing window with a size of $C \times C$ and a center at (x, y) , $\text{hist}(A)$ is the histogram function that computes the frequency distribution of each element in A , $\text{argmax}_A(\text{hist}(A))$ finds the element(s) in A which have the highest histogram values and $v_{x,y}$ is the value of the pixel at location (x,y) in the output image V , the operation of the filter can be demonstrated as shown bellows:

Step1: Set $C_{max} = 7$ and $V = B$.

Step2: Determine the set of noisy pixels in matrix B_{noisy}

$$B_{noisy} = \{b_{x,y} == G_{max} \text{ or } b_{x,y} == G_{min}\} \quad (2)$$

Step3: Set the binary mask, S , to detect the position of noisy pixels in the B according to the following:

$$S_{x,y} = \begin{cases} 1, & b_{x,y} \notin B_{noisy} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Step4: For each $b_{x,y}$ in B_{noisy} , set $C = 3$ and do the following:

Step5: Do while $C \leq C_{max}$,

If $C == 3$ and $\sum_{p,q \in W_{x,y}^{C \times C}} S_{p,q} \neq 0$, then

$$v_{x,y} = \frac{\sum_{p,q \in W_{x,y}^{C \times C}} b_{p,q} \times S_{p,q} \times \vartheta_{p,q}}{\sum_{p,q \in W_{x,y}^{C \times C}} S_{p,q} \times \vartheta_{p,q}} \quad (4)$$

Where $\vartheta_{p,q}$ is the weight which is calculated as

$$\vartheta_{p,q} = \frac{1}{|p - x| + |q - y|} \quad (5)$$

Otherwise, $C = C + 2$ and go to **step5**.

Elseif $3 < C \leq C_{max}$ and $\sum_{p,q \in W_{x,y}^{C \times C}} S_{p,q} \neq 0$, then

$$v_{x,y} = \text{mean} \left(\text{argmax}_B \left(\text{hist}(W_{x,y}^{C \times C}) \right) \right) \quad (6)$$

Otherwise, $C = C + 2$ and go to **step5**.

Elseif $C > C_{max}$, then

$$v_{x,y} = \text{argmax}_B (\text{hist}(W_{x,y}^{C \times C})) \quad (7)$$

Otherwise, go to **step4**.

Step6: Repeat **Step3** and **Step5** in order to process the remaining distorted pixels that are missing in the first round.

3. EVALUATION RESULTS

The section illustrates the noise reduction capability of the proposed filter for images distorted by salt-and-pepper noise with varying levels. The considered grey-scale images are Lenna, Cameraman, Baboon and Boats of a size 512×512. The chosen images have different details. Lenna has smooth edges while boats image has complex details. Baboon has many small details and cameraman has black and white areas. We add salt-and-pepper noise to these images. The range of noise is between 10% and 90% at a step of 10%. The results recorded from the proposed filter are compared with those obtained from six existing methods: PSMF [4], DBA [5], MDBUTMF [6], NAFSM [15], AWMF [12], and DAMF [14]. The comparison results are evaluated using Peak Signal to Noise Ratio (PSNR), image enhancement factor (IEF) and mean structural similarity index [20]. These measures are given as follows

$$PSNR = 10 \log_{10} \frac{255^2}{\frac{1}{G \times H} \sum_{x,y} (I_{x,y} - V_{x,y})^2} \quad (8)$$

$$IEF = \frac{\sum_{x,y} (B_{x,y} - I_{x,y})^2}{\sum_{x,y} (V_{x,y} - I_{x,y})^2} \quad (9)$$

$$SSIM = \frac{(2 \times m_I \times m_V + c1) + (2 \times cov_{IV} + c2)}{(m_I^2 + m_V^2) + (var_I^2 + var_V^2 + c2)} \quad (10)$$

Where I , V and B represents the original, noisy and filtered image respectively. m_I and m_V are the mean value of the I and V images respectively while var_I and var_V are the variance of the I and V images respectively; cov_{IV} is the covariance value of the I and V image; the default value of $c1 = (0.01 \times G_{max})^2$ and $c2 = (0.03 \times G_{max})^2$.

The visual quality of the considered filters on Cameraman image is illustrated in Figure1. The level of the added noise in this image is 90%. As can be seen in Figure1 that the first four filters

(PSMF, DBA, MDBUTMF, NAFSM) have bad visual quality. Meanwhile, the last three filters (AWMF, DAMF, proposed filter) have good visual quality. The PSMF yields the poorest visual quality and the NAFSM filter cannot deal with all noisy pixels where there are several dark and bright spots in the filtered image. The AWMF and the proposed filter yield approximately a similar visual quality. Table1, 2 and Figure2 display detailed analyses with regards to *PSNR*, *IEF* and *SSIM* measures respectively.

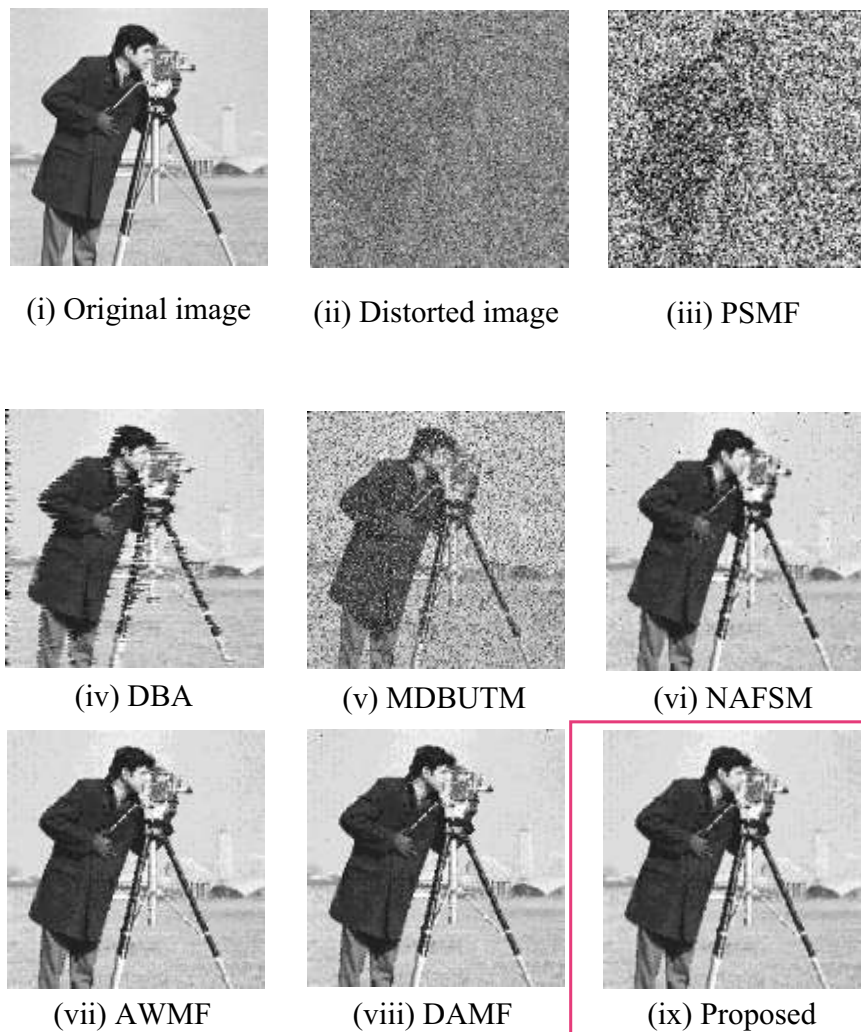


FIG. 1. The visual assessment of various filters on Cameraman image distorted with a noise level of 90%.

Table1 demonstrates the *PSNR* values after applying different filters on four images with a noise level between 10% and 90%. It can be observed that the behaviour of the filters can be divided into two categories. The first category performs well for all noise levels, which are AWMF, DAMF and the proposed filter while the noise reduction capability of the remaining

filters (PSMF, DBA, MDBUTMF and NAFSM filter) deteriorates for high noise levels. The proposed filter has almost the highest *PSNR* for all noise levels.

Table 1. The results of PSNR for the considered filters

Image	Filter	10%	20%	30%	40%	50%	60%	70%	80%	90%
Lenna	PSMF	36.29	31.62	28.14	24.37	20.39	12.26	9.92	8.07	6.61
	DBA	40.59	36.57	33.94	31.51	29.44	27.59	25.51	22.75	19.15
	MDBUTMF	42.26	38.60	36.14	33.99	31.78	28.57	24.54	20.11	15.84
	AWMF	37.30	36.85	35.60	34.35	33.15	31.69	30.26	28.41	26.10
	DAMF	42.26	38.60	36.18	34.20	32.71	31.28	29.88	28.15	25.77
	Proposed	42.49	39.09	37.01	35.31	34.01	32.68	31.44	29.73	27.28
Cameraman	PSMF	32.04	27.61	24.42	21.87	19.05	15.58	9.01	7.22	5.78
	DBA	40.18	35.55	32.34	30.20	27.61	25.54	23.31	20.69	17.44
	MDBUTMF	42.76	38.46	35.63	33.01	30.27	26.30	21.91	17.45	13.12
	AWMF	36.72	35.64	34.63	33.58	32.23	30.60	28.75	26.70	23.76
	DAMF	42.83	38.47	35.67	33.37	31.55	29.87	28.25	26.35	23.46
	Proposed	42.81	39.23	36.95	35.14	33.49	31.96	30.20	28.15	24.95
Baboon	PSMF	27.19	25.88	24.19	21.98	19.00	15.67	9.81	8.03	6.56
	DBA	33.03	29.62	27.33	25.50	23.98	22.53	21.30	19.72	17.75
	MDBUTMF	34.59	31.16	29.09	27.35	25.78	24.00	21.69	18.71	15.30
	AWMF	31.94	30.02	28.68	27.48	26.25	25.02	23.71	22.24	20.40
	DAMF	34.59	31.16	29.09	27.40	26.00	24.69	23.44	22.04	20.25
	Proposed	35.11	31.76	29.72	28.14	26.79	25.56	24.35	22.98	21.14
Boats	PSMF	33.56	30.43	27.63	24.49	20.56	16.54	9.92	8.08	6.60
	DBA	39.00	34.91	32.30	30.11	28.18	26.34	24.69	22.72	20.20
	MDBUTMF	41.07	37.16	34.58	32.53	30.42	27.55	23.90	19.90	15.78
	AWMF	37.01	35.25	33.93	32.72	31.43	30.08	28.64	26.92	24.51
	DAMF	41.07	37.16	34.60	32.67	31.02	29.56	28.26	26.64	24.27
	Proposed	41.04	37.65	35.50	33.85	32.43	31.08	29.74	28.09	25.58

The *IEF* values are also calculated in Table 2 for all the considered filters across various noise levels. In a similar way, the proposed filter has the highest *IEF* values for lower and higher noise levels. The PSMF has the smallest *IEF* values on the Baboon image even for lower noise levels.

Table 2. The results of *IEF* for the considered filters.

Image	Filter	10%	20%	30%	40%	50%	60%	70%	80%	90%
Lenna	PSMF	121.11	83.18	55.93	31.32	15.70	2.88	1.97	1.47	1.18
	DBA	326.13	259.98	212.37	162.01	126.19	98.72	71.53	43.22	21.20
	MDBUTMF	478.84	414.85	352.75	286.88	216.16	123.51	57.17	23.52	9.9123
	AWMF	158.81	277.37	311.74	311.22	296.39	253.74	213.45	159.21	105.25
	DAMF	478.84	414.85	355.79	301.14	267.82	230.57	195.68	150.06	97.40
	Proposed	503.97	463.81	431.43	388.42	361.12	318.38	280.45	215.96	137.85
Cameraman	PSMF	54.99	40.01	28.80	21.11	13.88	7.44	1.92	1.45	1.17
	DBA	357.97	249.07	178.64	143.76	99.57	73.83	51.78	32.33	17.18
	MDBUTMF	648.23	486.86	381.30	274.75	183.74	87.97	37.46	15.33	6.36
	AWMF	161.46	254.20	302.47	313.50	288.05	236.45	181.07	129.10	73.72
	DAMF	659.15	488.21	384.20	298.82	246.81	199.84	161.34	119.07	68.83
	Proposed	655.89	582.15	516.66	449.21	385.14	323.44	252.53	180.12	96.88
Baboon	PSMF	14.93	22.32	22.64	18.20	11.42	6.36	1.93	1.46	1.17
	DBA	57.27	52.82	46.64	40.97	35.95	30.94	27.21	21.63	15.45
	MDBUTMF	82.03	75.34	69.95	62.75	54.43	43.36	29.77	17.11	8.78
	AWMF	44.63	57.88	63.62	64.66	60.67	54.81	47.45	38.57	28.43
	DAMF	82.03	75.34	69.99	63.36	57.29	50.81	44.59	36.86	27.49
	Proposed	92.43	86.52	80.87	75.18	68.63	62.16	55.01	45.79	33.72
Boats	PSMF	65.16	64.06	50.00	16.37	16.37	7.74	1.98	1.47	1.18
	DBA	227.98	179.61	146.65	118.00	94.53	73.98	59.47	43.00	27.10
	MDBUTMF	366.71	301.41	247.64	206.14	158.51	97.73	49.48	22.49	9.81
	AWMF	144.06	194.25	213.15	215.41	200.15	175.09	147.34	113.09	73.08
	DAMF	366.71	301.41	248.82	213.03	182.10	155.27	135.00	106.07	69.28
	Proposed	364.62	337.21	306.30	279.23	251.93	220.50	190.13	148.29	93.65

The *SSIM* values for the best three filters (AWMF, DAMF, proposed filter) are plotted in Figure 2 at a noise level of 90%. As can be seen that the AWMF and DAMF have approximately a similar noise reduction capability. Meanwhile, the proposed filter records the highest *SSIM* values. The lowest *SSIM* values have been recorded for Baboon image. This is perhaps because this image has many small details.

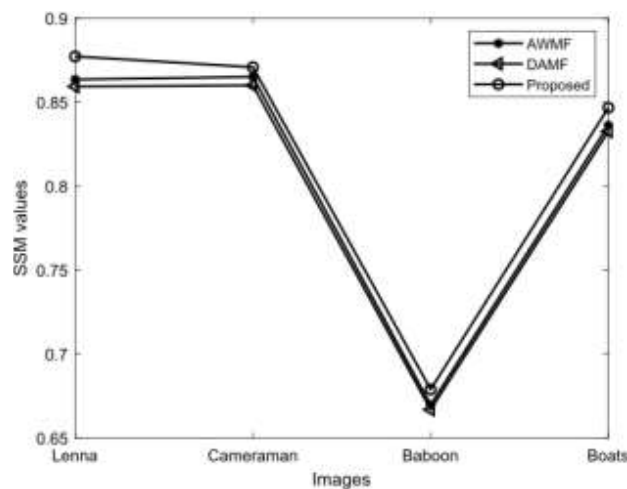


FIG. 2. The results of SSIM for the best filters at noise level 90%.

4. CONCLUSIONS

A new filter has been developed for dealing with salt-and-pepper noise in grey-scale images. The filter consists of noise detection and filtration stages where the size of the window is changed in an adaptive manner. According to the local image content, the filter output is calculated as the weighted mean value of undistorted pixels when the window size is 3×3 and calculated as the mean of undistorted pixels with the highest frequency distribution when the window size is greater than 3×3 . The evaluation results indicate that the proposed filter has an improved restoration capability with regards to *PSNR*, *IEF* and *SSIM* measures.

Acknowledgement

This work was supported by Mustansiriyah University / Ministry of Higher Education / Iraq (www.uomustansiriyah.edu.iq).

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