EURASIP Journal on Applied Signal Processing 2004:16, 2434–2440
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Impulsive Noise Suppression from Images with the Noise Exclusive Filter

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Received 25 August 2003; Revised 1 March 2004

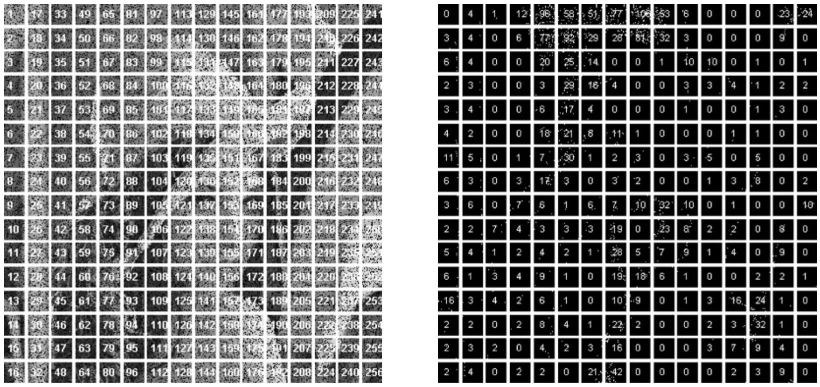
A novel impulsive noise elimination filter, entitled noise exclusive filter (NEF), which shows a high performance at the restoration of images distorted by impulsive noise, is proposed in this paper. NEF uses chi-square goodness-of-fit test in order to detect the corrupted pixels more accurately. Simulation results show that the proposed filter achieves a superior performance compared with the other filters mentioned in this paper in terms of noise suppression and detail preservation, particularly when the noise density is very high. The proposed method also achieves the robustness and detail preservation perfectly for a wide range of impulsive noise density. NEF provides efficient filtering performance with reduced computational complexity.

Keywords and phrases: impulsive noise suppression, statistical noise detection.

1. INTRODUCTION

Corruption of images by impulsive noise is a frequently encountered problem in acquisition, transmission, and processing of images, therefore one of the most common signal processing tasks involves the removal of impulsive noise from signals. Preservation of image details while eliminating impulsive noise is usually not possible during the restoration process of corrupted images. However, both of them are essential in the subsequent processing stages. It has been approved that the standard median filter (SMF) [1] and its modifications [2, 3, 4, 5, 6, 7, 8, 9, 10] offer satisfying performance in suppression of impulsive noise. However, these approaches are implemented invariantly across the image, thus they tend to alter the pixels undisturbed by impulsive noise and increase the edge jitters when the noise density is high. Consequently, achieving a good performance in the suppression of impulsive noise is usually at the expense of blurred and distorted image features. One way of avoiding this problem is to include a decision-making component in the filtering structure, based on a very simple but effective impulse detection mechanism. The function of the impulse detection mechanism is to check each pixel in order to find out whether it is distorted or not. When the mechanism indicates corruption, the nonlinear filtering scheme is performed for the distorted pixels, while the noise-free pixels are left unaltered in order to avoid excessive distortion. Recently, impulse-detection-based filtering methods with thresholding operations have been realized by using different modifications of impulse detectors, where the output is switched between the identities or filtering scheme [2, 3, 4].

For the impulse detection mechanism, the proposed filter, NEF, uses *chi-square goodness-of-fit test*-based statistic, which supplies more efficient results than the classical impulse detection mechanisms. NEF performs the restoration of degraded images with no blurring even when the images are highly corrupted by impulsive noise. In order to evaluate the performance of the proposed filter, it is compared with the SMF and the recently introduced complex-structured impulsive noise removal methods: minimum maximum exclusive mean filter (MMEM) [5], progressive switching median filter (PSM) [4], iterative median filter (IMF) [4], impulse rejecting filter (IRF) [6], recursive adaptive center-weighted median filter (AMF) [7], two-state recursive signal



(a) (b)

Figure 1: An illustrative example to detect whether the pixels possessing the intensity level of 128 are corrupted or not: (a) 32×32-pixel-sized subimages of the corrupted Lena image, which is at the noise density of 20% (corrupted pixels were marked as black for illustration) and (b) the spatial positions of the pixels possessing the intensity value of 128 (these pixels were marked with white dots for illustration) and the counted values of the pixels which possess the value of 128 in each of the subimages.

dependent rank order mean filter (SDR) [8], multistate median filter (MSM) [9], and tri-state median filter (TSM) [10].

The rest of the paper is organized as follows: the proposed method is explained in Section 2. Experiments are given in Section 3, and finally, conclusions are presented in Section 4.

2. PROPOSED FILTER

The proposed filter, NEF, is realized in two main steps: in the first step, impulse detection is carried out and in the second step, restoration of corrupted pixels is performed.

2.1. Impulse detection

In real images, noisy pixels scatter *positionally uniform* throughout the image surface, since the corruption probability of each pixel is numerically equal. Therefore, the intensity levels that scatter positionally uniform over the image surface have the probability of being noise. In this paper, chi-square significance probability value of chi-square goodness-of-fit test has been used in order to detect whether the intensity levels scatter positionally uniform throughout the image surface or not. If one intensity level has been detected as scattering positionally uniform, then the pixels possessing this intensity value are considered as corrupted pixels.

The chi-square goodness-of-fit test, which uses chi-square significance probability value, can be applied to many distribution models such as *Uniform, Gaussian, Weibull, Beta, Exponential*, and *Lognormal* distribution models [11, 12, 13, 14]. Therefore, the chi-square goodness-of-fit test can be used in order to detect corrupted pixels more accurately even if the uniform assumption is not exactly satisfied.

In this paper, the image surface is divided into 32×32-pixel-sized unoverlapping subimages, in order to statistically analyze impulsive behavior of the intensity levels. For each intensity level, the number of the pixels, which possess this intensity level, is counted for each subimage. These *counted values* have been used for investigating the chi-square significance probability value of an intensity level. It is observed empirically that the intensity levels, whose chi-square significance probability values are greater than the *threshold* 0.002 ± 0.0005, belong to the corrupted pixels. The value of the threshold has been verified by the experiments, which were realized using various test images under different noise densities for the commonly known statistical distribution models, such as Uniform, Gaussian, Weibull, Beta, Exponential, and Lognormal distribution models [11].

An illustrative example has been given in Figure 1, in order to detect whether the pixels possessing the intensity level of 128 are corrupted or not. For this example, the chi-square significance probability value, p has been computed as $p = 0.00$ ($p <$ threshold) for the 256 counted values of 0, 3, 6, 2, 3, 4, 11, 6, 3, 2, 5, 6, 16, 2, 2, 2, 4, 4, 4, 3, 4, 2, 5, 3, 6, 2, 4, 1, 3, 2, 3, 4, 1, 0, 0, 0, 0, 0, 0, 0, 0, 7, 1, 3, 4, 0, 2, 0, 12, 6, 0, 0, 0, 0, 1, 3, 7, 4, 2, 4, 2, 2, 0, 2, 96, 77, 20, 3, 6, 18, 7, 17, 6, 3, 4, 9, 6, 8, 4, 2, 58, 92, 25, 29, 17, 21, 30, 3, 1, 3, 2, 1, 1, 4, 2, 0, 51, 29, 14, 16, 4, 8, 1, 0, 6, 3, 1, 0, 0, 1, 3, 21, 77, 28, 0, 4, 0, 11, 2, 3, 7, 19, 28, 19, 10, 22, 16, 42,106, 81, 0, 0, 0, 1, 3, 2, 10, 0, 5, 18, 9, 2, 0, 0, 53, 32, 1, 0, 0, 0, 0, 0, 32, 23, 7, 6, 0, 0, 0, 0, 6, 3, 10, 3, 1, 0, 3, 0, 10, 8, 9, 1, 1, 0, 0, 0, 0, 0, 10, 3, 0, 0, 5, 1, 0, 2, 1, 0, 3, 2, 3, 0, 0, 0, 0, 4, 0, 1, 0, 3, 1, 2, 4, 0, 16, 3, 7, 2, 0, 0, 1, 1, 1, 1, 5, 8, 0, 0, 0, 2, 24, 32, 9, 3, 23, 9, 0, 2, 3, 0, 0, 0, 0, 8, 9, 2, 1, 1, 4, 9, 24, 0, 1, 2, 0, 0, 0, 2, 10, 0, 0, 1, 0, 0, 0, 0 which are given in Figure 1b. Therefore, the pixels possessing the intensity level of 128 are detected as uncorrupted pixels.

2.2. The chi-square goodness-of-fit test

For the computation of the chi-square goodness-of-fit test-based chi-square significance probability value [11, 12, 13, 14] of an intensity level, 256 counted values, which denote

(1) Pad the noisy image by reflecting one pixel at the edges of the noisy image in order to obtain full windows for the edge pixels.
(2) Find the corrupted pixels within the corrupted image, as explained in Sections 2.1 and 2.2.
(3) Start the iterative computation process of NEF and perform the following steps for each corrupted pixel within the corrupted image.
  (a) Let W be a 3×3-pixel-sized sliding window whose center pixel is a corrupted pixel. Find the number of uncorrupted pixels that exist within the current window, W. Perform the following steps if the number of the uncorrupted pixels that exist within the current W is else than zero.
    (i) For the current window, compute the Euclidean distances, d_t, between the center pixel and the uncorrupted pixels by using the formula

$$d_t = \left|\sqrt{k_t^2 + \ell_t^2}\right|, \quad t = 1, 2, 3, \ldots, s, \tag{2}$$

where s denotes the number of uncorrupted pixels that exist within the current window, W. (k, ℓ) are integers $(-1 \le k \le 1, -1 \le \ell \le 1)$, which denote the spatial coordinates of the uncorrupted pixels within the W. The spatial coordinate of the center pixel of W is $(k = 0, \ell = 0)$.
    (ii) Convert the computed d_t values to *distance weight*, h_t, by using (3) given below:

$$h_t = \left(\frac{d_t}{\sum_{t=1}^{s} d_t}\right)^{-1}. \tag{3}$$

    (iii) Restore the intensity value of the center pixel in the current window with the value of v_t, which is computed by using (4), given below:

$$v_t = \sum_{t=1}^{s} h_t \rho_t, \tag{4}$$

where ρ_t denotes the intensity values of the uncorrupted pixels within the current window.
  (b) If the number of the uncorrupted pixels in current W is equal to zero, then don't replace the intensity value of the center pixel.
  (c) Repeat the steps (a), (b), and (c) until each of the corrupted pixels has been restored.
(4) Delete the padded pixels in order to obtain restored image at the same size of the original distorted image.

ALGORITHM 1

the number of the related intensity level within the subimages, have been used. Firstly, the normal distribution parameters, that is, mean, μ, and standard deviation, σ, values have been computed. Then, the inverse of the normal cumulative distribution function values, which denote the equally spaced probability interval values, have been computed from 5%–95% (with an incremental step of 10% for 10 intervals) by using the parameters of μ and σ. Then these values have been used at the computational phase of the frequency counts, J_i $(i = 1, 2, \ldots, 10)$. Frequency counts have been obtained by counting the number of the counted values that exist in each of the probability intervals. By using the frequency counts, the chi-square significance probability value, p, has been obtained as

$$p = 1 - \tilde{\chi}^2\left(\sum_{i=1}^{10} \frac{(J_i - 25.6)^2}{25.6} \,\middle|\, 25\right), \tag{1}$$

where $\tilde{\chi}^2(\sum_{i=1}^{10}((J_i - 25.6)^2/25.6)|25)$ returns the chi-square cumulative distribution function [11] value with 25 degrees of freedom at the value of $\sum_{i=1}^{10}((J_i - 25.6)^2/25.6)$.

2.3. Implementation of the proposed filter

The computational algorithm of NEF is defined step-by-step in Algorithm 1.

3. EXPERIMENTS

A number of experiments were realized in order to evaluate the performance of the proposed NEF in comparison with SMF and the recently introduced and highly approved filters, MMEM, PSM, IMF, IRF, AMF, SDR, MSM, and TSM. The experiments were carried out on the Lena, the Mandrill, and the Bridge test images, which are 512×512 pixels-sized and 8 bits per pixel. All the simulations were

Figure 2: Restoration results of the Lena image for the noise density of 50%: (a) original Lena image, (b) corrupted Lena image (noise density = 50%), (c) NEF (proposed), (d) MMEM, (e) PSM, (f) IMF, (g) IRF, (h) SMF, (i) AMF, (j) SDR, (k) MSM, and (l) TSM.

realized on Matlab v6.5, which is a highly approved language in signal processing community for technical computing [11].

The restoration results of the proposed NEF and the comparison filters for the noise densities of 50% and 95% are illustrated in Figures 2 and 3, respectively, where it is easily seen that noise suppression and detail preservation are satisfactorily attained by using the proposed NEF. The restoration results for a high noise density, 95%, are given in Figure 3, in order to emphasize that NEF provides visually more pleasing images even if noise density is very high. The major improvement achieved by the proposed NEF has been demonstrated with the extensive simulations of the mentioned test images corrupted at different noise densities. Restoration performances of the proposed method and the comparison filters are quantitatively measured by the well-known mean squared error (MSE) criterion [11] and documented in Tables 1, 2, and 3, where it is exactly seen that the proposed NEF provides a substantial improvement compared with the simulated filters, especially at the high noise densities. Impulsive noise removal and detail preservation are best achieved by the proposed NEF. Robustness is one of the most important requirements of modern image enhancement filters and Tables 1, 2, and 3 indicate that the proposed NEF provides robustness substantially across a wide variation of noise densities.

Apart from the numerical behavior of any algorithm, a realistic measure of its practicality and usefulness is the computational complexity, which determines the required computing power and run time. Therefore in order to evaluate the computational complexities of the mentioned methods in this paper, the average run times of 50 runs were obtained in seconds and documented in Table 4, where it is seen that the run time of the proposed method is smaller than the

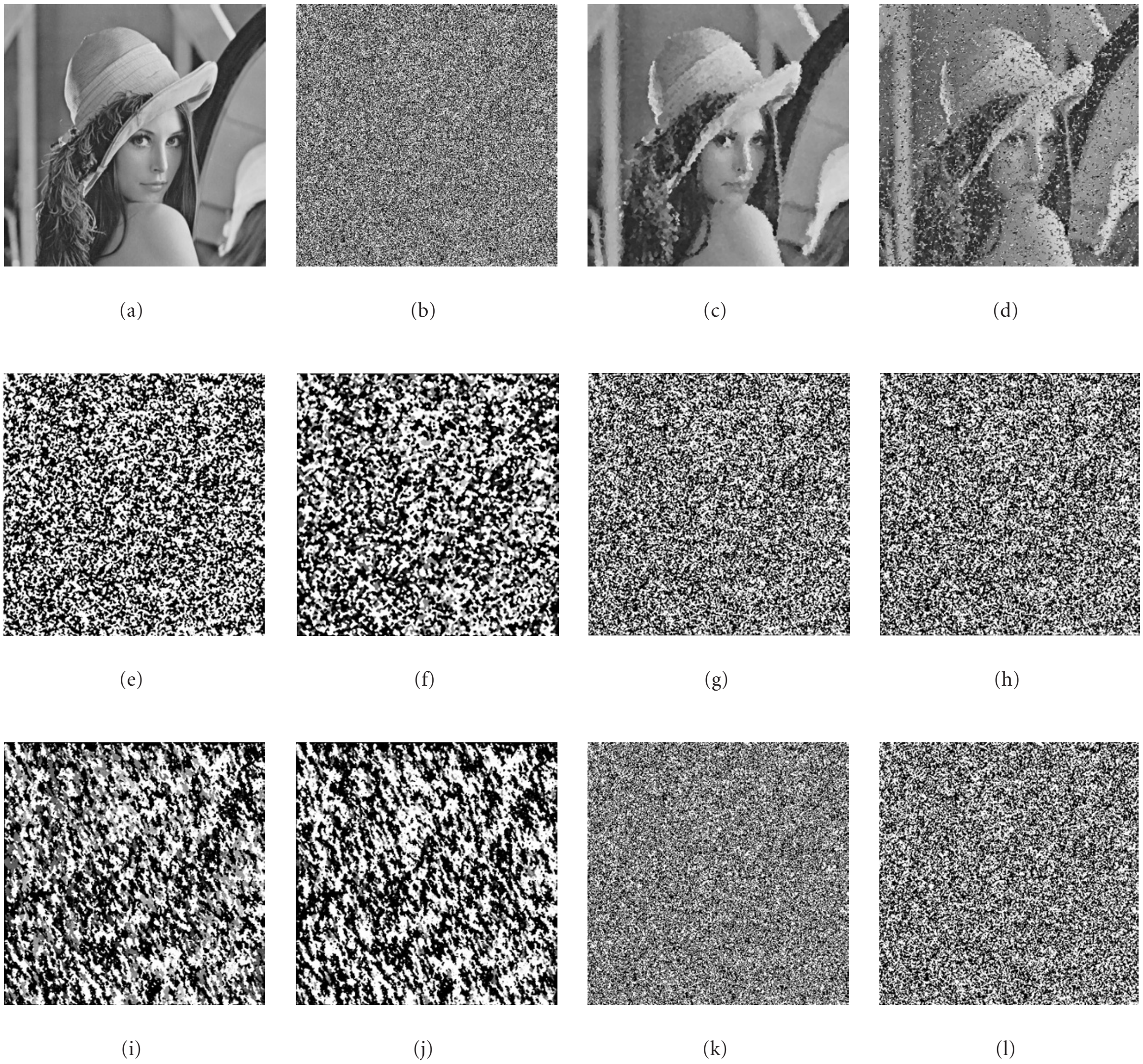


Figure 3: Restoration results of the Lena image for the noise density of 95%: (a) original Lena image, (b) corrupted Lena image (noise density = 95%), (c) NEF (proposed), (d) MMEM, (e) PSM, (f) IMF, (g) IRF, (h) SMF, (i) AMF, (j) SDR, (k) MSM, and (l) TSM.

Table 1: Restoration results in MSE for the Lena image.

	Noise density						
	5%	20%	35%	50%	65%	80%	95%
Noisy Lena	944.55	3712.70	6478.80	9258.90	12051.00	14884.00	17641.00
NEF (proposed)	**1.35**	**5.74**	**11.00**	**19.72**	**33.23**	**64.05**	**180.67**
MMEM	5.78	13.22	20.65	31.33	50.12	116.63	1925.20
PSM	9.27	37.92	92.45	517.78	2803.80	9502.40	16534.00
IMF	46.55	57.12	76.38	131.92	509.93	3922.80	13931.00
IRF	6.08	62.37	474.57	1934.10	4971.00	10076.00	16310.00
SMF	23.58	81.38	488.72	1936.80	4963.40	10062.00	16304.00
AMF	4.26	32.60	118.34	326.58	991.48	3768.50	13246.00
SDR	5.91	29.05	105.44	317.91	1117.20	5131.80	15724.00
MSM	18.24	703.32	2765.40	6075.00	10122.00	14353.00	17679.00
TSM	7.03	158.18	1065.90	3358.00	7307.10	12730.00	17601.00

Table 2: Restoration results in MSE for the Mandrill image.

	Noise density						
	5%	20%	35%	50%	65%	80%	95%
Noisy Mandrill	886.96	3563.90	6197.60	8783.50	11480.00	14151.00	16807.00
NEF (proposed)	**0.84**	**3.97**	**8.98**	**19.33**	**41.79**	**91.86**	**339.63**
MMEM	3.72	12.21	21.36	36.38	65.49	143.13	1742.20
PSM	3.13	15.83	53.25	425.31	2816.70	9416.90	16066.00
IMF	106.65	117.61	138.77	196.56	654.86	3703.70	13353.00
IRF	8.46	64.30	472.53	1833.80	4800.10	9581.60	15593.00
SMF	33.65	94.82	505.19	1862.40	4818.70	9587.80	15593.00
AMF	5.05	30.07	94.72	286.04	946.53	3345.10	12520.00
SDR	7.40	31.74	98.29	313.06	1164.80	4817.40	15312.00
MSM	20.89	698.17	2669.10	5763.30	9643.50	13630.00	16846.00
TSM	8.43	164.49	1043.60	3234.70	7036.90	12128.00	16784.00

Table 3: Restoration results in MSE for the Bridge image.

	Noise density						
	5%	20%	35%	50%	65%	80%	95%
Noisy Bridge	972.93	3902.10	6799.30	9767.80	12660.00	15621.00	18469.00
NEF (proposed)	**19.40**	**54.31**	**92.45**	**146.41**	**226.13**	**368.75**	**845.93**
MMEM	80.54	116.58	148.51	198.78	277.93	451.30	2601.60
PSM	42.53	111.08	223.07	729.70	3337.10	9923.30	17180.00
IMF	235.97	261.65	307.48	394.44	946.22	4303.40	14671.00
IRF	71.35	170.29	664.27	2252.60	5497.50	10668.00	17112.00
SMF	148.78	242.71	718.68	2279.70	5497.10	10650.00	17103.00
AMF	45.98	128.01	281.17	625.63	1462.90	4373.60	14239.00
SDR	71.51	144.99	288.78	653.90	1684.60	5922.40	16514.00
MSM	53.53	809.53	2997.70	6520.00	10716.00	14976.00	18463.00
TSM	77.86	279.73	1280.70	3786.70	7968.30	13448.00	18410.00

Table 4: Average run times in seconds.

Filter	Run times (s)
NEF (proposed)	**3.04**
MMEM	153.03
PSM	180.63
IMF	1.92
IRF	6.06
SMF	0.29
AMF	280.77
SDR	6.35
MSM	4.86
TSM	2.88

run times of the majority of comparison algorithms. The run time analysis of the proposed filter and concerned filters was conducted for test images using Pentium IV, 1.6 GHz with 512 Mb RAM computer on Windows XP.

4. CONCLUSIONS

The effectiveness of the proposed filter in processing different images can easily be evaluated by appreciating Tables 1, 2, and 3, which are given to present the restoration results of NEF and the comparison filters for images degraded by impulsive noise, where noise density ranges from 5%–95%. It is seen from Tables 1, 2, and 3 that the proposed NEF gives absolutely better restoration results and a higher resolution in the restored images compared with the restoration performances of MMEM, PSM, IMF, IRF, SMF, AMF, SDR, MSM, and TSM. In addition, the proposed NEF supplies a more pleasing restoration results aspect of visual perception and also provides the best trade-off between impulsive noise suppression and detail preservation, as can be seen from Figures 2 and 3. In order to appreciate the computational complexities of the NEF and the comparison methods, the average run times are documented in Table 4, where it is seen that the run time of the proposed method is smaller than the run times of the majority of comparison algorithms. NEF yields satisfactory results in suppressing impulsive noise with no blurring while requiring a simple computational structure.

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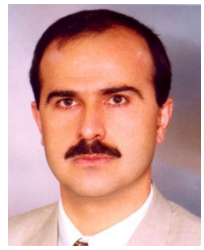

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