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Decision Based Adaptive Neighborhood Median Filter

Aswini Kumar Samantaray, Priyanka Mallick

Department of Electronics & Telecommunication Engineering,
C. V. Raman College of Engineering,
Bidya Nagar, Mahura, Janla, Bhubaneswar, India – 752054

Abstract

Impulse noise in an image degrades the performances of the image processing and analysis stages. Therefore the noise removal and correction is an important processing required before performing any subsequent image processing approaches in the image data. In this paper a novel approach is proposed to remove the impulse noise from gray images. In this technique, all the pixels having gray value 0 and 255 are considered as the noisy pixels. The proposed method consists of three stages of filtering by considering the neighborhood pixels. The proposed method outperforms the Standard median Filter, Improved Fast Peer Group Filter and Modified Decision Based Unsymmetric Trimmed Median Filter.

I Introduction

Most of the time an image gets corrupted by impulse noise. Impulse noise is otherwise known as salt and pepper noise, spike noise, shot noise or binary noise. The image corrupted by impulse noise has white spot in black area and black spot in white area of the image [1]. The impulse noise is caused by sudden disturbances in image signal caused by sensor and memory problems due to which the pixels are assigned with minimum gray value "0" and maximum gray value "255". The chances of getting salt and pepper noise are equal as the noise distribution is equiprobable. Since the impulse noise affects the performance of image processing operations such as image enhancement, image segmentation, image compression etc, it is highly required to detect the corrupted pixels and restore their original intensity value in the image.

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Vector median filters are robust filters for impulse noise reduction in images. Because these filters are based on robust statistics [2]. Standard median filter is the most popular filter to handle the salt and pepper noise because of it's simplicity. The variants of standard median filter are weighted median filter (WMF) [3] and center weighted median filter (CWMF) [4]. CWM filters are more efficient for it's good de-noising power. A variant of CWM filter is known as adaptive center weighted median filter (ACWMF) which is excellent than SMF and CWMF in terms of noise removal and detail preserving capability. In vector median filter and other classical methods, the filtering operation is applied on every image pixel regardless whether the pixel is noisy or not. Hence these filters are not able to preserve the fine details of an image and introduce blurring effect. Because of non-linearity and vector field approach, the vector median filter has higher computational complexity.

In order to overcome the above draw-backs, Camarena et. el.[6] proposed a peer group technique which efficiently detects the corrupted pixels in an impulse noise corrupted image before applying the arithmetic mean filtering. This method is briefly discussed in the next section. Similarly Esakkirajan et.el.[8] proposed a decision based un-symmetric trimmed median filter in which it considered all pixels having gray value "0" and "255" as noisy pixels. Then it used mean as well as median filters to remove all the noisy pixels which are described in the subsequent sections.

The rest part of the paper is structured as follows. A better introduction to improved fast peer group filter and Modified decision based un-symmetric trimmed median filer in section II and section III respectively. Section IV describes the proposed technique in detail with algorithm and in section V, result discussion is given. Finally section VI describes the conclusion.

II. IFPGF Algorithm

This method is divided into noise detection step and noise filtering step. Before it applies the following phases, it first calculates peer group of a pixel by considering an appropriate threshold value. The noise detection step is performed in two phases. In the first phase, the image is partitioned into dis-joint blocks. For each partition window W of size nxn, n=3,5..centered at x_i, they applied the following procedure taking a fixed value of m $\{m\in 1,\ldots(n^2-1)\}$.

If $\#p(x_i,d)\geq(m+1)$ (# denotes cardinality)
Then for all $x_j\in p(x_i,d)$, x_j is declared as non-corrupted and for all $x_k\in W- p(x_i,d)$, x_k is declared as non-diagnosed.
Else x_i is declared as corrupted and $x_k\in W- \{x_i\}$, x_k is declared as non-diagnosed.

For second phase detection step, they have taken another experimental value m'{1,2,…(m-1)} and have applied the following procedure on every non-diagnosed pixel x_i centered in an window W by forming peer group.

If $p(x_i,d)$ contains m' non-corrupted pixels, then x_i is declared as non-corrupted'
Else if $\#p(x_i,d)\geq(m+1)$, then for all $x_j\in p(x_i,d)$, x_j is declared as non-corrupted,
Else x_i is declared as corrupted.

After the noise detection phase, the arithmetic mean filter is applied on each noisy pixel to restore the gray value.

III. MDBUTMF Algorithm

This method proposed a median filter named as Modified Decision Based Un-symmetric Trimmed Median Filter (MDBUTMF) for the removal of high density salt and pepper noise from a corrupted image. In this approach, the authors tried to overcome the draw backs of symmetric trimmed median filter through un-symmetric trimmed median filter. In this a 3X3 window is considered over a pixel having 0 or 255 gray value. Then the pixel values 0's and 255's are removed from the elements of the windows considered. The median value of the remaining pixels is evaluated to replace the center pixel of the window. If all pixels in the window are having 0 and 255 gray values, then the center pixel is replaced by the average value of the pixels in that window.

IV. Proposed Algorithm

In this technique, every pixel having gray value “0” or “255” is considered as a noisy pixel. Once a noisy pixel is detected, a 3X3 window is considered by taking the noisy pixel as the center pixel the window. Then the un-corrupted pixels (Which are not having gray value “0” or “255”) are identified in that window. The filtering process of this proposed method consists of three phases. In the first phase, it considers only the first order neighborhood pixels. In that if it finds one un-corrupted pixel, then that un-corrupted pixel replaces the noisy center pixel. If it finds more than one un-corrupted pixel among the first order neighborhood pixels, then the median value of those un-corrupted pixels replaces the noisy center pixel. The second phase is followed by the first phase if and only if it does not find at least one un-corrupted pixel in the first order neighborhood pixels.
In the second phase, it considers only the diagonal neighborhood pixels. In that if it finds one un-corrupted pixel, then that un-corrupted pixel replaces the noisy center pixel and if it finds more than one un-corrupted pixel, then the median value of those un-corrupted pixels replaces the noisy center pixel. If the method fails in above two phases i,e. if it does not find at least one un-corrupted pixel in it’s neighborhood, then it goes to the third phase. In this phase it calculates the mean of all the neighborhood pixels and replaces the noisy center pixel by the calculated mean value. This method is applied iteratively until all the noisy pixels are removed from the image.

Algorithm

1. Read the noisy image.
2. Consider a 3X3 window of the image having center pixel x_i.
3. If $0<x_i<255$, then x_i is noise free. Leave x_i as such and move to the next window.
   Else x_i is noisy. So move to the next step.
4. Consider the first order neighborhood pixels of x_i. If #non-noisy pixel=1; say A1, then x_i=A1.
   Else if #non-noisy pixels>1; say A1, A2, A3, then x_i= median (A1, A2, A3).
   Else #non-noisy pixels=0, go to next step.
5. Consider the diagonal neighborhood pixels and count the number of un-corrupted pixels.
6. If #non-noisy pixel=1; say B1, then x_i=B1.
   Else if #non-noisy pixels>1; say B1, B2, B3, then x_i= median (B1, B2, B3).
   Else #non-noisy pixels=0, then go to next step.
7. Calculate the mean of all the neighborhood pixels and replace x_i by the calculated mean.

V. Simulation Results

The performance of the proposed algorithm is verified in both qualitatively and quantitatively and it is done by taking different gray images. In this paper, we have considered three different test images shown in Fig.1 and the noise density is varied from 10% to 90%. The computer which is used for the simulation purpose has the following configuration: i3 processor, 2GB RAMS, 2MB L2 cash, 2.4 GHz. The denoising performance is measured quantitatively by the PSNR which is defined in (1).

$$PSNR\ in\ dB = 10\log_{10}\frac{255^2}{MSE} \qquad (1)$$

$$MSE = \frac{\sum_i\sum_j (f(i,j)-\hat{f}(i,j))^2}{M\times N} \qquad (2)$$

Where PSNR stands for peak signal to noise ratio, MSE stands for mean square error, MxN is size of the image, ‘f’ represents the original image and ‘$\hat{f}$’ represents the filtering output image.

The PSNR computed for the different test images for the proposed algorithm has been compared with the PSNR of SMF, IFPGF and MDBUTMF filtering methods at different noise densities starting from 10% to 90% and is shown in table for Baboon, Flower and Lena image. From PSNR comparison table, it has been observed that the performance of our proposed method (DBANMF) is better than the existing algorithms at low as well as high noise densities. The qualitative analysis of the proposed method has also been done against the existing methods at 80% and 90% noise densities for the Baboon, Flower and Lena images which are shown in Fig.2, 3 and 4 respectively. In this the first column represents the baboon, flower and lena images corrupted by 80% and 90% noise densities. The subsequent columns represent the denoised images using SMF, IFPGF, MDBUTMF and our proposed method. Observing the Fig 2, 3 and 4, it has been observed that our proposed method is much better than the other existing methods in terms of noise removal capability and finer detail preservance capability.

(i) (ii) (iii)

Fig 1. Original test images: (i) Baboon, (ii) Flower, (iii) Lena

% of noise		10	20	30	40	50	60	70	80	90
Baboon	SMF	47.82	44.51	43.03	40.99	38.14	35.69	33.63	30.81	28.52
	IFPGF	51.23	49.52	47.84	45.96	43.62	40.04	34.99	28.22	20.14
	MDBUTMF	51.63	50.20	48.64	46.96	45.33	43.56	41.48	38.38	32.39
	DBANMF	68.62	61.33	57.14	53.97	51.41	49.13	46.97	44.82	42.26
Flower	SMF	58.12	50.96	47.29	44.56	40.45	36.09	29.89	21.37	18.04
	IFPGF	61.35	54.03	49.88	46.88	43.52	39.13	33.37	26.99	19.27
	MDBUTMF	62.50	55.50	51.51	48.63	46.57	43.90	41.54	38.03	32.47
	DBANMF	66.53	57.53	53.03	50.08	48.07	45.91	43.86	42.08	40.01
Lena	SMF	59.01	55.23	51.70	47.01	42.12	36.12	29.31	22.45	17.41
	IFPGF	64.90	60.25	56.25	52.47	48.06	42.74	35.38	28.01	19.43
	MDBUTMF	65.78	61.33	58.01	54.88	51.59	47.26	41.90	36.58	32.65
	DBANMF	73.42	65.53	61.14	58.32	55.40	52.64	49.92	46.47	41.68

Table. PSNR comparison of different filtering methods with the proposed DBANMF for Baboon, Flower and Lena images.

VI. Conclusion

In this paper, a new novel algorithm has been proposed which is more efficient in comparison with SMF, IFPGF, MDBUTMF filters and other impulse noise removal filtering methods in terms of PSNR and noise removal. The proposed algorithm also tested in 10, 20, 30, 40, 50, 60, 70, 80 and 90 percent of noise conditions. It has been seen that the proposed algorithm out performs the other filtering methods at lower as well as higher density of noise. In result we have reported both visual and qualitative measure to validate our proposed algorithm. The proposed algorithm is effective and faster for impulse noise removal in high density noisy images.

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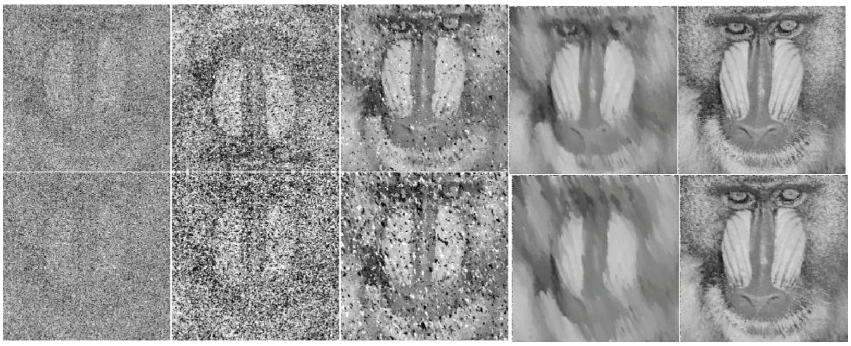
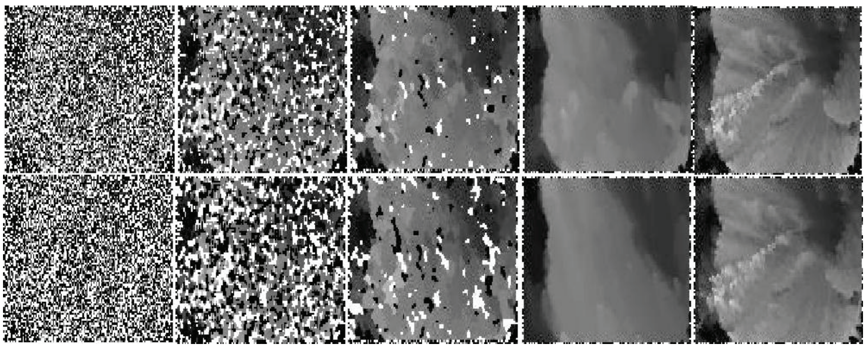


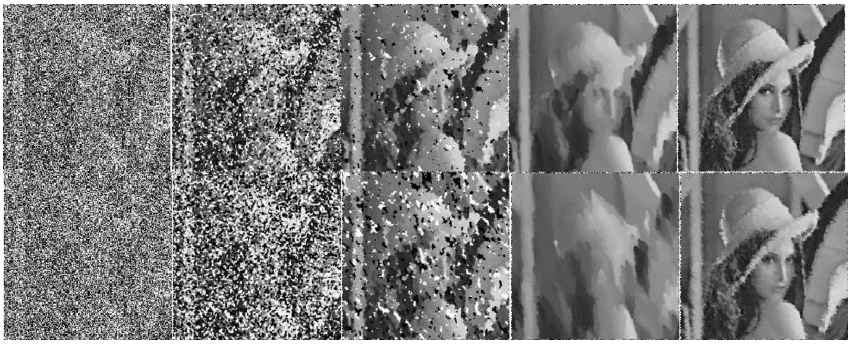
(i) (ii) (iii) (iv) (v)

Fig 2.(i) Baboon image with 80% and 90% noise: (ii) output of SMF (iii) output of IFPGF (iv) output of MDBUTMF (v) Output of proposed method



(i) (ii) (iii) (iv) (v)

Fig 3. (i) Flower image with 80% and 90% noise: (ii) output of SMF (iii) output of IFPGF (iv) output of MDBUTMF (v) output of proposed method



(i) (ii) (iii) (iv) (v)

Fig 4. (i) Lena image with 80% and 90% noise: (ii) output of SMF (iii) output of IFPGF (iv) output of MDBUTMF (v) Output of proposed method