International Journal of Information Technology and Knowledge Management
July-December 2010, Volume 2, No. 2, pp. 573-577

Image Denoising Using Non Linear Filters

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Noise in an image is a serious problem In this paper, the various noise conditions are studied which are: Additive white Gaussian noise (AWGN), Bipolar fixed-valued impulse noise, also called salt and pepper noise (SPN), Random-valued impulse noise (RVIN), Mixed noise (MN). Digital images are often corrupted by impulse noise during the acquisition or transmission through communication channels the developed filters are meant for online and real-time applications. In this paper, the following activities are taken up to draw the results: Study of various impulse noise types and their effect on digital images; Study and implementation of various efficient nonlinear digital image filters available in the literature and their relative performance comparison.

1. Introduction

Today digital imaging is required in many applications e.g., object recognition, satellite imaginary, biomedical instrumentation, digital entertainment media, internet etc. The quality of image degrades due to contamination of various types of noise. Noise corrupts the image during the process of acquisition, transmission, storage etc[1]. For a meaningful and useful processing such as image segmentation and object recognition, and to have very good visual display in applications like television, photo-phone, etc., the acquired image signal must be noise free and made deblurred. The noise suppression (filtering) and deblurring come under a common class of image processing tasks known as image restoration.

In common use the word noise means unwanted signal. In electronics noise can refer to the electronic signal corresponding to acoustic noise (in an audio system) or the electronic signal corresponding to the (visual) noise commonly seen as 'snow' on a degraded television or video image. In signal processing or computing it can be considered data without meaning; that is, data that is not being used to transmit a signal, but is simply produced as an unwanted by-product of other activities. In Information Theory, however, noise is still considered to be information. In a broader sense, film grain or even advertisements in web pages can be considered noise.

In early days, linear filters were the primary tools in signal and image processing However, linear filters have poor performance in the presence of noise that is not additive as well as in systems where system nonlinearities or non-Gaussian statistics are encountered. Linear filters tend to blur edges, do not remove impulsive noise effectively, and do not perform well in the presence of signal dependent noise. To overcome these shortcomings, various types of nonlinear filters have been proposed in the literature.

2. Median Based Filters

In order to effectively remove impulse noise as described in while preserving image details, ideally the filtering should be applied only to the corrupted pixels, and the noise-free pixels should be kept unchanged. This can be achieved by determining whether the current pixel is corrupted, prior to possibly replacing it with a new value. Decision-based filters correspond to a well-known class of filters that appear to be particularly efficient to reduced impulse noise. In this work, we propose an impulse detection scheme by successfully combining the SM filter with CWM filter.

2.1. Tri-State Median Filter

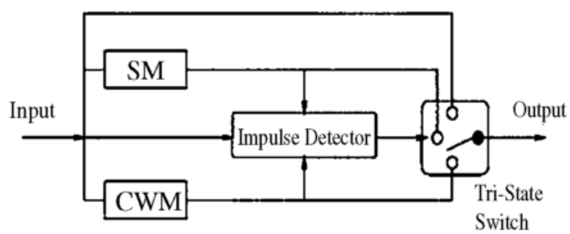

Fig.1: Tri-State Median Filter

A novel and effective median filter, called tri-state median (TSM) filter [2], is proposed and discussed in this section. Noise detection is realized by an impulse detector, which takes the outputs from the SM and CWM filters and compares them with the origin or center pixel value in order to make a tri-state decision. The switching logic as shown

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in Fig. 1 is controlled by a threshold T ([0; 255] for gray-scale images).

The capabilities of preserving image details inherited by the identity filter, the CWM filter and the SM filter descend in the abovementioned order. On the aspect of noise suppression, in contrast, they ascend in the same order. An attractive merit of the proposed TSM filtering scheme is that it provides an adaptive decision to detect local noise simply based on the outputs of these filters. As a result, impulse noise can be removed for those corrupted pixels through SM or CWM filtering. For those uncorrupted pixels identified, they remain unchanged in order to preserve the local image details. Consequently, the tradeoff between suppressing noise and preserving detail is well balanced.

The Experimental results are shown in Table. 1for WF (3 * 3) TSM Filter.

Table 1
WF (3 * 3) TSM Filter

Noise	PSNR with Noisy	PSNR after Filtering
10	15	34
20	12	30
30	11	24
40	9.5	20

The Experimental results are shown in Table.2 for WF (5 * 5) TSM Filter.

Table.2
WF (5 * 5) TSM Filter

Noise	PSNR with Noisy	PSNR after Filtering
10	15	21
20	12	19
30	11	19
40	9.5	19

The Experimental results are shown in Table.3 for WF (7 * 7) TSM Filter.

Table. 3
WF (7 * 7) TSM Filter

Noise	PSNR with Noisy	PSNR after Filtering
10	15	14
20	12	7. 3
30	11	6
40	9.5	5.9

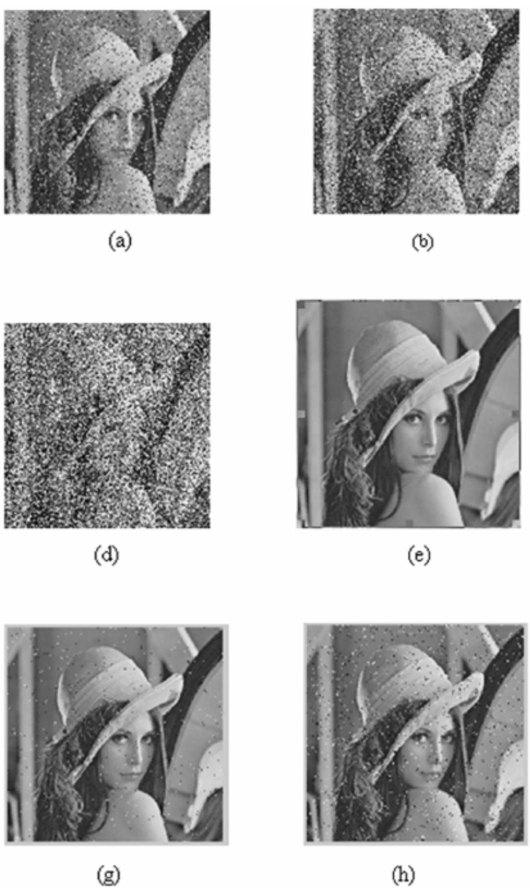

Fig. 2

Fig.2 a, b, c, d are noisy images of Lena (512×512) corrupted by salt and pepper noise with noise density of 10%, 20%, 30%, 40% respectively and corresponding restored image by TSM are in e, f, g, h for WF (3 * 3)

An Efficient Detail Preserving Adaptive Noise Detection & Suppression Filter

A new switching based median filter with adaptive noise detection and suppression (ANDS)[3] method is proposed to restore images corrupted by salt & pepper impulse noise. The proposed algorithm works well for suppressing impulse noise with noise ratios from 5 to 60% while preserving image details. The algorithm is based on the following two schemes: (1) Adaptive noise detection scheme and (2) Adaptive filtering scheme.

We begin by introducing neighborhood differentiation preprocessing step to quantify the increments in each local neighborhood of the noisy image. A correlation map is then derived by adaptive shareholding and used to designate pixels as noisy or noise free. Finally, the noise is attenuated by estimating the values of the noisy pixels with a switching based median filter applied exclusively to those neighborhood pixels not labeled as noisy. The size of filtering window is adaptive in nature, and it depends on the number of noise-free pixels in current filtering window.

Intensive simulations were carried out using several monochrome images, from which "Lena," chosen for demonstrations.

The Experimental results are shown in Table.4 for WF (3 * 3) ANDS Filter.

Table 4
WF (3 * 3) ANDS Filter

Noise	PSNR with Noisy	PSNR after Filtering
10	15	28
20	12	21
30	11	16
40	9.5	13

The Experimental results are shown in Table.5 WF(5* 5) ANDS Filter below.

Table 5
WF (5* 5) ANDS Filter

Noise	PSNR with Noisy	PSNR after Filtering
10	15	20
20	12	14
30	11	11
40	9.5	9.6

The Experimental results are shown in Table.6 WF (7 * 7) ANDS Filter.

Table 6
WF (7* 7) ANDS Filter

Noise	PSNR with Noisy	PSNR after Filtering
10	15	16
20	12	12
30	11	10
40	9.5	9. 3

Fig.3 a, b, c, d are noisy images of Lena (512×512) corrupted by salt and pepper noise with noise density of 10%, 20%, 30%, 40% respectively and corresponding restored image by ANDS are in e, f, g & h for WF (3 * 3).

Table 7
WF (3* 3) ANDS Filter

Filter Used	TSM	ANDS	
Noise	Input PSNR	Output PSNR	Output PSNR
10 %	15	34	28
20 %	12	30	21
30 %	11	24	16
40 %	9.5	20	13

Table 8
WF (5 * 5) ANDS Filter

Filter Used	TSM	ANDS	
Noise	Input PSNR	Output PSNR	Output PSNR
10 %	15	21	20
20 %	12	19	14
30 %	11	19	11
40 %	9.5	19	9.6

Table 9
WF (7 * 7) ANDS Filter

Filter Used	TSM	ANDS	
Noise	Input PSNR	Output PSNR	Output PSNR
10 %	15	21	20
20 %	12	19	14
30 %	11	19	11
40 %	9.5	19	9.6

The PSNR value for comparison of above two filters are plotted inFig.4 & Fig. 5 graph below

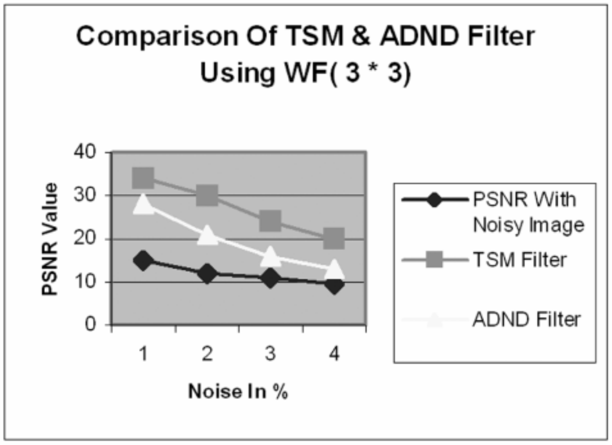

Fig.5: Comparison of TSM & ADND Filter

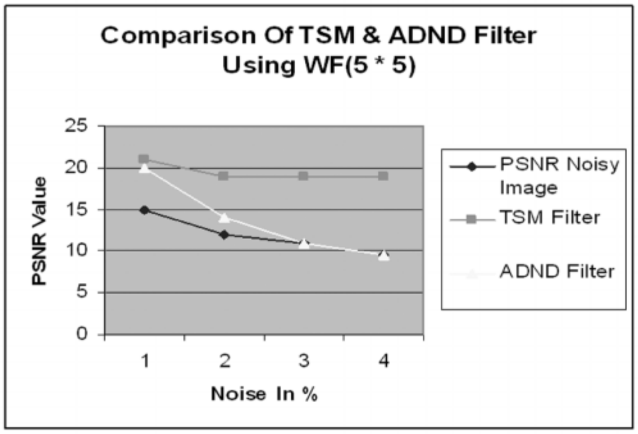

Fig. 5: Comparison Of TSM & ADND Filter Using WF (3 * 3) Using WF (5 * 5)

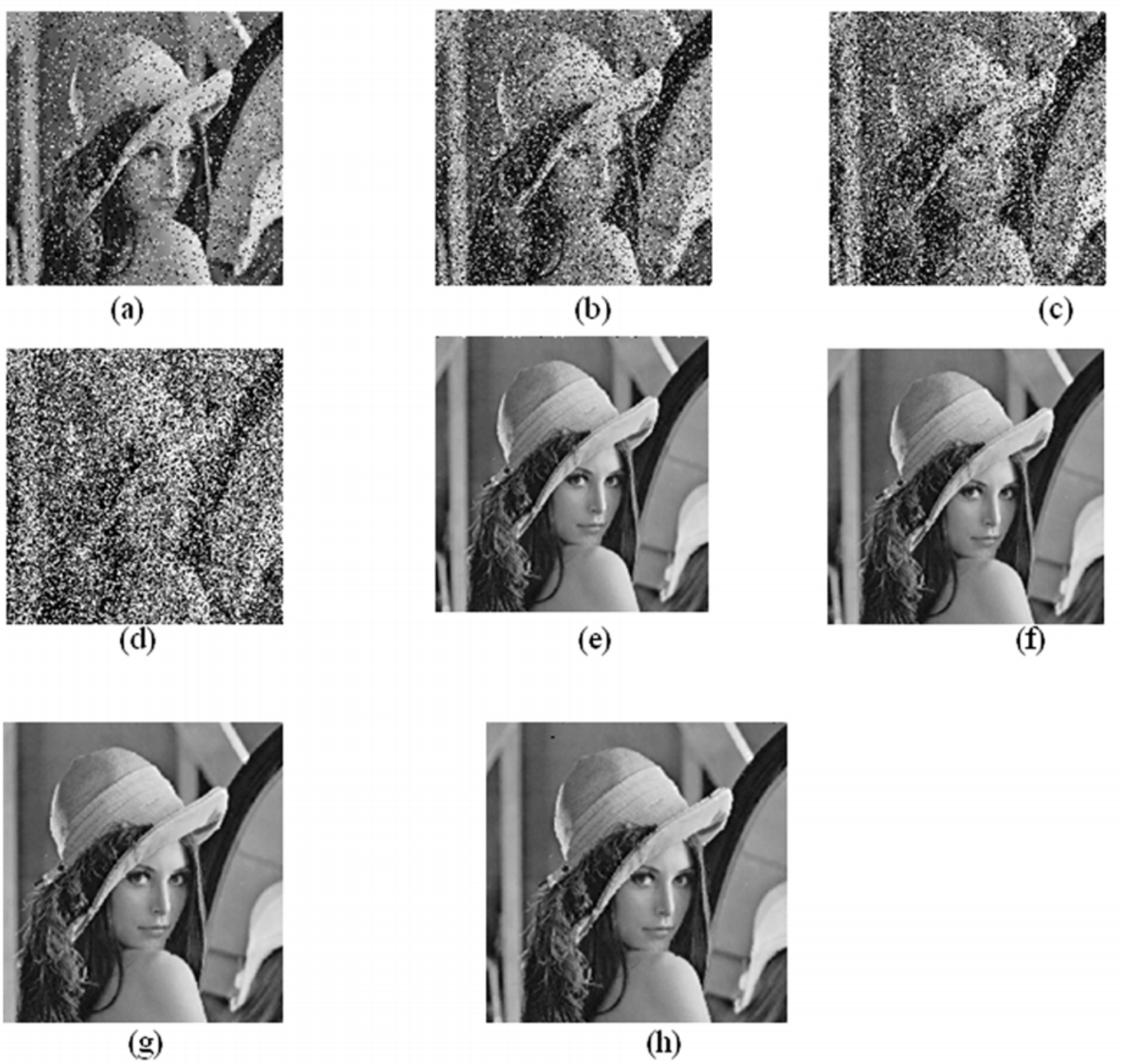

Fig. 3

From the PSNR value mention in the simulation result & from the PSNR graph it is very clear that TSM Filter shows better performance in suppressing impulsive noise compare to ANDS filter in suppressing impulse Noise when noise from 10 % to 40 % & Secondly extensive experimental result show that if we increase window size i.e. 5 * 5 & 7 * 7,we find that by increasing the window size image get more & more corrupted & filter is not able to suppress impulsive noise effectively compare to when window size in filter was (3 * 3) in filter. Though simulation time required is less, which is given in table below.

Table. 10
Average Run Time in Sec

Filter Used	TSM	ANDS
Window Size	Time In Sec	Time In Sec
WF (3 * 3)	16sec	28sec
WF (5 * 5)	14sec	21sec
WF (7 * 7)	13sec	18sec

Therefore from the above table it is very cleared that as window size increases image get more & more blurred & distorted though it requires less simulation time compare to that when window size in filter was (3 * 3). So mostly window size of WF (3 * 3) is preferred compare to that of WF (5 * 5) & WF (7 * 7).

CONCLUSION

In this entire paper, two different non-linear filters are implemented and extensive experiments are performed to obtain the results with various parameters to assess the performance of each filter. The plot of PSNR for these two filters is given above. The Table.7, 8 &9 above shows the PSNR value obtain using Lena Image of size 512 x 512.

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