Vol. 1, Issue 1, pp. 084-087

Image Denoising

1) Mr. Vijay R. Tripathi,

Lecturer In College of Engg & Technology,Akola-444004

Abstract: Noise in an image is a serious problem In this project, 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.

3 Noise Exclusive 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.

3.1 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 uniformover 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 chisquare significance probability value, can be applied to many distribution models such as *Uniform, Gaussian, Weibull, Beta, Exponential*, and *Lognormal* distribution models 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

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

For the computation of the chi-square goodness-of-fit testbased chi-square significance probability value, of an intensity level, 256 counted values, which denote 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, . . . , 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

$$p = 1 - \chi^2 \left(\sum_{i=1}^{10} (J - 25.6)^2 / 25 \right) \text{ --------- } (1)$$

The capabilities of preserving image details inherited by the identity filter, the CWM filter and the SM filter descend in the above mentioned 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

3.3. Implementation of the proposed filter

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

(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 3.1 and 3.2 .

(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

$$d_t = | \sqrt{K_t^2 + l_t^2} | , t = 1,2,3,\text{-----} \quad (2)$$

where s denotes the number of uncorrupted pixels that exist within the current window,W. (k, _) are integers (−1 ≤ k ≤ 1, −1 ≤ _ ≤ 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, l= 0).

(ii) Convert the computed d_t values to *distance weight*, h_t, by using (3) given below:

$$h_t = (d_t / \sum_{i=1}^{s} d_t)^{-1}$$

(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:

$$V_t = \sum_{t=1}^{s} h_t \rho_t$$

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.

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

Table 1. WF (3 * 3) NEF 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) NEF Filter

Table 2. WF (5 * 5) NEF 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) NEF Filter

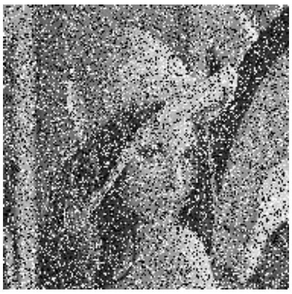
Table 3. WF (7 * 7) NEF Filter

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

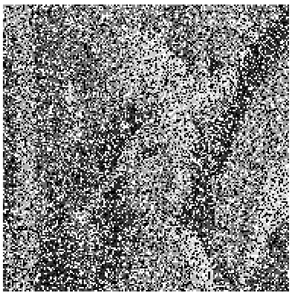
.

(a)

(b)



(c)



(d)

(e)

(f)

(g)

Filter Used		NEF		
Noise	Input PSNR	Output PSNR		
		(WF (3 * 3))	WF(5*5)	WF(7*7)
10 %	15	34	21	14
20 %	12	30	19	7. 3
30 %	11	24	19	6
40 %	9.5	20	19	5.9

(h)

Figure 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 NEF are in e, f, g, h for WF (3 * 3)

Conclusion: -

In this entire dissertation work, 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 below. The Table.7, 8 &9 below shows the PSNR value obtain using Lena Image of size 512 x 512.

From the PSNR value mention in the simulation result it is very clear that NEF Filter shows better performance in suppressing impulsive noise compare to other filters in suppressing impulse Noise when noise increases 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.

Table10: Average Run Time In Sec

Filter Used	NEF
Window Size	**Time In Sec**
WF (3 * 3)	**35sec**
WF (5 * 5)	**20sec**
WF (7 * 7)	**10sec**

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).

Reference: -

[1] R.C. Gonzalez and R.E. Woods Digital Image Processing Second Edition

[2] “NEF Filter For Image Denoising”, Pınar C¸ ivicio˘ glu , Mustafa Alc¸ı & Erkan Bes¸dok IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 8, NO. 12, DECEMBER 1999