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Design of Improved Method of Noise Removal from Digital Image

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Abstract:
Most of the nonlinear filters used in removal of noise work in two successive phases, i.e. noise detection followed by filtering, only the corrupted pixels keeping uncorrupted ones intact. Performance of such filters is dependent on the performance of detection schemes. In this work, thrust has been put to devise an accurate detection scheme and a improved adaptive filtering mechanism. The proposed method consists of noise detection followed by the removal of detected noise by median filter using selective pixels that are not noise themselves. The noise detection is based on simple thresholding of pixels. Computer simulations were carried out to analyse the performance of the proposed method and the results obtained were compared to that of conventional median filter and center weighted median (CWM) filter and mean filter.

Key words: *Improved median filter; conventional median filter; center weighted median (CWM) filter; Impulse noise; Salt and pepper; Image denoising; Non linear filters*

1. Introduction

The problem of extraction of information from noisy signals has led to the development of many techniques, most of which may be easily adapted to two dimensions and applied to image processing. Early techniques used for noise removal were linear [l]. Linear techniques possess mathematical simplicity, but in plenty situations they provide inadequate performance. If a signal which possesses sharp edges is corrupted by noise, then linear filters designed to remove the noise will also smooth out the edges. In addition, signal-dependent noise and impulsive noise cannot be suppressed sufficiently by linear filtering. In such cases, some form of nonlinear or adaptive filtering would be preferable. Amongst the initial nonlinear techniques used for noise removal was homomorphic filtering. This was applied for multiplicative noise removal [3]. Later, median filtering was shown to be computationally efficient and it preserved edges, while suppressing impulsive noise components quite well [5] -[7]. However, inspite of the advantages of median filtering, it often fails to provide sufficient smoothing of non-impulsive noise components.

Vision is the most advanced of our senses. So it is not surprising that the images play the single most important role in human perception. However, unlike humans who are limited to the visual band of the electromagnetic (EM) spectrum

Imaging machines cover almost the entire EM spectrum ranging from gamma to radio waves. They can operate on the images generated by sources that humans are not accustomed to associating with images. Thus digital image processing encompasses a wide and varied field of applications. Image processing operations can be roughly divided into three major categories [2]

- Image Compression
- Image Enhancement and Restoration
- Measurement Extraction

2. Related Work

In Image representation one is concerned with the characterization of the quantity that each picture element represents. An image could represent luminance of objects in a scene, the absorption characteristics of the body tissue, the radar cross section of the target, the temperature profile of the region or the gravitational field in an area. In general, any two dimensional function that bears information can be considered an image.

An important consideration in image representation is the fidelity or intelligibility criteria for measuring the quality of an image or the performance of processing technique. Specification of such measures requires models of perception of contrast, spatial frequencies, colours and so on. The fundamental requirement of digital processing is that images be sampled and quantized. The sampling rate has to be large enough to preserve the useful information in an image. It is determined by the bandwidth of the image.

In image enhancement, the goal is to accentuate certain image features for the subsequent analysis or for image display. Examples include contrast and edge enhancement, pseudo colouring, noise filtering, sharpening and magnifying. Image enhancement is useful in feature extraction, image analysis and visual information display. The enhancement process itself does not increase the inherent information display in the data. It simply emphasizes certain specified image characteristics. Enhancement algorithms are generally interactive and application dependent.

Image restoration refers to the removal or minimization of known degradations in an image. This includes de-blurring of images degraded by the limitations of a sensor or its environment, noise filtering and correction of geometric distortion or non-linearity due to sensors. A fundamental result in filtering theory used commonly for image restoration is called Weiner filter. This filter gives the best linear mean square estimate of the object of the observation. It can be implemented in the frequency domain via the fast unitary transform, in spatial domain by two dimensional recursive techniques similar to FIR non-recursive filters. It can also be implemented as a semi-recursive that employs a unitary transformation is one of the dimensions and a recursive filter in the other. Several other image restoration methods such as least squares, constraint least squares and spleen interpolation methods can be shown to belong to the class of Weiner filtering algorithms. Other methods such as maximum likelihood, minimum entropy is non-linear techniques that require iterative solutions.

Image analysis is concerned with making quantitative measurements of an image to produce a description of it. In simplest form, this task is reading a label on a grocery item, sorting different parts on an assembly line or measuring the size and orientation of blood cells in a medical image. More advanced image analysis systems measure quantitative information and use it to make a sophisticated decision such as controlling an arm of a robot to move an object after identifying it or navigating an aircraft with the aid of images acquired along its trajectory. Image analysis techniques require extraction of certain features that aid in the identification of an object.

Segmentation techniques are used to isolate the desired object. Quantitative measurements of object features allow classification and description of the image.

Image data compression is required for the amount of data associated with visual information is so large that its storage would require enormous storage capability. Although the capacities of several storage media are substantial, their access speeds are usually inversely proportional to their capacities. Typical television images data rates exceeding ten million bytes per second. There are other image sources that generate even higher data rates. Storage and transmission of such data require large capacity or bandwidth could be very expensive. Image data compression techniques are concerned with the reduction of the number if bits required to store or transmit images without any appreciable loss of information [2]. Image transmission applications are in broadcast television; remote sensing via satellite, aircraft, radar, sonar, teleconferencing, computer communications and facsimile transmission. Image storage is required most commonly for educational and business documents, medical images used in patient monitoring system. Because of their wide applications, data compression is of great importance in digital image processing.

3. Noise Models

The noise model used in [7], which assumes the maximum value for pixels corrupted by positive impulse noise, and the minimum value for those corrupted by negative impulse noise, is a somewhat special situation. If such a noise model is used, one only has to detect whether a pixel value is equal (or close) to the maximum or minimum value, and then apply a median filtering to those pixels. A fairly good performance can thereby be achieved. In order to simulate a more general situation, we model the noise as follows: We let $s_{i,j}$ denote the original image value at the ijth pixel, we let $x_{i,j}$ denote the nose corrupted image value at the ijth pixel, and let n denote the noise value. Thus:

$$x_{i,j} = s_{i,j} \quad \text{with probability } 1-p_e$$
$$x_{i,j} = s_{i,j} + n \quad \text{with probability } p_e$$

Impulse Noise model

Noise can be classified as salt-and-pepper noise (SPN) and random-valued impulse noise (RVIN). An image containing impulsive noise can be described as follows:

$$x(i,j) = \begin{cases} \eta(i,j), & \text{withprobability } p \\ y(i,j), & \text{with probability } 1-p \end{cases}$$

Where x (i,j) denotes the noisy image pixel where y (i,j) denotes a noise free image pixel and η(I,j) denotes a noisy impulse at the location (i,j) In salt-and-pepper noise, noisy pixels take either minimal or maximal values i.e.

$$\eta(i,j) \in \{L_{\min}, L_{\max}\}$$

and for random-valued impulse noise, noisy pixels take any value within the range minimal to maximal value i.e.

$$y(i,j) \in [L_{\min}, L_{\max}]$$

Where L_{max} , L_{min} denote the lowest and the highest pixel luminance values within the dynamic range respectively

$$R_{i,j} \in \{n_{\min}, n_{\max}\}$$

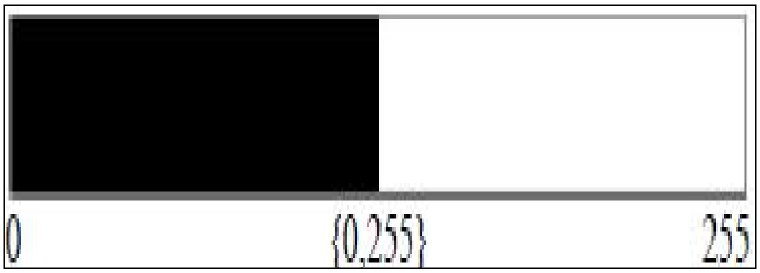

Figure 1: Representation of Salt & Pepper Noise

- Gaussian Noise

The PDF of a Gaussian random variable, z is given by

$$P(z) = \frac{1}{2\pi\sigma} e^{-(z-\mu)^2/2\sigma^2}$$

Where z represents gray level, μ is the mean of the average value of z, and σ is its standard deviation. The standard deviation squared σ^2 is called the variance of z. Because of its mathematical tractability in both the spatial and frequency domains, Gaussian (also called normal*)* noise models are frequently used in practice. In fact, this tractability is so convenient that it often results in Gaussian models being used in situations in which they are marginally applicable at best.

- Impulse (salt-and-pepper) noise

The PDF of impulse noise is given by

$$p(z) = \begin{cases} p_a, & for\ z = a \\ p_b, & for\ z = b \\ 0, & otherwise \end{cases}$$

If b > a, gray-level b will appear as a light dot in the image. Conversely will appear like a dark dot. If either Pa or Pb is zero, the impulse noise is called uni-polar. If neither probability is zero and especially if they are approximately equal impulse noise values will resemble salt-and-pepper granules randomly distributed over the image. For this reason bipolar impulse noise is also called s*alt-and-pepper noise*. Shot and spike noise terms are also used to refer this type of noise. Noise impulses can be negative or positive. Scaling usually is part of the image digitizing process. Because impulse corruption usually is large compared with the strength of the image signal, impulse noise generally is digitized as extreme (pure white or black) values in an image. Thus the assumption usually is that a and b are “saturated” values in the sense that they are equal to the minimum and maximum allowed values in the digitized image. As a result, negative impulses appear as black (pepper) points in an image. For the same reason, positive impulses appear white (salt) noise. For an 8-bit image this means that a = 0 (black) and b = 255 (white). Several noise detection techniques have the detection of impulse noise.

4. Proposed Algorithm

Noise Detection

In the proposed method for filtering, noise detection is done by simple thresholding. The steps involved in the noise detection algorithm are given below.

- Check for pixels that are possibly noise in the image is done, i.e. pixels with values 0 or 255 are considered.
- For each such pixel *p*, a sub window of size 3×3 around the pixel *p* is taken.
- Find the absolute differences between the pixel *p* and the surrounding pixels.
- The arithmetic mean (AM) of the differences for a given pixel *p* is computed.
- The AM is then compared with the “threshold” to detect whether the pixel *p* is informative or corruptive.

a. If AM is greater than or equal to the threshold the pixel is considered noisy.
b. Otherwise the pixel is considered as information

The threshold is a user defined value between the minimum and maximum pixel value (0,255) which is used to distinguish an informative pixel from a noise pixel.

To improve the performance of the noise detection algorithm at the borders of the image, the value of the pixel outside the image were considered to have a value of m rather than the conventional value of zero. The value of m is the mean value of the four corner pixels of the image.

$$PSNR=20\log_{10}\frac{255}{RMSE}$$

where,

RMSE (Root Mean Square Error)

$$RMSE=\boxed{\sqrt{\frac{1}{MN}\sum_{i,j}\left(y_{ij}-x_{ij}\right)^2}}$$

COR (Correlation)

$$COR=\boxed{\frac{\sum_{i,j}(y_{ij}-\mu_y)(x_{ij}-\mu_x)}{\sqrt{\sum_{i,j}(y_{ij}-\mu_y)^2\sum_{i,j}(x_{ij}-\mu_x)^2}}}$$

Where, yij and xij denote the pixel values of the restored and original image respectively, M×N is the size of the image, μx and μy represent the mean of the original and restored images.

The results obtained for the gray level Lena image in TABLE I was at a threshold of zero where the proposed method produced maximal result. These need not correspond to the maximum correlation values. These results are compared to that of a conventional median filter obtained using a 3×3 window applied once on the noisy image. The weights for the CWM filter were set at three for maximum performance.

The threshold by itself takes only discrete values 0, 31.875, 63.75, 95.625, 127.5, 159.325, 191.25, 223.125 in binary images. Any value between these values produces the same result as that corresponding to the nearest upper threshold [4]. For e.g., a threshold of 140.45 produces the same result as that corresponding to 159.325. These values are nothing but arithmetic means when the mask contains only one noisy pixel, two noisy pixels and so on respectively till there is only one information pixel in the neighbourhood. Therefore these thresholds put a restrain on the minimum number of noisy pixels that can be present in the neighbourhood so that the pixel might not be considered as noise.

5. Result Analysis

PSNR values for different filters on 'Lena' image

Noise (%)	Median Filter		CWM Filter		CWM Large Weight		ACWM		Improved Median Filter	
	PSNR dB	COR	PSNR dB	COR	PSNR dB	COR	PSNR dB	COR	PSNR dB	COR
10	32.5680	0.9775	29.0970	0.9662	18.1393	0.7796	35.8021	0.9412	31.8185	0.9343
20	29.3744	0.9674	23.4579	0.9148	14.0440	0.5812	31.7606	0.9352	26.4961	0.9081
30	24.0044	0.9228	19.0083	0.8087	11.7340	0.4415	26.9520	0.9125	23.0840	0.8621
40	19.0680	0.8126	15.4692	0.6536	9.9979	0.3256	22.0654	0.8519	20.3490	0.7924
50	15.4397	0.6634	12.9198	0.5070	8.7935	0.2497	18.2646	0.7494	18.2937	0.7082
60	12.3686	0.4890	10.8016	0.3630	7.8284	0.1810	14.7985	0.5870	16.4047	0.5904
70	9.8679	0.3236	9.0731	0.2413	7.0221	0.1238	11.9439	0.4094	14.7168	0.4508
80	8.0646	0.2068	7.7528	0.1530	6.3940	0.0816	9.7737	0.2584	13.3977	0.3072
85	7.2305	0.1336	7.1240	0.0989	6.0876	0.0525	8.7584	0.1697	12.7001	0.2134
90	6.5346	0.0829	6.5840	0.0583	5.8269	0.0335	7.9169	0.1024	12.1223	0.1289
91	6.3818	0.0795	6.4820	0.0585	5.7758	0.0330	7.7384	0.0959	11.9878	0.1197
92	6.2855	0.0689	6.4018	0.0480	5.7344	0.0276	7.6014	0.0770	11.8961	0.0948
93	6.1818	0.0680	6.3214	0.0481	5.6957	0.0276	7.4658	0.0747	11.8133	0.0903
94	5.9984	0.0490	6.1709	0.0323	5.6202	0.0194	7.2527	0.0497	11.6146	0.0601
95	5.9102	0.0459	6.1066	0.0322	5.5868	0.0185	7.1652	0.0452	11.5634	0.0486
96	5.7919	0.0353	6.0202	0.0230	5.5372	0.0137	7.0181	0.0308	11.4690	0.0296
97	5.6715	0.0288	5.9193	0.0174	5.4925	0.0121	6.8661	0.0219	11.3441	0.0166
98	5.5579	0.0196	5.8237	0.0105	5.4405	0.0071	6.7327	0.0058	11.2146	-0.0092
99	5.4531	0.0116	5.7459	0.0069	5.4023	0.0047	6.6141	-0.0054	11.1428	-0.0238

Table 1: PSNR and COR at Different Noise Density for 'Lena' Image

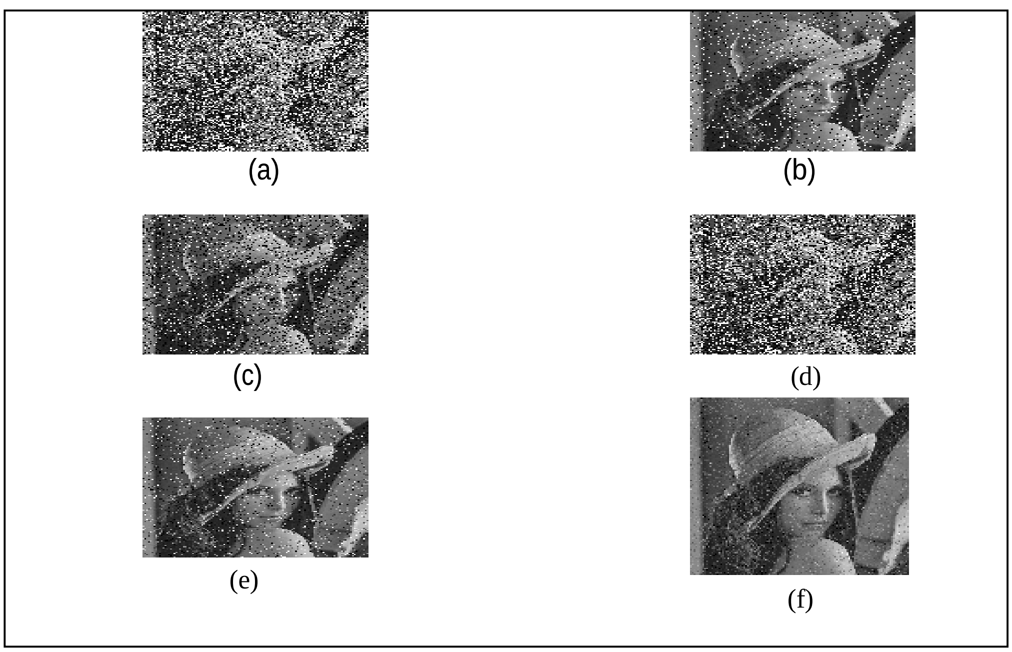

Figure 2: (A) Corrupted with 60% Noise (B) Output from Median Filter (C) Output from CWM Filter (E)Output from CWM with Large Weight (F) Output from ACWM (G) Output from Improved Filter

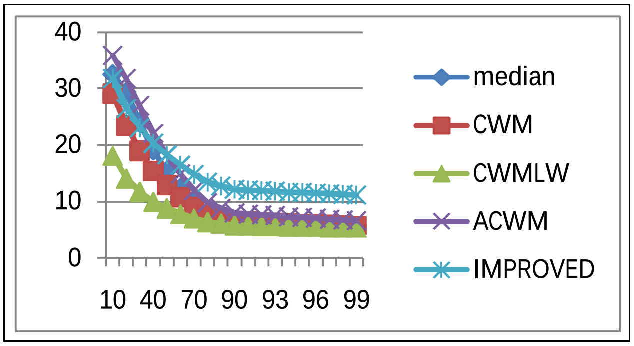

Figure 3: Plot for PSNR Values of Lena Image

6. Conclusion and Future Scope

From the experimental results obtained for the filter as a denoising technique at various noise densities for both gray level and binary images the following conclusions are drawn

- The proposed method provides better image restoration compared to the conventional median filter and mean and center weighted median filter at both low and high noise densities in the case of binary and gray level images.
- In addition, the studied method uses simple fixed length window, and hence, it requires significantly lower processing time compared with other methods. The simulation results show that the studied method can be applied to different types of images and provide very satisfying results. It has significant improvement over the existing methods. In the future, various techniques can be considered to incorporate in this scheme to further improve the performance and preserve more edges in both high and low corrupted images.
- The threshold chosen for gray level images is zero for which the filter performs its best. This means in gray level images all minimum and maximum gray level values that occur abnormally are considered as noise (0,255).

The only difficulty faced by the proposed filter is the threshold which is to be given manually for binary images that varies from image to image. The threshold has to be checked for performance by trial and error every time which is quite tedious and time consuming. This can be overcome by an algorithm that decides the threshold and is adapted to the image. This provides future scope for the improvement of the proposed filter as a denoising technique. Also the noise detection technique used was of the simplest form and a better detector is expected to improve the performance of the filter.

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