Noise Reduction Using Arithmetic Mean Filtering (A Comparison Study of Application to Different Noise Types)

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Abstract: ***Images are often corrupted by unwanted signals otherwise known as noise during acquisition and transmission alike, leading to loss of clarity of information in severe cases. Image restoration aimed at reduction in degradation and noise removal thus becomes imperative in digital image processing. This work focuses on the restoration of corrupted images in the presence of noise only. The arithmetic mean filter was applied to denoise an image sample corrupted by different noise types and its performance on the noise types was compared using the average percentage difference in the pixel values of the original and denoised image as well as the Peak-signal-to-noise ratio (PSNR). Simulation results show that the Arithmetic Mean Filter performs best on the image corrupted by Poisson Noise.***

Keywords: Degradation, Denoising, Mean Filters, Restoration, PSNR.

1. Introduction

Images are frequently corrupted by noise due to the errors generated in noisy sensors and communication channels [3], [4]. Generally, noise is any form of unwanted signal and can come in a whole lot of forms ranging from periodic to random noises which can be additive or multiplicative.[1]-[4] Some examples include Gaussian noise, Impulse noise, Speckle noise and many others. The impulse noise is Fat-tail distributed or "impulsive" noise is sometimes called salt-and-pepper noise [2], [8] or spike noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc. It can be mostly eliminated by using dark frame subtraction and interpolating around dark/bright pixels.

2. Types of Image Noise

2.1 Gaussian Noise

Gaussian noise in digital images arises mostly during acquisition. It is caused usually by one or more of several factors including poor illumination, high temperature, electronic circuit noise and so on. [3] The standard model of this noise is additive, independent at each pixel and independent of the signal intensity.

The PDF of a Gaussian random variable, z is given by [4];

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(Z-Z')^2/2\sigma^2} \quad (1)$$

Where z'= mean value of z
σ^2= variance of z

2.2 Salt and Pepper (Impulse) noise

In salt and pepper noise (sparse light and dark disturbances), pixels in the image are very different in color or intensity from their surrounding pixels; the defining characteristic is that the value of a noisy pixel bears no relation to the color of surrounding pixels. [3] Generally this type of noise will only affect a small number of image pixels. When viewed, the image contains dark and white dots, hence the term salt and pepper noise. It can be caused by camera dust and overheated or faulty charge-coupled devices elements.

Its PDF is given by [4];

$$p(z) = \begin{cases} P_a & for\ z = a \\ P_b & for\ z = b \\ 0 & otherwise \end{cases} \quad (2)$$

2.3 Speckle Noise

Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and synthetic aperture radar (SAR) images. Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean grey level of a local area. Speckle noise in SAR is generally more serious, causing difficulties for image interpretation. It is caused by coherent processing of backscattered signals from multiple distributed targets. Common causes include signals from elementary scatters, the gravity-capillary ripples, and manifests as a pedestal image, beneath the image of the sea waves.

2.4 Poisson or Shot Noise

Shot noise or Poisson noise is a type of electronic noise which can be modeled by a Poisson process. In electronics shot noise originates from the discrete nature of electric charge. It occurs when the finite number of particles that carry energy, such as electrons in an electronic circuit or photons in an optical device, is small enough to give rise to detectable statistical fluctuations in a measurement.

Individual photon detections can be treated as independent events that follow a random temporal distribution. As a result, photon counting is a classic Poisson process, and the number of photons N measured by a given sensor element over a time interval t is described by the discrete probability distribution

$$\Pr(N=k)=\frac{e^{-\lambda t}(\lambda t)^k}{k!} \quad (3)$$

Where λ is the expected photons per unit time.

3. System Modeling

The system is modeled to have an image f(x,y) as the input which is then degraded by a degradation function H which is added to a noise term to produce a corrupted image g(x,y). This process is called **degradation.** If we have sufficient knowledge about the degradation function H and the noise term η(x,y), an attempt can be made get an estimate f'(x,y) of the original image to as close as possible, depending on the amount of information at our disposal. [4]

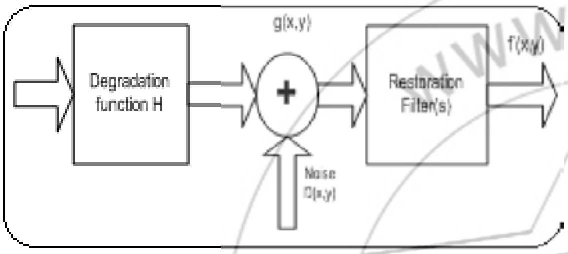

Figure 1: Image Restoration Model

In spatial domain

$$g(x,y)=h(x,y)\otimes f(x,y)+\eta(x,y) \quad (4)$$

In frequency domain

$$G(u,v)=H(u,v).F(u,v)+N(u,v) \quad (5)$$

Where

$$H(u,v)=\mathrm{F}\{h(x,y)\} \quad (6)$$
$$G(u,v)=\mathrm{F}\{g(x,y)\} \quad (7)$$
$$N(u,v)=\mathrm{F}\{\eta(x,y)\} \quad (8)$$

F implies Fourier Transform and $\otimes$ is the convolution operator.

For the purpose of this work, our interest is in the degradation due to noise only and hence H is taken as the identity operator.

In spatial domain and frequency domain, equations (4) and (5) are thus reduced to;

$$g(x,y)=f(x,y)+\eta(x,y) \quad (9)$$
$$G(u,v)=F(u,v)+N(u,v) \quad (10)$$

Usually, the noise terms are not known so the process of noise removal cannot be done by subtracting the noise function from the corrupted image.

4. Spatial Filtering

Spatial domain refers to the original image plane itself. When image processing is done by direct manipulation of pixels in the spatial plane, the process is called spatial filtering. [4]

A spatial filteris an image operation where each pixel value f(x,y) is changed by a function of the intensities of pixels in a neighborhood of (x,y).

Generally, spatial domain processes will be represented by;

$$g(x,y)=T[f(x,y)] \quad (11)$$

Where f(x,y) is the input image
g(x,y) is the output image

T is an operator on f defined over a neighbourhood of point (x,y).

If a point (m,n) is defined as the pixel to operate on, a 3x3 neighborhood about the point (m,n) is as shown in Figure 2;

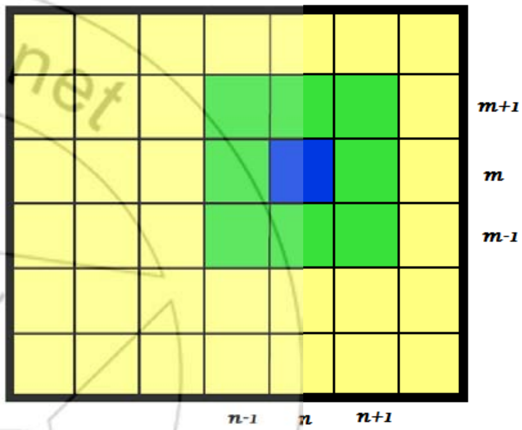

Figure 2: A 3x3 Neighborhood mask

The spartial mask coefficients are then generated based on the specified neighbourhood designations as given in Figure 2.

5. Filtering Method

In selecting the type and technique to apply in noise reduction algorithm, it is necessary to put a number of factors into consideration. These may include but is not limited to:

- The specific capacity and handling power of hardware like computers and cameras to be used.
- The allowable degree of aggressiveness in image handling processes i.e. whether sacrificing some real detail is acceptable.
- The characteristics of the noise.

Based on the requirement of this work, the arithmetic mean filter was adopted and applied to image sample corrupted by Gaussian, Salt and pepper, Speckle and Poisson noise.

5.1 Arithmetic Mean Filter

This is the simplest of the mean filters. Let S_{xy} represent the set of coordinates in a rectangular subimage window of size m X n, centered at point (x, y).The arithmetic mean filtering process computes the average value of the corrupted image g(x, y) in the area defined by Sxy.The value of the restored image at any point (x, y) is simply the arithmetic mean computed using the pixels in the region defined by S.

Mathematically;

$$f'(x,y) = \frac{1}{mn} \sum_{(s,t) \in S_{xy}} g(s,t) \qquad (12)$$

A mask size of 3x3 was used so each coefficient has a value of 1/9.

5.2 Performance Evaluation Measure

The performance evaluation of noise removal using the proposed method was quantified by;

A. Peak signal- to-noise ratio (PSNR) calculated using the standard formula given as follows;

$$PSNR = 10log_{10}\left[\frac{L^2}{mse}\right] \qquad (13)$$

Where L = dynamic range of allowable intensities,

$$mse = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(y_{ij} - x_{ij}\right)^2 \qquad (14)$$

B. Percentage difference in pixel value between original image and reformed image calculated by.

$$V = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{y_{ij} - x_{ij}}{x_{ij}} * 100\% \qquad (15)$$

The procedural steps followed are given by the flow chart of Figure 3.

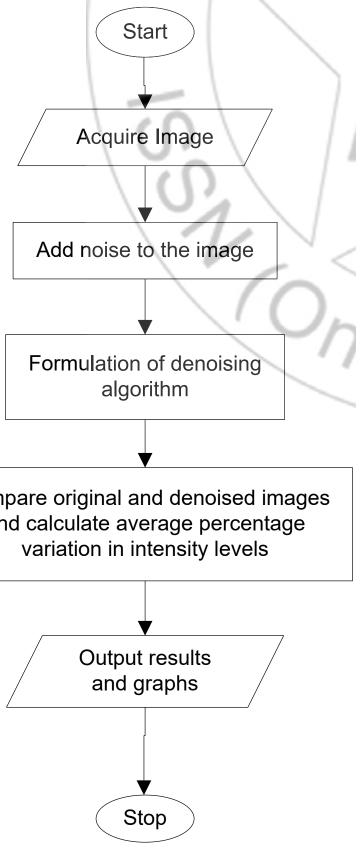

Figure 3: Flow Chart

6. Results and Discussions

To evaluate the noise removal capability of the arithmetic mean filtering (AMF) technique and its performance with different noise samples, the grayscale rice image was used. This was corrupted with Gaussian noise, salt& pepper noise, speckle noise and poisson noise. This degraded image is filtered through the AMF. Performance of the AMF algorithm on the noise types was then compared by taking average percentage difference in the pixel values of the original and denoised image and the PSNR as performance criteria.

The simulation results are as presented.

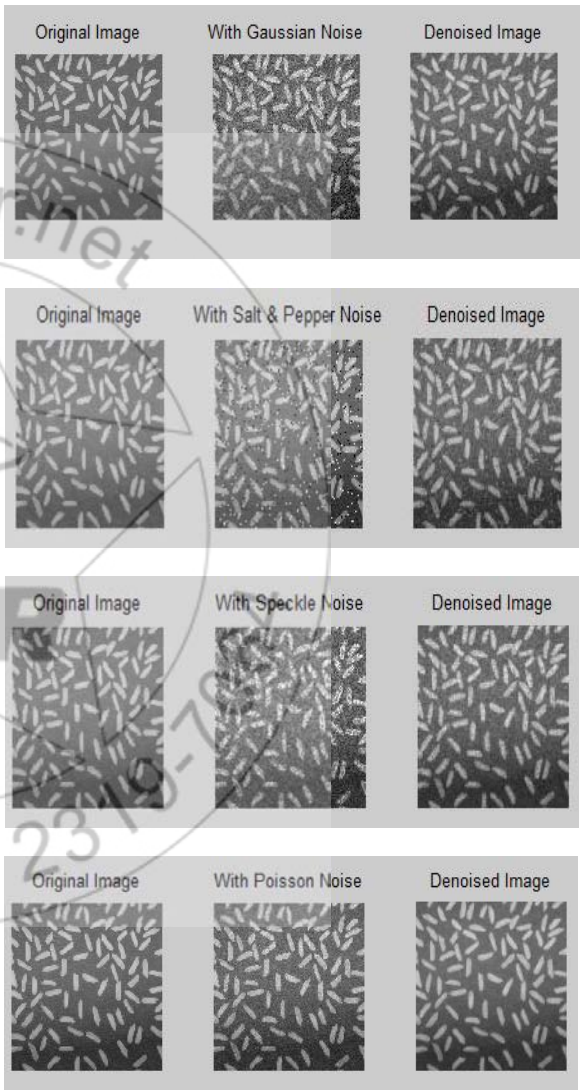

Figure 4: Results of Denoising using Arithmetic Mean Filter: (a) Gaussian noise (b) Salt and pepper noise (c) Speckle noise (d) Poisson noise

Table 1: Performance Evaluation using Percentage Variation in Pixel Intensity

Noise Type	Gaussian	Salt and pepper	Speckle	Poisson
% variation in Pixel Value	9.617	10.0548	8.8385	6.8891

Table 2: Performance Evaluation using PSNR

Noise Type	PSNR
Gaussian	11.1886
Salt and pepper	66.3277
Speckle	38.9860
Poisson	5.3479

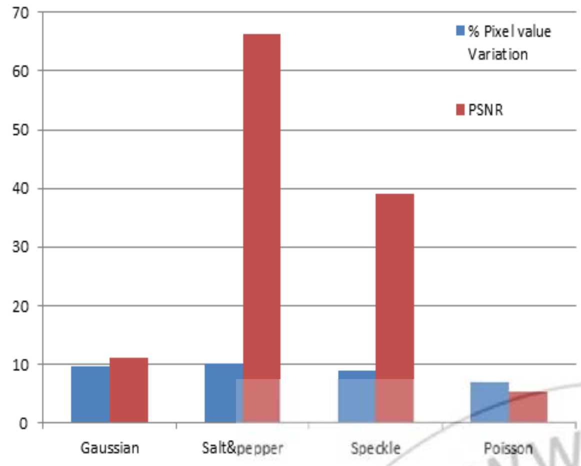

Figure 5: Performance Evaluation

7. Conclusion

In this research work, the arithmetic mean filter was applied to a sample image corrupted by four different types of noise. A neighborhood consisting of 3x3 element mask was used and pixels were regenerated using mean values of pixels in its neighborhood. Simulation results show good results and considerable reduction in noise for all four noises considered. However, it was shown that the filter performs best when applied to the sample corrupted with poisson noise using the two performance indexes considered.

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