Image Restoration Filters in Spatial Domain for various Noise Density Ranges

Smita Agrawal¹ Sunil Kumar² Anurag Bajpai³ Vivek Kumar⁴
¹,²,³,⁴Department of Electronics Design & Technology
¹,²,³,⁴NIELIT, Gorakhpur, India

Abstract— Image Restoration is an area of image processing that deals with the removal of noise by various filtering techniques. There are various filters that exist in literature for various types of noise. Most of them are specific to the noise type and particular noise ranges. These are classified into linear and non-linear filters. Linear filters are more suitable for gaussian noise removal even at higher noise densities (>30%) and at times for speckle noise removal, whereas non-linear filters are more suitable for impulse noise removal, especially at low and medium level densities. However, at higher noise densities, non-linear filtering efficiency generally gets degraded. In this paper, a comparative analytical treatment is done for six filtering methods, at medium to high noise densities, and the choice of the most suitable filter technique is determined for particular noise ranges. The noise and filter functions are implemented in MATLAB.

Key words: SNR, PSNR, MSE, Salt and Pepper Noise, Speckle Noise, Gaussian Noise, Hybrid Median Filter

I. INTRODUCTION

Noise removal from a corrupted image has been a prominent field of research and a large number of algorithms have been implemented, tested and their results are compared [2][3][16][18][20]. The main thrust on all such algorithms is to remove impulse noise while preserving image details [21]. Non-linear filters are most suitable for performing noise removal as well as edge preservation, while linear filters cause blurring of images [17][20][21][22][23]. Linear filtering of an image is accomplished through an operation called convolution. Convolution of neighbour-hood operation in which each output pixel is the weighted sum of neighbouring input pixels. The matrix of weights is called the convolution kernel, also known as the filter. A convolution kernel is a correlation kernel that has been rotated 180 degrees [22]. The operation called correlation is closely related to convolution. In correlation, the value of an output pixel is also computed as a weighted sum of neighbouring pixels. The difference is that the matrix of weights, in this case, called the correlation kernel, is not rotated during the computation. Major linear filters include Mean Filter, Adaptive Wiener Filter, Gaussian Filter. Linear filters are more suited for frequency domain as these work on the frequency spectrum [19][20]. These remove speckle noise and also, gaussian noise to a great extent, thereby reducing the size of the image, however, in doing that, they cause blurring of images, with Wiener filter being an exception. Non-linear filtering methods, on the other hand, give excellent salt and pepper (impulse) noise removal in spatial domain. These, however, are not suited for gaussian noise removal as their statistical analysis is very difficult.

II. NOISE

Noise arises as a result of un-modelled or un-modellable processes going on in the production and capture of the real signal [2]. It is not part of the ideal signal and may be caused by a wide range of sources, e.g., variations in the detector sensitivity, environmental variations, the discrete nature of radiation, transmission or quantization errors, etc. It is also possible to treat irrelevant scene details as if they are image noise (e.g. surface reflectance textures). The characteristics of noise depend on its source, as does the operator which best reduces its effects [10][14][15]. Many image processing packages contain operators to artificially add noise to an image. Deliberately corrupting an image with noise allows us to test the resistance of an image processing operator to noise and assess the performance of various noise filters. Noise can generally be grouped into two classes:

- Independent noise.
- Noise which is dependent on the image data.

Image independent noise can often be described by an additive noise model, where the recorded image f(x,y) is the sum of the true image s(x,y) and the noise n(x,y): f(x,y) = s(x,y) + n(x,y)

(1)

The noise n(x,y) is often zero-mean and described by its variance σ₂. The impact of the noise on the image is often described by the signal to noise ratio (SNR), which is given by:

\[
SNR = \frac{\sigma_s^2}{\sigma_n^2} = \left(\frac{\sigma_s^2}{\sigma_n^2}\right)^{-1} - 1
\]

(1)

Where σ₂ and σ₂ are the variances of the true image and the recorded image, respectively. In the second case of data-dependent noise (e.g. arising when monochromatic radiation is scattered from a surface whose roughness is of the order of a wavelength, causing wave interference which results in image speckle), it is possible to model noise with a multiplicative, or non-linear, model. These models are mathematically more complicated; hence, if possible, the noise is assumed to be data independent. The major types of noise that occur in MRI and ultrasound spectroscopy are impulse noise and speckle noise. In this work, three types of noise are filtered; viz., salt and pepper (impulse) noise, speckle noise, and gaussian noise; and the results are analysed by three parameters; viz., SNR, PSNR and MSE. Six filters are used for noise removal separately and their performance is observed for different noise densities.

A. Impulse Noise

The impulse noise may be classified into salt-and-pepper noise and random valued noise. The salt and pepper noise pixels can take only the maximum gray and the minimum gray values. But in random valued noise pixels can take any random value between the maximum and minimum gray values. Thus, it could severely degrade the image quality and
cause some loss of information. An image containing impulse noise can be represented as
\[
g(x, y) = \begin{cases} 
    n(x, y) & \text{with probability } P \\
    f(x, y) & \text{with probability } 1 - P
\end{cases}
\]
(3)

The detection of random valued impulse noise is much difficult than the detection of salt-and-pepper. The mean square error (MSE) is used to determine the peak signal to noise ratio (PSNR).
\[
MSE = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (g(x, y) - f(x, y))^2 \\
PSNR = 10 \log \left( \frac{255^2}{MSE} \right)
\]
(4)
(5)

O(x, y) is the original image, f(x, y) represents the denoised image, and M x N is the size of the image. Idea behind in this PSNR is to compute a single number that reflects the quality of the restored image. Salt-and-pepper noise is a form of noise sometimes seen on images. It is also known as fixed valued impulse noise. This noise can be caused by sharp and sudden disturbances in the image signal. It presents itself as sparsely occurring white and black pixels. Here, the noise is caused by errors in the data transmission

III. RESULTS

A. Gaussian Noise

This kind of noise is due to the discrete nature of radiation, i.e. the fact that each imaging system is recording an image by counting photons. Allowing some assumptions (which are valid for many applications) this noise can be modelled with an independent, additive model, where the noise n(x, y) has a zero-mean Gaussian distribution described by its standard deviation σ, or variance. This means that each pixel in the noisy image is the sum of the true pixel value and a random, Gaussian distributed noise value. Gaussian noise is statistical noise having a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed. Image noise is the random variation of brightness or colour information in images produced by the sensor and circuitry of a scanner or digital camera. The probability density function p of a Gaussian random variable z is given by:
\[
p_c(z) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}
\]
(6)

In digital image processing, Gaussian noise can be reduced using a spatial filter, though when smoothing an image, an undesirable outcome may result in the blurring of fine-scaled image edges and details because they also correspond to blocked high frequencies. Conventional spatial filtering techniques for noise removal include: mean (convolution) filtering, median filtering and Gaussian smoothing.

B. Speckle Noise

Speckle is a granular 'noise' that inherently exists in and degrades the quality of the active radar, synthetic aperture radar (SAR), medical ultrasound and optical coherence tomography images. The vast majority of surfaces, synthetic or natural, are extremely rough on the scale of the wavelength. Images obtained from these surfaces by coherent imaging systems such as laser, SAR, and ultrasound suffer from a common phenomenon called speckle. Speckle, in both cases, is primarily due to the interference of the returning wave at the transducer aperture. The origin of this noise is seen if we model our reflectivity function as an array of scatterers. Because of the finite resolution, at any time we are receiving from a distribution of scatterers within the resolution cell. These scattered signals add coherently; that is, they add constructively and destructively depending on the relative phases of each scattered waveform. Speckle noise results from these patterns of constructive and destructive interference shown as bright and dark dots in the image. Speckle noise is a multiplicative noise, i.e. it is in direct proportion to the local gray level in any area. The signal and the noise are statistically independent of each other. The sample mean and variance of a single pixel are equal to the mean and variance of the local area that is centred on that pixel. Gaussian filters perform best removal of speckle noise as their impulse response is a gaussian function itself.

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p_c(z) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}
\]
At high noise densities, average (mean) filters perform marginally better than other filters for speckle noise removal. They, however, behave poorly for salt and pepper noise removal.

Adaptive Wiener Filters perform fairly well for speckle and gaussian noise removal at medium to high noise densities but not for salt and pepper noise.

Gaussian filters perform the best noise filtering at lower noise densities, and they fairly well for higher noise densities also. However, these are highly inefficient for gaussian noise and impulse noise removal.

Salt and pepper noise

Speckle noise

Gaussian noise

Fig. 2: Average Filtering at 30% Noise

Fig. 3: Adaptive Wiener Filtering at 30% Noise

Fig. 4: Gaussian Filtering at 30% Noise

Fig. 5: Standard Median Filtering at 30% Noise
Salt and pepper noise

Spence noise

Gaussian noise

Fig. 6: Weighted Median Filtering at 30% Noise
Standard Median Filters exhibit quite superior filtering for salt and pepper noise at even very high noise densities.

Table 1: Filter performance at 10% noise

<table>
<thead>
<tr>
<th>NOISE Type</th>
<th>Parameter</th>
<th>Average SNR (dB)</th>
<th>Adaptive Wiener SNR (dB)</th>
<th>Gaussian Filter SNR (dB)</th>
<th>Standard Median Filter SNR (dB)</th>
<th>Weighted Median Filter SNR (dB)</th>
<th>Hybrid Median Filter SNR (dB)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>MSE</td>
<td>0.0102</td>
<td>0.0124</td>
<td>0.0188</td>
<td>0.0063</td>
<td>0.0499</td>
<td>0.0061</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>0.0079</td>
<td>0.0051</td>
<td>0.0044</td>
<td>0.0080</td>
<td>0.0092</td>
<td>0.0065</td>
</tr>
<tr>
<td>Gaussian Noise</td>
<td>SNR (dB)</td>
<td>8.781</td>
<td>7.565</td>
<td>5.384</td>
<td>9.578</td>
<td>5.254</td>
<td>6.191</td>
</tr>
<tr>
<td></td>
<td>PSNR (dB)</td>
<td>17.616</td>
<td>17.438</td>
<td>15.257</td>
<td>19.451</td>
<td>12.398</td>
<td>15.026</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>0.0173</td>
<td>0.0180</td>
<td>0.0290</td>
<td>0.0113</td>
<td>0.0576</td>
<td>0.0334</td>
</tr>
</tbody>
</table>

Fig. 7: Hybrid Median Filtering at 30% Noise
Hybrid Median Filters perform best noise removal for salt and pepper noise at low noise densities. They behave, however, quite poorly, at higher noise density values.

Table 2: Filter performance at 30% noise

From Table 1, it is evident that median filters and their derivations provide best discrete impulse noise removal at lower noise densities (Figure 8).

Fig. 8: Bar Graphs for salt and pepper noise filtering at 10% noise density

However, median filters tend to minimize the mean square error better than the linear filters for this purpose. Overall, hybrid median filters provide convenient results both in terms of SNR and MSE (Figure 9). At lower noise densities, standard median filters exhibit superior performance for Gaussian noise removal both in terms of SNR as well as MSE.
六种不同的滤波器已被用于本工作，以测试在不同噪声密度下的滤波性能。在低和中等噪声密度范围内，混合中值滤波器对盐和胡椒噪声的去除效果最好。然而，它们的性能随着噪声密度的增加而急剧下降。在高噪声密度下，它们仅在斑点噪声过滤中给出满意的结果。加权中值滤波器在大多数噪声密度下都不如其他滤波方法有效，因此需要某种适应性改进来提高性能[4][24]。高斯滤波器在低以及高噪声密度下都表现得最好，对斑点噪声过滤非常有效。虽然加权维纳滤波器适合于高斯噪声的去除，在低及高噪声密度下都表现得很好，但它们在高噪声密度下不能很好地减轻边缘的模糊。平均滤波器在高噪声范围下给出合理的结果，但模糊仍然是一个主要问题。标准中值滤波器在大多数情况下都能提供有用的结果，甚至在高噪声密度下。但它们在计算上非常昂贵，耗时且难以实现。进一步的研究需要更好的噪声去除方法，特别是在非常高的噪声水平和适当的自适应算法方面，特别是非线性滤波器。
REFERENCES


