# Filter-based Denoising Methods for AWGN corrupted images

Sumit Singh Parihar[1], Shailesh Khaparkar[2]
*Student[1], Assistant Professor[2]*
*Department of Electronics & Communication Engineering[1, 2],*
*Gyan Ganga Institute of Technology & Sciences, Jabalpur*

***ABSTRACT:*** *Visual information transfer in the form of digital images becomes a vast method of communication in the modern scenario, but the image obtained after transmission is many a times corrupted with noise. The received image requires some processing before it can be used. Image denoising includes the manipulation of the image data to produce a visually high-quality image. In this paper a review of some existing denoising algorithms, such as filtering approach; wavelet-based approach and their comparative study has been done. Different noise models including additive and multiplicative types are discussed. It includes Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. Selection of the denoising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise present in the image so that one can opt the appropriate denoising algorithm. The filtering approach seems to be a better choice when the image is corrupted with salt and pepper noise. Whereas, wavelet-based techniques are suited for more detailing. In this paper denoising techniques for AWGN corrupted image has been mainly focused.*

***KEYWORDS:*** *AWGN, Image Denoising, Noise, Filtering, DWT, threshold.*

## I. INTRODUCTION

A very large portion of digital image processing is dedicated to image restoration. It includes research in algorithm development and routine goal-oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained. Degradation comes from blurring as well as noise due to electronic and photometric sources.[12] Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contributes to the degradation [13].

Let us now consider the representation of a digital image. A 2-dimensional digital image can be represented as a 2-dimensional array of data $s(x,y)$, where $(x,y)$ represent the pixel location. The pixel value corresponds to the brightness of the image at location $(x,y)$. Some of the most frequently used image types are binary, gray-scale and color. Binary images are the simplest type of images and can take only two discrete values, black and white. Black is represented with the value „0" while white with „1". Note that a binary image is generally created from a gray-scale image. A binary image finds applications in computer vision areas where the general shape or outline information of the image is needed. They are also referred to as 1 bit/pixel images [5]. Gray-scale images are known as monochrome or one-color images. The images used for experimentation purposes in this thesis are all gray-scale images. They contain no color information. They represent the brightness of the image. This image contains 8 bits/pixel data, which means it can have up to 256 (0-255) different brightness levels.

For representation of pixels in brightness format "0" represents black and "255" denotes white. In between values from 1 to 254 represent the different gray levels. As they contain the intensity information, they are also referred to as intensity images. Color images are considered as three band monochrome images, where each band is of a different color. Each band provides the brightness information of the corresponding spectral band [6]. Typical color images are red, green and blue images and are also referred to as RGB images. This is a 24 bits/pixel image.

The main aim of this paper is to review all the existing methodology which are used for estimation of the uncorrupted image from the distorted or noisy image, and is also referred to as image "denoising". There are various methods to help restore an image from noisy distortions. Selecting the appropriate method plays a major role in getting the desired image. The denoising methods tend to be problem specific. For example, a method that is used to denoise satellite images may not be suitable for denoising medical images. In this paper it is proposed that a study would made on the various denoising algorithms. In case of image denoising methods, the characteristics of the degrading system and the noises are assumed to be known.

## II. BASIC NOISE THEORY

Noise is defined as an unwanted signal that interferes with the communication or measurement of another signal. A noise itself is an information-bearing signal that conveys information regarding the sources of the noise and the environment in which it propagates.

 

There are many types and sources of noise or distortions and they include [7], thermal noise and shot noise, Acoustic noise, Electromagnetic noise Electrostatic noise, Quantization noise. Signal distortion is the term often used to describe a systematic undesirable change in a signal and refers to changes in a signal from the non-ideal characteristics of the communication channel, signal fading reverberations, echo, and multipath reflections and missing samples. Depending on its frequency, spectrum or time characteristics, a noise process is further classified into several categories:

## II.I Additive and Multiplicative Noises

Noise is present in an image either in an additive or multiplicative form. An additive noise follows the rule [9]:

$$w(x,y) = s(x,y) + n(x,y)$$

While the multiplicative noise satisfies

$$w(x,y) = s(x,y) X\, n(x,y)$$

Where s(x,y) is the original signal, n(x,y) denotes the noise introduced into the signal to produce the corrupted image w(x,y), and (x,y) represents the pixel location.

## II.II Gaussian Noise

Gaussian noise is evenly distributed over the signal this means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function given by,

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(g-m)^2}{2\sigma^2}}$$

Where g represents the gray level, m is the mean or average of the function and σ is the standard deviation of the noise.

## II.III Salt and Pepper Noise

Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, *a* and *b*. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255 [16]. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. The probability density function for this type of noise is shown in Figure 2.

## II.IV Speckle Noise

Speckle noise is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR (Synthetic Aperture Radar) imagery. The source of this noise is attributed to random interference between the coherent returns. Fully developed speckle noise has the characteristic of multiplicative noise. Speckle noise follows a gamma distribution and is given as:

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!\,\alpha^{\alpha}} e^{\frac{g}{\alpha}}$$

Where variance is $a^2\alpha$ and $g$ is the gray level.
On an image, speckle noise (with variance 0.05) looks as shown in Figure 3

## II.V Brownian Noise

Brownian noise comes under the category of fractal or $1/f$ noises. The mathematical model for $1/f$ noise is fractional Brownian motion. Fractal Brownian motion is a non-stationary stochastic process that follows a normal distribution. Brownian noise is a special case of $1/f$ noise. It is obtained by integrating white noise. It can be graphically represented as shown in Figure 5. On an image, Brownian noise would look like Image 6.

# III. FILTER-BASED IMAGE DENOISING

## A. Linear and Nonlinear Filtering Approach

Filters play a major role in the image restoration process. The basic concept behind image restoration using linear filters is digital convolution and moving window principle. Let $w(x)$ be the input signal subjected to filtering, and $z(x)$ be the filtered output. If the filter satisfies certain conditions such as linearity and shift invariance, then the output filter can be expressed mathematically in simple form as

$$Z(X) = \int W(t)h(x-t)dt$$

Where $h(t)$ is called the point spread function or impulse response and is a function that completely characterizes the filter. The integral represents a convolution integral and, in short, can be expressed as:

$$z = w * h.$$

For a discrete case, the integral turns into a summation as

$$z(i) = \sum_{-\infty}^{+\infty} w(t)h(i-t)$$

## B. Mean Filter

A mean filter acts on an image by smoothing it; that is, it reduces the intensity variation between adjacent pixels [3]. The mean filter is nothing but a simple sliding window spatial filter that replaces the center value in the window with the average of all the neighboring pixel values including itself. By doing this, it replaces pixels that are unrepresentative of their surroundings. It is implemented with a convolution mask, which provides a result that is a weighted sum of the values of a pixel and its neighbors. It is also called a linear filter. The mask or kernel is a square. Often a 3× 3 square kernel is used.:

## C. LMS Adaptive Filter

An adaptive filter does a better job of denoising images compared to the averaging filter. The fundamental difference

between the mean filter and the adaptive filter lies in the fact that the weight matrix varies after each iteration in the adaptive filter while it remains constant throughout the iterations in the mean filter [15]. Compared to other adaptive filters, the Least Mean Square (LMS) adaptive filter is known for its simplicity in computation and implementation. The basic model is alinear combination of a stationary low-pass image and a non-stationary high-pass component through a weighting function. Thus, the function provides compromise between resolution of genuine features and suppression of noise [9].

### D. Median Filter

A median filter belongs to the class of nonlinear filters unlike the mean filter [7]. The median filter also follows the moving window principle similar to the mean filter. A 3× 3, 5× 5, or 7× 7 kernel of pixels is scanned over pixel matrix of the entire image. The median of the pixel values in the window is computed, and the center pixel of the window is replaced with the computed median. Median filtering is done by, first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value [14]. Note that the median value must be written to a separate array or buffer so that the results are not corrupted as the process is performed.

### E. External Bilateral Filter

Filters based on Gaussian functions are of particular importance because their shapes are easily specified and both the forward and inverse Fourier transforms of a Gaussian function are real Gaussian functions. Further if the frequency domain filter is narrower, the spatial domain filter will be wider which attenuates the low frequencies resulting in increased smoothing/blurring. These Gaussian filters are typical linear filters that have been widely used for image denoising. Gaussian filters assume that images have smooth spatial variations and pixels in a neighborhood have close values, by averaging the pixel values over a local neighborhood suppresses noise while preserving image features. However, this assumption fails at edges where the spatial variations are not smooth and the application of Gaussian filter blurs the edges. Bilateral filter overcomes this by filtering the image in both range and domain (space). Bilateral filtering is a local, nonlinear and non-iterative technique which considers both gray level (color) similarities and geometric closeness of the neighboring pixels.

### F. Discrete Wavelet Transform Filter-banks

Wavelets are mathematical functions that analyze data according to scale or Resolution. They aid in studying a signal in different windows or at different resolutions. For instance, if the signal is viewed in a large window, gross features can be noticed, but if viewed in a small window, only small features can be noticed. Wavelets provide some advantages over Fourier transforms. For example, they do a good job in approximating signals with sharp spikes or signals having discontinuities. Wavelets can also model speech, music, video and non-stationary stochastic signals. Wavelets can be used in applications such as image compression, turbulence, human vision, radar, earthquake prediction, etc.

The term “wavelets” is used to refer to a set of Ortho-normal basis functions generated by dilation and translation of scaling function φ and a mother wavelet ψ. The finite scale multi resolution representation of a discrete function can be called as a discrete wavelet transform. DWT is a fast linear operation on a data vector, whose length is an integer power of 2. This transform is invertible and orthogonal, where the inverse transform expressed as a matrix is the transpose of the transform matrix. The wavelet basis or function, unlike sine and cosines as in Fourier transform, is quite localized in space. But similar to sine and cosines, individual wavelet functions are localized in frequency.

DWT is the multi resolution description of an image. The decoding can be processed sequentially from a low resolution to the higher resolution. DWT splits the signal into high and low frequency parts [8]. The high frequency part contains information about the edge components, while the low frequency part is split again into high and low frequency parts. The high frequency components are usually used for watermarking since the human eye is less sensitive to changes in edges. In two dimensional applications, for each level of decomposition, we first perform the DWT in the vertical direction, followed by the DWT in the horizontal direction. After the first level of decomposition, there are 4 sub-bands: LL1, LH1, HL1, and HH1. For each successive level of decomposition, the LL Sub-band of the previous level is used as the input. To perform second level decomposition, the DWT is applied to LL1 band which decomposes the LL1 band into the four sub- bands LL2, LH2, HL2, and HH2.To perform third level decomposition, the DWT is applied to LL2 band which decompose this band into the four sub-bands – LL3, LH3, HL3, HH3. This results in 10 sub-bands per component. LH1, HL1, and HH1 contain the highest frequency bands present in the image tile, while LL3 contains the lowest frequency band.

DWT is currently used in a wide variety of signal processing applications, such as in audio and video compression, removal of noise in audio, and the simulation of wireless antenna distribution [5].

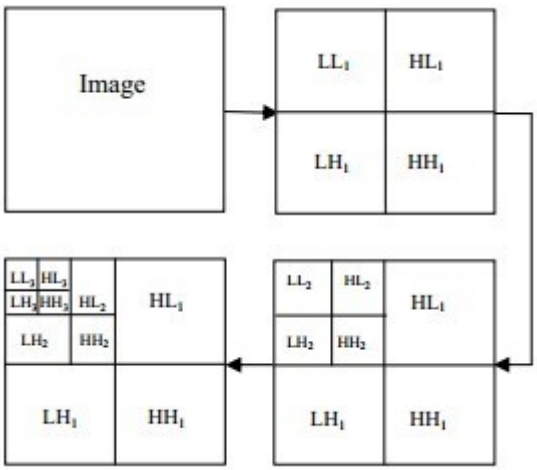


**Fig. 1: 3 level discrete wavelet decomposition**

Wavelets have their energy concentrated in time and are well suited for the analysis of transient, time-varying signals. Since most of the real life signals encountered are time varying in nature, the Wavelet Transform suits many applications very well. As mentioned earlier, the wavelet equation produces different wavelet families like Daubechies, Haar, Coiflets, etc [10].

## IV. WAVELET THRESHOLDING

The term wavelet thresholding is explained as decomposition of the data or the image into wavelet coefficients, comparing the detail coefficients with a given threshold value, and shrinking these coefficients close to zero to take away the effect of noise in the data. The image is reconstructed from the modified coefficients. This process is also known as the inverse discrete wavelet transform. During thresholding, a wavelet coefficient is compared with a given threshold and is set to zero if its magnitude is less than the threshold; otherwise, it is retained or modified depending on the threshold rule. Thresholding distinguishes between the coefficients due to noise and the ones consisting of important signal information [4].

A noisy image is decomposed into a low frequency approximation sub-image and a series of high frequency detail sub-images at different scales and directions via transform. To estimate the noise-free coefficients in detail sub-bands, a Bayesian estimator is developed [2].

The choice of a threshold is an important point of interest. It plays a major role in the removal of noise in images because denoising most frequently produces smoothed images, reducing the sharpness of the image [11]. Care should be taken so as to preserve the edges of the denoised image. There exist various methods for wavelet thresholding, which rely on the choice of a threshold value. Some typically used methods for image noise removal include VisuShrink, SureShrink and BayesShrink. Prior to the discussion of these methods, it is necessary to know about the two general categories of thresholding. They are hard- thresholding and soft-thresholding types.

Wavelet theory has been developed rapidly in recent years, which has increasingly wide application in image denoising. It is very important to select threshold function and threshold in wavelet threshold denoising algorithm. Different selections will affect the denoising effect directly. In [1], traditional soft and hard threshold functions were further analyzed and studied, advantages of denoising performances in both soft and hard threshold functions were combined for an improved threshold function. Threshold proposed by Donoho was improved according to characteristics of wavelet decomposition layers and noise wavelet coefficient in the paper [8].

## V. SIMULLATION RESULTS & DISCUSSIONS

To check the performance of image denoising with filtering techniques alone, simulation has been performed for Lena test image using bilateral filters only. The performance of bilateral filtered denoised image has been compared for MSE, MAE, PSNR and SSIM image quality parameters with recent similar kind of image denoising methods. Simulation results values of PSNR & MSE for different wavelets are tabulated in Table-I.

**Table-I: Simulation Results for Test Image Lena**

| *Noise Variance* | *Noisy Image* | | | | *Denoised using external bilateral Filtering* | | | |
|---|---|---|---|---|---|---|---|---|
| *σ* | PSNR (dB) | MSE | MAE | SSIM | PSNR (dB) | MSE | MAE | SSIM |
| *5* | 34.14 | 25.08 | 22 | 0.8421 | 34.58 | 22.65 | 38 | 0.9021 |
| *10* | 28.13 | 100.02 | 45 | 0.6070 | 32.04 | 40.60 | 53 | 0.8687 |
| *15* | 24.61 | 224.22 | 67 | 0.4466 | 30.64 | 56.18 | 71 | 0.8419 |
| *20* | 22.13 | 398.11 | 89 | 0.3409 | 29.73 | 69.17 | 82 | 0.8172 |
| *25* | 20.23 | 616.60 | 111 | 0.2700 | 29.05 | 80.84 | 88 | 0.7922 |
| *30* | 18.70 | 877.39 | 133 | 0.2202 | 28.47 | 92.31 | 92 | 0.7668 |


Figure 2: Original test image 'Lena' used for simulation.

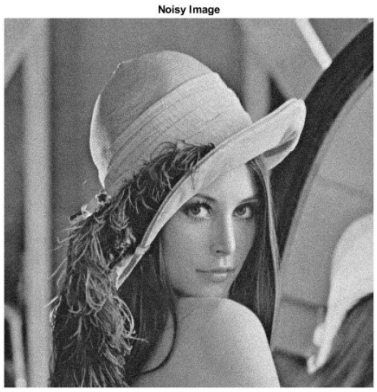


Figure 3: Gaussian noise corrupted test image 'Lena' for noise variance σ=10.

For simulation first image is taken and it is corrupted by gaussian noise from range of 5 to 30 dB, to check the effectiveness of bilateral filter approach for a wide range of noise variance, then the image is denoised using external bilateral filter.


Figure 4: Denoised noisy image 'Lena' using external bilateral filtering only.

To check the effectiveness simulations results comparison has been done, which is shown in Table-II. It can be seen that the bilateral filtering approach seems to outperforms many of the existing denoising methods, in terms of denoised image PSNR.

| Noise → Variance σ ↓ Algorithm | σ =10 | σ =20 | σ =30 |
|---|---|---|---|
| This Work | **32.04** | **29.73** | **28.47** |
| NIG-WT [5] | 31.97 | 28.42 | 26.27 |
| Visu-shrink [12] | 30.65 | 27.76 | 26.33 |

## VI. CONCLUSION

In this paper image denoising techniques for the AWGN corrupted has been given. This paper reviews the existing denoising algorithms, such as filtering approach; wavelet-based approach. Different noise models including additive and multiplicative types are used. They include Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. The filtering approach seems to be a better choice when the image is corrupted with salt and pepper noise and to check the performance of bilateral filtering approach a simulation exercise has been performed. The wavelet-based approach finds applications in denoising images corrupted with Gaussian noise. Selection of the denoising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise present in the image so as to select the appropriate denoising algorithm. In the sequel paper performance of external bilateral filtering along with wavelet domain thresholding will be checked.

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