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A Comparative Study of Various Image Filtering Techniques for Removing Various Noisy Pixels in Aerial Image

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Abstract

In advanced image processing, aerial image processing plays an important role in object extraction such as building extraction, road detection etc. The aerial images captured are usually bound to suffer from Gaussian noise, salt and pepper noise, speckle noise etc. Therefore obtaining of aerial image with high accuracy is very difficult task. A flawless aerial image is inevitable for further object extraction process. There are a number of filtering techniques to detach the noise for preserving the integrity of captured aerial image. In this paper we have applied mean filter, median filter, wiener filter, wavelet transform and curvelet transform for removal of various level of Gaussian noise, salt and pepper noise and speckle noise added separately in an aerial image. The performance of both the transforms and filtering methods are compared in terms of Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE).

Keywords*: aerial image, noise removal, filtering, mean, median, wavelet transform, curvelet transform*

1. Introduction

With growing application in science and engineering digital image processing is treated as a rapidly evolving field. In the real world signals do not exist without noise, which arises during image acquisition (digitization) and/or transmission. When images are acquired using a camera, light levels and sensor temperature are major factors affecting the amount of noise. During transmission, images are corrupted mainly due to interference in the channel used for transmission. Removing noise from images is an important problem in image processing.

In the early development of image processing, linear filters were the primary tools for image enhancement and restoration. Their mathematical simplicity and the existence of some desirable properties made them easy to design and implement. Moreover, linear filters offered satisfactory performance in many applications. However, they have poor performance in the presence of non additive noise and in situations where system nonlinearities or Gaussian statistics are encountered [5]. In image processing applications, linear filters tend to blur the edges and do not remove Gaussian and mixed Gaussian impulse noise effectively. Linear noise removal methods are not so effective when transient non-stationary wideband components are involved since their spectrum is similar to the spectrum of noise, the basic idea that the energy of a signal will often be concentrated in a few coefficients in the transform domain while the energy of noise is spread among all coefficients in transform domain. Therefore, the nonlinear methods will tend to keep a few larger coefficients representing the signal while the noise coefficients will tend to reduce to zero. Noise removal methods based on multiresolution transforms involves three steps: A linear forward transform, nonlinear thresholding step and a linear inverse transform. Wavelets are successful in representing point discontinuities in one dimension, but less successful in two dimensions. As a new multiscale representation suited for edges and other singularity curves, the curvelet transform has emerged as a

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powerful tool. The developing theory of curvelets predict that, in recovering images which are smooth away from edges, curvelets obtain smaller asymptotic mean square error of reconstruction than wavelet methods[7].

In this comparative study, various filtering algorithms are used to fully remove noise from aerial images and to preserve the quality of them. These filtering algorithms have various advantages and disadvantages. Among the different filters, none of them overcome others in respect to computation cost, noise removing and quality of resultant image. As a result, noise removal method can be improved and still is an open research area.

2. Types of Noise

Noise represents unwanted information which collapses image quality. In the image noise removal process, information about the type of noise present in the original image plays a significant role. Typical images are corrupted with noise modeled with either a Gaussian, uniform, or salt or pepper distribution. Another typical noise is a speckle noise, which is multiplicative in nature. The behavior of each of these noises is described below.

2.2. Gaussian Noise

Gaussian noise statistical noise that has a probability density function of the normal distribution that is also known as Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed. Gaussian noise is properly defined as the noise with a Gaussian amplitude distribution. Noise is modeled as additive white Gaussian noise (AWGN), where all the image pixels deviate from their original values following the Gaussian curve. That is, for each image pixel with intensity value f_{ij} $(1 \leq i \leq m, 1 \leq j \leq n$ for an m x n image), the corresponding pixel of the noisy image g_{ij} is given by,

$$g_{ij} = f_{ij} + n_{ij} \quad (1)$$

Where, each noise value n is drawn from a zero -mean Gaussian distribution.

2.2. Salt and Pepper Noise

Salt and pepper noise is caused by sharp, sudden disturbances in the image signal and its appearance is randomly scattered white or black (or both) pixels over the image. An image containing salt and pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This noise type can be caused by dead pixels, analog to digital converter errors and bit errors in transmission.

2.3. Speckle Noise

Speckle noise affects all inherent characteristics of coherent imaging, including medical ultra sound imaging. It is caused by coherent processing of backscattered signals from multiple distributed targets. Speckle noise is caused by signals from elementary scatters. In medical literature, speckle noise is referred to as 'texture' and may possibly contain useful diagnostic information. For visual interpretation, smoothing the texture may be less desirable. Physicians generally have a preference for the original noisy images, more willingly, than the smoothed versions because the filter, even if they are more sophisticated, can destroy some relevant image details. Thus it is essential to develop noise filters which can preserve the features that are of interest to the physician. Several different methods are used to eliminate speckle noise, based upon different mathematical models of the phenomenon. In our work, we recommend hybrid filtering techniques for removing speckle noise in ultrasound images. The speckle noise model has the following form (denotes multiplication). For each image pixel with intensity value f_{ij}

($1 \leq i \leq m$, $1 \leq j \leq n$ for an m x n image), the corresponding pixel of the noisy image g_{ij} is given by,

$$g_{ij} = f_{ij} \, . \, f_{ij} n_{ij} \qquad (2)$$

Where, each noise value n is drawn from uniform distribution with mean 0 and variance σ^2.

3. Some Existing Filtering Techniques

3.1. Mean Filter

Mean filtering is a simple, intuitive and easy to implement method to reduce noise in images by reducing the amount of intensity variation between one pixel and the next. It is often used for *smoothing*. The idea of mean filtering is simply to replace each pixel value in an image with the mean or average value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean. Often a 3×3 square kernel is used, as shown in Figure 1, although larger kernels for example 5×5 squares can be used for more severe smoothing.

The main problem with mean filtering is that a single pixel with a very unrepresentative value can significantly affect the mean value of all the pixels in its neighborhood.

$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$

Figure 1. 3×3 Averaging Kernel often used in Mean Filtering

3.2. Median Filter

Median filter often does a better job than the mean filter of preserving useful detail in the image. Like the mean filter, the median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the *mean* of neighboring pixel values, it replaces it with the *median* of those values. The median is calculated 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.

In general, the median filter allows a great deal of high spatial frequency detail to pass while remaining very effective at removing noise on images where less than half of the pixels in a smoothing neighborhood have been effected. As a consequence of this, median filtering can be less effective at removing noise from images corrupted with Gaussian noise.

One of the major problems with the median filter is that it is relatively expensive and complex to compute. To find the median it is necessary to sort all the values in the neighborhood into numerical order and this is relatively slow, even with fast sorting algorithms such as quick sort.

3.3. Wiener Filter

The Wiener filter is the MSE-optimal stationary linear filter for images degraded by additive noise and blurring. Calculation of the Wiener filter requires the assumption that the signal and noise processes are second-order stationary (in the random process sense). Wiener filters are often applied in the frequency domain. Given a degraded image X (n, m), one takes the Discrete Fourier Transform (DFT) to obtain X (u, v). The original image spectrum is estimated by taking the product of X (u, v) with the Wiener filter G (u,v):

$$\hat{S}(u,v) = G(u,v)\,X(u,v) \quad (3)$$

The inverse DFT is then used to obtain the image estimate from its spectrum. The Wiener filter is defined in terms of these spectra:

H (u, v) is the Fourier transform of the point spread function (PSF).

$P_s(u, v)$ is the Power spectrum of the signal process, obtained by taking the Fourier transform of the signal autocorrelation.

$P_n(u, v)$ is the Power spectrum of the noise process, obtained by taking the Fourier transform of the noise autocorrelation.

The Wiener filter is:

$$G(u,v) = \frac{H*(u,v)P_s(u,v)}{|H(u,v)|^2 P_s(u,v) + P_n(u,v)} \quad (4)$$

Dividing through by P_s makes its behavior easier to explain:

$$G(u,v) = \frac{H*(u,v)}{|H(u,v)|^2 + \frac{P_n(u,v)}{P_s(u,v)}} \quad (5)$$

The term P_n/P_s can be interpreted as the reciprocal of the signal-to-noise ratio. Where the signal is very strong relative to the noise, $P_n/P_s \approx 0$ and the Wiener filter becomes $H^{-1}(u, v)$ -the inverse filter for the PSF. Where the signal is very weak, $P_n/P_s \rightarrow \infty$ and $G(u, v) \rightarrow 0$.

For the case of additive white noise and no blurring, the Wiener filter simplifies to:

$$G(u,v) = \frac{P_n(u,v)}{P_s(u,v) + \sigma_n^2} \quad (6)$$

Where σ_n^2 is the noise variance.

3.4. Wavelet Transform

Wavelet domain is advantageous because DWT make the signal energy concentrate in a small number of coefficients; hence, the DWT of a noisy image consists of number of coefficients having high Signal to Noise Ratio (SNR) while relatively large number of coefficients is having low SNR. After removing the coefficients with low SNR, the image is reconstructed using inverse DWT [3]. Time and frequency localization is simultaneously provided by Wavelet transform. Moreover, wavelet methods represent such signals much more efficiently than either the original domain or Fourier transforms [8].

The DWT is same as hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition. Image is decomposed into four sub-bands and critically sampled by applying DWT as shown in Figure 1. These sub bands are formed by separable applications of horizontal and vertical filters. Sub-bands with label LH1, HL1 and HH1 correspond to finest scale coefficient while sub-band LL1 represents coarse level coefficients [6] [3]. The LL1 sub band is further decomposed and critically sampled to find out the next coarse level of wavelet coefficients as shown in Figure 1. It results in two level of wavelet decomposition.

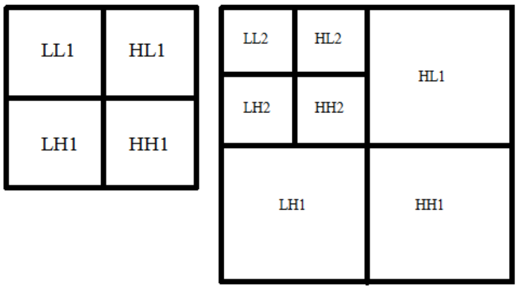

Figure 2. Image Decomposition by using DWT

Wavelet thresholding is a signal estimation technique that exploits the capabilities of Wavelet transform for removal of noise from signal. It removes noise by killing coefficients that are irrelevant relative to some threshold [6] .Several studies are there on thresholding the Wavelet coefficients. The process, commonly called Wavelet Shrinkage, consists of following main stages:

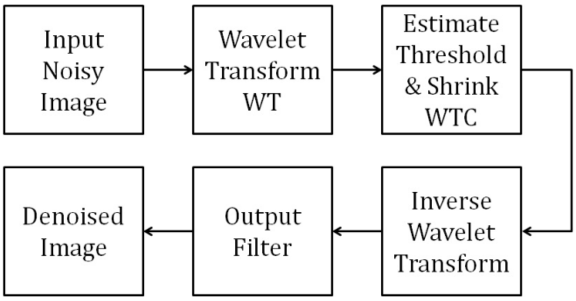

Figure 3. Block Diagram of Image Noise Removal using Wavelet Transform

- Read the noisy image as input.
- Perform DWT of noisy image and obtain Wavelet coefficients.
- Estimate noise variance from noisy image.
- Calculate threshold value using various threshold selection rules or shrinkage rules.
- Apply soft or hard thresholding function to noisy coefficients.
- Perform the inverse DWT to reconstruct the denoised image.

There are two thresholding functions frequently used as Hard threshold [4] and Soft threshold. Hard thresholding function keeps the input if it is larger than the threshold; otherwise, it is set to zero. Soft thresholding function takes the argument and shrinks it toward zero by the threshold. Soft thresholding rule is chosen over hard thresholding, for the soft thresholding method yields more visually pleasant images over hard thresholding. A small threshold may yield a result close to the input, but the result may still be noisy. Large threshold alternatively, produces signal with large number of zero coefficients. This leads to a smooth signal.

3.5. Curvelet Transform

The Curvelet transform is a higher dimensional generalization of the wavelet transform designed to represent images at different scales and different angles. Curvelet transform is a special member of the multiscale geometric transforms. It is a transform with multiscale pyramid with many directions at each length scale. Curvelets will be superior over wavelets in following cases: [1]

- Optimally sparse representation of objects with edges.
- Optimal image reconstruction in severely ill-posed problems.
- Optimal sparse representation of wave propagators.

The idea of the Curvelet transform is first to decompose the image into subbands means to separate the object into a series of disjoint scales. Curvelets are initially introduced by Candes and Donoho[9]. The Discrete Curvelet transform (DCT) takes as input a Cartesian grid of the form f(n1, n2), 0≤n1, n2<n, and outputs a collection of coefficients cD(j, l, k) defined by,

$$C^D = \sum_{n_1,n_2} f(n1,n2)\overline{\emptyset^D_{j,l,k}(n1,n2)} \qquad (7)$$

Where $\emptyset^D_{j,l,k}$ are digital curvelet waveforms which preserve the listed properties of the continuous curvelet. DCT can be implemented in two ways. The first method is based on unequally spaced fast Fourier transform (USFFT) and the second is based on the Wrapping of specially selected Fourier samples [2]. The two implementations essentially differ by spatial grid used to translate curvelets at each scale and angle.

For the 2D image, the architecture of the DCT via Wrapping is as follows:

- Apply the 2D FFT and obtain Fourier samples.

f [n1, n2], -n/2≤ n1, n2 <n/2

- For each scale j and angle l, form the product.

$U_{j,l}$ [n1, n2] f[n1, n2]

- Wrap this product around the origin and obtain.

$f'_{j,l}$ [n1, n2] = W ($U_{j,l}$ f) [n1, n2]

- Apply the inverse 2D FFT to each $f'_{j,l}$ [n1, n2] hence collecting the discrete coefficients $c^D(j, l, k)$.

The curvelet noise removal method consists of the following steps:

- Estimate the noise standard deviation σ in the input image.
- Calculate the Curvelet transform of the input image. We get a set of bands w_j, each band w_j contains N_j coefficients and corresponds to a given resolution level.
- Calculate the noise standard deviation σ_j for each band j of the Curvelet transform.
- For each band j do: Calculate the maximum of the band and multiply each curvelet coefficient.
- Reconstruct the image from the modified curvelet coefficients.

4. Comparative Study

The experimental evaluation is performed on aerial image *pentagon.tiff* of size 1024*1024 pixels downloaded from the USC-SIPI image database. The objective quality of the reconstructed image is measured by Root Mean Square Error (RMSE) and Peak Signal to Noise Ratio (PSNR). RMSE is a measure of the "average" error, weighted according to the square of the error. PSNR is defined as the ratio of signal power to noise power. It basically obtains the gray value difference between resulting image and original image.

$$RMSE = \sqrt{\frac{\sum (f(i,j) - g(i,j))^2}{mn}} \quad (8)$$

$$PSNR = 20log_{10}\frac{255}{RMSE} \quad (9)$$

Here f (i, j) is the original aerial image with noise, g (i, j) is the enhanced image and m and n are the total number of pixels in the horizontal and vertical dimensions of the image. The low value of RMSE indicates the better enhancement approach but the high PSNR value indicates the better ones. The original noisy image and filtered image obtained by various filtering techniques are shown in Figure 4 to 8. Visual comparison of PSNR and RMSE of Gaussian noise, salt and pepper noise and speckle noise removal with respect to Mean Filter, Median Filter, Wiener Filter, Wavelet Transform and Curvelet Transform are shown in Figure 9 to 11. Table 1 to 6 show the RMSE and PSNR values of image filtered by five different types of filters.

5. Conclusion

Noise is one of obstructions in automatic image understanding and noise reducing is very important to improve the results of further processing. In this paper various filtering techniques are implemented on aerial image to remove different types of noise. The results are analyzed and evaluated. The comparative study is conducted with Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). Through this work it is observed that in case of Gaussian noise the performance of all the filters and transformation techniques are almost same. On the other hand for salt and pepper noise the filters work better than the transforms especially median filter performs the best. In addition wavelet transform performs better than all the filters and transforms for speckle noise. The results achieved through this paper are useful for various purposes to analyze the image.

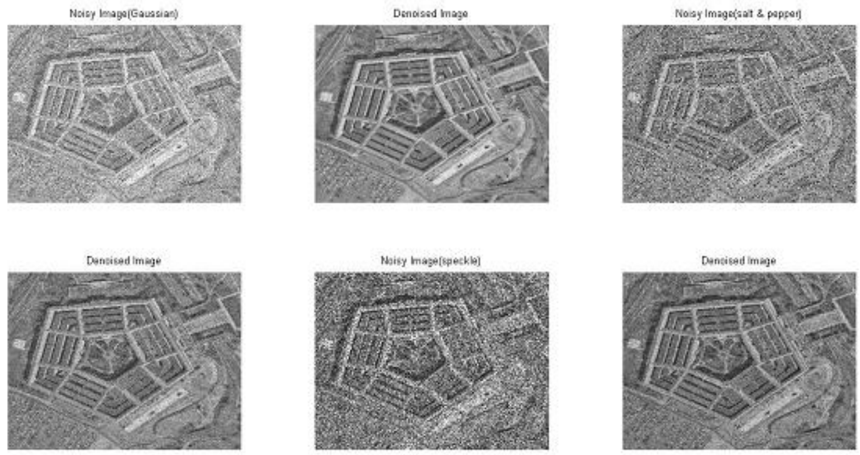

Figure 4. Three Different Types of Noise and Corresponding Enhanced Image using Mean Filter

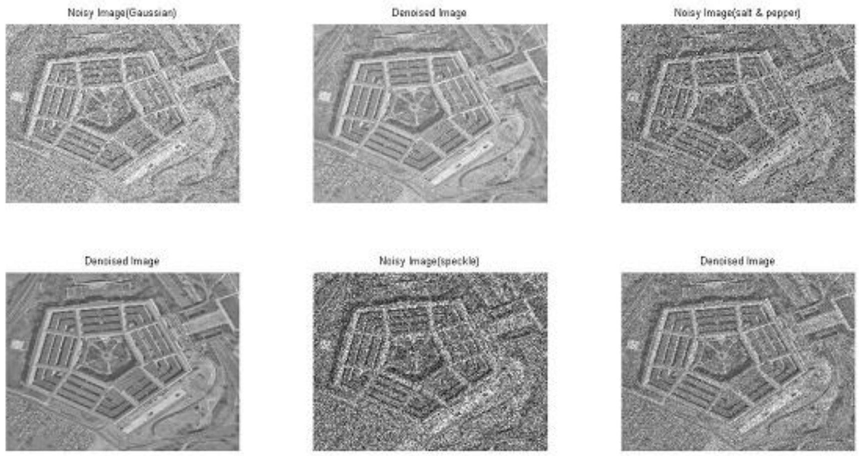

Figure 5. Three Different Types of Noise and Corresponding Enhanced Image using Median Filter

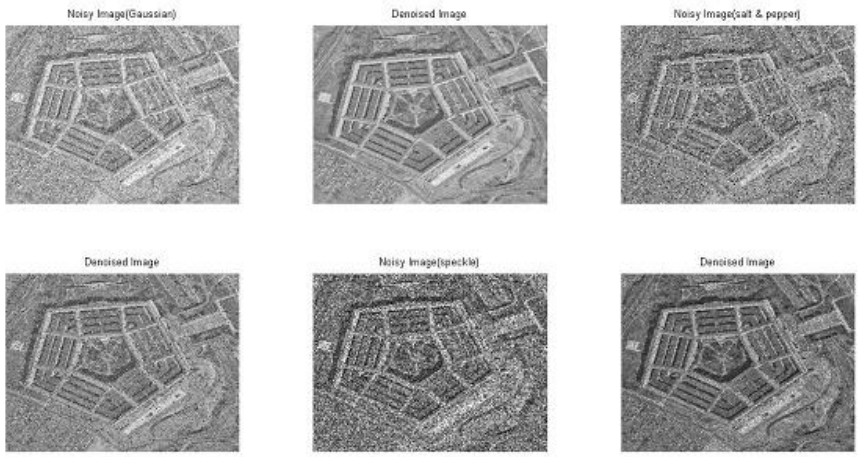

Figure 6. Three Different Types of Noise and Corresponding Enhanced Image using Winner Filter

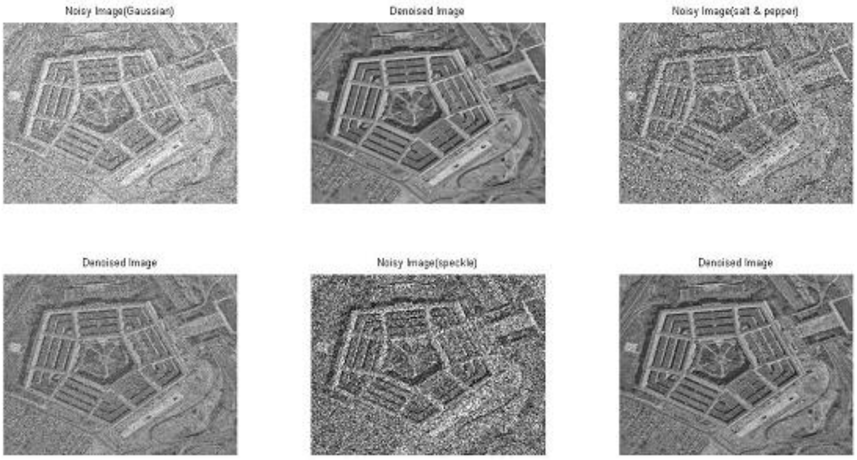

Figure 7. Three Different Types of Noise and Corresponding Enhanced Image using Wavelet Transform

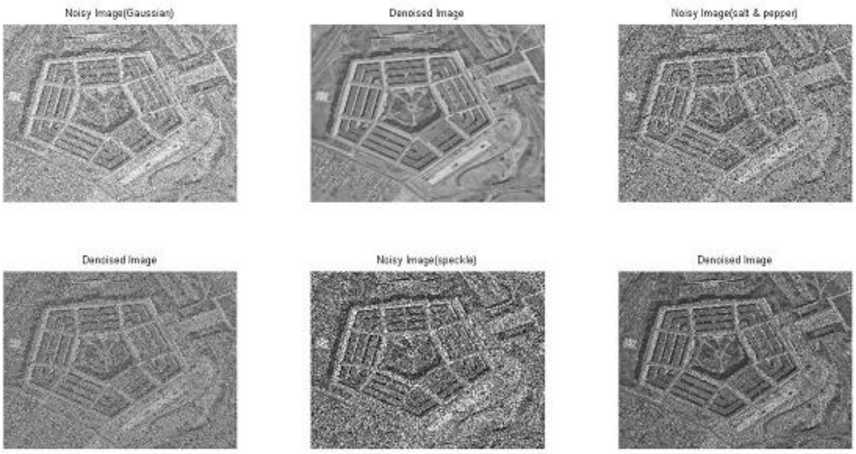

Figure 8. Three Different Types of Noise and Corresponding Enhanced Image using Curvelet Transform

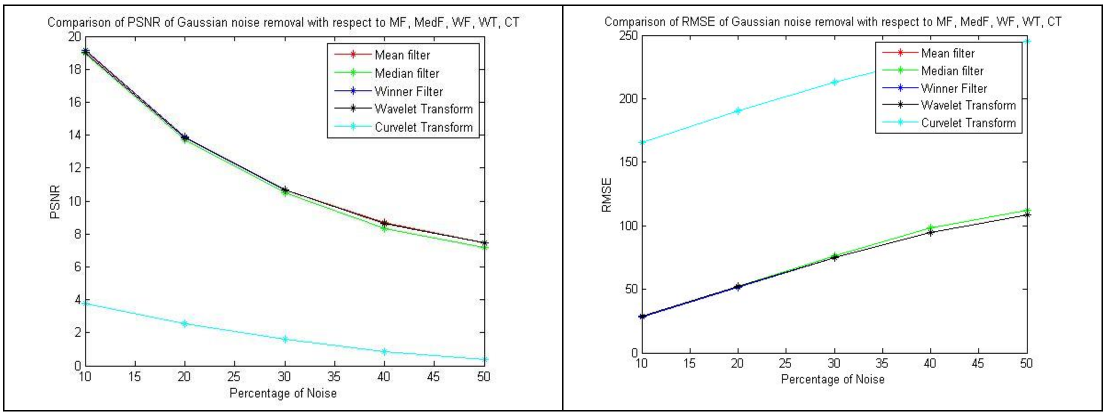

Figure 9. Comparison of PSNR and RMSE of Gaussian Noise Removal with Respect to MF, MedF, WF, WT and CT

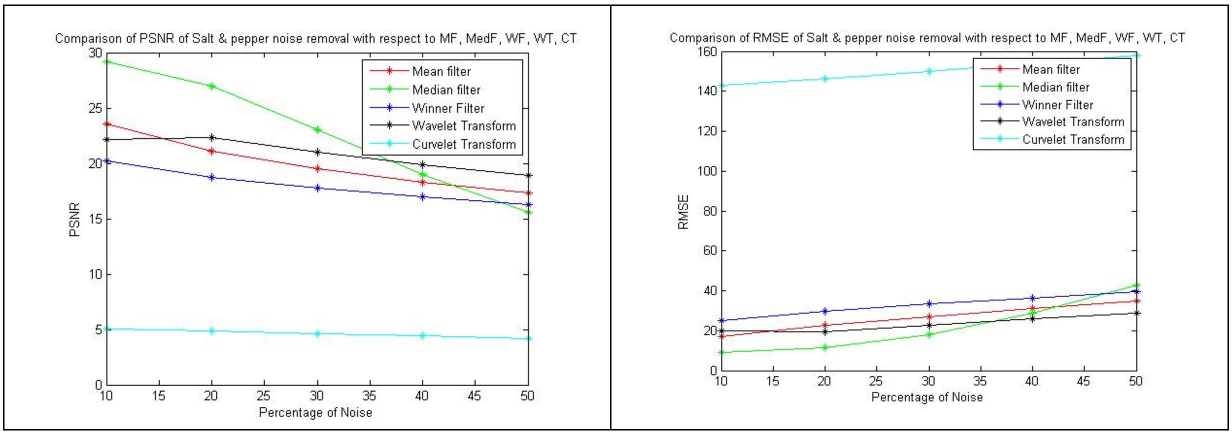

Figure 10. Comparison of PSNR and RMSE of Salt and Pepper Noise Removal with Respect to MF, MedF, WF, WT and CT

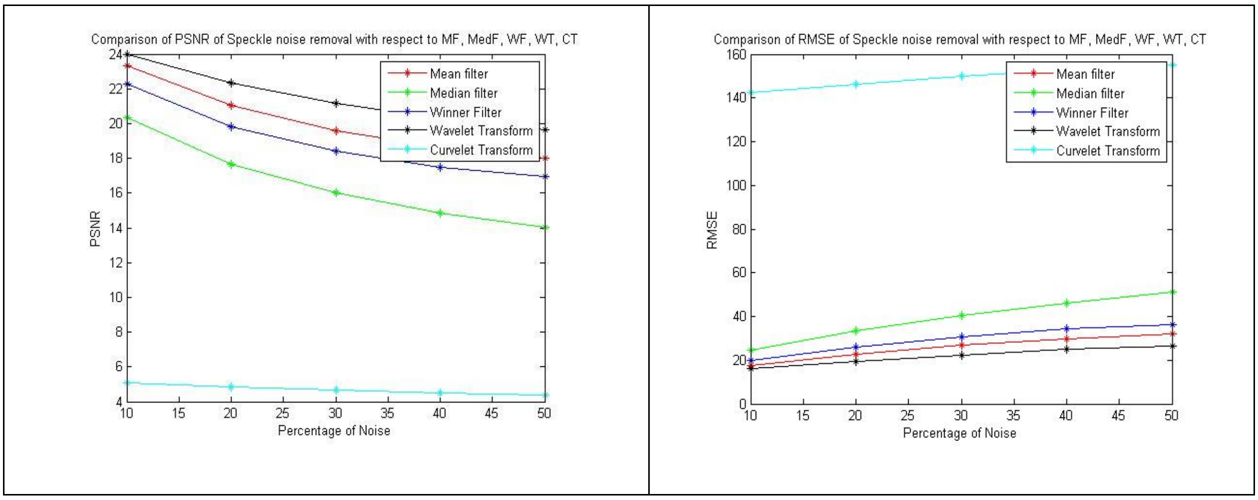

Figure 11. Comparison of PSNR and RMSE of Speckle Noise Removal with Respect to MF, MedF, WF, WT and CT

Table 1. RMSE Values for 1024*1024 Aerial Images with Different Percentage of Gaussian Noise Denoised by MF, MedF, WF, WT and CT

Filter Type	10%	20%	30%	40%	50%
Mean	28.2451	51.7816	74.7164	94.4168	108.2353
Median	28.8517	52.6167	76.704	98.2739	112.5381
Winner	28.209	51.8465	74.8726	94.5835	108.4485
WT	28.691	52.105	75.0553	94.6587	108.4633
CT	165.7823	190.4116	213.2655	232.3373	245.2936

Table 2. RMSE values for 1024*1024 aerial images with Different Percentage of Salt and Pepper Noise Denoised by MF, MedF, WF, WT and CT

Filter Type	10%	20%	30%	40%	50%
Mean	16.982	22.4605	26.9777	31.0613	34.8761
Median	8.8981	11.4271	18.08	28.7584	42.8411
Winner	24.9245	29.6095	33.2423	36.3916	39.3651
WT	19.9036	19.5159	22.8162	25.8868	28.9843
CT	142.8528	146.1774	150.034	153.9973	158.1127

Table 3. RMSE values for 1024*1024 Aerial Images with Different Percentage of Speckle Noise Denoised by MF, MedF, WF, WT and CT

Filter Type	10%	20%	30%	40%	50%
Mean	17.4412	22.6716	26.7676	29.9276	32.2137
Median	24.6193	33.6461	40.5063	46.2263	51.0681
Winner	19.6618	26.106	30.6589	34.2094	36.3184
WT	16.1649	19.5505	22.3364	24.8429	26.6302
CT	142.2755	146.376	149.8805	152.8253	155.0543

Table 4. PSNR Values for 1024*1024 Aerial Images with Different Percentage of Gaussian Noise Denoised by MF, MedF, WF, WT and CT

Filter Type	10%	20%	30%	40%	50%
Mean	19.1459	13.8813	10.6965	8.6638	7.4774
Median	18.9614	13.7423	10.4684	8.316	7.1388
Winner	19.157	13.8704	10.6783	8.6485	7.4603
WT	19.0099	13.8272	10.6572	8.6416	7.4591
CT	3.774	2.5709	1.5864	0.8424	0.3711

Table 5. PSNR values for 1024*1024 Aerial Images with Different Percentage of Salt and Pepper Noise Denoised by MF, MedF, WF, WT and CT

Filter Type	10%	20%	30%	40%	50%
Mean	23.56	21.1364	19.5447	18.3204	17.3142
Median	29.1789	27.0061	23.0208	18.9895	15.5276
Winner	20.2323	18.7362	17.731	16.9448	16.2626
WT	22.1862	22.357	20.9999	19.9032	18.9215
CT	5.067	4.8672	4.641	4.4145	4.1855

Table 6: PSNR Values for 1024*1024 Aerial Images with Different Percentage of Speckle Noise Denoised by MF, MedF, WF, WT and CT

Filter Type	10%	20%	30%	40%	50%
Mean	23.3333	21.0551	19.6126	18.6434	18.004
Median	20.3393	17.6261	16.0143	14.867	14.0018
Winner	22.2923	19.83	18.4337	17.4819	16.9623
WT	23.9933	22.3416	21.1846	20.2607	19.6573
CT	5.1022	4.8554	4.6499	4.4809	4.3551

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