

# Design and Analysis of Image De-Noising Filter Based on Pattern Recognition: A Practical Approach

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## Abstract

Image filtering algorithms are applied on images to remove the different types of noise that are either present in the image during capturing or injected in to the image during transmission. Digital images when captured usually have Gaussian noise, Speckle noise and salt and pepper noise [10]. The performances of the filters are compared using the Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) [8-9]. In this paper we proposed a spatial domain filter based on pattern recognition technique [1] using varying size mask not necessarily square matrix but ranging from 4 x 4 to 7 x 7 size mask. In the proposed filter the MSE is reduced to 43 % in case of salt & pepper noise, 51 % for Gaussian noise, 52 % for speckle noise and PSNR is increased to 6 % in case of salt & pepper noise, 12 % for Gaussian noise, 12 % for speckle noise. The image used for the purpose of analysis is standard woman hat image taken by Ron Bucci.

## Keywords

Salt and Pepper Noise, Gaussian Noise, Speckle Noise, Pattern Recognition Filter, PSNR, MSE

## I. Introduction

An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows. In a (8-bit) grayscale image each picture element has an assigned intensity that ranges from 0 to 255. A grey scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of grey. A normal grayscale image has 8 bit color depth = 256 grayscales. A "true color" image has 24 bit color depth =  $8 \times 8 \times 8$  bits =  $256 \times 256 \times 256$  colors = ~16 million colors. Image de-noising is a vital image processing task i.e. as a process itself as well as a component in other processes. There are many ways to de-noise an image or a set of data and methods exists. The important property of a good image de-noising model is that it should completely remove noise as far as possible as well as preserve edges. Traditionally, there are two types of models i.e. linear model and non-linear model. Generally, linear models are used. The benefits of linear noise removing models are the speed and the limitations of the linear models are, the models are not able to preserve edges of the images in an efficient manner. On the other hand, Non-linear models can handle edges in a much better way than linear models. The form that low-pass filters usually take is as some sort of moving window operator. The operator usually affects one pixel of the image at a time, changing its value by some function of a "local" region of pixels ("covered" by the window). The operator "moves" over the image to affect all the pixels in the image. The window is basically a 2 D square matrix of some odd order, the mask is moved from pixel to pixel and the center most pixel is replaced from the neighborhood pixels that are covered by the mask or window.

In this paper we introduced a spatial domain filter which is used to detect and reduce the noise from the images. In the proposed filter the mask of varying size is used as per the position of the pixel in the image, therefore the mask can vary from 4 x 4 to 7 x 7, not necessarily the square matrix all the time. The proposed

filter can process the corner pixels without padding; here we are considering the surrounding pixels up to three layers around the corrupted pixel or the pixel under consideration. The core spatial-domain filtering activities are:

1. Read the image
2. Introduce the noise
3. Apply various filters for reduction of noise
4. Compare the results of proposed filter with the existing filter such as mean and median filter.

## II. Types of Noises

Noise in an image is a very common problem. An image gets corrupted with different types of noise during the processes of acquisition, transmission/ reception, and storage/ retrieval. Noise may be classified as substitutive noise (impulsive noise: e.g., salt & pepper noise, random-valued impulse noise, etc.) and additive noise (e.g., additive white Gaussian noise).

### A. Salt and Pepper Noise

Salt and pepper noise [5] is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels. 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. An effective noise reduction method for this type of noise involves the usage of a median filter or a contra harmonic mean filter. Salt and pepper noise creeps into images in situations where quick transients, such as faulty switching, take place [6-7].

### B. Gaussian Noise

Gaussian noise is statistical noise that has its probability density function 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. Gaussian noise is noise that has a random and normal distribution of instantaneous amplitudes over time. A special case is white Gaussian noise [6], in which the values at any pairs of times are statistically independent (and uncorrelated). In applications, Gaussian noise is most commonly used as additive white noise to yield additive white Gaussian noise.

### C. Speckle Noise

Speckle noise [2-3] is multiplicative noise. It is commonly found in synthetic aperture radar images, satellite images and medical images [4]. Speckle noise is also known as texture. It 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.

### III. Image De-Noising Filter

#### A. Linear Smoothing Filter (LSF) or Average Filter or Mean Filter

Linear Smoothing Filter or Average Filter is windowed filter of linear class that smoothes signal (image). The filter works as a low-pass one. The basic idea behind the filter is that, for any element of the signal (image) take an average across its neighborhood.

$$f(x,y) = \frac{\sum g(s,t)}{mn} f(x,y) = \frac{\sum g(s,t)}{mn} \quad (1)$$

#### B. Median Filter (MF)

Median Filter is windowed filter of nonlinear class, which easily removes destructive noise while preserving edges. Median filter [6-7] replaces the value of a pixel by the median of the gray levels in the neighborhood of that pixel. The basic idea behind filter is for any element of the signal (image) look at its neighborhood and pick up the element most similar to others. Median filter in its properties resembles mean filter, or average filter, but much better in treating “salt and pepper” noise and edge preserving.

$$f(x,y) = \text{median}(\sum g(s,t)) \quad (2)$$

#### IV. Proposed Filter (Pattern Recognition Filter (PRF))

A proposed algorithm for de-noising filters as follows:

##### Step 1:

A 2-D window of max. size 7 x 7 is selected around the pixel to be processed P(x, y) (P(x, y) is the corrupted pixel). If 7 x 7 matrix is not possible then maximum possible size of the window is selected. Using this concept possible size of the matrix will be any subset between 4 x 4 matrix and 7 x 7 matrix. In this concept the mask size is not always the square matrix, it may vary with respect to the position of the corrupted pixel.

##### Step 2:

Determine the matrix with respect to the pixel P(x, y). Let's assume that the pixels immediate next to P(x, y) form the set for m1, Pixels next to immediate next form the set for m2 and the pixels next to the pixels in m2 form the set for m3.

##### Step 3:

If P(x, y) is a corrupted pixel then it is processed in the following way:

Find w1 by taking the minimum intensity pixel from set for m1. Similarly find w2 and w3 correspondingly from the set of the pixels for m2 and m3.

Find the array w4 with the following elements as member's w1, w2 and w3.

If  $p(x, y) > w1 + w1/2$  then replace  $p(x, y) + \text{mean}(m1) * \text{mean}(m1) 0.10$ .

Otherwise, If  $p(x, y) \geq \text{mean}(w4)$  then replace  $p(x, y)$  with  $p(x, y) + p(x, y) * 0.10$

Otherwise  $p(x, y) = \max(w4) + \max(w4) * 0.10$

### V. Performance Measures

#### A. MSE (Mean Square Error)

The Mean Squared Error (MSE) which for two  $m \times n$  monochrome images  $I_1$  and  $I_2$  where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{\sum_{m,n} [I_1(m,n) - I_2(m,n)]^2}{M \cdot N} \quad (3)$$

#### B. Peak Signal to Noise Ratio (PSNR)

PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codec's (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codec it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric. It is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content.

$$PSNR = 10 \log_{10} \left( \frac{R^2}{MSE} \right) \quad (4)$$

### VI. Performance Evaluation

The proposed algorithm is tested on various standard images. The algorithm is applied using various performance indices (namely MSE, PSNR) at different values & types of noises (Salt & Peeper Noise, Gaussian noise & speckle noise). The result of proposed filter to detect and reduce the above mentioned noise is given below:

#### A. Result of Proposed Filter to Reduce Salt & Pepper Noise

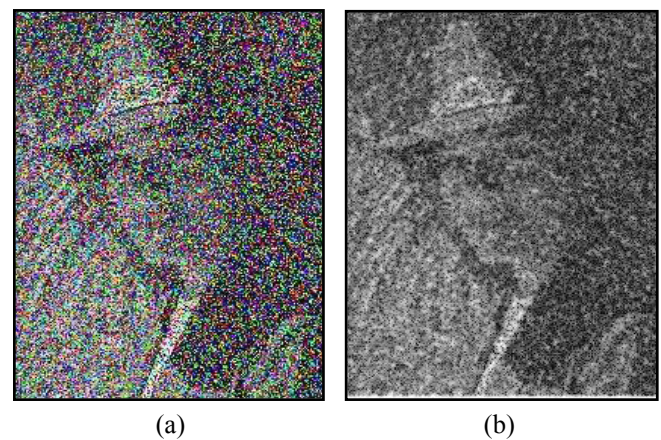


Fig. 1(a): Image affected with salt & pepper noise of variance 0.5  
(b) Filtered image using proposed filter

#### B. Result of Proposed Filter to Reduce Gaussian Noise

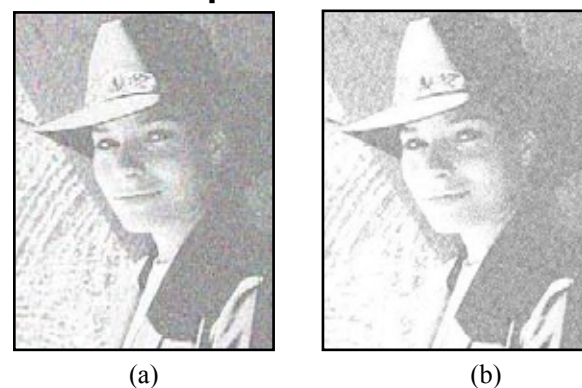


Fig. 2(a): Image Affected with Gaussian Noise of Variance 0.5  
(b) Filtered Image Using Proposed Filter

**C. Result of Proposed Filter to Reduce Speckle Noise**

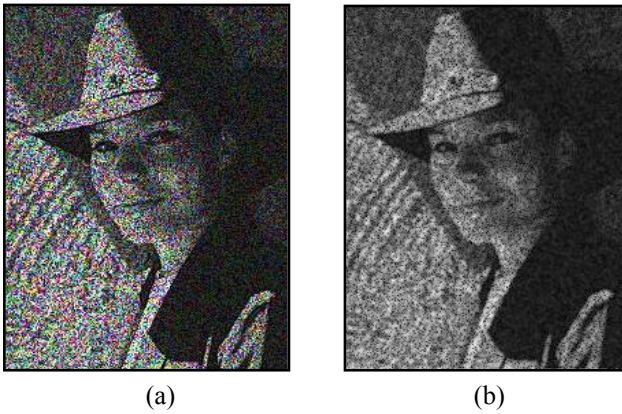


Fig. 3(a): Image Affected with Speckle Noise of Variance 0.5 (b) Filtered Image Using Proposed Filter

**VII. Simulation Results**

The implementation of proposed filter is done in MatLab. The results shows that our proposed filter gives better results as compare with exiting filters. The proposed filter is used to detect and reduce noise from digital images affected with Salt & Pepper noise, Gaussian noise and Speckle noise. The performance evaluation and the graphical representation of results are given below.

**A. MSE v/s Noise Variance (Sigma) of Salt & Pepper Noise**

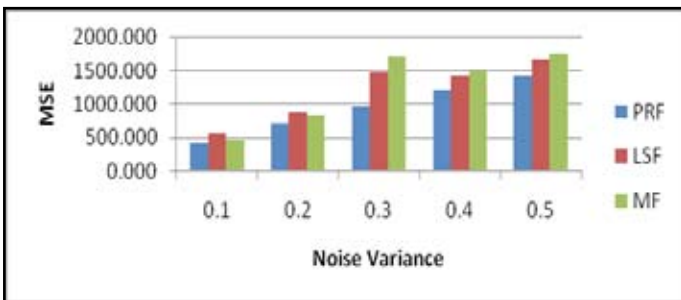


Table 1: Comparison of proposed algorithm with other algorithms on the basis of MSE for Salt & Pepper noise

NOISE VARIANCE	PRF	LSF	MF
0.1	428.148	562.229	471.477
0.2	714.361	870.824	835.971
0.3	959.767	1481.000	1693.000
0.4	1205.900	1420.500	1485.400
0.5	1426.700	1670.600	1762.700

**B. PSNR v/s Noise Variance (Sigma) of Salt & Pepper Noise**

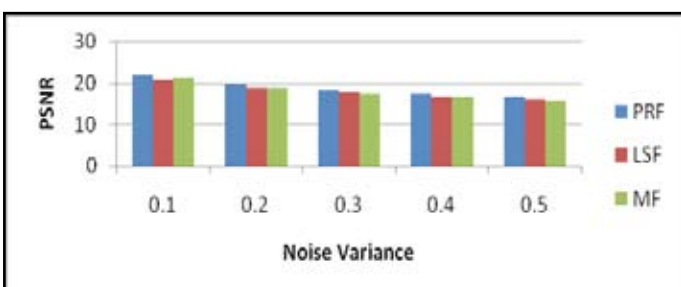


Table 2: Comparison of Proposed Algorithm With Other Algorithms on the Basis of PSNR

NOISE VARIANCE	PRF	LSF	MF
0.1	21.8149	20.6317	21.3962
0.2	19.5916	18.7315	18.9089
0.3	18.3091	17.5311	17.4516
0.4	17.315	16.6063	16.4125
0.5	16.5874	15.902	15.669

**C. MSE v/s Noise Variance (sigma) of Gaussian Noise**

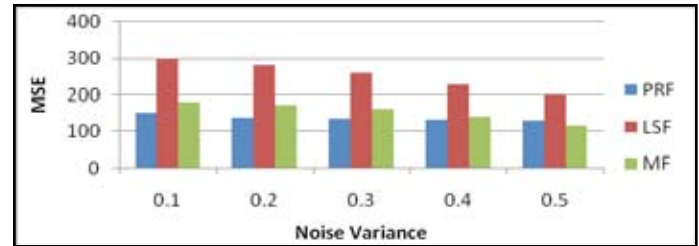


Table 3: Comparison of Proposed Algorithm With Other Algorithms on the Basis of MSE for Gaussian Noise

NOISE VARIANCE	PRF	LSF	MF
0.1	149.74	298.739	180.4377
0.2	136.128	280.6479	172.6846
0.3	135.1643	259.4276	160.5574
0.4	132.8845	228.9094	139.344
0.5	130.1092	198.8445	116.4309

**D. PSNR v/s Noise Variance (sigma) of Gaussian Noise**

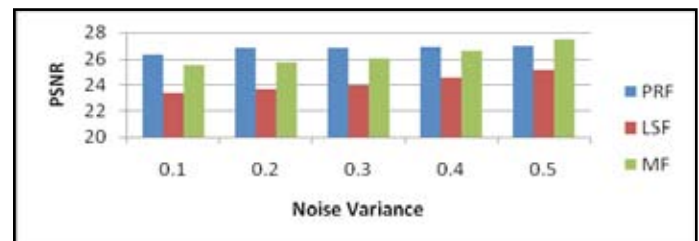


Table 4: Comparison of Proposed Algorithm With Other Algorithms on the Basis of PSNR for Gaussian Noise

NOISE VARIANCE	PRF	LSF	MF
0.1	26.3774	23.3779	25.5675
0.2	26.7913	23.6492	25.7583
0.3	26.8222	23.9906	26.0745
0.4	26.8961	24.5342	26.6899
0.5	26.9877	25.1457	27.4701

**E. MSE v/s Noise Variance (sigma) of Speckle Noise**

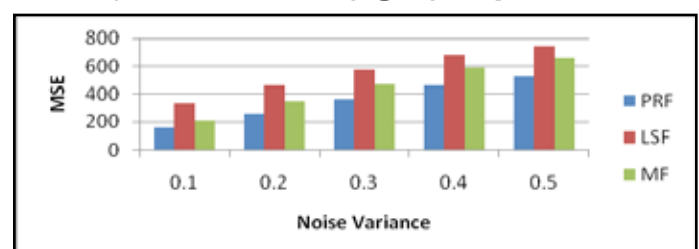


Table 5: Comparison of Proposed Algorithm With Other Algorithms on the Basis of MSE for Speckle Noise

NOISE VARIANCE	PRF	LSF	MF
0.1	162.3491	335.8834	208.8907
0.2	262.467	464.6972	348.2303
0.3	363.3894	573.6731	469.0896
0.4	461.7432	681.4975	590.8879
0.5	528.3455	746.6277	662.493

**F. PSNR v/s Noise Variance (Sigma) of Speckle Noise**

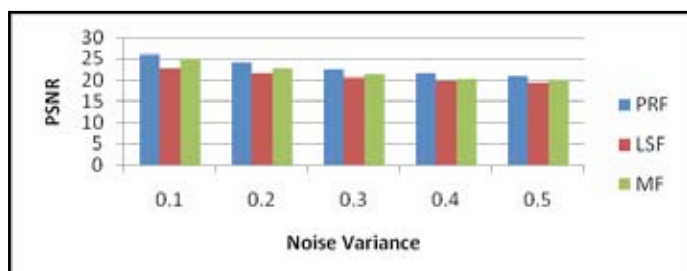


Table 6: Comparison of Proposed Algorithm With Other Algorithms on the basis of PSNR for Speckle Noise

NOISE VARIANCE	PRF	LSF	MF
0.1	26.0263	22.8689	24.9316
0.2	23.9401	21.4591	22.7121
0.3	22.5271	20.5442	21.4182
0.4	21.4868	19.7962	20.4158
0.5	20.9016	19.3998	19.991

**VII. Conclusion**

In this paper, various spatial-domain filters for suppression of salt and peppers noise, Gaussian noise & speckle noise, available in literature, are studied and their performances are analyzed. Considering the limitations of the existing filters, efforts have been made to develop a spatial-domain filter. The performances of the proposed filter are compared with existing spatial-domain filters (Mean filter & Median filter). The objective evaluation metrics: Peak-Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE) is considered for comparing their filtering performances.

**IX. Future Work**

Some new directions of research in the field of image de-noising are not yet fully explored. There is sufficient scope to develop very effective filters in the directions mentioned below.

1. The pattern recognition technique could be further explored to get some better results for de- noising the colored image.
2. The widow size of different filters can be made adaptive for efficient de-nosing. The shape of the window can also be varied and made adaptive to develop very effective filters.
3. Techniques for analyzing the pixel whether it is corrupted or not could be explored further so that only the corrupted pixels are replaced instead of averaging the entire image.

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