CHAPTER 2

STUDY OF IMAGE DENOISING FILTERS REVIEW

2.1 BACKGROUND

Whenever an image reaches the user end, it is usually noisy. Noise in an image is defined as an unwanted signal that gets attached with the signal during its acquisition and/or transmission. The performance of an image acquisition is affected by a variety of factors, such as environmental conditions, quality of the sensing elements and the quality of analog to digital (A/D) converter. For example, in image acquisition with a CCD camera, light levels and temperature are the major factors affecting the volume of noise in the resulting image. During transmission, images are corrupted due to interference in the channel. For example, in wireless networks, the image may be corrupted due to lightening and other atmospheric disturbances. Therefore, noise filtering is the first step in any image processing system.

Image noise suppression is very much needed in digital imaging systems design. Impulsive noise is frequently encountered during the processes of acquisition, transmission and storage and retrieval. In the area of image denoising, many filters are proposed in literature. The main steps in this process are classification (detection) and reconstruction (filtering). Classification is used to separate uncorrupted pixels from corrupted pixels. Reconstruction involves replacing the corrupted pixel values with estimated values.

There are various filters existing in literature, which are used for filtering out salt- and-pepper impulse noise and random-valued impulse noise. There are some special types of filters which are used for suppressing salt-and-pepper noise as well as random-valued impulse noise. In this chapter, some well-known,
standard and benchmark filters, which are available in literature, are studied. Novel filters, designed and developed in this research work, are compared against these filters in subsequent chapters. Therefore, attempts are made here for a detailed and critical analysis of these existing filters.

2.2 NOISE MODELS FOR COLOR IMAGES

In color images, noise can be of two types: (i) uncorrelated color noise and (ii) correlated color noise. In the first case, noise affects the R, G and B planes independently with the given percentage. In the second case, the presence of noise in a component of color pixel also depends on its presence in other components. It is generated in two steps. In the first step, noise is added in the same way as uncorrelated noise. In the second step, for each noise-free component in any plane, it is checked if other two corresponding components in other planes are corrupt, and if so, noise-free component is made noisy based on the correlation factor [104, 112].

2.3 LITERATURE REVIEW

Noise in an image is a serious problem. Efficient suppression of noise in an image is a very important issue. Denoising finds extensive applications in many fields of image processing. Conventional techniques of image denoising using linear and nonlinear filters have already been reported and sufficient literature is available in this area. Recently, various nonlinear and adaptive filters have been suggested for the purpose. The objectives of these schemes are to reduce noise and to retain, as far as possible, the edges and fine details of the original image in the restored image as well. However, both the objectives conflict each other and the reported schemes are not able to perform satisfactorily in both aspects. Hence, still various research workers are actively engaged in developing better filtering schemes using latest signal processing techniques.
2.3.1 Filters for Suppression of Additive Noise

Traditionally, AWGN is suppressed using linear spatial domain filters such as Mean filter [60], Wiener filter [49, 18, 19, 50-55] etc. The traditional linear techniques are very simple in implementation but they suffer from the disadvantage of blurring effect further, they also do not perform well in the presence of signal dependant noise. To overcome this limitation, nonlinear filters [55] are proposed. Some well known nonlinear mean filters are harmonic mean, geometric mean, $L_p$ mean, contra-harmonic mean proposed by Pitas et al. [102] and these are found to be good in both preserving edges and suppressing the noise. Another good edge preserving filter is Lee filter [75] proposed by J.S. Lee. The performance of this filter is also good in suppressing noise as well as in preserving edges. Anisotropic diffusion [103, 104] is also a powerful filter where local image variation is measured at every point, and pixel values are averaged over neighborhoods whose sizes and shapes depend on local variations. The basic principle of these methods is the numbers of iterations. The use of large numbers of iterations are used may lead to instability; in addition to edges, noise becomes prominent. Rudin et al. proposed total variation (TV) filter [106] which is also iterative in nature. In a later stage of research, simple and non-iterative scheme of edge preserving smoothing filters were proposed. One of them is the bilateral filter [47]. Bilateral filter works on the principle of geometric closeness and photometric similarity of gray levels or colors. Many variants of bilateral filters are proposed in literature that exhibit better performance under high noise condensation [48, 49]. A filter named non-local means (NL-Means) [50] averages similar image pixels defined according to the similarity their local intensity.

Based on robust statistics, a number of filters are proposed. T. Rabie [51] proposed a simple blind denoising filter based on the theory of robust statistics. Robust statistics addresses the problem of estimation when the idealized assumptions about a system are occasionally violated. Another denoising method based on the bi-weight mid-regression proposed by Hou et al. [52] is found to be
effective in suppressing AWGN. Kernel regression is a nonparametric class of regression method used for image denoising [53].

Now-a-days, wavelet transform is employed as a powerful tool for image denoising [55-57], which, is effective when using wavelet techniques because of its ability to capture most of the energy of a signal in a few significant transform coefficients, when natural image is corrupted with Gaussian noise.

2.3.2 Filters for Suppression of Impulsive Noise

An impulsive noise of low and moderate noise densities can be removed easily by simple denoising schemes available in the literature. A simple median filter [58] works very satisfactorily for suppressing impulsive noise of low density and is easy to implement. However, its cost distorts the edges and the fine details of an image. The distortion increases as the filtering window size is increased to suppress high density noise. Specialized median filters such as weighted median filter [28], center weighted median filter [70, 128, 82] and Recursive Weighted Median Filter (RWMF) are proposed in literature to improve the performance of the median filter by giving more weight to some selected pixel(s) in the filtering window. However, they are still implemented uniformly across an image without considering whether the current pixel is noisy or not.

Additionally, they are prone to edge jitter in cases where the noise density is high. As a result, their effectiveness in noise suppression is often at the expense of blurred and distorted image features.

The conventional median filtering approach applies the median operation everywhere without considering whether it is uncorrupted or not. As a result, image quality degrades severely. An intuitive solution to overcome this problem lies in the implementation of an impulse-noise detection mechanism prior to filtering; hence, only those pixels identified as corrupted would undergo the filtering process, while those identified as uncorrupted would remain intact. By incorporating such noise
detection mechanism or intelligence into the median filtering framework, so-called switching median filters [19, 40, 129] have shown significant performance improvement. A number of modified median filters have been proposed [111], e.g., minimum–maximum exclusive mean (MMEM) filter proposed by W.Y.Han et al., pre-scanned minmax center-weighted (PMCW) filter [128] proposed by Wang, and decision-based median filter [40] proposed by D.A.Florencio et al.. In these methods, the filtering operation adapts to the local properties and structures in the image. In decision-based filtering [2] for example, image pixels are first classified as corrupted and uncorrupted, and then passed through the median and identity filters, respectively. The main issue of the decision-based filter lies in building a decision rule, or a noise measure, that can discriminate the uncorrupted pixels from the corrupted ones as precisely as possible.

In the MMEM filter, the pixels that have values close to the maximum and minimum in a filter window are discarded, and the average of remaining pixels in the window is computed to estimate a pixel. If the difference between the center pixel and average exceeds a threshold, the center pixel is replaced by an average one otherwise, it is unchanged. The performance of this filter depends on the selection of threshold value. The simple switching filter Adaptive Center-Weighted Median (ACWM) [26] proposed by T.Chen et al, Center-Weighted Median (CWM) [70] have been used to detect noisy pixels in the first stage. The objective is to utilize the center-weighted median filters that have varied center weights to define a more general operator, which realizes the impulse detection by using the differences defined between the outputs of CWM filters and the current pixel of concern. The ultimate output is switched between the median and the current pixel itself. While still using a simple thresholding operation, the proposed filter yields superior results to other switching schemes in suppressing both types of impulses with different noise ratios. However its estimation efficiency is poor. Florencio et al. [40] proposed a decision measure, based on a second order statistic called normalized deviation.
The peak and valley filter proposed by Windyga, is a highly efficient nonlinear non-iterative multidimensional filter. It identifies noisy pixels by inspecting their neighborhood, and then replaces their values with the most conservative ones out of the values of their neighbors. In this way, no new values are introduced into the neighborhood and the histogram distribution range is conserved. The main advantage of this filter lies in its simplicity and speed, which makes it very attractive for real time applications. A modified peak and valley filter, detail preserving impulsive noise removal [5] scheme has also been proposed by N. Alajlan. This filter provides better detail preservation performance; but it is slower than the original peak and valley filter.

The tri-state median filter [28] proposed by T.Chen et al. further improved switching median filters that are constructed by including an appropriate number of center-weighted median filters into the basic switching median filter structure. These filters exhibit performance that is better than the standard and the switching median filters at the expense of increased computational complexity. Z.Wang et al. have proposed a progressive switching median filter (PSM) [129] for the removal of impulse noise from highly corrupted images where both the impulse detector and the noise filter are applied progressively in an iterative manner. The noise pixels processed in the current iteration are used to help the processing of the other pixels in the subsequent iterations. The main advantage of such a method is location of some impulse pixels in the middle of large noise blotches can also be properly detected and filtered. Therefore, better restoration results are expected, especially for the cases where the images are highly corrupted. A new impulse noise detection technique [139] for switching median filters proposed by S. Zhang et al. is based on the minimum absolute value of four convolutions obtained using one-dimensional Laplacian operators. It ensures performance that is better than many of the existing switching median filters with comparable computational complexity.
Early developed switching median filters which are commonly found being non-adaptive to a given, but unknown, noise density and prone to yielding pixel misclassifications especially at higher noise density interference. In order to address this issue, the noise adaptive soft-switching median (NASM) filter is proposed H.L. Eng et al, which consists of a three-level hierarchical soft-switching noise detection process. The NASM achieves a fairly robust performance in removing impulse noise, while preserving signal details across a wide range of noise densities, ranging from 10% to 50%. However, for those corrupted images with noise density greater than 50%, the quality of the recovered images suffers significant degradation, due to the sharply increased number of misclassified pixels.

The signal-dependent rank-ordered mean filter [2] is a switching mean filter that exploits rank order information for impulse noise detection and removal. The structure of this filter is similar to that of the switching median filter except that the median filter is replaced with a rank-ordered mean of its surrounding pixels. This filter has been proved to exhibit better noise suppression and detail preservation performance than some conventional and state-of-the-art impulse noise cancellation filters for both gray scale [2] and color [129] images.

The adaptive two-pass rank order filter has been proposed by X.Xu, to remove impulse noise from highly corrupted images. Between the passes of filtering, an adaptive process detects irregularities in the spatial distribution of the estimated noise and selectively replaces some pixels changed by the first pass with their original values. These pixels are kept unchanged during the second filtering. Consequently, the reconstructed image maintains a higher degree of fidelity and has a smaller amount of noise.

A variational approach to remove outliers and impulse noise [96] by M.Nikolova, is an edge and detail-preserving restoration technique to eliminate impulse noise efficiently. It uses a non-smooth data fitting term together with edge-preserving regularization functions. A combination of this variational method [96] with an impulse detector has also been presented in an iterative procedure for
removing random-valued impulse noise. The filter offers good filtering performance but its implementation complexity is higher than most of the previously mentioned filters.

The method proposed by I. Aizenberg et al. [4], employs boolean functions for impulse noise removal. In this approach, the gray level noisy input image is decomposed into a number of binary images by gray level thresholding. Detection and removal of impulse noise are then performed on these binary images by utilizing specially designed boolean functions. Finally, the resulting boolean images are combined back to obtain a restored gray level image.

A number of filters utilize the histogram information of the input image. In image restoration using parametric adaptive fuzzy filter [126] and an adaptive fuzzy filter for restoring highly corrupted image by histogram estimation [127], the histogram information of the input image is used to determine the parameters of the membership functions of an adaptive fuzzy filter. The filter is then used for the restoration of noisy images. An adaptive vector filter exploiting histogram information is also proposed for the restoration of color images.

With boundary discriminative noise detection (BDND) algorithm proposed by Pei-Eng Ng et al, which is a highly-accurate noise detection algorithm, an image corrupted even up to 70% noise density may be restored quite efficiently. However there is no remarkable improvement in the results at higher noise density.

In addition to the median and the mean based filtering methods discussed above, a number of nonlinear impulse noise filtering operators based on soft computing methodologies have also been presented [108]. These filters exhibit relatively satisfactory noise removal and detail preservation capability than the median and the mean based operators. However, the implementation complexities of these filters is generally too much and the required filtering window size is usually larger than the other methods. Indeed, neuro-fuzzy (NF) [137] systems inherit the ability of neural networks to learn from examples and derive the capability of fuzzy
systems to model the uncertainty which is inevitably encountered in noisy environments. Therefore, neuro-fuzzy systems may be utilized to design line, edge, and detail preserving impulse noise removal operators provided that the appropriate network topologies and processing strategies are employed. The method proposed by Wenbin Luo et al. uses a fuzzy classifier for pixel-classification and a simple median filter is employed for replacement of corrupted pixels. The methods proposed by F.Russo [58] and F. Farbiz et al. [70], uses neuro-fuzzy technique for filtering purpose.

In recent years, a number of methods have been proposed which work on both random-valued noise and salt-and-pepper noise. The method proposed by V.Crnojevic et al, namely Advanced Impulse Detection Based on Pixel-Wise MAD, [31] is a modification of absolute deviation from median (MAD). MAD is used to estimate the presence of image details. An iterative pixel-wise modification of MAD is used here that provides a reliable removal of impulse noise. An improved version of this algorithm is impulse noise filter with adaptive MAD based threshold [34] proposed by Vladimir et al. In this system, the threshold value is changed from pixel to pixel based on local statistics. Since it is a non-iterative algorithm, its execution time is quite reasonable and less than that required by PWMAD.

The performance of both the methods is quite good under low noise density. However, they fail miserably at high noise densities. In the same category, another method proposed by Tzu–Cho Lin is known as progressive decision based mean type filter [134]. This is based on Dempster- Shafer (D-S) evidence theory for pixel classification. The mass functions are generated based on information available in the filtering window which is used for the D-S evidence theory. Decision rules can determine whether the pixel is noisy or not based on the noise-corrupted belief value. Both detection and filtering are applied progressively through several iterations. The corrupted pixels are replaced by the mean of the noise-free pixels in the filter window an efficient method developed by Jianjun Zhang [49] performs well for filtering random-valued noise. In this method, an adaptive center
weighted median filter is used to identify pixels which are likely to be corrupted and restored by using median filter.

A simple iteration procedure is used for noise detection and filtering purpose. In Iterative Adaptive Switching Median Filter, a two-pass algorithm is employed for identification of a noisy pixel and replacing the corrupted pixel by a valid median. Another iterative filter is proposed by R.H.Chan et al [143] for effective suppression of random-valued noise. As it takes a large number of iterations, its execution time is too much. Further, it fails to retain the edges and fine details of an image at higher noise densities.

The method proposed by Haindi Ibrahim et al. [55] is an adaptive median filter to remove impulse noise from highly corrupted images. In fact, it is a hybrid of an adaptive median filter with a switching median filter. The adaptive median filter changes its size according to local noise density estimated. The switching framework helps to speed up the process of filtering. This method preserves the local details and edges of an image at medium noise densities. However there is no remarkable improvement in the results at higher noise densities.

Recently, a number of algorithms are proposed [145,29, 127] for suppressing impulse noise. Different types of noise detection and correction techniques are proposed for filtering based on statistics and neural network. They work effectively; but, they fail to retain edges and fine details of an image at high noise densities even though they have high computational complexities. However, none of the filters available in literature is able to achieve very good restoration without distorting the edges and fine details. Further, there is a need to reduce computational complexity of a filtering algorithm for its use in real-time applications.
2.4 DENOISING OF IMAGES

Denoising of images means, suppressing the effect of noise to the extent that the resultant image becomes acceptable. The spatial domain or transform (frequency) domain filtering can be used for this purpose. There is a one to one correspondence between linear spatial filters and filters in the frequency domain. However, spatial filters offer considerably more versatility because they can also be used for nonlinear filtering, something which we cannot do in the frequency domain [106]. Recently, wavelet transform is also being used to remove the impulse noise from noisy images [77].

Historically, in early days, filters were used uniformly on the entire image without discriminating between the noisy and noise-free pixels. Mean filters such as arithmetic mean filters, geometric mean filters, and contra harmonic mean filters, alpha trimmed mean filters, rank-ordered mean filters, etc. were used to remove the impulse noise from the images [3]. In fact, these filters were useful for the Gaussian noise and not for the impulse noise. When these filters were applied to remove impulse noise from the images, it was found, that besides removal of the noise, the recovered images were severely blurred. Hence, the emphasis shifted to non-linear filtering in case of impulse noise. Classification of image denoising techniques for impulse noise is shown in Figure 2.1. Image denoising in spatial domain can be classified into five main categories: (i) techniques based on thresholding (ii) techniques employing some operator (iii) statistics-based (iv) ANFIS-based switching median filtering.

Median filtering is a non-linear process which helps to remove the impulse noise while preserving the edges. In median filtering, if the pixel under consideration is an outlier in the observation window, it is replaced by the median value of that window [93, 94]. In time domain noise filtering for monochrome images, most of the filtering techniques use some kind of switching-based filtering in which, first of all, a decision is made about every pixel of the image as to whether the pixel under consideration is noisy or not.
Figure 2.1 Classification of impulse removal techniques
If the pixel is noisy, it is filtered by using a simple median or some of its variants like adaptive weighted median filter or center weighted median (CWM) filter [28-71]. The block diagram of a switching-based filter is shown in the Figure 2.2. The output of this filtering system is given by,

\[
y(i,j) = \begin{cases} 
  x(i,j) & \text{if } f(i,j) = 0 \\
  \text{med}(W_{\text{woper}}(i,j)) & \text{if } f(i,j) = 1 
\end{cases}
\]

(2.1)

where \(x(i,j)\) denotes the input pixel, \(y(i,j)\) is the filtered output of the pixel and \(f(i,j)\) is the output of the detector which gives value ‘1’ if the image is noisy and ‘0’ in case of noise-free pixel. \(\text{med}(W_{\text{woper}}(i,j))\) is the median (med) of a window of size \(n \times n\) centered at the location of \(x(i,j)\).

Figure 2.2 Block diagram of a general switching-based filtering

It can be easily visualised that the success of such filtering system is primarily governed by the capability of the impulse noise detector. Various algorithms based on different principles have been developed to detect the noisy pixels. The following sections give a brief account of the various spatial domain image denoising techniques.

2.4.1 Threshold-based Switching Median Filtering

In this type of filtering systems, a suitable threshold value is chosen based on the image characteristics and compared with the difference between pixel
under consideration and the median of the window [90-57]. One such example, shown in Figure 2.3, is named as Tri-state median filtering [27].

In this method, when the impulse detector finds the current pixel noisy, either simple median or weighted median filter is used, based on the difference between pixel under consideration and median of the window, in which multiple copies of the central pixel are included in the filtering window according to the weight assigned to the central pixel before computing the median.

![Figure 2.3 Block diagram of Tri-State median filtering](image)

In this scheme, weight assigned to the central pixel is ‘3’ for better details preservation. The output of the filtering system is given by,

\[
y(i,j) = \begin{cases} 
  x(i,j) & \text{if } T \geq d_1 \\
  y^{(CWM)}(i,j) & \text{if } d_2 \leq T < d_2 \\
  y^{(SM)}(i,j) & \text{if } T < d_2 
\end{cases}
\]  

(2.2)

where \(y^{(CWM)}(i,j)\) and \(y^{(SM)}(i,j)\) are the outputs of CWM and SM filters respectively and \(d_1 = |x(i,j) - y^{(SM)}(i,j)|\) and \(d_2 = |x(i,j) - y^{(CWM)}(i,j)|\) the value of threshold(T) is chosen between 10 to 30 for optimal results for various images.
The generalized form of TSM filter is called the multi-state median (MSM) [27] filter. In this filtering scheme, instead of using only one CWM, many CWM filters with increasing weights like $3, 5, \ldots, N-2$. are used, where $N$ denotes the total number of pixels in the filtering window. Also, instead of a switch, a classifier is used to decide about which filter should produce the final filtered output. The output of this filtering system is given by,

$$y(i,j) = \begin{cases} 
    x(i,j) & \text{if } d_1 < T \\
    y^{(N+1-w)}(i,j) & \text{if } d_w < T \leq d_{w-2}, \ 3 \leq w < N-2 \\
    y^{(1)}(i,j) & \text{if } d_{N-2} \geq T
\end{cases} \quad (2.3)$$

where $y(w) (i, j)$ is the output of CWM with weight $w$, $N$ is the total number of pixels in the filtering window and $|dw = x(i, j) - y(w) (i, j)|$, $w = 1, 3, \ldots, N-2$.

The value of threshold is kept between 20 and 50 depending upon the image and noise percentage.

In these schemes, the selection of a suitable threshold and weight assignment to the central pixel is difficult. In order to improve the performance of the impulse detector, some schemes such as progressive switching median (PSM) [134] filter work in an iterative manner. In this method, the impulse detection is done iteratively using the principle of basic switching median filter. To deal with the problem of a fixed threshold for the entire image, another scheme based on median of the absolute deviations from the median (MAD) is used [28]. In this filter, $dw$ is compared with a threshold which is adaptive in nature and is defined by,

$$T = s \times MAD + \delta_w \quad (2.4)$$

If $dw > Tw$ for any value of $w = 0, 1, 2, 3$, then the current pixel is considered as noisy and is replaced by SM of the window. From the simulations conducted on several images it has been observed that the selection $[80, 81, 82, 83] = [40, 25, 10, 5]$ yields good results for random valued impulse noise whereas setting the selection $[80, 81, 82, 83] = [55, 40, 25, 15]$ helps to remove fixed valued impulses. It has also been observed empirically that good
results could be obtained using $0 \leq s \leq 0.6$ for suppressing both types of impulses from various types of images.

2.4.2 Operator-based Switching Median Filtering

In this type of filtering methods, the impulse detection is performed by using some kind of operators like Laplacian, Lulu, etc. [144]. In the following example, impulse detection is performed by a set of four one dimensional Laplacian operators as shown in the Figure 2.4. For this purpose, a 5×5 window around the pixel under observation is selected an then this window is convolved with masks given is what follows.

![Figure 2.4 Four 5×5 Laplacian kernels (Kp)](image)

Then, the minimum absolute value of these four convolutions, denoted as given by $r(i,j)$ is

$$r(i,j) = \min \{ x(i,j) \otimes K_p ; p = 1 \text{ to } 4 \}$$

(2.5)
Another scheme, called directional weighted median (DWM) [28] filtering, is an improved version of the earlier scheme. In this method also the detection principle is similar to that of the above scheme except some changes in the weights of the neighbours as shown in Figure 2.5

![Figure 2.5: Four 5x5 modified Laplacian kernels for DWM filtering](image)

Here also \( r(i, j) \) is calculated as earlier, and compared with a threshold to decide whether the current pixel is noisy. This technique is different than the earlier one in the sense that this method is applied recursively. In this technique, during the first iteration, threshold is kept very high to ensure that no false detection takes place and then it is decreased by twenty percent in subsequent iterations. Filtering is done after every iteration using an improved version of median filter. For filtering, a 3x3 window is selected and the standard deviation is calculated in all the four directions. Then the weight of those pixels which lie in the direction of minimum deviation is increased to 2. Now, the median of these pixels replaces the noisy pixel. In this method, the number of iterations is governed by the percentage
of noise in the image and can vary from 6 to 11. This scheme works well with most of the impulse noise models. However, as of now, there is no method to find the optimal number of iterations.

2.4.3 Statistics-based Switching Median Filtering

There are several filtering techniques available in literature [8,9], which, in some manner, utilize the pixel statistics in the filtering window. Some of the most important techniques are considered here. Described is what follows:

(i) Boundary Discriminative Noise Detection (BDND)

BDND is a powerful impulse noise detection scheme. To determine whether the central pixel is noisy, the BDND algorithm first classifies the pixels of a localised window, centering on the current pixel into three groups: lower intensity impulse noise, uncorrupted pixels, and higher intensity impulse noise. Then, the center pixel will be considered as clean if it belongs to the ‘uncorrupted pixel group’, otherwise corrupted. The steps in the BDND schemes are:

**Step I:** Impose a 21x21 window, which is centred around current pixel.

**Step II:** Sort the pixels in the window in ascending order and find the median \( (med) \), of the sorted vector \( vo \).

**Step III:** Compute the intensity difference between each pair of adjacent pixels and across the sorted vector \( vo \), and obtain the difference vector \( vd \).

**Step IV:** For the pixel intensities between the lowest value of intensity in the window and \( med \) in \( vo \), find the maximum intensity difference in \( vd \) of the same range and mark its corresponding pixel in \( vo \) as the boundary b1.

**Step V:** Similarly, the boundary b2 is identified between \( med \) and highest value of intensity in the window.
Step VI: If the pixel under consideration belongs to the middle cluster, it is classified as ‘noise-free’ and classification process stops, otherwise, second iteration will be invoked.

Step VII: Repeat the steps II to V with a 3x3 window, centered around pixel under consideration.

Step VIII: If the pixel under consideration belongs to the middle cluster, it is classified as ‘noise-free’ otherwise ‘noisy’.

Step IX: Based on the decisions for all the pixels, a binary decision map is prepared in which ‘0’ represents the noise-free pixel location and ‘1’ represents the noisy pixel location. This map gives an estimate of noise percentage as well.

Step X: Based on a binary decision map, ‘no filtering’ is applied to the uncorrupted pixels, while SM with adaptively determined window size is applied to each corrupted pixel. Window size of the filtering window is kept 3x3 for noise percentage upto 20, 5x5 for noise percentage between 21 to 40 and 7x7 for noise percentage more than 40.

The above filtering scheme works very well for all types of salt and pepper noise, however, window size in the first iteration is too big. Also, the scheme fails if salt and pepper noise has small bands and within a band all the impulses are not equip-probable.

(ii) High performance detection filter (HPDF)

This filtering scheme is based on image statistics of the natural images which indicates that each noise free pixel in the filtering window has a certain minimum number of similar neighbours. The noise detection process consists of four phases. In every phase, the first step is to subtract central pixel from other pixels of the window and get the absolute differences.

\[ |x(i,j) - x(m,n)| = M_j; m,n \in W_{no}^{(i,j)}(i, j) \text{ and } j=1,2,\ldots,N_k-1 \]  

(2.6)
where $N_k$ is window size in $k^{th}$ phase. Now we count the number of pixels in the window $(W_{(i,j)}^{(x)}(i,j))$ for which $M_j$ is less than a pre-defined intensity $D_k$ in $k^{th}$ phase.

$$c = \text{number of } (M_j \leq D_k); \quad k = 1, 2, 3, 4 \quad (2.7)$$

Now, $c$ is compared with a threshold $T_k$ to determine whether the pixel is noisy or not. If the pixel is detected as noisy, it is indicated as ‘1’ in the binary flag image, otherwise ‘0’ is flagged for noise-free pixel. The same steps are performed for all the pixels in the image. In all the phases, a window of size 5x5, $D_k = 40,30,20,10$ and $T_k = 7,5,3,2$ are used in the first, second, third and fourth phases, respectively. In the restoration process, a window of size 3x3 is considered centered around a noisy pixel and is replaced by the mean value of noise-free pixels only. Any pixel, if detected as noisy in any phase, will be excluded from detection in the subsequent phases and will also be not used in the restoration process.

(iii) **Noise adaptive switching median-based filter (NASMBF)**

In this method, which is quite similar to the previous methods, first of all a window of size say $n \times n$ is considered initially and all the pixels in this window are considered for local extreme (min or max) values. As we know that in a conventional sliding window system every pixel is a part of some window for $N$ number of times, where $N$ indicates the total number of pixels within the filtering window, therefore, a pixel in this system, is considered noisy if it appears to be local extremum for $N$ times. For filtering, median of noise-free pixels is considered. This method is most suitable for salt and pepper noise for highly corrupted images [39].

(iv) **Histogram-Based filtering scheme [60]**

In this filtering scheme also, the decision about the presence of noise is displayed by a binary matrix in which ‘0’ represents the noise-free pixel location and ‘1’ represents the noisy pixel location. The main steps in this scheme are:
Step I: Impose a 21×21 window, which is centered at the current pixel.

Step II: Calculate the histogram of the local window where bin indices are the gray levels. Find the maximum (max) and minimum (min) gray levels of the local window.

Step III: For the indices between min and (min+max)/2, calculate the difference of non-zero indices. Find the maximum difference and mark the corresponding index as boundary $b_1$.

Step IV: Similarly, $b_2$ is computed between Max and (min+max)/2. Thus, three clusters are formed.

Step V: The pixel is declared uncorrupted if it belongs to the middle cluster, otherwise, pixel is declared as noisy.

Step VI: If the pixel is declared noisy, process is repeated by considering a 3×3 window, which is centered around the current pixel. In second iteration also, if the pixel does not belong to the middle cluster, then it is classified as noisy, otherwise noise-free.

Step VII: For filtering the noisy pixel, a window of size 3×3 is considered initially and pixel is replaced by SM of the noise-free pixels in the filtering window. If the number of noise-free pixels in the filtering window is less than three, size of the filtering window is increased.

In comparison with BDND, the above scheme has the following advantages from computational complexity point of view, which are:

- No sorting operation is required.
- Filter window size is likely to be smaller than used in BDND.

However, the performance of this filtering scheme rather poor if fixed valued impulses are of more than two intensity values with sufficient separation.
(v) **Advanced Boundary Discriminative Noise Detection (ABDND)** [126]

In this method, by using histogram of the image, the range of gray values of noise is estimated. Based on this noise range, a threshold is calculated, which is compared with the absolute difference of the current pixel with the brightest and darkest pixels in the working window, to determine whether the current pixel is corrupted by the impulse noise. To avoid any false alarm generated in the first stage, the noise candidates are passed through a second stage using local statistics. For restoration of noisy pixel, noise adaptive switching median filter is used. This technique performs well on all types of fixed valued impulses included in the present study.

### 2.4.4 Morphology-based Switching Median Filtering

Morphology is basically a branch of biology that deals with the shapes of the living things. In the context of image filtering, mathematical morphology governed by set theory, is used to remove impulse noise [101].

**Morphological filtering system:** The block diagram of a morphological filtering system [41] is shown in Figure 2.6. This scheme uses the opening and closing operations [51] for detection and filtering of noise. The closing operation is defined as dilation of an image $X$ by the structuring element $b$ followed by erosion, and the opening operation is defined as erosion of an image by the structuring element followed by the dilation. Here, the dilation of $X$ by $b$ is the set of all displacement points of $b$ such that the reflection of $b$ and $X$ overlap by at least one element, and the erosion of $X$ by $b$ is the set of all displacement points of $b$ such that $b$ is contained in $X$.

![Figure 2.6 Morphological filtering scheme](image-url)
In this filtering system, noisy image is fed to the MRD detector which is governed by the following equations:

\[ D_0 = X - X \circ b \text{ and } D_c = X \bullet b - X \]

where \( \circ \) and \( \bullet \) are the closing and opening operations. \( D_0 \) and \( D_c \) denote the opening and closing distances from the input signal respectively, and \( b \) is the structuring element. Noisy pixels are detected by comparing \( D_0 \) and \( D_c \) to with a small threshold \( T \).

\[
f(i,j) = \begin{cases} 
1 & D_0 \geq T \text{ and } D_c = T \\
-1 & D_c \geq T \text{ and } D_c = T \\
0 & \text{otherwise}
\end{cases}
\]  

(2.8)

If \( f(i,j) = 1 \), then \( x(i,j) \) is considered as salt noise, if \( f(i,j) = -1 \), then \( x(i,j) \) is considered as pepper noise else it is treated as noise free. Two filters using open-close sequences are employed to remove the noise. The first one called open close filter (OCF) is defined as

\[ OCF \left( X \right) = (X \circ b_1) \bullet b_2 \]  

(2.9)

The size of \( b_1 \) must be small enough to preserve details of the image and size of \( b_2 \) is larger than \( b_1 \). This filter removes pepper noise effectively. However, pepper noise whose size exceeds that of \( b_1 \) can not be eliminated. The second one is called close open filter (COF) and is defined as

\[ COF \left( X \right) = (X \bullet b_1) ^ \circ b_2 \]  

(2.10)

This filter removes salt noise effectively. After application of two filters, the image will have black and white blocks which are corrected pixel by pixel using median of the surrounding window of suitable size.

In another morphological filtering system [145], a conditional morphological detector is used in which conditional opening and conditional closing is used to compute absolute deviation which is compared with a predefined threshold for the pixel under consideration and for its value more than a
predefined threshold, the pixel is considered noisy, otherwise noise-free. For calculating the absolute deviation  
\[ d(i,j) = \left| \frac{(x \cdot b)^c(i,j) + (x \circ b)^c(i,j)}{2} - x(i,j) \right| \]  
(2.11)

where \((x \cdot b)^c\) and \((x \circ b)^c\) denote the conditional closing and conditional opening, respectively.

Conditional dilation and erosion is required for computing conditional closing and opening. Conditional dilation is computed with the help of the erosion gradient, structuring element and noisy image whereas the conditional erosion is computed with the help of dilation gradient, structuring element and noisy image. Conditional closing is defined as the conditional dilation followed by the classical erosion and conditional opening is defined as the conditional erosion followed by the classical dilation.

The performance of the detector depends upon the size of structuring element and threshold. For filtering of the noisy pixel, a 3×3 window is considered and average value of the noise-free pixels replaces the corrupted pixel. If all the pixels in the filtering window are noisy, then window size is increased. This type of filtering system works well with pure salt and pepper noise only.

2.4.5 Adaptive Neuro-Fuzzy Inference-based Switching Median Filtering

These filtering systems are based on a noise filter followed by a first order Sugeno-type fuzzy system. The internal parameters of the system are tuned by a computer generated artificial image, and the adaptation of neuro-fuzzy parameters is accomplished by using Levenberg-Marquardt optimization algorithm [62-63]. Figure 2.7 shows the basic structure of a neuro-fuzzy system for improving the performance of an impulse noise filter.
Figure 2.7 NF method for improving the performance of an impulse filter

This filter has two inputs \((X_1, X_2,.)\) and one output neuro-fuzzy system. One of the inputs is fed by noisy image while the other input is fed with the filtered image obtained by processing the noisy image by the noise (median) filter. Each input has three generalized bell type membership functions whereas the output has a linear membership function [140-142]. The inference rules of the neuro-fuzzy system are as follows:

1. If \((X_1 \text{ is } M_{11}) \text{ and } (X_2 \text{ is } M_{21})\), then \(R_1 = F_1(X_1, X_2)\),
2. If \((X_1 \text{ is } M_{11}) \text{ and } (X_2 \text{ is } M_{22})\), then \(R_2 = F_2(X_1, X_2)\),
3. If \((X_1 \text{ is } M_{11}) \text{ and } (X_2 \text{ is } M_{23})\), then \(R_3 = F_3(X_1, X_2)\),
4. If \((X_1 \text{ is } M_{12}) \text{ and } (X_2 \text{ is } M_{21})\), then \(R_4 = F_4(X_1, X_2)\),
5. If \((X_1 \text{ is } M_{12}) \text{ and } (X_2 \text{ is } M_{22})\), then \(R_5 = F_5(X_1, X_2)\),
6. If \((X_1 \text{ is } M_{12}) \text{ and } (X_2 \text{ is } M_{23})\), then \(R_6 = F_6(X_1, X_2)\),
7. If \((X_1 \text{ is } M_{13}) \text{ and } (X_2 \text{ is } M_{21})\), then \(R_7 = F_7(X_1, X_2)\),
8. If \((X_1 \text{ is } M_{13}) \text{ and } (X_2 \text{ is } M_{22})\), then \(R_8 = F_8(X_1, X_2)\),
9. If \((X_1 \text{ is } M_{13}) \text{ and } (X_2 \text{ is } M_{23})\), then \(R_9 = F_9(X_1, X_2)\),

\[(2.12)\]

where \(M_{ij}\) denotes the \(j\)th membership function of the \(i\)th input, \(R_k\) denotes the output of the \(k\)th rule, and \(F_k\) denotes the \(k\)th output membership function. The input membership functions are expressed as:

\[
M_{ij}(u) = \frac{1}{1 + \left|\frac{u - a_{ij}}{b_{ij}}\right|^{2c_{ij}}} \quad i = 1,2 \text{ and } j = 1,2,3 
\]

\[(2.13)\]

The output membership functions are chosen to be linear:

\[
F_k(u_1, u_2) = d_{k1}u_1 + d_{k2}u_2 + d_{k3}, k = 1, \ldots, 9
\]

\[(2.14)\]
Here the parameters $a$, $b$ and $d$ are constants that characterize the shape of membership functions. The internal parameters of the neuro-fuzzy system are trained by the suitable training images [62, 141]. The weighing factors of the rules are calculated as follows:

\[
\begin{align*}
    w_1 &= M_{11}(X_1).M_{21}(X_2) \\
    w_2 &= M_{11}(X_1).M_{22}(X_2) \\
    w_3 &= M_{11}(X_1).M_{23}(X_2) \\
    w_4 &= M_{12}(X_1).M_{21}(X_2) \\
    w_5 &= M_{12}(X_1).M_{22}(X_2) \\
    w_6 &= M_{12}(X_1).M_{23}(X_2) \\
    w_7 &= M_{13}(X_1).M_{21}(X_2) \\
    w_8 &= M_{13}(X_1).M_{22}(X_2) \\
    w_9 &= M_{13}(X_1).M_{23}(X_2)
\end{align*}
\]

(2.15)

The output is given by

\[
Y_r = \frac{\sum_{k=1}^{9} w_k R_k}{\sum_{k=1}^{9} w_k}
\]

(2.16)

Further improvement in the above filtering system can be obtained by changing the filtering methods and increasing the number of filters such as suggested in [140] where in place of a simple median filter, four CWMF with weights 0,1,2 and 3 are used. In similar filtering method, instead of using CWMF, four NF filters are used as inputs to the postprocessor to generate the final output [141].

In some of the filtering methods, besides using filtered pixel and noisy pixel information, other information of the pixel as well such as whether the pixel is lying on some edge etc is also used. Filtering based on this approach is given in [142] in which ANFIS has three inputs i.e. current pixel, filtered output from SM and edge detector output. Performance of such systems depends upon not only the filter that is used but also on the edge detector's capability to detect the edges correctly.
In some of the other approaches, ANFIS is used for detecting the noisy pixels instead of filtering [143]. Two NF sub-detectors are used with inputs from horizontal and vertical directions from the window under consideration for identifying the noisy pixel and their outputs are fed to the decision maker which averages the two inputs for final decision. The performance of such detectors can be further improved by considering two more directions [47] as shown in Figure 2.8.

![Diagram of ANFIS and average output](image)

**Figure 2.8** The general structure of the neuro-fuzzy impulse detector

This type of system can be used with any type of impulse denoising filter and is reported to give good results with fixed valued impulses.

### 2.4.6 Alpha-trimmed Mean Filter

The alpha-trimmed mean (ATM) filter [67] is based on order statistics and varies between a median and mean filter. It is so named because, rather than averaging the entire data set, a few data points are removed (trimmed) and the remainders are averaged. The points which are removed are most extreme values, both low and high, with an equal number of points dropped at each end (symmetric trimming). In practice, the alpha-trimmed mean is computed by sorting...
the data low to high and finding the average of the central part of the ordered array. The number of data values which are dropped from the average is controlled by trimming parameter $\alpha$ (alpha) and hence the name alpha-trimmed mean filter.

Let $g_{k,h}(i,j)$ be a sub-image of noisy image $g(i,j)$. For simplicity, $g_{k,h}(i,j)$ is referred as $g_{k,h}$. Suppose the $\frac{\alpha}{2}$ lowest and the $\frac{\alpha}{2}$ highest gray-level values of $g_{k,h}$ are deleted from the neighborhood. Let $g_r$ represent the remaining $(mn-\infty)$ pixels. A filter formed by averaging these remaining pixels is called alpha-trimmed mean filter whose output may be expressed as:

$$\bar{f}(i,j) = \frac{1}{mn-\alpha} \sum_r f_r$$  \hspace{1cm} (2.17)

Choice of parameter $\alpha$ is very critical and it determines the filtering performance. Hence, the ATM filter is usually employed as an adaptive filter whose may be varied depending on the local signal statistics. Therefore, it is a computation-intensive filter as compared to a simple median filter. Another problem of ATM is that the detailed behavior of the signal cannot be preserved when the filter window is large.

2.4.7 Center Weighted Median Filter (CWM)

The center weighted median (CWM) [64] filter is a special case of weighted median (WM) filters. This filter gives more weight only to the central pixel of a window and thus it is easy to design and implement. CWM filter preserves more details at the expense of lesser amount of noise suppression like other non adaptive detail preserving filters.

Let $g(i,j)$ be a noisy image. Consider a sub-image $g_{k,h}(i,j)$ of size $P = Q = 2L+1$, centered at $(i,j)$. The output of the CWM filter, in which a weight adjustment is applied to the center pixel within the sliding window, can be described as
\[ \hat{f}(i, j) = \text{med} \left\{ (g_{k,l}(i-k, j-l) \mid (k,l) \neq (0,0), w_{c} \text{ copies of } g_{k,l}(i, j) \mid (k,l) = (0,0)) \right\} \]

(2.18)

For a (3\times3) window, the median is computed based on those 8+w_c pixel values. Note that integer w_c is positive and odd, and the CWM filter becomes the median filter when w_c=1. On the other hand, when w_c is greater than or equal to the window size (e.g., w_c \geq 9 for a (3\times3) window), it becomes an identity filter, which always takes the origin pixel value g(i, j) as the output. A CWM filter with a large center weight performs better in detail preservation. However, its performance is not acceptable at high noise densities.

2.5 DETECTION FOLLOWED BY FILTERING

The filters which are discussed in section 2.1 are those without the noise detection stage. Thus, even non-noisy pixels are also replaced by some estimates. In view of this, the performance of these filters is not good. To overcome this problem, a new filtering technique is introduced. This type of filtering involves two steps: In first step, it identifies noisy pixels and in second step, it filters only those pixels that are identified as noisy. The performance of these filters depends on impulse detector and estimator by which noisy pixels are replaced in the filtering process.

In this section some well-known, standard and benchmark filters, available in literature, are described.

2.5.1 Tri-State Median Filtering (TSM)

The tri-state median (TSM) filter [30] incorporates the median filter (MF) and the center weighted median (CWM) filter in a noise detection framework. Noise detection is realized by an impulse detector, which takes the outputs from the median and center weighted median filters and compares them with the center pixel value in order to make a tri-state decision. The switching logic is controlled by a threshold value. Depending on this threshold value, the center pixel value is replaced
by the output of either median filter (MF), CWM filter or identity filter. The output of TSM is given by

\[
\hat{f}(i,j) = \begin{cases} 
  g(i,j), & T \leq d_1 \\
  g_{CWM}^{MF}(i,j), & d_1 < T \leq d_2 \\
  g_{MF}(i,j), & T > d_2 
\end{cases}
\]  

(2.19)

where, \( g_{CWM}^{MF}(i,j) \) and \( g_{MF}(i,j) \) are the outputs of CWM and MF filters respectively, \( g(i,j) \) is noisy image and \( d_1 = |g(i,j) - g_{MF}(i,j)| \) and \( d_2 = |g(i,j) - g_{CWM}(i,j)| \). The threshold \( T \) affects the performance of impulse detection. Usually, a threshold, \( T \in [10, 30] \) is good enough [28]. Of course, its value should adaptively be chosen for better results.

2.5.2 Adaptive Median Filters (AMF) [58]

For good impulse classification, removal of the positive and negative impulse noises one after another is preferred. There are a number of algorithms which resolve this problem, but they are more complex. This algorithm is simple and better in removing a high density of impulse noise as well as non-impulse noise while preserving fine details. The size of filtering window of median filter is adjusted based on noise density.

This algorithm is based on two level tests. In the first level of tests, the presence of residual impulse in a median filtered output is tested. If there is no impulse in the median filtered output, then the second level tests are carried out to check whether the center pixel itself is corrupted or not. If the center pixel is uncorrupted, then it is retained at the output of filtered image. If not, the output pixel is replaced by the median filter output. On the other hand, if the first level detects an impulse, then the window size for median filter is increased and the first level tests are repeated. The maximum filtering window size taken is 11×11 if the noise density is of the order of 70% [58].
2.5.3 Progressive Switching Median (PSM) Filter for the Removal of Impulse Noise from Highly Corrupted Images

The Progressive switching median (PSM) filter is a median based filter [134]. It consists of two points (i) switching scheme an impulse detection algorithm is used before filtering; thus only noisy pixels are filtered and (ii) progressive methods – both impulse detection and progressive filtering are applied through several iterations one after the other. Hence, it is referred to as PSM filter.

In the first stage, an impulse detection algorithm is used to generate a sequence of binary flag images. This flag image indicates the location of noise in the input image. If the binary flag image pixel is 1, it indicates that the pixel in that position in the input image is noisy. On the other hand, if the binary flag is 0, then it is considered noise-free. In the second stage, filtering is applied based on binary flag image generated in the first stage. Both these steps are progressively applied through several iterations. The noisy pixels processed in the current iteration are used to help the processing of the other pixels in the subsequent iterations. Therefore, better restoration results are expected, even under high noise density conditions.

2.5.4 Advanced Impulse Detection Based on Pixel-Wise MAD (PWMAD)

This method is used for filtering both random valued and salt-and-pepper valued impulse noise. In this method, median of the absolute deviations from the median, MAD is modified and used to efficiently separate noisy pixels from the image details. An iterative pixel-wise modification of MAD called PWMAD provides reliable removal of arbitrarily distributed impulse noise.

Let $g(i,j), m(i,j)$ and $d(i,j)$ represent pixels with coordinates $(i, j)$ of noisy image, median image and absolute deviation image, respectively. Also, let $(i,j), m(i,j) \text{ and } d(i,j)$ denote matrices (sub-image) whose elements are pixels of the corresponding images contained within the $(2L + 1) \times (2L + 1)$ size window, centered around at position $(i, j)$. The median image and absolute deviation image may be defined as:
\[ med \ (i, j) = med \ (g(i, j)) \] (2.20)

\[ d(i, j) = | (g(i, j)) - m(i, j) | \] (2.21)

The median of the absolute deviations from the median, denoted by MAD, is defined as:

\[ MAD(i, j) = med \ (| g(i, j) - med \ (g(i, j)) |) \] (2.22)

Note that a single median value is subtracted from all the pixels within \( g_s(i, j) \). In order to make MAD consistent with definition of absolute deviation image, where its corresponding median image pixel \( m(i, j) \) is subtracted from each pixel, a modified Pixel-Wise MAD (PWMAD) image is given by

\[ PWMAD \ (i, j) = med \ (d(i, j)) = med \ (| g(i, j) - m(i, j) |) \] (2.23)

The absolute deviation image \( d(i, j) \) consists of noise and image details eliminated from the noisy image by median filtered. If a median is applied to (absolute deviation image), a PWMAD image is generated. By subtracting the PWMAD image from \( d(i, j) \), details are eliminated and only the noise is left behind. If this process is repeated several times, then the image, obtained after the final iteration, consists of pixels that are corrupted with impulsive noise. This image can be used for generation of binary image.

The whole iteration procedure can be represented as:

\[ d^{(n+1)}(i, j) = | d^{(n)}(i, j) - PWMAD \ (d^{(n)}(i, j)) | \]

i.e. \[ d^{(n+1)}(i, j) = | d^{(n)}(i, j) - med(d^{(n)}(i, j)) | \] (2.24)

where \( d^{(0)}(i, j) \) is a primary absolute deviation image defined in (2.24). The iteration is terminated after \( n = N - 1 \), and \( d^{(N)}(i, j) \), thus obtained, is used for generation of binary flag image, which is defined as
\[ d(i, j) = \begin{cases} 1 & d^{(n)}(i, j) \geq T \\ 0 & d^{(n)}(i, j) < T \end{cases} \] (2.25)

The value of \( T \) is in the range \([0\ text{ to } 30]\). The simulation is carried with \( T = 5 \) and number of iterations, \( N = 3 \) and the results are presented in the Chapter-4.

2.6 IMPORTANT ISSUES

Ideally, a filtering scheme should perform satisfactorily for different types of noise. Also, it should not be very sensitive to the choice of various parameters when used for filtering of images with different characteristics and at different noise levels. In the case of the fixed valued impulse noise, the main requirement of the filtering scheme is that it should be able to remove the noise, present anywhere within the allowed gray scale. Also, it should be able to differentiate between the noisy and noise-free pixel of the same gray value. For random valued impulse noise removal, the emphasis is on more accurate detection of the noisy pixels. Also, if the scheme is iterative in nature, a proper stopping criterion is required.

In the case of color images, the filtering algorithm must restore both the intensity and the color of the image effectively. To attain this objective, efficient use of information available in three channels of the noise-free components is required. Also, preferably, the filtering algorithm should attempt to alter only the noisy components so as to ensure that the restored pixel is as close to the original one as possible.

2.7 SUMMARY

This chapter aims to provide a complete scenario of some existing filters. Only a few important filters are presented in this chapter. Hence, there is sufficient scope to develop more efficient filters to suppress impulse and Gaussian noise as described in the succeeding chapters.