CHAPTER 1
INTRODUCTION

1.1 PREAMBLE

An image is worth a thousand words. In this contemporary world, images are the most familiar and convenient means of communicating information. Visual information in the form of digital images allows humans to perceive and understand the world surrounding them in a better manner. Consequently, image processing plays a really vital character and has been making a significant consciousness of the researchers over the last few decades.

Digital imaging is very essential in many applications such as object recognition, biomedical instrumentation, satellite imaging, entertainment media, internet etc. Due to contamination of various types of noise, the quality of the image degrades during acquisition, transmission, and retrieval from storage media. The acquired image signal must be noise free to convey meaningful information to the end user and to have very good visual presentations in applications like mobile phones, medical imaging, entertainment media etc. Thus an effective denoising algorithm is essential to remove noise in images.

1.2 THE GENESIS OF THE THESIS

Images are frequently corrupted by impulse noise which occurs in the process of image acquisition, transmission and storage. Two types of impulse noise are: (a) Fixed valued impulse noise, also called, Salt & Pepper Noise (SPN) where the noise value may take either minimum or maximum
value of the dynamic grayscale range of image and (b) Random-Valued Impulse Noise (RVIN) where the noisy pixel value is limited by the scope of the dynamic grayscale range of the image. Though numerous noise suppressing algorithms is proposed to date, most of them fail to perform well for moderate and higher noise densities. Hence, there is an extensive scope to explore and produce novel and effective algorithms for suppressing impulse noises especially at higher noise densities.

1.3 LITERATURE REVIEW

Noise in an image is a serious problem. The noise could be Additive White Gaussian Noise (AWGN), SPN, RVIN, or a mixed noise. Image restoration and filtering is one of the prime areas of image processing and its objective is to recover the images from degraded observations. The techniques involved in image restoration and filtering are oriented towards modelling the degradations and then applying an inverse operation to obtain an approximation of the original image.

The literature survey mainly focuses on filtering techniques used for suppression of impulse noise. The mathematical model of impulse noise is given in 1.3.1.

1.3.1 Impulse Noise Model

Image noise is a random, usually unwanted, variation in brightness or color information in an image. Image noise, especially impulse noise (SPN and RVIN) originate in film grain, malfunctioning pixels in camera sensors or faulty memory locations in hardware and errors in data transmission. The SPN has only two possible values, 0 or 255 whereas RVIN can take any value between 0 and 255.
When an image is corrupted by impulse noise, only a fraction of the pixels is replaced with noise values. To be precise, let $x(i,j)$ and $f(i,j)$ denote the intensity values of the original image and the noisy image at the location $(i,j)$ respectively. $C.A = \{1,2,\ldots, M\} \times \{1,2,\ldots, N\}$, respectively.

Image containing impulse noise with probability $\rho$ can be given by Equation (1.1).

$$f(i,j) = \begin{cases} x(i,j), & \text{with probability } 1 - \rho \\ n(i,j), & \text{with probability } \rho \end{cases}$$ (1.1)

Where $n(i,j)$ stands for noise value at the location $(i,j)$ independent from $x(i,j)$. For SPN noise, the values of the corrupted pixels are equal to $n_{\min}$ or $n_{\max}$ with equal probability of 1/2. For RVIN, $n(i,j)$ is uniformly distributed random number in $[n_{\min}, n_{\max}]$, with probability $1/(n_{\max} - n_{\min})$. For 8 bit images, $n_{\min} = 0$ and $n_{\max} = 255$.

The literature survey pertaining to this research work is classified into the following headings.

1.3.2 Linear Filters

During the past several decades, considerable research has been done on de-noising. Different algorithms are used depending on the noise models. There are many approaches to deal with additive noise in natural images, such as average filters and mean filters. Even though linear filters are useful in a wide variety of applications, there are some situations in which they are not adequate (Astola & Kuosmanen, 1997). For example, linear filters do not take into account any structure in images. Therefore, linear filters tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of noise.
1.3.3 Nonlinear Filters

The solution to the above problem is to use Median Filter (MF) (Astola & Kuosmaneen, 1997), which is the most popular order statistics filter under the nonlinear filter classes.

1.3.3.1 Median filter

A simple median filter presented by Brownrigg (1984) works very nicely for suppressing impulsive noise of low density and is easy to implement. But the cost paid for it distorts edges and fine details of an image. The median filter, especially with a bigger window size destroys the fine image details due to its rank ordering process. Applications of the median filter require caution because median filtering tends to get rid of image details such as thin lines and corners while cutting down the noise.

Gonzalez & Woods (2002), Jain (1989) also reported that the median filter is one of the most popular nonlinear filters. It is very simple to implement and much efficient as well. The median filter, especially with a bigger window size destroys the fine image details due to its rank ordering process. It plays like a low pass filter which blocks all high frequency components of the image like edges and noise, thus obscuring the image. Every bit the noise density increases, the filtering window size is increased to have a sufficient number of uncorrupted pixels in the region. Depending upon the sliding window mask, there may be many variations of median filters.

Bednar & Watt (1984) proposed Alpha-Trimmed Mean Filter (ATMF), which 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 details which are removed are most extreme values, both low and high,
with an equal number of points dropped at each end (symmetric trimming). During exercise, the alpha-trimmed mean is calculated by sorting the data low to high and finding the average of the central portion of the ordered array. The number of data values which drop from the average is controlled by trimming parameter (alpha) and hence the name alpha-trimmed mean filter.

Choice of parameter is very vital and it specifies the filtering operation. Hence, the ATMF is commonly used as an adaptive filter, which may be changed depending on the local signal statistics. Thus, 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.

Order Statistics Filters are nonlinear spatial filters whose response are based on ordering (ranking) the pixels contained in the region embraced by the filtering window. Usually, sliding window technique which is presented by Gonzalez & Woods (2002), Jain (1989) is employed to perform pixel-by-pixel operation in a filtering algorithm. The local statistics obtained from the vicinity of the center pixel give a great deal of data about its anticipated value. If the neighborhood data are ranked (sorted), then ordered statistical information is received. The center pixel in the sliding window is put back with the value determined by the ranking effect.

1.3.3.2 Detection and filtering methods

The filters, which are discussed in the previous section are the filters without noise detection stage. Thus, even non-noisy pixels are also replaced by some estimates. Because of this, the performance of these filters is not good. To surmount this trouble, a new filtering technique is presented. This case 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 the estimator by which noisy pixels are replaced in the filtering process.

To improve the performance of median filters, weighted median (WM) filters reported by Brownrigg (1984), Justusson (1981), Loupos et al (1989), Yin et al (1996), which are an extension of the median filter that gives more weight to some values within the window. It emphasizes or de-emphasizes specific input samples, because in most applications, not all samples are equally important.

The Center Weighted Median (CWM) filter proposed by Ko & Lee (1991) is a peculiar example of WM (Brownrigg 1984) filter. This filter gives more weight only to the central pixel of a window and thus it is easy to plan and carry out. CWM filter preserves more details at the expense of less noise suppression like other non-adaptive detail preserving filters.

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

A two-stage iterative method for RVIN is proposed by Chan et al (2004). Adaptive Center Weighted Median Filter (ACWMF) technique proposed by Chen & Wu (2001) is used to identify the noisy pixels in phase 1. In phase 2, Edge Preservation Regularization (EPR) technique is employed to preserve edges and fine details. The proposed filter (ACWMF-EPR) performs better compared to some of the non-linear filters and preserves edges well, however, it fails to suppress noise at higher noise densities.
Conventional median filtering approaches apply the median operation to each pixel unconditionally, that is, without considering whether it is uncorrupted or corrupted. As a result, the image details contributed from the uncorrupted pixels are still subject to be filtered, and this causes image quality degradation. An intuitive solution to overcome this problem is to implement 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, the so-called Switching Median Filters (SWM) (Chen et al 1999), (Wang & Zhang 1999), (Zhang & Karim 2002), (Eng & Ma 2001), (Pok et al 2003), (Hwang & Haddad 1995) had shown significant performance improvement, however it fails to preserve edges and fine details at noise densities above 50%.

Hwang & Haddad (1995) proposed Adaptive Median Filters (AMF). For good impulse classification it is preferred to remove the positive and negative impulse noise one after another. There are a number of algorithms which resolve this problem, but they are more complex. This algorithm is simple and better performing in removing a high density of impulse noise as well as non-impulse noise while preserving fine details. The size of the filtering window of median filter is set based on noise density. This algorithm is established on two level tests. At the beginning level of tests, the presence of residual impulse in a median filtered output is examined. If there is no impulse in the median filtered output, then the second grade tests are extended out to determine whether the center pixel it is corrupted or not. If the center pixel is uncorrupted then it is kept in the yield of the filtered image. If not, the output pixel is substituted 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%, hence the restored image gets blurred at higher noise densities.

In Minimum–Maximum Exclusive Mean (MMEM) filter; proposed by Han & Lin (1997), 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 average; otherwise, unchanged. The performance of this filter is not in good quality, since it depends on the selection of the threshold value.

The idea behind the bilateral filtering introduced by Tomasi & Manduchi (1998) is to combine domain filtering with range filtering. Domain filtering is the traditional filtering framework that takes advantage of the similarity of spatially close pixels which are assumed to be more correlated to the centered pixel than more distant pixels. As a consequence, a weighted-averaging of close pixels considerably reduces the noise level. However, in the vicinity of the edges, this solution is not satisfying.

The Tri-State Median filter (TSM) proposed by Chen et al (1999), 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 better performance than the standard and the switching median filters at the expense of increased computational complexity.

A new tri-state median filter proposed by Chen et al (1999) incorporates the MF and CWM filter (Ko & Lee 1991) 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 to the center pixel value in order to make a tri-state decision. The switching logic is kept in line with a threshold value. Depending on this threshold value, the center pixel value is replaced by the output of either MF, CWM filter or identity filter. The threshold T affects the carrying out of impulse detection.

Wang & Zhang (1999) have presented a Progressive Switching Median Filter (PSMF) is basically a median based filter, consisting 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 as PSMF. 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 at 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 the binary flag image generated in the first stage. Both these steps are progressively applied through various iterations. The noisy pixels processed in the current iteration are used to facilitate the operation of the other pixels in the subsequent iterations. Since the filter passes through several iterations, computational complexity is more and also the performance is not good at higher noise densities.

The peak and valley filter proposed by Windyga (2001), 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 mode, no new values are brought out into the neighborhood and the histogram
distribution range is maintained. The primary advantage of this filter is its simplicity and speed, however it not attractive in suppressing impulse noise at higher noise densities.

A modified peak and valley filter, detail preserving impulsive noise removal scheme has also been proposed by Alajlan et al (2004). This filter provides better detail preservation performance; but it is slower than the original peak and valley filter.

Eng & Ma (2001) proposed a Noise Adaptive Soft-switching Median (NASM) filter. The filter uses a soft-switching noise-detection scheme to identify each pixel’s characteristic, followed by proper filtering operation. In the noise-detection scheme, global (i.e., based on the entire picture) and local (i.e., based on a small window) pixel statistics are utilized in the first and the remaining two decision-making levels respectively.

A new impulse noise detection technique for Switching Median Filter (SMF) proposed by Zhang et al (2002) is based on the minimum absolute value of four convolutions obtained using one-dimensional Laplacian operators. It provides better performance than many of the existing switching median filters with comparable computational complexity. Early developed switching median filters 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. The NASM achieves a fairly robust performance in removing impulse noise, while preserving signal details across a full scope of noise densities, ranging from 10% to 50%. Nevertheless, for those corrupted images with noise density greater than 50%, the caliber of the recovered images become significantly degraded, due to the sharply increased number of misclassified pixels.
Pok et al (2003) introduced the homogeneity level information to detect impulse and proposed a two-stage method named the Conditional Signal Adaptive Median (CSAM) filter to reduce them. The current pixel is identified by analysis of the number of the homogeneous pixels in a small local window. The first identification discovers the majority of the noise candidates in a $3 \times 3$ window and then a refining process is followed in a $5 \times 5$ window. The difference between the CSAM filter and other filters are, that they have different fields of view when making decisions.

To identify the impulse more efficiently, the Differential Rank Impulse Detector (DRID) is presented by Aizenberg & Butakoff (2004) in which it incorporates the signal intensities and the ranks of signal values. Recently, the two-stage methods have been widely investigated and popularly used for removing impulse noise. The basic idea of the two-stage scheme is that the noise candidates in an image are firstly determined using a detector, and then the detected noises are reconstructed by a filter method.

Luo filter (Luo 2007) and the Genetic Programming (GP) filter (Petrovic & Crnojevic 2008) are representative filters used for removing impulse noise. However, the removal of random-valued impulse noise is relatively more difficult in comparison with salt-and-pepper impulse noise. Especially, when noise levels are high, the above-mentioned filters are not satisfactory in the removal of random-valued impulse noise.

Directional Weighted Median (DWM) filter proposed by Dong & Xu (2007) and Modified Switching Median (MSWM) filter presented by Kang & Wang (2009) usually perform well, however, the principle drawback is that they have limited performance in terms of false and missed detections. To reduce these effects and improve impulse noise detection, a new Adaptive Switching Median (ASWM) is introduced by Smal Akkoul et al (2010). The originality of ASWM is that no a priori threshold is to be given
as in the case of a classical SWM (Sun & Neuvo 1994). Instead, the threshold is computed locally from image pixels intensity values in a sliding window using weighted statistics.

A new two-stage filter—the Homogeneous Amount Based (HAB) filter is proposed by Wu & Tang (2012) for the removal of random-valued impulse noise from highly corrupted images. In the noise detection stage, the noisy pixels are distinguished in an unrestricted field of view by analyzing the amount of similar pixels in brightness. In the noise cancellation stage, the detected impulses are reconstructed by an image inpainting method—the Total Variation Inpainting (TVI) model.

The homogeneous amount of a pixel provides a measure of how many similar pixels are connected to the current pixel in the entire image scope. We use the homogeneous amount to recognize corrupted pixels based on the two assumptions:

1) A noise pixel takes a gray value substantially larger than or less than those of its neighbors (Zhang & Wang 1998).
2) A noise-free image should be locally smoothly varying and is separated by edges (Sun & Neuvo 1994).

A variational approach to get rid of outliers and impulse noise proposed by Nikolova (2004) is an edge and detail-preserving restoration technique to eliminate impulse noise efficiently. It practices a non-smooth data fitting term together with edge-preserving regularization functions. A compounding of this variational method with an impulse detector reported by Chan et al (2004) has also been shown 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 Nonlocal Means Filter of (Buades et al 2005a, (Buades et al 2005b) is another famous instance of this class of denoising algorithms. One of the major challenges in these patch-based approaches is to efficiently fix the various degrees of freedom involved, i.e. the size and shape of the patches (a tradeoff between denoising quality and computational efficiency has to be found), the design of the two weighting functions \( H_b \) and \( H_c \), as well as the value of their respective smoothing parameters \( h \) and \( g \).

In Iterative Adaptive Switching Median Filter proposed by Saudia et al (2006), a two-pass algorithm is employed for the identification of a noisy pixel and replacing the corrupted pixel by a valid median. Another iterative filter is proposed by Chan et al (2004) for effective suppression of random-valued noise. As it contains a heavy number of iterations, its execution time is excessively much. Further, it flushes it to hold the edges and fine details of an image at higher densities.

The method proposed by Haindi Ibrahim et al (2008) is an adaptive median filter to remove impulse noise from highly corrupted images. In fact, it is a hybrid of adaptive median filter with switching median filter. The adaptive median filter changes its size according to local noise density estimated. The switching framework helps to quicken up the operation of filtering. This method preserves the local details and edges of an image at medium noise densities. But there is no remarkable improvement in the results at higher noise densities.

An adaptive vector filter exploiting histogram information is also proposed by Ma & Wu (2003) for the restoration of color images.

An effective method developed by Zhang & Wang (2008) uses an adaptive center weighted average filter to identify pixels which are probable to be corrupted and restored by using median filter. A simple iteration
procedure is applied to noise detection and filtering functions, however, it fails to perform well at higher noise densities.

For high noise densities Srinivasan & Ebenezer (2007), proposed Decision Based Algorithm (DBA). The algorithm processes only the noisy pixels and uses a window size of 3 X 3. However the filter produces streaking effect for noise densities above 70%. To overcome this, Aiswarya et al (2010) proposed Decision Based Unsymmetric Trimmed Median Filter (DBUTMF), and Jayaraj & Ebenezer (2010), proposed Modified Decision Based Algorithm (MDBA) in which the impulse values are directly predicted, however both the algorithms doesn’t perform well for noise densities above 80%.

Esakkirajan et al (2011) proposed a Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF) algorithm especially for images corrupted with high noise densities. In case of highly corrupted images, if all the pixels in processing window are corrupted, the algorithm replaces the centre pixel with the mean of the processing window which blurs the image at high noise densities.

Nasri et al (2013), Xuming Zhang et al (2013) proposed decision based mean filters for removal of salt and pepper noises. The algorithms use non-local windows for estimating the intensity value of pixel in candidate. The filter shows better PSNR values for noise densities above 50%.

In recent years, a number of methods have been proposed which work on both random-valued and salt-and-pepper noise, (Zhang 2008), (Chan et al 2004), (Dong & Xu 2007), (Yu et al 2008), (Wang et al 2010).

The method proposed by Crnojevic et al (2004), Advanced impulse detection based on Pixel-Wise Median Absolute Deviation (PWMAD), is a modification of Median Absolute Deviation (MAD). MAD is used to estimate the presence of image details. An iterative pixel-wise modification of MAD is used here that offers a reliable removal of impulse interference. An improved method of this algorithm is an impulse noise filter with adaptive MAD based threshold proposed by Crnojevic (2005). 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 execution of both the methods is quite good under low noise density. But they fail miserably at high noise densities.

Impulse noise filter with Adaptive MAD (AMAD)-Based Threshold which is an improved method of PWMAD was proposed by Crnojevic (2005). This is also employed for filtering both random valued and salt-and-pepper valued impulse noises. In this method, an annex to the switching system is employed, where the threshold T is varying from pixel to pixel. The threshold value is changed in accordance with variance, estimated by using MAD. No iteration is used for impulse detection, which reduces run time with the same quality as compared to PWMAD.

In the same class one more method proposed by Tzu-choLin (2008) is known as progressive decision based mean type filter. This is based on Dempster-Shafer (D-S) evidence theory for pixel-classification. The mass functions are generated based on data available on the filtering window which are utilized for the D-S evidence theory. Decision rules can specify whether the pixel is noisy or not based on the noise-corrupted belief value.
Both detection and filtering are applied progressively through various iterations. The corrupted pixels are replaced by the mean of the noise-free pixels in the filter window.

Advanced impulse detection based on PWMAD proposed by Zhang (2010) can be applied for filtering both random valued and salt-and-pepper valued impulse noise. In this method, the median of the absolute deviations from the median, MAD is modified and employed to efficiently separate noisy pixels from the image details. An iterative pixel-wise modification of MAD, PWMAD provides reliable removal of arbitrarily distributed impulse noise. Note that a single median value is subtracted from all the pixels within (i, j). In order to make MAD consistent with definition of absolute deviation image, where its corresponding median image pixel is subtracted from each pixel, a modified PWMAD image. The absolute deviation image 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, details are eliminated and only noise is left behind. If this procedure 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 output image is obtained by selective median filtering. The filter does not work well for RVIN.

The method proposed by Aizenberg et al (2005), 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 executed on these binary images by using specially designed boolean functions. In the end, the resulting boolean images are merged back to obtain a restored gray level image.
Pei-Eng Ng et al (2006) presented a switching median filter with Boundary Discriminative Noise Detection (BDND) for Extremely Corrupted Images. To find out whether a pixel is corrupted or not, the BDND algorithm first classifies the pixels of a localized window, focusing along the current pixel, into three groups: lower intensity impulse noise, uncorrupted pixels, and higher intensity impulse noise. The center pixel will then be considered as uncorrupted, provided that it belongs to the uncorrupted pixel group, else it is considered corrupted. The grouping of pixels depends on two boundaries. The accurate determination of these boundaries yields very high noise detection accuracy even up to 70% noise corruption. The algorithm is applied to each pixel of the noisy image in order to identify whether the pixel is corrupted or uncorrupted. To achieve this target, all the pixels within a pre-specified window that centers at the considered pixel are grouped into three clusters, low-intensity cluster, medium-intensity cluster and high-intensity cluster. For each pixel being considered, if $0 \leq b_1$, the pixel will be assigned to the lower-intensity cluster; otherwise, to the medium-intensity cluster for $b_1 < b_2$ or to the high-intensity cluster for $b_2 < \leq 255$. The current pixel is identified as uncorrupted only if it passes into the medium-intensity cluster; otherwise it is classified as corrupted. The algorithm proposed by Pei-Eng Ng et al (2006) gives better denoising performance for noise density up to 70%. But there is no remarkable improvement in the results at higher noise densities above 70%.

Luo & Dang (2007) proposed a new Directional Weighted Median (DWM) filter based on a threshold principle for noise detection and a weighted median filter for noise reconstruction. This method delivers good performance up to 60% noise rate, but it also shows slow convergence, because each noisy pixel needs 5-10 iterations to be restored.
Vijaykumar et al (2008) proposed a robust estimation based filter, which reduces the streaking effect, but for higher noise densities the image gets blurred.

Zhang (2010) proposed an adaptive switching median filter for removal of RVIN. The novelty of the design is that setting the global threshold is not necessary as in the case of conventional switching median filters. The algorithm works well for noise densities upto 50% only.

Thivakaran & Chandrasekaran (2010) proposed a new technique for removal of RVIN based on nonlinear AMF. The filter is more effective for small window, but for large window and in case of high noise densities it gives rise to more blurring.

Wu & Tang (2011) use two stage scheme for removal of salt and pepper noise in images. The algorithm uses a detection stage and in painting. In detection stage the difference between pixel in candidate and its neighbours is estimated. If the difference is above threshold the candidate pixel is declared as noisy. The noisy candidate is replaced by TVI method. However the algorithm shows poor performance for high noise densities above 90%.

Kalavathy & Suresh (2011) proposed an impulse noise removal method based on adaptive median filter and multistage median filter or the median filter based on homogeneity information are called “decision based” or “switching” filters. Here, the filter identifies possible noisy pixels and then replaces them with median value or its variants by leaving all the other pixels unchanged. On replacing the noisy pixels with some median value in their vicinity, the local features such as the possible presence of edges are not taken into account. Hence, details and edges are not preserved satisfactorily, especially when the noise level is high.
Saradhadevi & Sundaram (2011) proposed a new two-stage noise removal technique to deal with impulse noise. An Adaptive Neuro-Fuzzy Inference System (ANFIS) is designed for fast and accurate noise detection such that various widespread densities of noisy pixels can be distinguished well from the edge pixels. The proposed ANFIS uses Modified Levenberg-Marquardt Training Algorithm for reducing the execution time. After suppressing the impulse noise, the image quality enhancement is applied to enhance the visual quality of the resultant images. It consists of fuzzy decision rules based on the Human Visual System (HVS) for image analysis and Neural Network (NN) for image quality enhancement. If a noise-corrupted pixel is in the perception sensitive region, the proposed NN module is applied to this pixel for further quality compensation. The proposed approach effectively eliminates the impulse noise while preserving most fine details.

Deshpande et al (2012) proposed a Modified median filter. The filter incorporated a decision based technique in which the corrupted pixels are replaced by either the median pixel or neighborhood pixel. At higher noise densities, the median value may also be a noisy pixel. In that case, median of already processed neighborhood pixels are used for replacement. This provides good correlation between the corrupted pixel and neighborhood pixel which in turn gives rise to better edge preservation. To remove any sort of Grayness ambiguity and Geometrical uncertainty present Fuzzy Rule based approach is used. However the restored images still contains some traces of salt-and-pepper noise.

Harale & Chitode (2012) proposed an efficient impulse noise removal algorithm giving more weight to the central value of each window. The filter gives better image restoration compared to the conventional median filter (Astola & Kuosmaneen 1997) and CWMF (Ko & Lee 1991) for both
low and high noise densities. However the algorithm suffers from setting a proper threshold, as it has to be set manually and depends on the type of image.

Lan & Zuo (2014) proposed a new two stage detection filter in which the combination of Adaptive Non-local Switching Median (ANSM) detector and Edge-Preserving Regularization (EPR) (Nikolova 2004) method is used for efficient detection; however the filter performs well only for low and medium noise densities.

1.3.3.3 Rank order filters

Abreu et al (1996) reported a signal-dependent rank-ordered mean filter, which 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 shown 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 and color images.

Recently, a universal noise removal algorithm is proposed by Garnett et al (2005) in which a new image statistic called image Rank Ordered Absolute Differences (ROAD) is used to measure the similarity or closeness of a pixel value to its neighbor pixels. The value of ROAD is employed with the idea of bilateral filter in order to weigh every pixel in the image. The result was a new filter called universal trilateral filter, (ROAD-TRIF).

A new image statistic Rank Ordered Logarithmic Differences (ROLD) to improve the performance of ROAD (Garnett et al 2005) is
proposed by Dong et al (2007). The new approach called ROLD-EPR can restore corrupted images with 60% impulse noise rate. These methods are computationally inefficient due to the high cost of the minimization process. In addition, they yield poor performance when the noise rate exceeds 60%.

Yu et al (2008) proposed Rank order filter combining absolute and logarithmic differences statistics and used bilateral filters for filtering. The filter uses standard median filter as reference. The relative difference between input image and the reference image is calculated. The pixels which have this difference greater than a set threshold are identified as noisy. In second phase the corrupted pixels are removed using simple weighted mean filter. The algorithm in Yu et al (2008) performs well compared to ROAD-TRIF and ROLD-EPR. However setting threshold for detecting noisy pixels poses a major problem.

An efficient method for the removal of impulse noise is proposed by Luo & Dang (2006). In the proposed method ROAD is used with a pre-defined threshold as a noise detector to decide whether the current pixel is a noisy pixel or an original pixel. Although all the previously mentioned filters perform well with low noise rates, they generally exhibit poor performance for highly corrupted images, particularly when noise density is above 30%.

The adaptive two-pass rank order filter has been proposed by Xu et al (2004), 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 to their original values. These pixels are kept unchanged during the second filtering. Therefore, the reconstructed image maintains a higher point of fidelity and has a smaller quantity of disturbance.
Wang & Wu (2009) proposed a new impulse detection method which uses the combination of rank-ordered absolute difference and standard median filter. It provides good results in images that have many edges, but it needs to set up some external values. It fails to perform well for high density noisy images because it cannot choose a non-noisy pixel due to its use of standard median filter for obtaining a reference image.

The above filtering algorithms preserves edge details and show good performance for low noise densities, however they show very poor performance and blur images for noise densities above 50%.

### 1.3.3.4 Filters using soft computing techniques

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 by Russo & Ramponi (1996), Ville et al (2003), Xu et al (2004a), Choi & Krishnapuram (1997), Yüksel & Baştürk (2003), Xu et al (2004b). These filters offer relatively better noise removal and detail preservation performance than the median and the mean based operators. However, the implementation complexities of these filters are generally higher and the required filtering window size is usually larger than the other methods. In the last few years, there has been a growing research interest in the applications of soft computing techniques, such as neural networks and fuzzy systems, to the problems in digital image processing.

A number of filters utilize the histogram information of the input image. In image restoration using parametric adaptive fuzzy filter proposed by Wang & Lin (1998) and an adaptive fuzzy filter for restoring highly corrupted image by histogram estimation presented by Wang & Chiu (1999), 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 by Ma & Wu (2003) for the restoration of color images.

Majhi & Fathi (2005) proposed a novel method based on neuro-detector using functional link artificial neural network. The neural detector is based on the concept of training and it detects the impulse noise efficiently, however the training method must be precisely done. An improved spatial filtering technique is adopted for restoration.

Mansoor Roomi et al (2010) presented a new Edge Preserving Impulse Noise Filter based on Particle Swarm Optimization. The filter weights were adapted and optimized directionally to restore a corrupted pixel in a mean square sense. The major drawback is the number of the population used which restricts the performance for higher noise densities.

Preservation of edges and fine details in a denoised image is a difficult task. There are many approaches in the literature such as those in (Abdou & Pratt 1979), (Srinivasan et al 1995), (Spinu et al 1997), (Aydin et al 1996), (Qiang & Haralick 2002), (Chen & Yang 1995), (Caponetti et al 1994), (Hebert & Malagre 1994) which are proposed for detecting the edge pixels. Some approaches are based on error minimization, neural networks, wavelet transforms and morphological principles.

### 1.3.4 Performance Metrics used in Literature

The quality of an image is evaluated both by quantitative standards as well as visual quality. The most common metrics that are used as quantitative measures in the literature are viz., Peak Signal to Noise Ratio (PSNR) (Bovik 2000), Mean Square Error(MSE), Structural Similarity...
Index (SSIM) and Image Enhancement Factor (IEF). For visual interpretation the image is observed by the human eye and based on observation, interpretation is made (Eskicioglu & Fisher 1995), (Eckert & Bradley 1998), (Wang & Bovik 2002), (Wang et al 2004), (Sheikh & Bovik 2006). To facilitate the evaluation, the attention is usually traced to the artifacts visibility and edge sharpness.

1.3.4.1 PSNR

PSNR is defined as the proportion between the peak signal power to noise power and is given by Equation (1.2). Higher PSNR indicates better de-noising performance.

$$\text{PSNR in dB} = 10 \log_{10} \left( \frac{255^2}{\text{MSE}} \right)$$  \hspace{1cm} (1.2)

where,
MSE denotes Mean Square Error

1.3.4.2 MSE

MSE is defined as the mean of the square of the difference between intensity values of pixels in the original image to the corresponding pixels in the denoised image and is given by Equation (1.3). Lower the MSE better the performance of the filter.

$$\text{MSE} = \frac{\sum_i \sum_j \left( Y(i,j) - \overline{Y}(i,j) \right)^2}{M \times N}$$  \hspace{1cm} (1.3)

where,
M and N are the total number of pixels in the horizontal and the vertical direction in the image respectively. i.e. size of the image.
$Y(i,j)$ and $\tilde{Y}(i,j)$ denotes the original and filtered image pixels, respectively.

1.3.4.3 SSIM

SSIM is defined as the measure of signal preservation quality of the denoised image to the original image (Wang et al 2004) and takes into account the following similarities:

- the luminance similarity, which involves a local measure of the mean of the noisy image and noise-free image.
- the contrast similarity, which involves a local measure of the variance of the noise and noise-free image.
- The structural similarity, which also involves a local measure of the standard deviation of the noise and noise-free image, as well as a local measure of their correlation.

The SSIM is estimated using the formula which is given by Equation (1.4)

$$
\text{SSIM}(x, y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{\mu_x^2 + \mu_y^2 + C_1} \frac{(\sigma_{xy}^2 + C_2)}{\sigma_x^2 + \sigma_y^2 + C_2}
$$

(1.4)

where,

$\mu_x$ and $\mu_y$ are the mean intensities of original and restored images.

$\sigma_x$ and $\sigma_y$ are the standard deviations of original and restored images.

The default values of the two constants $C1$ and $C2$ are $C1 = (0.01L)^2$ and $C2 = (0.03L)^2$.
1.3.4.4 IEF

IEF is defined as the ratio between the square of the noise power in a noisy image to the square of the residual noise present in the denoised image and is given by Equation (1.5).

\[
IEF = \frac{\left(\sum_{m,n}[P(m,n) - Y(m,n)]^2\right)}{\left(\sum_{m,n}[\bar{Y}(m,n) - Y(m,n)]^2\right)}
\]  

(1.5)

where,

\(Y, \bar{Y}\) and \(P\) is the original, restored and corrupted image respectively.

1.3.5 Standard Test Images

The standard test images viz., lena, pepper, baboon, boat and bridge which are commonly used for evaluating the performance of the de-noising algorithms in literature are shown in Figure 1.1. All test images taken for testing are 8 bit gray scale images of size 512 x 512, which are commonly used for image denoising.
Figure 1.1 Standard test images (a) lena, (b) pepper, (c) baboon, (d) boat, (e) bridge
1.4 AIM AND CONTRIBUTIONS IN THE THESIS

The profusion of approaches proposed in the literature revealed that there are numerous algorithms for denoising digital images corrupted by impulse noise. Nevertheless, most of them do not perform well, particularly at higher noise densities. So an effort is reached in the thesis to design efficient de-noising algorithms for digital images corrupted by high noise densities. Thus the focus of the research is to propose effective and efficient filters that restrain the impulse noises, preserve edges and fine details in digital images at higher noise densities.

The aims of the thesis are,

1. To develop an efficient filter for removing high density salt and pepper noise in digital images by designing a Morphological based Adaptive Unsymmetrically Trimmed Mid-Point Filter (MAUTMPF) in which, the corrupted pixels in the image are replaced by the mid value of the maximum and minimum pixel intensity value, after unsymmetrically trimming all the corrupted pixels in the selected window.

2. To develop an algorithm for removing salt and pepper noise in a more efficient way by using a Two Stage Mid-Point Filter (TSMPF), which is a modified version of MAUTMPF. The result of the trimmed mid-point algorithm is compared with the results of the already processed pixels in the selected window and the corrupted pixels are replaced by the optimum value by using thresholding techniques. The experimental evaluation of TSMPF in terms of PSNR and MSE demonstrates better performance when compared to MAUTMPF and other existing methods. However the performance of the proposed two stage filter results in a slight blur at higher noise densities.

3. To overcome the drawbacks of the two stage mid-point filter, a new and novel Neighborhood Eight Window Trimmed Mid-Point Filter
(NEWTMPF) is designed. The NEWTMPF is basically a modified version of mid-point filter in which few modifications are made in selecting the windows for processing. Here, if all the pixels in the selected window are corrupted, instead of increasing the window size as in MAUTMPF and TSMPF, neighborhood eight windows in eight different directions are taken for processing, thereby effective preservation of edges and fine details are achieved along with improved PSNR, MSE, SSIM and IEF values even at high noise densities.

4. To develop an Adaptive Threshold Intensity Range Filter (ATIRF), which effectively suppresses RVIN in digital images.

5. To develop a new and novel directional detection technique for suppressing RVIN with the direction of scan being the shape of alphabets X, Y and Z (XYZDF- XYZ Directional Filter).

1.5 ORGANISATION OF THE THESIS

The rest of the thesis is organized as follows.

Chapter 2 discusses the design of MAUTMPF. In the selected 3 x 3 window, if the centre pixel is corrupted, and so all other corrupted pixels are trimmed unsymmetrically and the centre pixel is substituted by the mid-point value of the remaining uncorrupted pixels, if the number of uncorrupted pixels is at least 2. On the other hand, if the remaining pixels in the selected window are less than 2, then the window size is increased by 2 and the same procedure is repeated. The iterations in the algorithm are continued till window size reaches 7x7. If an estimate for noisy pixel can’t be reached in a 7x7 window also, then the centre pixel is replaced by the midpoint of minimum and maximum intensity values of already processed pixels in the initial selected 3x3 window. The performance of MAUTMPF algorithm is
evaluated quantitatively in terms of PSNR and MSE against varying noise densities with different standard test images.

Third chapter sets out the design of Two Stage Mid-Point Filter. The proposed approach consists of an impulse detector and a two stage mid-point filter. The impulse detector checks the value of the center pixel in the selected window. If the center pixel is 0 or 255, then it is identified as corrupted and the window passes through the two stage mid-point filter. Finally, the comparator unit in the filter replaces the centre pixel. The qualitative interpretation of the proposed approach is measured by visual examination and the quantitative interpretation in terms of PSNR and MSE. From the experimental results it is found that TSMPF perform better than MAUTMPF and other existing algorithms. However the TSMPF yields blurred image at very high noise densities.

Chapter 4 discusses about a new and novel NEWTMPF, which is an extension of the MAUTMPF. Instead of increasing the window size adaptively, neighborhood eight 3 x 3 windows are taken for processing, if all the pixels in the selected window are corrupted. The same mid-point filter approach is employed for obtaining high performance results to suppress the noise in a variety of corrupted images and to preserve the edges and fine details effectively. The performance of the proposed filter is measured quantitatively in terms of PSNR, MSE, SSIM and IEF and qualitatively by visual interpretation. The performance of the algorithm is tested against varying noise densities and also against different images.

The fifth chapter presents the design of a two stage Adaptive Threshold Intensity Range Filter to remove RVIN. In the first stage, a novel detection technique is employed, which detects noisy pixel based on the number of pixels which lie within a selected range of the center pixel in the selected window. In the second stage, filtering is performed by replacing the
center pixel with the mid-point out of maximum and minimum intensity values of uncorrupted pixels in the selected window. The visual quality and the objective evaluation of ATIRF are evaluated and compared with some of the existing algorithms.

The sixth chapter discusses the design of a novel directional detection technique for removal of random value impulse noise in digital images. The different directions of scanning adopted resemble the shape of alphabets X, Y and Z in the selected window and hence it is named as XYZ Directional Filter (XYZDF). The identified noisy pixels are filtered using mid-point filter. The performance of the proposed algorithm is evaluated both by visual quality and quantitative measurement in terms of PSNR, MSE, SSIM and IEF.

Seventh chapter gives a brief conclusion about the research by summarizing the performance of various filters in terms of quantitative and qualitative measures. Few suggestions are also given for future scope.