IMPROVEMENT OF QUANTIZED ADAPTIVE SWITCHING MEDIAN FILTER FOR IMPULSE NOISE REDUCTION IN GRAYSCALE DIGITAL IMAGE

By

AHMED KHALDOON ABDALAMEER

A Dissertation Submitted in Partial Fulfillment of the Requirement for the Degree of the Master of Science

June 2017

ACKNOWLEDGMENT

Many thanks to ALLAH who give me the power and the hope to succeed.

I would like to dedicate this work to our beloved Messenger Mohammad S.A.W.

There are no enough words to express my deepest gratitude and special thanks to my supervisor AP Dr. Haidi Ibrahim for his supervision, technical support, offering constant support and fruitful cooperation to fulfil this work in its final form. He has been everything that one could want in an advisor. Without his guidance, this thesis would be impossible.

I would like to appreciate the contribution of the examiners, Dr. Aeizal Azman Abdul Wahab and Dr. Nor Rizuan Mat Noor, for their insights into my research and their valuable corrections to this dissertation. Thanks also to Prof. Ir. Dr. Mohd Fadzil Ain for chairing the viva session.

I would like to thank my parents for their constant encouragement throughout my study, both undergraduate and graduate, and for fostering my aspirations to the highest levels of education and I thank them for their unconditional love and support.

I extend my gratitude to the great Malaysian people who gave their goodness and kindly helped me during my study in Malaysia.

TABLE OF CONTENT

LIST OF TABLE

LIST OF FIGURE

LIST OF ABBREVIATIONS

CWMF	Centre Weighted Median Filter
FBMF	Fuzzy Based Median Filter
FSM	Fuzzy Switch Median filter
IPSMF	Improved Progressive Switch Median Filter
QSAM	Quantized Switch Adaptive Median filter
SMF	Standard Median Filter
WMF	Weighted Median Filter

LIST OF SYMBOLS

C	the intensity value of the damaged image
D	the intensity value of the damaged image
F	the intensity value of the filtered image
h	the height of the sliding window or filter
N	the value of the noise
P	the noise density
P_1	the density of pepper noise
P_2	the density of salt noise
w	the width of the sliding window or filter

PENAMBAHBAIKAN PENURAS MEDIAN PENYESUAIAN PENSUISAN BERKUANTUM BAGI PENGURANGAN HINGAR DEDENYUT DALAM IMEJ BERDIGIT SKALA KELABU

ABSTRAK

Dalam disertasi ini, penambahbaikan kepada penuras Median Penyesuaian Pensuisan Berkuantum (QSAM) telah dilaksanakan, untuk membuat ia lebih berkesan dalam mengurangkan hingar dedenyut bernilai-tetap pada ketumpatan tinggi daripada imej berdigit skala kelabu. QSAM menggunakan pendekatan pensuisan, iaitu ia mempunyai blok pengesanan hingar dan pemansuhan hingar. Pendekatan ini meminimumkan perubahan yang tidak diingini daripada proses penapisan. QSAM juga menggunakan pendekatan penyesuaian, dengan saiz penapis dapat disesuaikan dengan kandungan hingar setempat. QSAM mempunyai dua peringkat utama. Pada peringkat pertama, imej ditapis menggunakan tetingkap penapisan dengan saiz yang dikuantumkan. Pada peringkat kedua, imej ditapis menggunakan saiz tetingkap penyesuaian. Penambahbaikan QSAM telah dilakukan dengan menggantikan formula yang digunakan untuk memulihkan piksel rosak. Berbanding menggunakan nilai median setempat, kaedah yang dicadangkan ini menggunakan nilai purata min setempat dan median setempat. Keputusan ujikaji menggunakan tiga imej berskala kelabu piawai dengan saiz 512×512 piksel menunjukkan bahawa kaedah yang dicadangkan mempunyai keupayaan untuk memulihkan imej yang rosak walaupun sehingga 95% kerosakan. Berbanding tiga belas penuras median yang lain, kaedah yang dicadangkan mempunyai Ralat Min Kuasa Dua (MSE) terendah dan menghasilkan keluaran dengan penampilan visual yang paling bagus.

IMPROVEMENT OF QUANTIZED ADAPTIVE SWITCHING MEDIAN FILTER FOR IMPULSE NOISE REDUCTION IN GRAYSCALE DIGITAL IMAGE

ABSTRACT

In this dissertation, an improvement to Quantized Adaptive Switching Median filter (QSAM) has been done, to make it more efficient in reducing high density fixed-valued impulse noise from grayscale digital images. QSAM uses the switching approach, where it has noise detection and noise cancellation blocks. This approach minimizes unwanted changes from the filtering process. QSAM also uses adaptive approach, where the filter size is adaptable to the local noise content. QSAM has two main stages. In the first stage, the image is filtered using the filtering window with quantized size. In the second stage, the image is filtered using adaptive window size. Improvement to QSAM has been carried out by replacing the formula used to restore the corrupted pixel. Instead of using the local median value, this proposed method uses the average of the local mean and local median values. Experimental results using three standard grayscale images of size 512×512 pixels show that the proposed method has the ability to restore the corrupted images even up to 95% of corruption. As compared to other thirteen median filters, the proposed method had the lowest Mean Square Error (MSE) and produce outputs with the best visual appearance.

CHAPTER 1

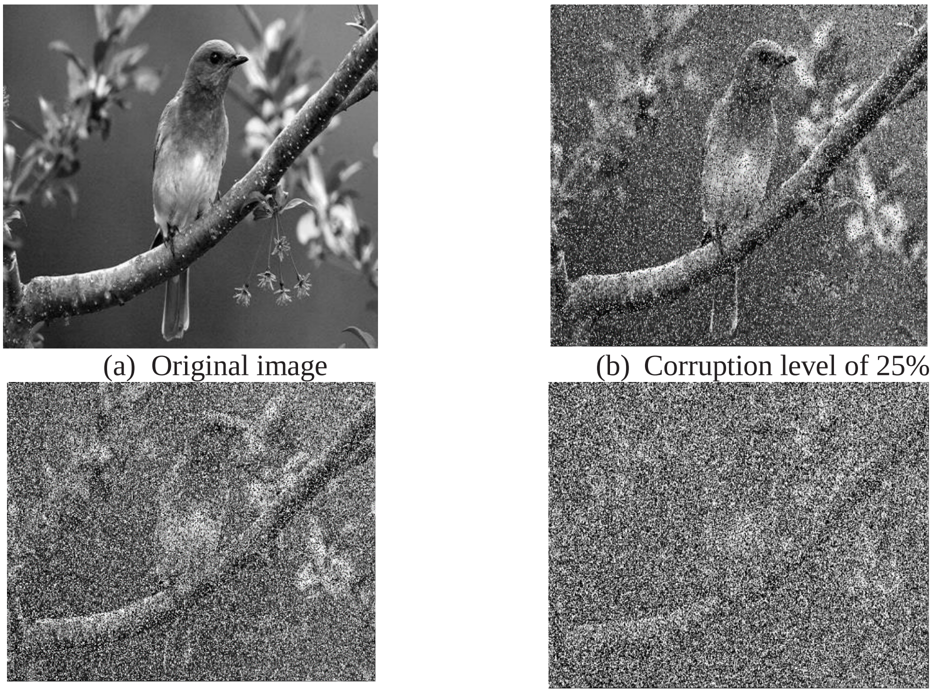
INTRODUCTION

1.1 Background

With the rise of technology and the wide use of the internet, one way to communicate is through sending digital images. Unfortunately, during the transmission, digital images could be corrupted by various types of noise. One of the common noise types that is normally corrupting digital images is impulse noise. Impulse noise appears as sprinkles, which normally presented by two intensity levels, in images. Therefore, impulse noise can be presented by two noise components. The first noise component is the salt noise, which is presented by high intensity level. It appears as bright colored dots on the image. The second component is the pepper noise, which has lower intensity level. It appears as dark colored dots on the image (Kunsoth & Biswas, 2016; Pang et al., 2016).

Several causes may contribute to the appearance of impulse noise on digital images. Impulse noise may occur during image transmission through noisy channels, especially in air transmission channels. In these transmission channels, some of the data may be replaced by noise. These channels are used in some common applications such as broadcasting, videophone, traffic observation, and autonomous navigation (Mélange et.al, 2011). In addition to this, impulse noise may be corrupted by bit errors in transmission, malfunctioning pixels, faulty memory locations and buffer overflow (Pham, 2015; Yuksel, 2006). Moreover, lighting, induction from industrial machines, weak insulation of high-voltage power lines, and various unprotected electric switches are other causes for impulse noise (Teoh & Ibrahim, 2012).

Figure 1.1 shows an example of image corrupted with different levels of impulse noise. As shown in this figure, the impulse noise makes the image appears grainy. Impulse noise can significantly reduce the quality and appearance of the image, even when the image is suffering from low density of impulse noise. At higher noise level, the structures on the images cannot be observed clearly.



(a) Original image
(b) Corruption level of 25%
(c) Corruption level of 50%
(d) Corruption level of 75%

Figure 1.1: Example of images corrupted by impulse noise.

Impulse noise on digital images may significantly affect the performance of image segmentation, edge detection, and feature extraction. Therefore, it is necessary to recover the digital images to get better results (Luo, 2006; Chen & Wu, 2001). The standard median filter is one of the popular ways to reduce the impulse noise level (Petrou & Bosdogianni., 1999). Yet, this technique still has several limitations. The standard median filter filters all the pixels in an image, even the pixels are uncorrupted. Therefore, unnecessary intensity modifications were carried out. As a consequence, the standard median filter may change the structure inside the image.

1.2 Problem Statements

Due to the drawbacks of the standard median filter, many modifications or improvements of the standard median filter have been proposed by researchers. Among these techniques is the Simple Adaptive Median Filter that has been introduced by Ibrahim et al. (2008). This technique is simple to be implemented, and effective to filter noise, even at high level of corruption. However, due to find the best filter size for each pixel, long processing time is needed to completely filter an image. Thus, modification to this filter, which is known as the Quantized Adaptive Switching Median (QSAM) filter, has been introduced by Ibrahim (2012). Although the performance of QSAM is better than the Simple Adaptive Median Filter in terms of accuracy and processing time, at high noise level, especially at 90% and 95% or corruptions, the accuracy is still relatively low. Therefore, there is still an opportunity to improve the accuracy of QSAM for high level of impulse noise corruption.

1.3 Objectives of the Research

The objectives of this project are:

1. To improve the QSAM filter in terms of noise cancellation ability.
2. To evaluate the performance of the proposed method by comparing it with other methods.

1.4 Scope of the Research

The research only limited to the impulse noise reduction technique. Other types of noise, such as Gaussian noise and Poisson noise, will not be covered by this research. The type of impulse noise considered in this research is the fixed-valued impulse noise.

This research is restricted to spatial-domain methods. This research will not cover methods in other domains, such as Fourier transform domain or Wavelet domain. Furthermore, only median filter based methods are considered for this project.

This research is also will concentrate on the restoration of grayscale images, which can be considered as a 2D signal data. Higher dimensional data, such as color images, or video, is not of the research interest. Finally, the input of digital images is limited to the standard test digital images.

1.5 Organization of Thesis

This thesis is organized into five chapters, which will be explained as follow. Chapter one introduces the background of this research. Next, Chapter 2 will present the literature review. This chapter will cover the definition of the impulse noise type that is used and the types of median filters that have been proposed by other researchers to remove the impulse noise from digital images. Then, Chapter 3 will describe the proposed method. In Chapter 4, the performance of the proposed method is compared with other median filters. The evaluation will be carried out by using one quality measure. Finally, Chapter 5 will present the conclusion of this research, together with some recommendations for the future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This thesis is focused on removing fixed-valued impulse noise from the digital images. Therefore, the definition of this noise type is important. Section 2.2 will present explanation about the type of impulse noise that will be used in this thesis. Next, because the research will concentrate on median filter based methods, Section 2.3 will review some of the median filter methods that are available in the literature. Section 2.4 will be summarized this chapter.

2.2 The Definition of Impulse Noise

Nowadays, digital images have been used in many applications that are related to our daily life. Unfortunately, these images could be corrupted by many types of noise. One of these common noises that could affect the digital images is known as impulse noise (i.e., salt-and-pepper noise) (Sakthidasan and Nagappan, 2016).

Impulse noise has many modules that had been studied by researchers. In this thesis, the focus is on fixed-valued impulse noise. The fixed-valued impulse noise (i.e. salt-and-pepper) have two intensity values, which are 0 or L-1, where L is the number of intensity levels. For example, if the image is an 8-bit-depth image, then L is 2^8, which is equal to 256. Thus, L-1 is the highest intensity level of an image.

Equation (2.1) presents fixed-valued impulse noise:

$$D = \begin{cases} C & : \text{ with probability } 1-P \\ N & : \text{ with probability } P \end{cases} \tag{2.1}$$

Where P is the probability of the noise, which is proportional to the noise density, D is the damaged image, N is the noise image and C is the noise-free image. The noisy pixels with intensity 0 will appear as black dots on the image. On the other hand, the noisy pixels with intensity L-1 will appear as white dots on the image. This noise module is also known as salt-and-pepper, data-drop-out noise, and spike noise. This module is widely used because of its simplicity and practicality (Ibrahim et al., 2012).

2.3 Median Filter

The median filter is one of the popular solutions for removing impulse noise, it is also known as a rank-order filter or order-statistic filter. The median filter is a non-linear filter and it works in the spatial domain. The median filter uses a sliding window approach, where only the value of the pixel that corresponds to the center of the window will be changed in each sliding iteration. This section will be divided into five subsections. Subsection 2.3.1 will present the standard median filter, which is the fundamental of the filter used in this research. Then, Subsection 2.3.2 will present a group of filters, known as a weighted median filter. Subsection 2.3.3 will describe adaptive median filter. Subsection 2.3.4 will review switching median filter, and Subsection 2.3.5 will presents median filters that incorporating fuzzy logics.

2.3.1 Standard Median Filter (SMF)

The standard median filter (SMF) was introduced by Tukey in (1971). SMF can be defined by the following equation:

$$F(i,j) = \text{median}_{(k,l)\in w_{h,w}} \{D(i+k, j+1)\} \quad (2.3)$$

Where $w_{h,w}$ is a sliding window of size $h \times w$, centered at coordinates (i, j). However, SMF with large window size can significantly reduce the quality of digital images. In addition to that, a large filter window will require more time for processing the corrupted image. This is because an SMF uses the sorting algorithm which arranges the pixels either in ascending or descending order. Therefore, the use of local histogram has been used to speed up the calculation of the median value. Fast approach to calculate local-median was proposed by Huang et al. (1979). In this scheme, by considering an overlapping area between two successive iterations, only two columns of samples (i.e., $2h$ samples) will be updated in each sliding-iteration instead of updating $h \times w$ samples.

2.3.2 Weighted Median Filter (WMF)

Median filter had many branches, one of these branches known as Weighted Median Filter (WMF) was introduced by Justusson in (1981), and further elaborated by Browning (1984). Both WMF and SMF are used to remove impulse noise from digital images, but the filter structure is different. The difference is in WMF structure, each of its elements is associated with weights that correspond to the number of sample duplication for median value calculation. In addition to that, these weights had been set in a way that it will decrease when its position is farther from the central pixel of the sliding window. By doing so, the central pixel will be more emphasized and this will improve the filter's ability for noise suppression while maintaining the quality and details of the image. Therefore, weight coefficients (and also the property of the input image) play a very important rule in the successfulness of WMF in preserving image information. Unfortunately, when the weight coefficients are set too large, WMF will require longer computation. Besides, it is also a difficult task to find the suitable weights for this filter.

Some researchers proposed adaptive weighted median filter which is an extension to WMF (Furutsu and Ishida, 1961; Chen and Wu, 2001). The idea of AWMF is that by using a fixed filter size, the weights or coefficients of the filter will be adaptively changed, according to the local noise content. Therefore, the local statistic could be used for the calculation of these weights.

Another type for WMF is called Centre Weighted Median Filter (CWMF) (Lee et al., 1997). CWMF can be defined by the following equation:

$$W_{h,w}(K,L) = \begin{cases} n_w: & (K,L) = (0,0) \\ 1: & \text{otherwise} \end{cases} \tag{2.4}$$

Where is a valid number, with a value equal or greater to one, and (*K*, *L*) =center) presents the centre of the filter. However, depending on n_w value, CWMF could act like other filters. If n_w is equal to 1, then CWMF will become like SMF. Also, when n_w is equal to the area covered by the filter, CWMF will act like an identity filter. In this condition, CWMR will not process the image and the output image will be the same as the input image. Finally, when the n_w value is large, CWMF perform better in preserving image details than noise cancellation.

2.3.3 Adaptive Median Filter

When the digital images corrupted by impulse noise, the distribution of noise intensity is different from one area to another inside the image. Therefore, the region with low intensity noise level will be filtered by the small sliding window, while the region with a high intensity level of noise will require large filter size. In other word, the filter needs to adapt its size according to the local noise content while doing the filtering. This type of filter is known as Adaptive Median Filter. However, generally, the filter will initialize its size to 3×3 pixels first. Then, the size will expand through processing, and will stop the expansion according to some criteria. These criteria could include the local maximum, the local minimum, and potential number of noise-free pixels, local mean, or local median value. Moreover, depending on the input image, some of these criteria may be impossible to be met. Therefore, some methods restrict the expansion of filter to certain size only. In spite of its better ability to reconstruct the corrupted image as compared to other methods, the adaptive median filter may require long computational time when most of the pixels require large sliding window (Ng and Ma, 2006; Hsieh et al., 2009). Two adaptive median filter techniques are reviewed. Simple Adaptive Median Filter (SAMF) is presented in Subsection 2.3.3.1, and Quantized Switching Adaptive Median Filter (QSAM) is presented in Subsection 2.3.3.2.

2.3.3.1 Simple Adaptive Median Filter (SAMF)

Ibrahim et.al, (2008) has proposed an efficient method for removing impulse noise (i.e. salt and pepper) from digital images. The method is known as Simple Adaptive Median Filter (SAMF), which is a hybrid of two filter types. The first filter type is an Adaptive Median Filter that had been used to provide flexibility in the method to change the filter's size based on the local noise density. The second filter type is known as Switching Median Filter. This type of filter has an ability to process only the noisy pixels and keep the noise-free pixels unchanged. This filter framework has been chosen to reduce the processing time, and to avoid from changing unnecessary pixels.

This filter type divides its process into two main stages. The first stage is known as noise detection, and the second stage is called noise cancellation.

The noise detection stage is able to detect the noise efficiently even for the high density of noise. All pixels with the lowest or highest intensity values are considered as the noise candidates. After the process of identifying the noisy pixels, the process will move to the second stage. At this stage, based on the number of noise-free pixels inside the filter, the filter will gradually adapt its size, until there are at least eight noise-free pixels within the filtering window (by using a framework for adaptive median filter). In this second stage, the switching framework for median filter has been used to process only the noisy pixel, while the noise-free pixels will be copied directly to the output image. The following points will summarize this noise-cancellation algorithm:

1) Initialize the filter size as $W = 2R_{\min} + 1$, where $R_{\min}$ is a small integer value.
2) Compute the number of noise-free pixels inside the filtering window that had been defined by $W \times W$ filter.
3) If the number of noise-free pixels is less than eight, then increase the filter size W by two. Then return to step 2.
4) Calculate the median value based on the number of noise-free pixels contained in $W \times W$ window.
5) Update the value of the corresponding pixel in the output image.

There are many advantages for this method like. The method is simple, and adaptive towards the noise content. In addition to that, this method is able to remove high density impulse noise. It also does not use any parameters to be tuned, also no need for previse turning.

2.3.3.2 Quantize Switching Adaptive Median Filter (QSAM)

Ibrahim (2012) has introduced a method known as Quantized Switching Adaptive Median Filter (QSAM). This algorithm is derived from SAMF (Ibrahim et.al, 2008). The main goal of this method is to reduce the processing time for SAMF. Furthermore, this could be done through several ways. First, by using the local intensity histogram and sorting algorithm for increasing the calculation speed of median values. Then, by manipulating with the sorting algorithm, the new local intensity histogram will be created. By using the sliding route, the processing time can be reduced successfully. However, to implement these new criteria, the size of filtering window needs to be fixed. Therefore, QSAM filter had been proposed for this purpose. There are two main stages in QSAM which are filtered using quantized windows, and filtering using modified SAMF.

In this stage, the input image can be represented by f will be classified into noise-free pixels or noisy pixels by using the following equation

$$\alpha(x,y) = \begin{cases} 1: & f(x,y) = 0 \text{ or } f(x,y) = L\text{-}1 \\ 0: & \text{otherwise} \end{cases} \tag{2.5}$$

Where $\alpha(x,y)$ represent the noise mask. Then, a new parameter has been created from mask α. It is defined by the following equation:

$$\beta(x,y) = \sum_{j=x-1}^{x+1} \sum_{k=y-1}^{y+1} \alpha(j,k) \tag{2.6}$$

Where the new parameter β represent the number of noisy pixels within the sliding window of size 3×3 pixels. Let's, put the output of this stage equal to f_1 then the following equation can describe the output for stage 1

$$f_1(x,y) = \begin{cases} f(x,y): & \alpha(x,y) = 0 \text{ or } \beta(x,y) = 9 \\ m(x,y): & \text{otherwise} \end{cases} \tag{2.7}$$

Where $m(x,y)$ is the median value calculated from noise-free pixels. From this equation f_1 will maintain the noise-free pixels of the input image without any changes. It also will not process the noisy pixel if all the neighboring pixels are also noisy pixels (i.e., $\beta(x,y)$=9). Moreover, if the current pixel is noisy and there is at least one noise-free pixel in the window of size $W \times W$ pixels is used to calculate the median value. The following equation is used to find the suitable value of W:

$$W \times W = \begin{cases} 3 \times 3: & \beta(x,y) = 1 \\ 7 \times 7: & \beta(x,y) = 8 \\ 5 \times 5: & otherwise \end{cases} \tag{2.8}$$

As there are only three sizes of the filter are utilized in QSAM, it is possible to speed up the local-median calculation by using the method proposed by Huang et al. (1979).

In this stage, the result of the previous stage (i.e. *f1*) is assigned as the input to the SAMF filter. Therefore, the equation 3.1.1 has been changed as in equation (2.9):

$$\alpha(x,y) = \begin{cases} 1: & \beta(x,y) = 9 \\ 0: & otherwise \end{cases} \tag{2.9}$$

After all pixels are processed, QSAM moved to its second stage. The aim of this stage is to complete the filtering process for the remaining noisy pixels from Stage 1 (i.e. pixels with β=9). As the noise cancellation is already carried out in Stage 1, the result of this stage can be considered has much lower noisy pixels if compared with the noisy image. Therefore, it is faster for QSAM to find its filter size.

2.3.4 Switching Median Filter

One of the popular median filtering approaches that had been used these days is Switching Median Filter, or also known as decision based median filter. This filter tries to reduce the unwanted alteration of uncorrupted pixels by the filter. Commonly, Switching Median Filter has two main stages. The first stage is the noise detection stage. The filters will go through each pixel to check if it is corrupted by noise or not. The second stage is the noise cancellation stage where the filter will process only the noisy pixels and send the noise-free pixels without any change in the output image.

The performance of the noise detection stage is depending on noise module used (e.g. salt-and-pepper noise). For a simple module, the noise can be detected by thresholding the intensity values of the damaged image. For more complicated noise modules, other methods check the current pixel and compare its value with surrounding pixels. Some researchers also use a spatial filter to do the noise detection. Next, the noisy pixels will be processed by the median filter, while the calculation of median filter will be done by taking only noise-free pixel as samples.

2.3.4.1 Improved Progressive Switching Median Filter (IPSMF)

One of the current works on Switching Median Filter was proposed by Boo et al., (2009). This method is known as the Improved Progressive Switching Median Filter (IPSMF). In IPSMF, both noise detection and filtering procedures are progressively repeated for a number of iterations. This method proposed to set the minimum number of noise-free pixels that need to be used in finding the median and mean value, and substitute the noisy pixel with 0.5 of median value and 0.5 of mean values. Experimental results show that the proposed algorithm performs a better noise filtering ability as the images are highly corrupted.

2.3.4.2 Iterative Non-Local Mean Filter (INLM)

Other current work on switching weighted mean filter was proposed by Wang et al., (2016). They proposed Iterative Non-Local Mean filter (INLM) for removal of impulse noise (i.e., salt and pepper). Moreover, the concept of the non-local mean (NLM) is based on the fact that any natural image contains many of similar patches with a repeated pattern, and these patches share the same value distribution for central pixel. Thus, the NLM will replace these values with weighted mean. The INLM consist of three stages as shown in Figure 2.1:

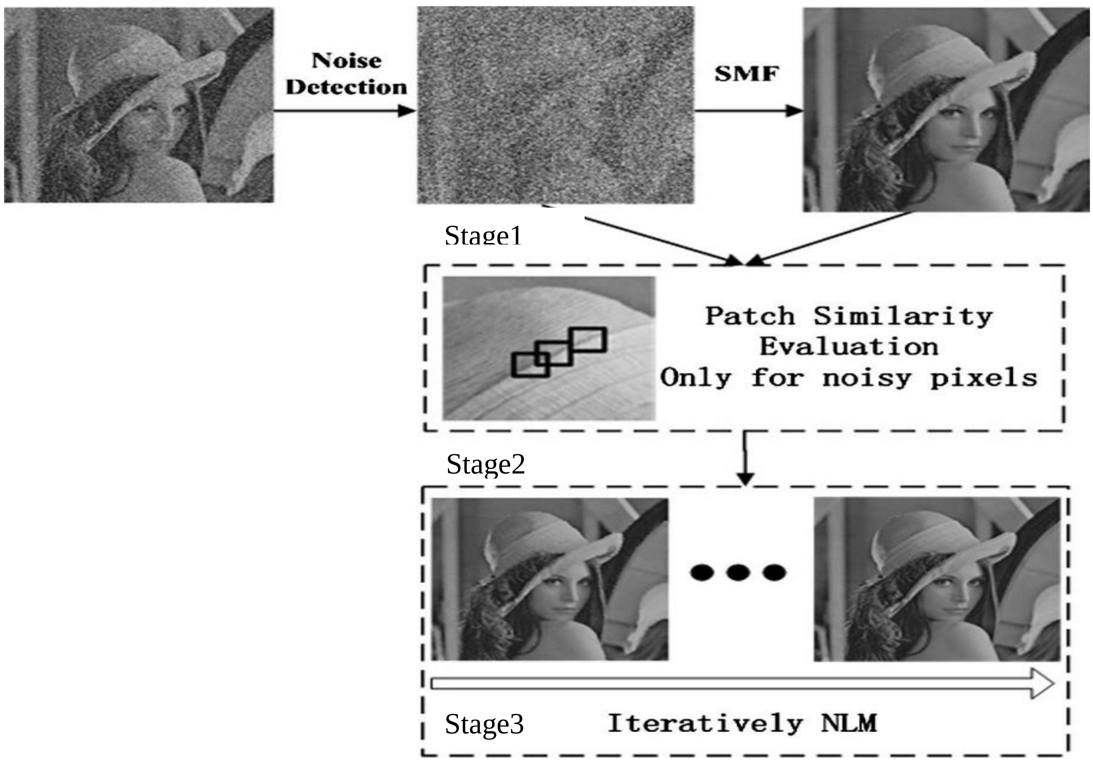


Figure 2.1: The flowchart of the INLM (Wang et al., 2006)

From Figure 2.1, in stage 1, the noise detection was performed to create a noise map which known as an N - map. Then, a combination of switching based median filter with location information on the N - map is used to obtain a pre-processed result. In stage 2, matching procedure for N-map is performed only for each noisy central window pixel. Finally, in stage 3, iterative framework is used to get an optimal value. This method provides a better result when comparing it with state-of-art methods.

2.3.5 Median Filter Incorporating Fuzzy Logic

Median filter has been widely used to remove the noise from digital images. In order for median filter to perform and give the desired result, it needs to use better noise detection techniques. Sometimes, it is difficult to detect the noisy pixels even when its fixed-value impulse noise (i.e. salt-and-pepper noise). This is because some uncorrupted pixels may take the same intensity values as occupied by noisy pixels (i.e. 0 or L-1). Therefore, some researchers have used the fuzzy logic approach in median filter processing.

However, there are many ways on how to use fuzzy logic in median filtering process. Some methods use the fuzzy logic as decision maker to select a proper filter from a filter bank, to the given input image. Also, it can be used as grade to measure how high the pixel effected by noise, and apply the proper correction. In addition to that, when the system starts to use the fuzzy logic, the corrupted image will go through fuzzification process. Next, based on fuzziness value that had been obtained, the system will start to execute the noise filtering process. Then, the de-fuzzification process will present the result. Furthermore, there are several difficulties when using fuzzy logic. These systems will become more computational expansive because of many fuzzy rules had been used. Also, the results from fuzzy logic depending on membership function and the parameters that control the shape of membership functions. Therefore, some of fuzzy logic methods cannot be used in real-time processing.

One of the recent works is done by Sravani & Rao (2014). They presented the removal of the high density of impulse noise level from digital images by using fuzzy based median filters (FBMF) algorithm. The idea of FBMF is to remove impulse noise by replacing its value with median value. FBMF calculates the median value in three different cases. The first case is when the current pixel is 0 or 255, and the other pixels in the chosen window area with different values. The second case is when all the pixels inside the filtering window are 0's or 255's. The third case is a combination of both. Then, the noisy pixels will be replaced by the fuzzy membership function value of the selected window. The following subsections will describe how FBMF algorithm work.

2.3.5.1. Fuzzy Set and Fuzzy Rules

The fuzzy membership function in the proposed algorithm is defined according to the number of zeros and 255's in the chosen window. However, the fuzzy set *S* in the universe *R* can be defined as an *R*= [0,1] mapping. The membership function ηf that will assign every element *r* in *R* a degree of membership $\eta f\,(R) \in [0,1]$ in the fuzzy set *f*. In addition to that, the function for the processing pixels can be defined as:

$$f(R) = \{ f_0, f_{255} \} \tag{2.10}$$

Where f_0 and f_{255} represent the number of zeros and 255's in the selected window. Then, by assuming $\eta f\,(R) \in [0,1]$ is the membership function of $f\,(R)$, the fuzzy rules have been defined in the following rules:

1) Rule 1: If f_0 is large negative or f_{255} is the smallest positive, then $\eta f\,(R)$ is very low.
2) Rule2: If f_0 is negative, then $\eta f\,(R)$ is low.
3) Rule3: If f_{255} is large positive or f_0 is small negative, then $\eta f\,(R)$ is very high.
4) Rule4: if f_{255} is positive, then $\eta f\,(R)$ is high.

For the membership function $\eta f\,(R)$:

1. If $f_0 \geq t_1$ membership function is replaced by the standard deviation of R.
2. If $t_2 < f_0 < t_1$ membership function is replaced by $\mathrm{std}(R)\times\left(\dfrac{f_0}{f_{255}}\right)$.
3. If $f_{255} \geq t_1$ membership function is replaced by mean of elements in R.
4. If $t_2 < f_{255} < t_1$ membership function will be replaced by $\mathrm{mean}(R)\times\left(\dfrac{f_{255}}{f_0}\right)$.

Here, R is selected from the neighboring pixel elements, "std" is standard deviation, and mean is the average value of the selected window elements. Also, the t_1 and t_2 are predefined threshold values.

2.3.5.2 FBMF Algorithm

There are several steps to describe this algorithm which are:

1) By assuming that $C_{x,y}$ is the current pixel, then select a two-dimensional window of size 3×3.
2) If $C_{x,y}$ has a value in between 0 and 255, it is considered as noise free pixel, and no need to be processed. Otherwise, go to step (3).
3) If $C_{x,y}$=0 or $C_{x,y}$=255 then $C_{x,y}$ is a noisy pixel. Then two cases have to be considered.

Case1: If $C_{x,y}$ is 0 or 255 and the pixels around it are not 0's or 255's, then eliminates 255's and 0's. Calculate the median value of neighboring pixels and replace it with median value.

Case2: If all pixels in the filtering window are 0's and 255's, then there will be four possibilities: very high, very low, high, and low. Based on salt-and-pepper intensity one of the possibilities will be selected.

4) Repeat the process from (1) to (3) until all pixels in the image will be processed.

The following three cases will define the threshold values for t_2 and t_1 which are:

Case1: If the filtering window 3×3 is used, then the number of elements inside the window will be 9. However, t_2 will be 4 if the 0's occurs more than 255's. The same logic will be used when the number of 255's is greater than zeros.

Case2: The value of t_2 is 6 if in the selected window the occurrence of 255 and 0 has occurred 6 times.

Case3: If all the pixels inside the filtering window are either 0's or 255's, then the processing pixel is replaced with the value 128, which is the arithmetic mean of the two extremes gray levels.

This method uses two kinds of approaches to compare the results of this method with other different types of median filters. They are the Peak Signal to Noise Ratio (PSNR) and Image Enhancement factor (IEF).

Another work was done by Rai et al. (2015). The goal of this work is to distinguish between the local variations and image structure when the filter process the edge of the noisy image. In order to understand how to implement this method, Rai et al. Had divided their method into two main stages. In the first stage, a window of size 3×3 pixels had been used to process the noisy image. This window is used to determine the noisy pixel inside the filtering window. A simple derivative has been used with respect to the central pixel (x,y) for all the eight directions (E, W, N, S, NW, NE, SW, SE) as shown in Figure 2.2.

NW	N	NE
W	(x,y)	E
SW	S	SE

Figure 2.2: The filtering window for Rai et al., (2015)

Here, Figure 2.2 represents the filtering window for this method. After this, fuzzy filtering was used to calculate the fuzzy derivatives. Based on this, the central pixel is considered as not an edge element if any two values from the rules are small. In the second stage, the method will use other fuzzy rule for smoothing the image. For particular adaptive parameter value K, the fuzzy logic was repeated until the desired value of PSNR is reached. This method is performed well in removing high density of salt and pepper noise and Gaussian noise with less processing time, better output quality, and less hardware requirements when comparing it with Wiener filter.

Another proposed method had been tested on ultrasound images. Ultrasound is used for capturing images that contain internal body structures such as muscle and blood vessels. The most important reason for using ultrasound for capturing images of the internal body is because of its safety and cost effectiveness. However, the physicians may have difficulties when they try to diagnose the ultrasound images because of speckle noise, which reduce the image quality. Saadia and Rashdi (2016) proposed fuzzy weighted mean and fractional integration filter to remove the speckle noise and enhanced the image quality. To implement this method, Saadia and Rashdi divide this method into two main stages.

In the first stage, echo sounder images will be processed by using 3×3 pixel filter. Instated of replacing it with the mean value, weights had been assigned to current pixel and all pixels in the neighborhood. By calculating the intensity differences between the processed pixel and the pixels around, this will lead to better results. Moreover, fuzzy logic is being used to assign weights for each pixel inside the filter. Then the pixel will change with center weighted mean value. The second stage, the resulting image from stage one will be enhanced by using fraction order integration filter. This method ensures noise suppression and preserving edge and other important features of the image.

Some researchers use machine learning to differentiate between the noisy pixel and noise-free pixel as the work proposed by Roy et al., (2016). Support Vector Machine (SVM) classification based fuzzy filter (FF) was proposed for removing impulse noise and enhance the quality of grayscale images. In order to ensure better performance for SVM classification, a set of the optimal feature was used in the training phase, where the pixels of the grayscale images were classified into noisy class and noise-free class. This will make the system highly trained to detect the noisy pixels in the corrupted image. After training the system, another set of test images will be applied. In the testing phase, the system will test the pixels of the corrupted image one by one and classified it into noisy class and noise-free class.

The feature vector per pixel has to be of the same size as taken in the training phase. Fuzzy filtering will be performed based on the classification result from testing phase. This method performs well in removing low and high-density salt and pepper noise pixels from grayscale images. In addition to this, this method provides 98.5% true-recognition at the time of classifying noisy class and free-noise class when the density of impulse noise level is 90%. There are many advantages of using this method like preserving of more image details, less blurring and more homogeneity for the reconstructed images.

The new method based on fuzzy logic was presented by Xiao et al. (2016), and it is focused on x-ray images. This method proposed a new scheme of enhancement for x-ray images. However, this method was divided into two main stages known as noise reduction and homomorphic filtering. Moreover, the noise reduction stage was divided into two subsections; the detection method and filtering method. In addition to that, the detection method itself has two subunits known as region detection and degree detection. This method uses fuzzy rules for the detection of the noisy pixels, and the membership function of the fuzzy rules had been calculated in the region detection. On the other hand, for degree detection, the central pixel in the filtering window was surrounded by four neighboring pixels crosspoint to directions {North (N), East (E), south (S), and West (W)} as it shown in Figure 2.3.

	N	
W	(x,y)	E
	S	

Figure 2.3: The window with central pixel

These four directional values are known as central gradient values around the central pixel (x, y). However, the values for noisy pixels and edge pixels are both large. In order to distinguish between them, two related gradient values in the same direction are calculated as the fuzzy gradient in this direction. Moreover, this method used two sets of fuzzy rules; one for noisy pixels and another one for noise-free pixels. After completing the calculations, the noisy pixels will be passed to the filtering method. Otherwise, it will consider noise-free pixels and send directly to the output image. In addition to that, the modified weighted median filter has been used to process the noisy pixels. Then, the result from filtering process will be going through homomorphic filtering for improving the brightness and contrast of the image. This method provides more efficient detection for noisy pixels by using region detection and degree detection and then filtering the noisy pixels, especially for low-level noise of salt and pepper (i.e., for noise level 0.04).

A new adaptive fuzzy median filter is presented by Sultana et al. (2013) to provide optimum detail preservation along with very high-density noise removal. The novelty of this research work comes from two directions. Firstly, the level of corruption was determined by using a triangular fuzzy membership function for each pixel that consequently ensures the replacement of noisy pixels according to the extent of corruption. Secondly, the threshold value is fully adaptive and automatically adjustable to provide ease of computation. In this work Sultana et al. (2013) proposed a fully adaptive fuzzy based median filter that avoids the drawbacks of the standard median filter and its variants by controlling the trade-off between attenuation of high probability impulse noise and preservation of fine details and edges. The experimental results show that the proposed filter outperforms other conventional and advanced filters in terms of both diagnosing and fine detail preservation of highly corrupted images.

Another work was done by Mahallati et al. (2013) the method applies fuzzy logic for removing the impulse noise. The results from this method are compared to those of median filter and mean filter. A novel and efficient impulse noise reduction method has been presented by the use of the fuzzy logic approach to do filtering on the noisy pixel. This method required eight, not noisy neighborhood pixels. The value of the corrupted pixel is replaced by the average value of the noise-free neighboring pixels. By this method, any number of corrupted pixels can be improved. Consequently, eight improved neighborhood pixels are obtained. Then the average value of the eight improved neighborhood pixels substitutes the noisy pixel. If the fuzzy median value of the eight improved neighborhood pixels substitutes the noisy pixel, the obtained result in term of noise removal is much better for higher noise densities. Experimental results validate the robustness of the proposed method in term of impulse noise reduction, especially in high levels of noise

Also, Chowdhury et al. (2007) presents an enhancement technique based on fuzzy set theory to reduce image noise and to increase the contrast of structures of interest in the image. Compared to other techniques, a fuzzy method can manage the ambiguity and vagueness in many image processing applications efficiently. The method is able to represent and process human knowledge and applies fuzzy if-then rules. The algorithm includes the following steps:

1. At first, the gray values of the neighboring pixels ($n \times n$ window) are stored in an array and then sorted in ascending or descending order.

2. Then, the fuzzy membership value is assigned to each neighbor pixels:

This step has the following characteristics:

I. A π-shaped membership function is used.

II. The highest and lowest gray values get the membership value 0.

III. Membership value 1 is assigned to the mean value of the gray levels of the neighboring pixels.

3. Now, we consider only $2 \times k+1$ pixels ($k/2 \leq n^2$) in the sorted pixels, and they are the median gray value and k previous and forward gray values in the sorted list.

4. Now, the gray value that has the highest membership value will be selected and placed as output.

A new fuzzy switching median (FSM) filter employing fuzzy techniques in image processing done by Toh et al., (2008). The proposed filter is able to remove salt-and pepper noise in digital images while minting image details and textures very well. By incorporating fuzzy reasoning in correcting the detected noisy pixel, the low complexity FSM filter is able to outperform some well-known existing salt-and pepper noise fuzzy methods. The FSM filter is composed of two semi-dependent modules, namely the salt and pepper noise detection module and the fuzzy noise cancellation module. The fuzzy set used for noise cancellation does not require time-consuming tuning of parameters and thus no training scheme is required. This marked the simplicity of the proposed algorithm.