# Image Restoration Using Five level Modified weighed Fuzzy Mean Filter

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**Abstract**

A new fuzzy filter for the removal of heavy additive impulse noise, called the Modified Weighted Fuzzy Mean filter (MWFMF) is proposed and analyzed in this paper. The MWFM-filtered output signal is the mean value of the corrupted signals in a sample matrix, and these signals are weighted by a membership grade of an associated fuzzy set stored in a knowledge base. The knowledge base contains a number of fuzzy sets derived from the histogram of a reference image. The Proposed filter performances are then compared with the conventional filters performances. Criteria such as MSE and PSNR are adopted for evaluating the performances of the proposed and the conventional filters. The proposed approach restores the noisy images very effectively and the PSNR improvement achieved is 3 to 5 db more than the conventional approaches.

**Keywords** : Knowledge base, Histogram, Impulse noise, Fuzzy estimator, membership function.

## 1. Introduction

When images are transmitted over channels, they are often corrupted by impulse noise due to faulty communications or noisy channels [2]. Impulse noise consists of very large positive or negative spikes of short duration. They both are easily detected by the eyes and degrade the image quality. Hence, their removal is an important task in image processing. Although the generalized mean filters and nonlinear filters [1], [2],[11],[13] have been proposed for removing impulse noise from images, they suffer from the inability to remove positive and negative spikes simultaneously. Moreover conventional filters are not suitable for cases when noise probability is greater than 0.3 [9]. Since fuzzy set emerged, fuzzy reasoning as a non-linear methodology has been used in noise removal from image [15]. Fuzzy reasoning is very well suited to model the uncertainty that typically occurs when both noise cancellation and detail preservation represent very critical issues. Since 1992, the number of different approaches has been progressively increasing. [3], [4], [7], [8][12],[14].

In this paper, a novel filtering technique with better noise removal capability, compared to conventional nonlinear filter is proposed. Fuzzy set theory is being used to develop a new kind of filter; five levels modified Weighted Fuzzy Mean Filter (MWFMF), a powerful tool for removing additive impulse noise from images, especially when noise probability increases. The proposed five level MWFMF gives better performance compared with the three set Weighted Fuzzy Mean (WFM) filter proposed by Lee. [5].

This paper is organized as follows. In section 2, a knowledge base supported image noise removal process is proposed. In section 3, the definition and design methodology of the proposed five level MWFMF is

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presented. The properties of five levels MWFMF are also discussed in detail. In section 4, some experimental results which confirm the improved performance of the proposed five level MWFMF are presented. Finally section 5 concludes the paper.

## 2. Knowledge Base Supported Image Noise Removal Process

In general for the experimental purposes the noisy image is obtained by the addition of the desired type of noise to the noise free source image. The knowledge base is derived from the histogram of the source image. Based on the knowledge base the fuzzy sets are obtained. The noisy image is then converted into matrix and then it is being processed by the proposed five level weighted fuzzy mean filters.

Figure 1 shows the block diagram of the proposed noise removal process with a dynamic knowledge base for images transmitted over a communication channel. This process consists of a sender phase and a receiver phase, but the knowledge base must be transmitted from the sender side to the receiver side along with the image to be filtered. The sender phase establishes the knowledge base about the source image by referring to the histogram of the source image. The completed knowledge base consists of a few fuzzy sets specifying the gray-level features of the noise-free source image and is referred by five level MWFMF when removing impulse noises during the receiver phase. The receiver phase filters the received corrupted images by invoking five levels MWFMF and referring to the information stored in the knowledge base. This phase is the main noise removal step and is called the filtering phase.

It is natural that filtering noise by referring to the source image is better than that without such reference. But it is usually impossible to store complete source images in the receiver side. Moreover, knowledge base about the source image should not be transmitted with too much overhead. Therefore, a tradeoff that removes noise from images via simple dynamic source image knowledge is desired and reasonable. Fuzzy set theory is applied in this work to realize this.

The Proposed filter performances are then compared with the conventional filters performances. Criteria such as MSE and PSNR[10] are adopted for evaluating the performances of the proposed and the conventional filters

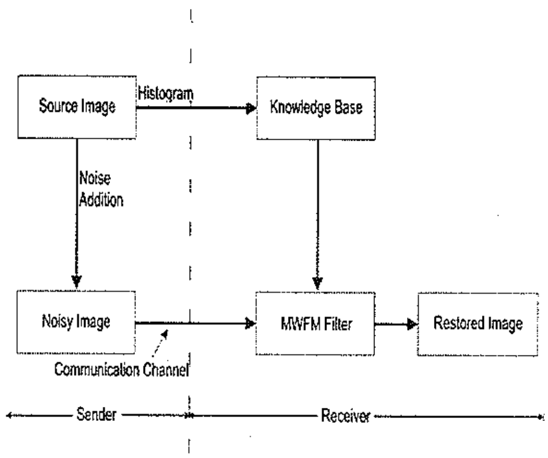


**Figure 1 :** Block Diagram Of The Proposed Filter

The generation of the knowledge base is as follows:

Consider a noise-free image S sized $N_1 x N_2$ pixels with L gray levels, where $N_1$, $N_2$ are the size of the sample window and L is the maximum gray level value. It is denoted as $S = [s(i, j)] N_1 \times N_2$ where s(i,j) is the original image. $s(i, j) \in \{0,1 \ldots, L-1\}$ is a pixel of the source image without any noise, for $0 \leq i \leq N_{1-1}$ and $0 \leq j \leq N_2 1$ where i and j are values which lies between 0 and their respective size of the sample window. Then, some fuzzy subsets defined on the universe of discourse, {0 . . . . . L-1} can be built. Each of the fuzzy subsets represents an abstract concept for the gray level of image pixels for five regions namely, very dark (VDK), dark (DK), medium (MD), bright (BR) and very bright (VBR) and its membership function specifies the membership grade which a pixel with a certain gray level belongs to.

The fuzzy sets describing the intensity features of a noise free image can be derived from the histogram of the source image, and they together constitute the proposed knowledge base. The histogram of a digital image with gray levels in the range [0, L-1] is a discrete function as given in equation (1).

$$p(s_k) = \frac{n_k}{n} \qquad (1)$$

where $s_k$ is the $k^{th}$ gray level of noise free image S, $n_k$ is the number of pixels with the $k^{th}$ gray level in S, where k = 0, 1,2 ..... L-1 and n is the total number of pixels in S. $p(s_k)$ gives the estimate of the probability of occurrence of gray level $s_k$.

Before the algorithm for generating fuzzy sets to be stored in the knowledge base is presented, their membership function type is defined first.

### 2.1 Membership Function For Fuzzy Sets

Earlier works proposed by Lee et. al. [5] used the L-R type fuzzy number to generate the fuzzy sets which are used in the knowledge base and weighed fuzzy mean (WFM) filter. The weighed fuzzy mean filter using the triangular membership function gave good performance compared with conventional filters. But there are many applications which require complete restoration of images or close to 100% elimination of noise. Keeping this in mind an attempt is made to improve the restoration performances of the fuzzy mean filter applied to images. Generally, most of the noise patterns follow the Gaussian distribution. So a Gaussian function is used to generate a fuzzy set instead of a Triangular membership function. The corresponding Gaussian membership function is generated using the following equations.

To realize Gaussian membership function, sigmoids and products of sigmoids are used. Left-edge fuzzy sets are generated by decreasing sigmoids as given in equation (2).

$$f(x) = \frac{1}{1 + e^{(x-c)/\alpha}} \qquad (2)$$

Right-edge fuzzy sets may be generated by increasing sigmoids using the equation (3).

$$f(x) = \frac{1}{1 + e^{(x-c)/\beta}} \qquad (3)$$

Where c is the center of the sigmoid $\alpha$ and ß value is selected based on the slope or width requirements.

Symmetrical middle fuzzy sets may be generated by product of two sigmoids given in equations (2) and (3). The resulting equation is given in equation (4).

$$f(x) = \left(\frac{1}{1 + e^{(c-5w-x)/\alpha}}\right)\left(\frac{1}{1 + e^{(x-c-5w)/\beta}}\right) \qquad (4)$$

f(x) is the function that generates the membership value of the fuzzy mean process which can be represented as a triplet [c, $\alpha$, ß]. The width of the distribution can be adjusted using the exponential factor (c-5w). This equation is being used to generate the membership function for five regions namely very dark, dark, medium, bright and very bright fuzzy sets.

An important advantage of using this type of membership is that it covers the entire gray level spectrum. Moreover to cover the entire gray level spectrum five Gaussian functions are used by employing suitable translation. The algorithms to construct Gaussian fuzzy set is explained below:

**2.2 Construction Algorithm Of The Proposed Fuzzy Sets Stored In Knowledge Base**

Step 1: Decide the intervals of [$VDK_{begin}$, $VDK_{end}$], [$DK_{begin}$, $DK_{end}$], [$MD_{begin}$, $M_{Dend}$], [$BR_{begin}$, $BR_{end}$] and [$VBR_{begin}$, $VBR_{end}$] for the five fuzzy sets VDK, DK, MD, BR and VBR respectively.

Step1.1: $$\text{Set } VDK_{end} = \left[\frac{L-1}{N_f}\right],$$

$$VBR_{begin} = (N_f-1)\times\left[\frac{L-1}{N_f}\right],$$

$$DK_{begin} = VDK_{end} \text{ -left\_overlap},$$

$$DK_{end} = (N_f-3)\times\left[\frac{L-1}{N_f}\right],$$

$$MD_{end} = (N_f-2)\times\left[\frac{L-1}{N_f}\right],$$

$$MD_{begin} = DK_{end} \text{ -left\_overlap},$$

$$BR_{end} = VBR_{begin} \text{+right\_overlap},$$

$$BR_{begin} = MD_{end} \text{ -left\_overlap},$$

where $N_f$ is the number of fuzzy sets, L is the maximum gray value, left overlap and right overlap denote the overlapping range of the fuzzy sets.

Step 1.2: Set $VDK_{begin}$ be the first $S_k$ such that $n_k > t$ from 0 to $VDK_{end}$, where t is a threshold.

Step 1.3: Set $VBR_{end}$ be last $S_k$ such that $n_k > t$ from $VBR_{begin}$, to L-1.

Step 2: Find a point $S_k$ with the maximum value of $P(S_k)$ in the interval of [$VDK_{begin}$, $VDK_{end}$], then generate the membership function $f_{DK}$ of the fuzzy set DK by the following substeps:

Step 2.1: $m_{VDK} \leftarrow s_k$,

Step 2.2: $\alpha_{VDK} \leftarrow m_{VDK} - VDK_{begin}$,

Step 2.3: $\beta_{VDK} \leftarrow VDK_{end} - m_{VDK}$,

Step 3: Find a point $S_k$ with the maximum value of $P(S_k)$ in the interval of [$MD_{begin}$, $MD_{end}$] to generate the membership function $f_{MD}$ of the fuzzy set MD by the following substeps:

Step 3.1: $m_{DK} \leftarrow s_k$,

Step 3.2: $\alpha_{DK} \leftarrow m_{DK} - DK_{begin}$,

Step 3.3: $\beta_{DK} \leftarrow DK_{end} - m_{DK}$,

Step 4: Find a point $S_k$ with the maximum value of $P(S_k)$ in the interval of [$MD_{begin}$, $MD_{end}$] to generate the membership function $f_{MD}$ of the fuzzy set MD by the following substeps:

Step 4.1: $m_{MD} \leftarrow s_k$,

Step 4.2: $\alpha_{MD} \leftarrow m_{MD} - MD_{begin}$,

Step 4.3: $\beta_{MD} \leftarrow MD_{end} - m_{MD}$,

Step 5: Find a point $S_k$ with the maximum value of $P(S_k)$ in the interval of [$BR_{begin}$, $BR_{end}$] then generate the membership functionion fBR of BR by the following substeps:

Step 5.1: $m_{BR} \leftarrow s_k$,

Step 5.2: $\alpha_{BR} \leftarrow m_{BR} - BR_{begin}$,

Step 5.3: $\beta_{BR} \leftarrow BR_{end} - m_{BR}$, Step 6 : Find a point $S_k$ with the maximum value of $P(S_k)$ in the interval of $[BR_{begin}, BR_{end}]$ then generate the membership function $f_{BR}$ of BR by the following substeps:

Step 6.1: $m_{BR} \leftarrow s_k$,

Step 6.2: $\alpha_{BR} \leftarrow m_{BR} - BR_{begin}$,

Step 6.3: $\beta_{BR} \leftarrow BR_{end} - m_{BR}$,

Step 7: Stop.

The above mentioned construction algorithm is explained with an illustrative example and is as follows: Figure 2 shows the original Lena image which is the sample image of size 256 * 256. Figure 3 is the histogram of the sample image. Fig 4 shows the fuzzy sets constructed from the reference histogram, where the parameters l and r are left_overlap and right_overlap, respectively.

By the construction algorithm, five fuzzy numbers are represented by the triplet [m, a, ß] to build the proposed knowledge base. The knowledge base also contains another fuzzy interval for a fuzzy estimator represented by a quadruplet [$m_l$, $m_r$, α, ß], as shown in Figure 5. Obviously the knowledge base is very simple, composed of only nineteen values, the parameters of VDK, DK, MD, BR, VBR and the fuzzy estimator.

**Figure 2 :** Original Lena Image

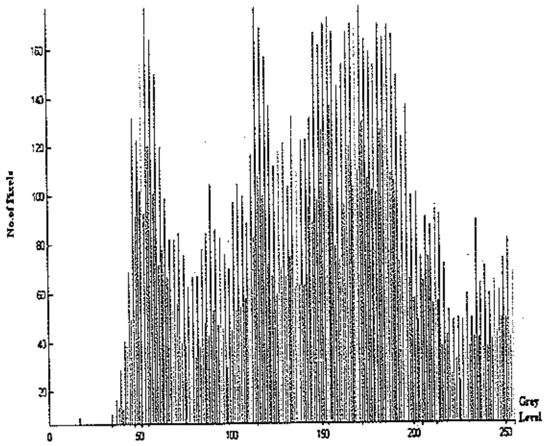


**Figure 3 :** Histogram Of A Sample Image

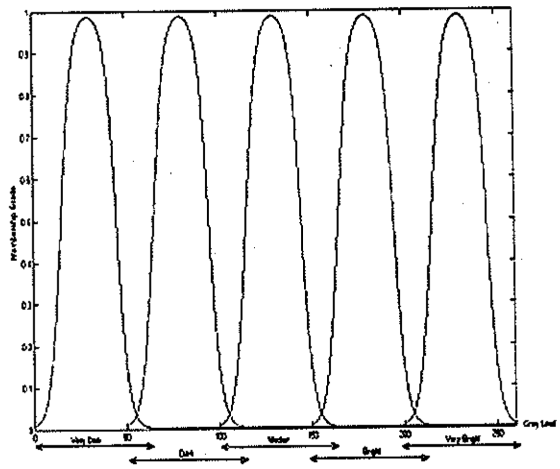

**Figure 4 :** Fuzzy Set Constructed From The Reference Histogram

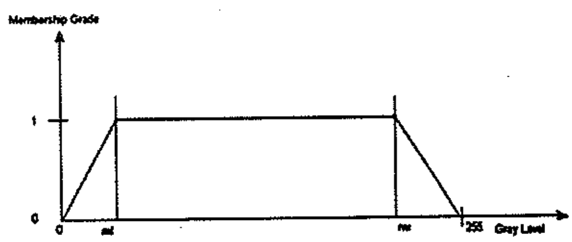


**Figure 5.** Fuzzy Estimator Process

### 3. Proposed Five Level Weighed Fuzzy Mean Filter Using Modified Membership Function

The proposed five level MWFMF is basically a mean filter operating with fuzzy numbers. Conventional mean filters are inefficient for heavy-tailed additive noise, but MWFMF can remove such kind of noise efficiently and simply. The MWFMF adopts a 3×3 sample window to determine the gray level value of each filtered signal, and the pixel to be filtered stands in the central cell of the sample window. Let $X = [x(i, j)]_{N1XN2}$ and $Y = [y(i, j)]_{N1XN2}$ be the original input image and filtered output image, respectively where N1 and N2 are the sample size of the matrix window. In X, each entry x (i, j) may be corrupted by a noise n (i, j) so that it has the gray level as given in equation (5)

$$x(i,j) = s(i,j) + n(i,j) \qquad (5)$$

Now, let MWFMF(.) denote the function of MWFMF. Then, the (i, j)$^{th}$ pixel of the filtered image Y can be formulated as

$$y(i,j) = MWFMF(X(i,j)) \qquad (6)$$

where X (i, j) is a 3 × 3 sample matrix centered at the input pixel x(i,j) being filtered, that is,

$$X(i,j) = \begin{bmatrix} x(i-1,j-1) & x(i-1,j) & x(i-1,j+1) \\ x(i,j-1) & x(i,j) & x(i,j+1) \\ x(i+1,j-1) & x(i+1,j) & x(i+1,j+1) \end{bmatrix} \qquad (7)$$

MWFMF operation consists of five fuzzy mean processes and one decision process. The five fuzzy mean processes are called "fuzzy mean process for very dark", "fuzzy mean process for dark", "fuzzy mean process for medium", "fuzzy mean process for bright", and "fuzzy mean process for very bright", respectively. Each of these fuzzy mean processes outputs a value for the pixel being filtered. Then, from these five values, a final decision process selects the value closest to the fuzzy estimator. This is the filtered pixel value. For filtering the (i, j)$^{th}$ pixel, assume the size of the sample matrix X(i, j) is n1 x n2, then a fuzzy mean process for the corresponding fuzzy set output could be obtained.

Fig 4 shows the transformation from histogram to the fuzzy sets. The histogram of the source image is used as the reference to derive the membership function of the fuzzy mean process for very dark, dark, medium, bright and very bright fuzzy sets and fuzzy estimator process. The intervals of the very dark, dark, medium, bright and very bright fuzzy sets are derived from the algorithm. Gaussian membership function is used for the fuzzy mean process for very dark, dark, medium, bright and very bright fuzzy sets. Trapezoidal membership function is used for fuzzy estimator process.

#### 3.1 Fuzzy Mean Process For Very Dark Sets

The output $Y_{VDK}(i, j)$ is generated by the weighted average approach. The pixels of the noise corrupted image located in the sample windows are weightedly summed to get a mean value. Moreover, the weight associated with each pixel is decided by referring to the membership function $f_{VDK}$ of associated fuzzy intensity feature VDK stored in the knowledge base.

*begin*

  *if*

$$\sum_{k=-\left(\frac{n_1-1}{2}\right)}^{\left(\frac{n_1-1}{2}\right)} \sum_{l=-\left(\frac{n_2-1}{2}\right)}^{\left(\frac{n_2-1}{2}\right)} f_{VDK}(x(i+k,j+l)) \neq 0$$

  *then*

$$y_{VDK}(i,j) \leftarrow \frac{\sum_{k=-\left(\frac{n_1-1}{2}\right)}^{\left(\frac{n_1-1}{2}\right)} \sum_{l=-\left(\frac{n_2-1}{2}\right)}^{\left(\frac{n_2-1}{2}\right)} f_{VDK}(x(i+k,j+l)) \times x(i+k,j+l)}{\sum_{k=-\left(\frac{n_1-1}{2}\right)}^{\left(\frac{n_1-1}{2}\right)} \sum_{l=-\left(\frac{n_2-1}{2}\right)}^{\left(\frac{n_2-1}{2}\right)} f_{VDK}(x(i+k,j+l))}$$

  *else*

$$y_{VDK}(i,j) \leftarrow 0$$

*end*

When all pixels in the sample window have a zero membership grade of $f_{VDK}$ according to their gray levels, the $Y_{VDK}(i,j)$ is set to zero. The output for very dark, medium, bright and very bright could also be obtained by the above process. Any algorithm used to estimate the value of an unknown parameter is called an estimator of $\theta$. A fuzzy estimator (FE) is used which is more powerful for the removal of noise.

### 3.2 Membership Function For Fuzzy Estimator Process

A fuzzy interval I is of LR-type [6] if there exists two shape functions L and R and four parameters $m_l$, $m_r$, a and ß constitutes the membership function of I.

$$f_{LRI}(x) = \begin{cases} L\left(\frac{m_l - x}{\alpha}\right) & \text{for } x \le m_l, \\ 1 & \text{for } m_l \le x \le m_r, \\ R\left(\frac{x - m_r}{\beta}\right) & \text{for } x \ge m_r. \end{cases}$$

Where $f_{LRI}$ is the membership function for fuzzy estimator, $m_l$ and $m_r$ are the start and end point of the function with membership value 1. The fuzzy interval is then denoted by $I = [m_l, m_r, \alpha, \beta]$. If I is the fuzzy interval stored in the knowledge base, then a fuzzy estimator $f_{LRIE}(.)$ can be produced by the following formula.

$$f_{LRE}(X(i,j)) \leftarrow \frac{\sum_{k=-\left(\frac{n_1-1}{2}\right)}^{\left(\frac{n_1-1}{2}\right)} \sum_{l=-\left(\frac{n_2-1}{2}\right)}^{\left(\frac{n_2-1}{2}\right)} f_{LRI}(x(i+k, j+l)) * x(i+k, j+l)}{\sum_{k=-\left(\frac{n_1-1}{2}\right)}^{\left(\frac{n_1-1}{2}\right)} \sum_{l=-\left(\frac{n_2-1}{2}\right)}^{\left(\frac{n_2-1}{2}\right)} f_{LRI}(x(i+k, j+l))}$$

where X (i, j) is a n1 x n2 sample matrix centered at the input pixel x(i,j). The MWFMF decision process decides the output of each filtered pixel by selecting the value which is nearest to $f_{LRE}(X(i, j))$.

### 3.3 Decision Process Of Five Level Mwfmf Filter Using Gaussian Function

The five fuzzy set outputs are compared with the fuzzy estimator and the output that is closer to the fuzzy estimator is the final output. The values $y_{VDK}(i, j)$, $y_{DK}(i, j)$, $y_{MD}(i, j)$, $y_{BR}(i,j)$ and $y_{VBR}(i, j)$ are the outputs of the very dark, dark, medium, bright and very bright fuzzy sets respectively. Thus each pixel value of the noisy image is replaced with the restored value.

The algorithm for checking the fuzzy sets against the fuzzy estimator is given below:

begin

$if\ (|y_{VDK}(i,j) - f_{LRE}(X(i,j))|) < (|y_{DK}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{MD}(i,j) - f_{LRE}(X(i,j))| \,\&$
$|y_{BR}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{VBR}(i,j) - f_{LRE}(X(i,j))|)$
$then\ y(i,j) \leftarrow y_{VDK}(i,j);$
$elseif\ (|y_{DK}(i,j) - f_{LRE}(X(i,j))|) < (|y_{VDK}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{MD}(i,j) - f_{LRE}(X(i,j))| \,\&$
$|y_{BR}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{VBR}(i,j) - f_{LRE}(X(i,j))|)$
$then\ y(i,j) \leftarrow y_{DK}(i,j);$
$elseif\ (|y_{MD}(i,j) - f_{LRE}(X(i,j))|) < (|y_{VDK}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{DK}(i,j) - f_{LRE}(X(i,j))| \,\&$
$|y_{BR}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{VBR}(i,j) - f_{LRE}(X(i,j))|)$
$then\ y(i,j) \leftarrow y_{MD}(i,j);$
$elseif\ (|y_{BR}(i,j) - f_{LRE}(X(i,j))|) < (|y_{VDK}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{DK}(i,j) - f_{LRE}(X(i,j))| \,\&$
$|y_{MD}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{VBR}(i,j) - f_{LRE}(X(i,j))|)$
$then\ y(i,j) \leftarrow y_{BR}(i,j);$
$elseif\ (|y_{VBR}(i,j) - f_{LRE}(X(i,j))|) < (|y_{VDK}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{DK}(i,j) - f_{LRE}(X(i,j))| \,\&$
$|y_{MD}(i,j) - f_{LRE}(X(i,j))| \,\&\, |y_{BR}(i,j) - f_{LRE}(X(i,j))|)$
$then\ y(i,j) \leftarrow y_{VBR}(i,j);$

end

## 4. Experimental Results

In the experimental noise model, the source image is corrupted by additive impulsive noise with probability p. It should be remembered that the major drawback in the use of generalized mean and nonlinear mean filters for impulse noise removal is that they cannot remove positive and negative spikes simultaneously. However, median filters have been extensively used for mixed impulse noise removal. In this work, comparisons between the proposed five levels MWFMF and the conventional filters like Mean, Median and weighed fuzzy mean filter [5] are emphasized. To construct the knowledge base for the experiment, $N_f = 5$, $t = 10$ are assigned for image "Lena". This gives the parameter sets [m, $\alpha$, ß] to be stored in the knowledge base.

In the first experiment performances of the proposed five levels MWFMF is determined and compared with the other conventional filters. The experiment is performed on the image 'Lena' corrupted by additive impulse noise. The proposed MWFMF approach is implemented and simulated successfully using Pentium IV computer in VC++. Fig 5 shows the original Lena Image. The corrupted Lena image with noise probability p=0.5 is shown in Figure 6. The restored images using conventional filters such as Mean, Median and WFM with three fuzzy sets due to Lee et al are shown in Figures 7, 8 and 9 respectively. The restored image using the proposed five level MWFMF filter is shown in Figure 10.

**Figure 5.** Original Lena Image

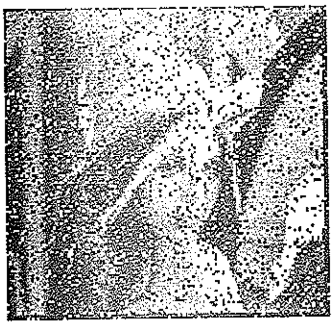

**Figure 6.** Corrupted Lena Image With p=0.5

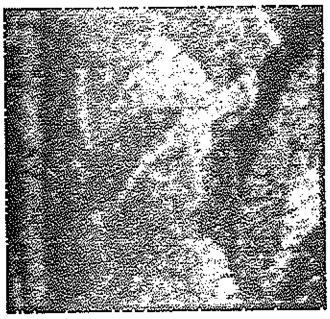

**Figure 7.** Image Restored Using Mean Filter, PSNR = 18 db

**Figure 8.** Image Restored Using Median Filter, PSNR= 24.20 db

**Figure 9.** Image Restored Using WFMF With 3 sets. PSNR = 27.5 db

**Figure 10.** Image Restored Using MWFMF With 5 sets. PSNR= 33.16

A plot showing noise probability versus PSNR for different filters is depicted in Figure 11. In another set of eexperiments Mean Squared Error (MSE) is computed for the proposed approach and for the conventional filters like Median, Mean and WFMF for various levels of additive noise i.e., for noise probability P varying from 0 to 1. A graph showing MSE versus noise probability P is shown in Figure 12. From the graph it is found that the proposed approach restores the noisy images very effectively and the PSNR improvement achieved is 3 to 5 db compared to WFMF.

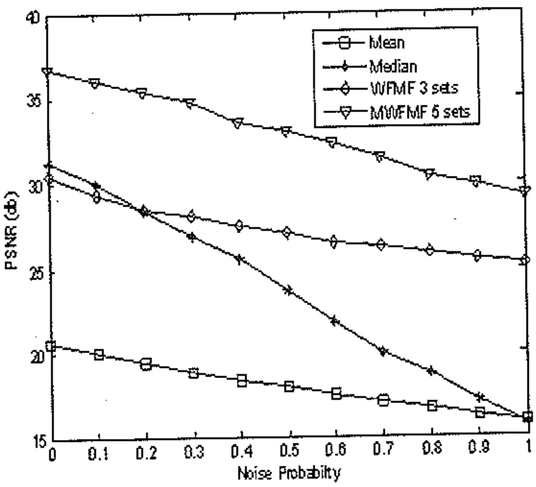


**Figure 11.** Psnr Curves Of The MWFM, WFM, Median and Mean Filters For The "Lena" Image Corrupted By Additive Impulse Noise Of Various Probability p.

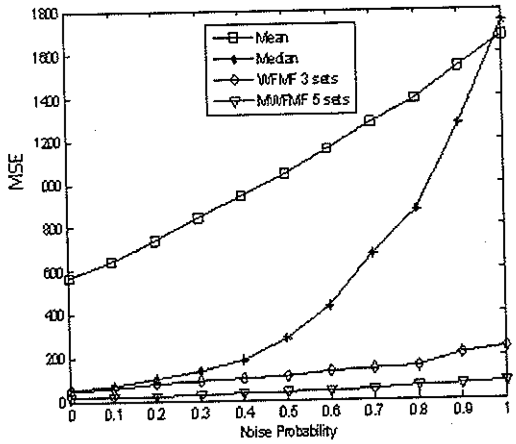


**Figure 12.** MSE curves of the MWFM, WFM, Median and Mean filters approach for the "Lena" image corrupted by additive impulse noise with probability p

## 5. Conclusion

A new type of filter, MWFMF, applying the fuzzy modeling technique is proposed and analyzed in this chapter. Conventional filters, including the median filter, are unsuitable for cases where additive impulse noise is heavy, especially when noise probability is larger than 0.3. MWFMF shows good stability for the full range of impulse noise probability and for the MSE, PSNR criteria .

The major operation in MWFMF's filtering procedure is the simple weighted average approach. Therefore, MWFMF's computational complexity is less than that of the conventional filters. According to the experimental results, the proposed five level MWFMF performance is better than the conventional approach in terms of various noise removal evaluation criteria, both quantitative and subjective. Moreover as the number of fuzzy set increases there is a definite amount of improvement in MSE and PSNR values.

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