

Weighted Fuzzy Mean Filters For Image Processing

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ABSTRACT

A New fuzzy filter for the removal of heavy additional impulse noise called the Weighted Fuzzy Mean (WFM) filter is proposed. In this WFM filter we generate five fuzzy sets for an image such as dark (DK), median (MD), bright (BR), very dark (VDK) and very bright (VBR). The WFM-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 decided by experts or derived from the histogram of a reference image. When noise probability exceeds 0.3, WFM gives very superior performance compared with conventional filters when evaluated by mean square error (MSE), peak signal-to-noise-rate (PSNR). In this mean filter we are using the method fuzzy logic. This splits the image in to blocks. By comparing the pixel value in the each block we can increase the resolution of the image based on the SNR values.

Keywords: Weighted fuzzy mean filter, Image processing, Knowledge base, Histogram, Impulse noise, fuzzy estimator.

INTRODUCTION

When image is transmitted over channels, it is often corrupted by impulse noise due to faulty communications or noisy channels. Impulse noise consists of very large

positive or negative spikes of short duration. A positive spike has a value much larger than those of background signals and appears like a bright spot on the image. On the other hand, a negative spike has a value much smaller than those of background signals and appears like a dark spot on the image. 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 filter and nonlinear mean filter have been proposed for removing impulse noise from image, they suffer from an inability to remove positive and negative spikes simultaneously. The median filter is the best performing and most popular stack filter in heavy noise situation, but its performance deteriorates rapidly when spike probability exceed 50%. In this paper, we introduce a novel filtering technique with superior noise removal capacity compared to conventional nonlinear filter. Fuzzy set theory has been successfully applied to control and pattern recognition fields. It is suitable for dealing with problems containing high levels of uncertainty to which class pattern recognition or image processing problems usually belong. WFM is a powerful tool for removing additional impulse noise from images especially when noise probability is larger than 0.3.

KNOWLEDGE BASE SUPPORTED IMAGE NOISE REMOVAL PROCESS

Our WFM is supported by a simple knowledge base which can be a static knowledge base built by human experts or by referring to sample images or a dynamic knowledge base built in run time. A 1-10 mins set-up time is initially required for WFM static knowledge base.

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but this is an one-time process. The dynamic knowledge base is a constant automatic delay of less than 1s. It is equivalent to the knowledge base of our WFM is supported by a simple knowledge base which can be a static knowledge base built by human experts or by referring to sample images, or a dynamic knowledge base built in run time. A 1-10 mins set up time is initially required for WFM static knowledge base, but this is a one time process. The dynamic knowledge base has a constant automatic delay of less than 1s. its equivalent of knowledge base set-up.

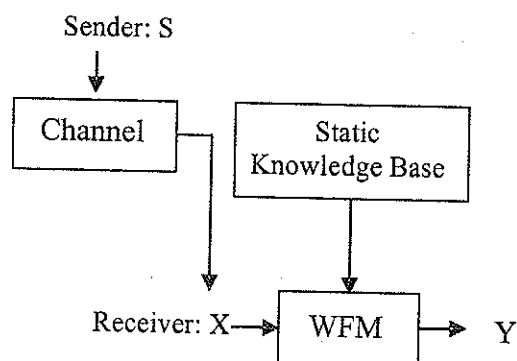
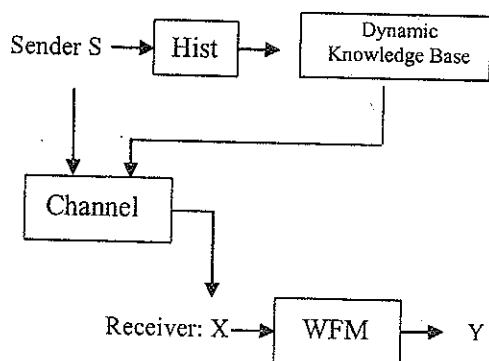


Figure 1: Transmission Process

The image transmission process is shown in fig 1. This process consists of two phases: sender phase and receiver phase. The sender phase sends the source image to the receiver. The static knowledge base is pre-established by image experts or by referring to sample image, which may be independent of the image to be filtered.

Figure2 (a): Noise Removal Process



The proposed noise removal process uses a dynamic knowledge base. This process also consists of a sender phase and receiver phase but the knowledge base must be transmitted from the sender side to the receiver side along with the image to be filtered. Fig2 (a) describes the image transmission process when WFM is applied to remove noise.



Figure2 (b): Sender Phase

The sender phase is shown fig2 (b). The knowledge base is updated with the source image after histogram processing. This phase also called knowledge base building phase the completed knowledge base consists of few fuzzy sets specifying the gray-level features of the noise free source image and is referred by WFM. When removing impulse noise during the receiver phase as shown in fig 2(c), the receiver phase filter receives corrupted images by invoking WFM and referring to the information stored in the knowledge base.

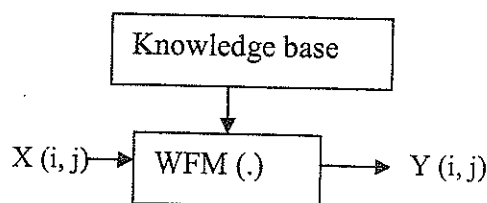


Figure2 (c): Receiver Phase

The generation of the dynamic or static base is as follows: consider a noise free image S sized $N_1 \times N_2$ pixels with L gray levels. For convenience we denote it as $S = [s(i,j)]_{N_1 \times N_2}$. $s(i,j) \in \{0, 1, \dots, L-1\}$ is a pixel of the source image without any noise for $0 \leq i \leq N_1-1$ and $0 \leq j \leq N_2-1$. 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.

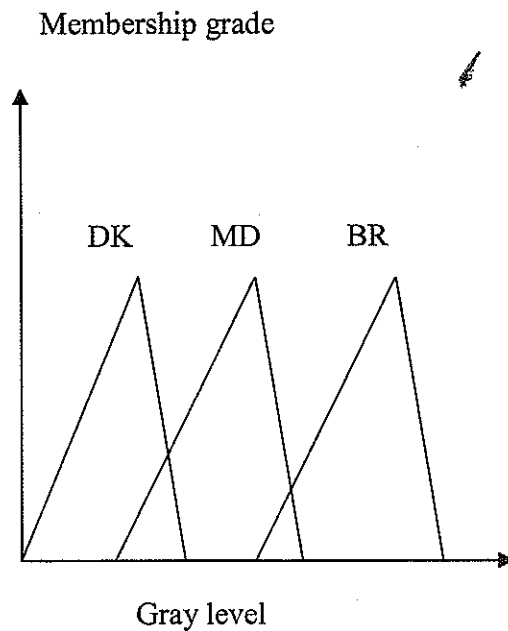


Figure 3 : Membership Grade Function

Fig:3 Example pf membership functions for the fuzzy sets DK, MD, and BR the membership grade usually a value in the range [0, 1] where “1” denotes a full membership and “0” denotes no membership. According to fig 3, we know that for instance. pixels (i, j) with the gray level 160 has the intensity property: “not dark”, “quite median”, and “poorly bright”.

The fuzzy sets describing the intensity features of a noise free source 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. Where S_k is the kth gray level of image S, n_k is the number of pixel with the k th gray level in s, n is the total number of pixel in s and $k=0,1,2,\dots,L-1$. In other words $p(sk)$ gives an estimate of the probability of occurrence of gray level sk . Before the algorithm for generating fuzzy sets to be stored in the knowledge base, membership function type has to be defined first.

CONSTRUCTION ALGORITHM OF FUZZY SETS STORED IN KNOWLEDGE BASE

Step 1: Decide the intervals of $[DK_{begin}, DK_{end}]$, $[MD_{begin}, MD_{end}]$ and $[BR_{begin}, BR_{end}]$ for the fuzzy sets DK, MD and BR, respectively

Step 1.1: Set $DK_{end} = \left\lceil \frac{L-1}{N_f} \right\rceil$, $BR_{begin} = (N_f - 1)$

$\left\lceil \frac{L-1}{N_f} \right\rceil$, $MD_{begin} = DK_{end} - \text{left overlap}$, and

$MD_{end} = BR_{begin} + \text{right overlap}$, where N_f is the number of fuzzy sets and left overlap and right overlap denote the overlapping range of the fuzzy sets.

Step 1.2: Set DK_{begin} be the first s_k such that $n_k > t$ from 0 to DK_{end} where t is a threshold;

Step 1.3: Set BR_{end} be the last s_k such that $n_k > t$ from BR_{begin} to $L - 1$.

Step 2: Find a point s_k with the maximum value of $p(s_k)$ in the interval of $[DK_{begin}, DK_{end}]$, then generate the membership function f_{DK} of fuzzy set DK by the following sub steps:

Step 2.1: $m_{DK} \rightarrow S_k$,

Step 2.2: $\alpha_{DK} \rightarrow M_{DK} - DK_{begin}$,

Step 2.3: $\beta_{DK} \rightarrow DK_{end} - M_{DK}$.

Step 3: Find a point s_k with the maximum value of $p(s_k)$ in the interval of $[MD_{begin}, MD_{end}]$, then generate the membership function f_{MD} of MD by the following sub steps:

Step 3.1: $M_{MD} \rightarrow S_k$,

Step 3.2: $\alpha_{MD} \rightarrow M_{MD} - , DK_{begin}$,

Step 3.3: $\beta_{MD} \rightarrow MD_{end} - M_{MD}$.

Step 4: 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 sub steps:

Step 4.1: $m_{BR} \rightarrow S_k$,

Step 4.2: $\alpha_{BR} \rightarrow M_{BR} - BR_{begin}$,

Step 4.3: $\beta_{BR} \rightarrow BR_{end} - M_{BR}$.

Step 5: Stop

Weighted Fuzzy Mean Filter

The proposed WFM is basically a mean filter operating with fuzzy members. Conventional mean filter are inefficient for heavy tailed additive noise, but WFM can remove such kind of noise efficiently and simply, WFM adopts a 3x3 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 $X=[x(i, j)] N1 \times N2$ and $Y=[y(i, j)] N1 \times N2$ be the original input image and filtered output image, respectively. In the X each entry $x(i, j)$ may be corrupted by noise $n(i, j)$ so that has the gray level

$$X(i, j) = s(i, j) + n(i, j)$$

Now let $WFM(.)$ denote the function of WFM. Then the (i, j) -th pixel of the filtered image Y can be formulated as $Y(i, j) = WFM(X(i, j))$

Where $X(i, j)$ is a 3x3 sample matrix centered at the input pixel $x(i, j)$ being filtered that is

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

WFM operation consists of three fuzzy mean processes and one decision making process. The three fuzzy mean processes are called "fuzzy mean process for dark", "fuzzy mean process for median", and "fuzzy mean process for bright", respectively. Each of these fuzzy mean processes outputs a value for the pixel being filtered. Then from these three 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 $n1 \times n2$.

Fuzzy mean process for Dark

Begin

$$\text{If } \sum_{k=-(n_1-1)/2}^{(n_1-1)/2} \sum_{t=-(n_2-1)/2}^{(n_2-1)/2} f_{DK}(x(i+k, j+t)) \neq 0$$

$$\text{Then } \bar{y}_{DK}(i, j) \leftarrow \frac{\sum_{k=-(n_1-1)/2}^{(n_1-1)/2} \sum_{t=-(n_2-1)/2}^{(n_2-1)/2} f_{DK}(x(i+k, j+t)) x(i+k, j+t)}{\sum_{k=-(n_1-1)/2}^{(n_1-1)/2} \sum_{t=-(n_2-1)/2}^{(n_2-1)/2} f_{DK}(x(i+k, j+t))}$$

Else

$$\bar{y}_{DK}(i, j) \leftarrow 0$$

End

WFM decision process then determines the final filtered output of each pixel. This decision is made by referring to a fuzzy estimator which is derived from fuzzy interval stored in the knowledge base.

The maximum-likelihood estimator (MLE) has been widely used in statistics. Now we propose a new estimator called a fuzzy estimator (FE) which is similar to MLE but more powerful for the removal of noise.

Definition

A fuzzy interval l is of L-R Type if there exists two shape function L and R and four parameters (ml, mr) .

$$f_{LR}(x) = \begin{cases} L\left(\frac{m_l - x}{\alpha}\right) & \text{for } x \leq m_l, \\ l & \text{for } m_l \leq x \leq m_r, \\ R\left(\frac{x - m_r}{\beta}\right) & \text{for } x \geq m_r, \end{cases}$$

Definition

If I is the fuzzy interval stored in the knowledge base, then a fuzzy estimator can be produced by following formula

$$f_{LRE}(X(i, j)) = \frac{\sum_{k=-(n_1-1)/2}^{(n_1-1)/2} \sum_{l=-(n_2-1)/2}^{(n_2-1)/2} f_{LR}(x(i+k, j+l)) \cdot x(i+k, j+l)}{\sum_{k=-(n_1-1)/2}^{(n_1-1)/2} \sum_{l=-(n_2-1)/2}^{(n_2-1)/2} f_{LR}(x(i+k, j+l))}$$

Where X (i, j) is an n1 x n2 sample matrix centered at the input pixel x (i, j). In our experiment we let the fuzzy interval I be follows:

$$f_{LR}(x) = \begin{cases} 0 & \text{for } x \leq m_l, \\ l & \text{for } m_l \leq x \leq m_r, \\ 0 & \text{for } x \geq m_r \end{cases}$$

Decision process of WFM Filter

Begin

If

$$|\bar{y}_{DK}(i, j) - f_{LRE}(X(i, j))| < |\bar{y}_{MD}(i, j) - f_{LRE}(X(i, j))|$$

Then $y(i, j) \leftarrow \bar{y}_{DK}(i, j);$

Else $y(i, j) \leftarrow \bar{y}_{MD}(i, j);$

If

$$|\bar{y}_{BR}(i, j) - f_{LRE}(X(i, j))| < |y(i, j) - f_{LRE}(X(i, j))|$$

Then $y(i, j) \leftarrow \bar{y}_{BR}(i, j);$ **End**

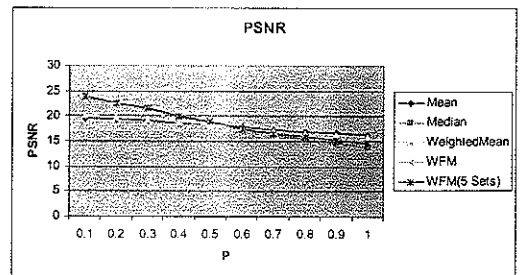
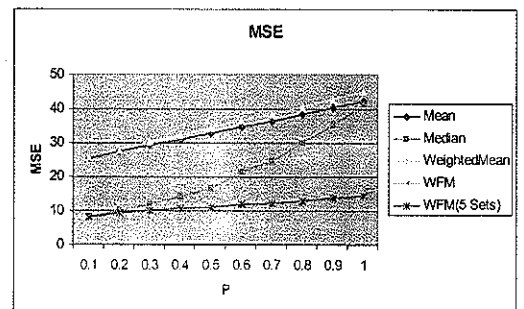
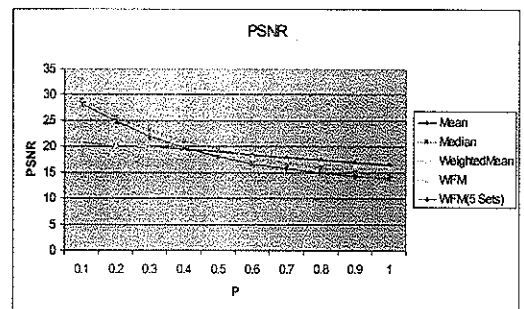
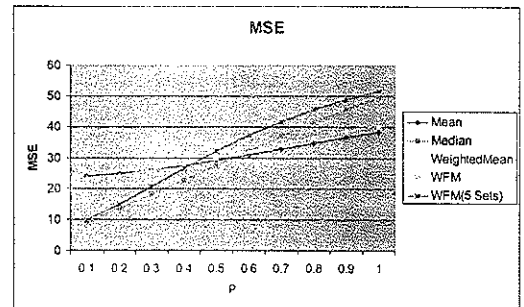
EXPERIMENT RESULT

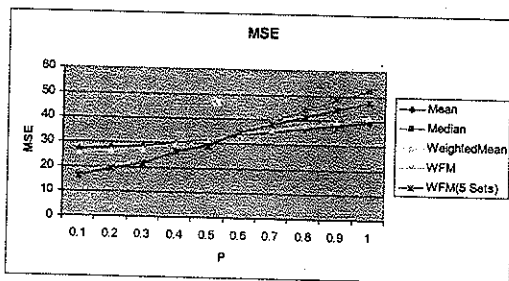
In our experimental noise model the source image is corrupted by additive impulsive noise with probability p.

$x(i, j) =$

$$\begin{cases} s(i, j) + n(i, j), & \text{with probability } \frac{1}{2} p. \\ s(i, j) - n(i, j), & \text{with probability } \frac{1}{2} p. \\ s(i, j), & \text{with probability } 1 - p. \end{cases}$$

It should be remembered that the major drawbacks in the use of generalized mean and nonlinear mean filter for impulse noise removal is that they cannot remove positive and negative spikes, simultaneously. However median filter have been extensively used for mixed impulse noise removal. In this project comparison between WFM and the median filter are emphasized.





SOME CONCLUSIONS CAN BE DRAWN FROM OUR EXPERIMENTS

- 1) WFM with FE is always better than WFM with MLE.
- 2) Conventional filters, including the median filter, are unsuitable for cases where additive impulse noise is heavy, especially when noise probability is larger than 30.
- 3) WFM shows good stability for the full range of impulse noise probability and for the MSE and PSNR criteria.
- 4) WFM removes mixed spikes noise very well but most conventional mean filter cannot.

DISCUSSION AND CONCLUSION

A new type filter WFM applying the fuzzy modeling technique is proposed and analyzed in this project. This major operation in WFM's computational complexity is less than that of the median filter. Moreover according to the experimental results, the former is superior to the latter in terms of various noise removal evaluation criteria. A knowledge base supporting technique is also developed for WFM. The knowledgebase can be either a static knowledge base produced by consulting experts or referring to a set of sample image or dynamic knowledge base produced dynamically from each clean source image. Certainly the dynamic knowledge base scheme has the best noise removal performance, but the extra needs overhead to generate and transmit the knowledge base for each image. Subjective evaluation of WFM also shows high quality restoration of filter image.

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Author's Biography

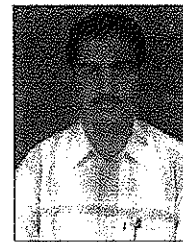


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