A New Fuzzy Logic Filter for Image Enhancement

Farzam Farbiz, Mohammad Bager Menhaj, Seyed A. Motamedi, and Martin T. Hagan

***Abstract*—This paper presents a new fuzzy-logic-control based filter with the ability to remove impulsive noise and smooth Gaussian noise, while, simultaneously, preserving edges and image details efficiently. To achieve these three image enhancement goals, we first develop filters that have excellent edge-preserving capability but do not perform well in smoothing Gaussian noise. Next, we modify the filters so that they perform all three image enhancement tasks. These filters are based on the idea that individual pixels should not be uniformly fired by each of the fuzzy rules. To demonstrate the capability of our filtering approach, it was tested on several different image enhancement problems. These experimental results demonstrate the speed, filtering quality, and image sharpening ability of the new filter.**

***Index Terms*—Edge enhancement, fuzzy logic, image processing.**

I. Introduction

NOISE smoothing and image enhancement are conflicting objectives in most image processing applications. The objectives of image enhancement are to remove impulsive noise, to smooth nonimpulsive noise, and to enhance edges or other salient structures in the input image. Noise filtering can be viewed as replacing the gray-level value of every pixel in the image with a new value depending on the local context. Ideally, the filtering algorithm should vary from pixel to pixel based on the local context. For example, if the local region is relatively smooth, then the new value of the pixel can be determined by averaging neighboring pixel values. On the other hand, if the local region contains edges or impulse noise pixels, a different type of filtering should be used. However, it is extremely hard, if not impossible, to set the conditions under which a certain filter should be selected, since the local conditions can be evaluated only vaguely in some portions of an image. Therefore, a filtering system needs to be capable of reasoning with vague and uncertain information; this suggests the use of fuzzy logic.

Noise smoothing and edge enhancement are inherently conflicting processes, since smoothing a region might destroy an edge, while sharpening edges might lead to unnecessary noise. Many techniques to overcome these problems have been proposed in the literature [1]–[3]. In this paper we propose a new filter, based on fuzzy-logic-control [4], that removes impulsive noise. Furthermore, it smoothes Gaussian noise, while edges and image details are efficiently preserved. The filter is based on the idea that individual pixels are not uniformly fired by each of the fuzzy rules.

The paper is organized as follows. Section II presents a brief review of fuzzy approaches to image filtering. In Section III, we introduce the proposed method and show its main properties. Section IV presents experimental results and compares them with a standard filter and with other recently proposed filters. In Section V, we suggest some modifications to improve the performance of the proposed filter. We provide further experiments in Section VI to demonstrate the capability of the modified method. In Section VII, we suggest two other fuzzy rules and incorporate them into the main fuzzy rules developed in Section III to make image edges sharper without noise magnification. Some experiments are included in Section VIII to show the performance of our sharpening method. In Section IX, we provide conclusions.

II. Previous Fuzzy-Based Work

Because fuzzy set theory has the potential capability to efficiently represent input/output relationships of dynamic systems, this theory has gained popularity, especially in pattern recognition and computer vision applications [5]–[8]. In these areas there have been many efforts to develop fuzzy filters for signal/image processing, with promising results [9]–[12]. In the well-known rule-based approach for image processing [13], one may use human knowledge expressed heuristically in linguistic terms. This approach is highly nonlinear in nature and cannot be easily characterized by traditional mathematical modeling. However, this approach allows us to incorporate heuristic fuzzy rules into conventional methods, leading to a more flexible design technique. For instance, in [14] Yang and Tou applied heuristic fuzzy rules to improve the performance of the traditional multilevel median filter.

Russo proposed fuzzy-rule-based operators for smoothing, sharpening, and edge detection [9], [10], [15]–[21]. He also employed heuristic knowledge to build the rules for each of the underlying operations. In [9] he proposed the use of operators with different window sizes (i.e., 5×5 or 7×7), where the window size is dependent on the uniformity of the local region. The degree of the region's uniformity is determined by employing a certain set of fuzzy rules [16]. Based on the uniformity detection rule, the two outputs from the 5×5 and 7×7 windowing operators are linearly combined. Since the fuzzy rules in this approach are constructed based on region contours, this approach is in fact performing smoothing while preserving image edges. In [19] Russo proposed the use of fuzzy if–then rules to sharpen edges in a noisy image. Furthermore, in [20] and [21], he presented a dual-step fuzzy-rule-based filter to detect and remove a large variety of patterns of noise pulses while preserving the original image.

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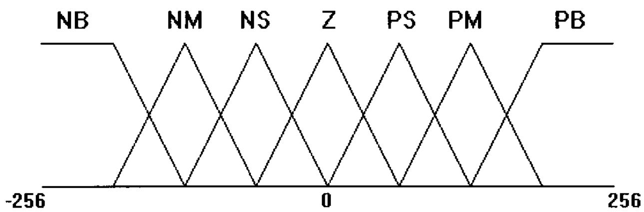


Fig. 1. Membership functions.

In [22], a fuzzy rule-based approach to image enhancement is presented that addresses seemingly conflicting goals:

a) removing impulsive noise;
b) smoothing out nonimpulsive noise;
c) enhancing edges or other salient features.

Three different filters for each task are derived using the weighted least mean squares method. Criteria for selecting each filter are defined. The criteria are based on the local context as well as the particular application. They constitute the antecedent clauses of the fuzzy rules, and the corresponding filters constitute the consequent clauses of the fuzzy rules. The overall result of the fuzzy-rule-based system is computed as a combination of the results of the individual filters, where each result contributes to the degree that the corresponding antecedent clause is satisfied. This approach gives us a powerful and flexible image enhancement paradigm.

In [23], a class of stack filters is enlarged by defining the output of a Boolean function to vary continuously from 0 to 1 (i.e., the stack filter is defined by a Boolean function). This filter is called the fuzzy weighted median filter (FWM). In [24], fuzzy stack filters were proposed to extend the filtering capability of conventional stack filters, and it was shown that such filters are capable of removing impulsive noise.

Muneyasu *et al.* [25] proposed a novel type of edge-preserving smoothing filter applicable to images corrupted with impulsive and white Gaussian noise. This kind of filter is based on weighted mean filters, whose coefficients can be varied adaptively using local features in the window. Fuzzy control laws are used for the implementation of this filter, and a standard optimization technique is employed for estimation of the membership function parameters.

References [26]–[28] describe the application of fuzzy clustering to the removal of impulsive noise. Other fuzzy filters for removing impulsive noise have been also proposed in [29]–[31]. Reference [32] presented a new hybrid filter design methodology containing a nonlinear filter for removing impulsive noise and a fuzzy weighted linear filter. This hybrid filter can efficiently remove large amounts of mixed Gaussian and impulsive noise while preserving the image details.

III. Proposed Method

This section presents the architecture of our proposed rule-based image processing system, the fuzzy control filter (FCF). In the FCF system we adopt the general structure of a fuzzy if–then–else rule mechanism. The approach here is based on the idea of not letting each point in the area of concern be uniformly fired by each of the basic fuzzy rules. (This idea is widely used

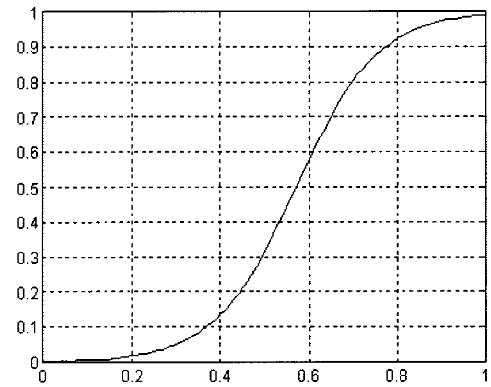


Fig. 2. Typical membership function for the fuzzy function "more."

in fuzzy control applications [4].) The nonuniformity will produce a reduced sensitivity to impulsive noise and will provide improved edge restoration, as we will discuss later.

The following fuzzy rules and membership functions, shown in Fig. 1, are proposed for image filtering:

$$
\begin{array}{lll}
\text{R1:} & \text{IF } (\textbf{more} \text{ of } x_i \text{ are } \mathbf{NB}) \text{ THEN} & y \text{ is } \mathbf{NB} \\
\text{R2:} & \text{IF } (\textbf{more} \text{ of } x_i \text{ are } \mathbf{NM}) \text{ THEN} & y \text{ is } \mathbf{NM} \\
\text{R3:} & \text{IF } (\textbf{more} \text{ of } x_i \text{ are } \mathbf{NS}) \text{ THEN} & y \text{ is } \mathbf{NS} \\
\text{R4:} & \text{IF } (\textbf{more} \text{ of } x_i \text{ are } \mathbf{PS}) \text{ THEN} & y \text{ is } \mathbf{PS} \\
\text{R5:} & \text{IF } (\textbf{more} \text{ of } x_i \text{ are } \mathbf{PM}) \text{ THEN} & y \text{ is } \mathbf{PM} \\
\text{R6:} & \text{IF } (\textbf{more} \text{ of } x_i \text{ are } \mathbf{PB}) \text{ THEN} & y \text{ is } \mathbf{PB} \\
\text{R0:} & \text{ELSE} & y \text{ is } \mathbf{Z}.
\end{array}
\tag{1}
$$

In the above, the x_i's are the luminance differences between neighboring pixels, P_i (located in a window of size $N \times N$), and the central pixel P: $x_i = P_i - P$. The output variable y is the quantity which is added to P to yield the resulting pixel luminance, P'. The term **more** represents a fuzzy function whose typical shape is shown in Fig. 2. The shape of this function enables the nonuniform firing of the basic fuzzy rules. This S-type function may be described by the following formula:

$$\mu_{\text{more}}(z) = \frac{1}{1 + e^{-(\alpha_1 z - \beta_1)}}. \tag{2}$$

A. The Rule's Activity Degree Calculation

The activity degree of R1 is computed by the following relationship (the other if–then rules' degrees of activity are computed similarly)

$$\lambda_1 = \min\{\mu_{\text{NB}}(x_i) \colon x_i \in \text{support(NB)}\} \times \mu_{\text{more}} \times \left[\frac{\text{number of } x_i \text{ which } x_i \in \text{support(NB)}}{\text{total number of } x_i}\right]. \tag{3}$$

For the ELSE rule, R0, we apply the following formula to evaluate the degree of activation

$$\lambda_0 = \text{Max}\left\{0, 1 - \sum_{i=1}^{6} \lambda_i\right\}. \tag{4}$$

Fig. 3. Complex test image.

To infer the output numerically from the fuzzy rules given in (1), we employ the *correlation-product* inference mechanism [4] as

$$y = \frac{\sum_{i=0}^{6} C_i w_i \lambda_i}{\sum_{i=0}^{6} w_i \lambda_i} \tag{5}$$

where C_i and w_i are, respectively, the center point and width of the membership function used in the ith fuzzy rule in (1).

Since all w_i's are equal and $C_0 = 0$, (5) can be simplified to

$$y = \sum_{i=1}^{6} C_i \lambda_i. \tag{6}$$

B. Main Properties

As observed from (3), the filter obtained through the rules given in (1), because of their nonuniform activities, will have the following advantages.

1) *Low Noise Sensitivity:* With typical values of signal to noise ratio, for pixels located in the windowed area of the image, the rules corresponding to the noisy pixels will be fired less frequently. Consequently, their contributions to the filter become less.
2) *Edge Preservation*: In the regions close to the boundaries, the output will be affected by the region that contains more pixels. Therefore image edges will not be blurred.

IV. Experimental Results

As mentioned above, the FCF has potential for edge preservation. To verify this property, we need to quantitatively evaluate the quality of filtering. The mean-square-error (MSE) between the edges of the original image and those of the image after filtering will be used as a measure of the edge preserving ability. We use the acronym MSEE to indicate this criterion. In the sequel we will perform some experiments to illustrate the performance of the FCF.

Experiment 1—Edge Preservation: The image given in Fig. 3, is the first test case for the FCF. The MSEE of the filtered images obtained from the FCF, the median filter, and the filters proposed in [22], [23], and [25] are summarized in Table I (the image edges are extracted by the Sobel operator). Notice that the FCF (with one iteration) has better edge preservation than the other filters.

TABLE I
Results of Experiment #1

Filter Type	MSEE
median 3×3	610
median 5×5	1682
FWM	506
EPS 5×5	847
EPS 7×7	1053
ENHANCE 3×3	577
ENHANCE 5×5	1102
FCF 3×3 (after 1 iteration)	76
FCF 3×3 (after 4 iterations)	359

Experiment 2—Impulsive Noise: In this experiment we consider Fig. 4(a), which is a test image that has been contaminated by 5% white and 5% black impulsive noise. The result of the FCF after 4 iterations is depicted in Fig. 4(b). From this restored image, we can see that the FCF can eliminate noise from the image without degrading the edges.

Experiment 3—Gaussian and Mixed Noise: In order to demonstrate the performance of the filter in a Gaussian noise environment, we consider the Lena image as another case study. This image is first contaminated by Gaussian noise with $\mu = 0$ and $\sigma^2 = 400$, and then it is applied to our filter. The result of the filtering process is depicted in Fig. 5(a). We observe from this figure that as the number of iterations increases, the MSE is reduced. To test the performance of the FCF in the mixed noise case, we add (2.5%, 2.5%) impulsive noise to the previous image. The result of the filtering process is shown in Fig. 5(b). For both Gaussian and mixed noise cases, the FCF provides improved image restoration as the number of iterations increases. However, in the next experiment we will see that we cannot increase the iteration number indefinitely.

Experiment 4—Effect of Iteration Number on Edge Preservation: In this experiment we want to see how the edge preservation property of the FCF is affected when the number of iterations of the filtering process increases. In this experiment we use the Lena image. Fig. 6 depicts the MSEE of the restored image obtained by the FCF as a function of iteration number. This figure shows that the edge preservation property of the filter is degraded as the number of iterations increases. From Figs. 5 and 6, we can see that there is a tradeoff between edge preservation and restoration of noisy images. In future experiments we will limit the number of iterations to four.

Experiment 5—Complex Images in Noise: In order to reemphasize the effectiveness of the FCF in a noisy environment, we consider the image given in Fig. 7. This image is obtained from the image given in Fig. 3 mixed with Gaussian noise (with $\mu = 0$ and $\sigma^2 = 400$) and (2.5%, 2.5%) impulsive noise.

Figs. 8–11 illustrate the operation of several different filters on the image in Fig. 7. Fig. 8 shows the performance using a median filter and the FWM filter [23].

(a) (b)

Fig. 4. (a) The 320 × 200 test image with 256 gray level contaminated by 10% impulsive noise (5% white, 5% black) and (b) result of the FCF after four iterations.

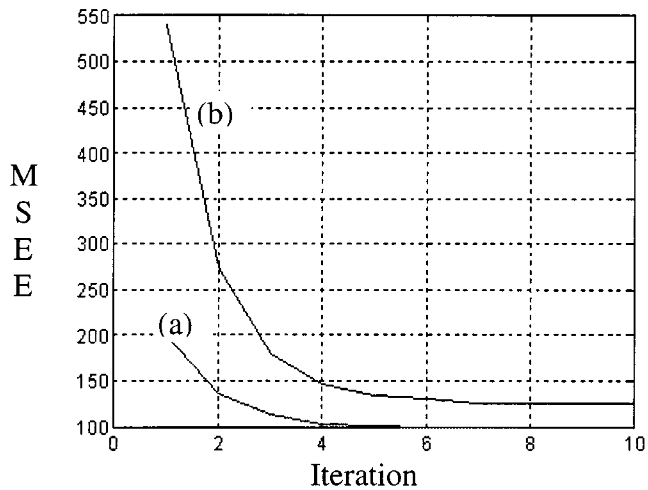


Fig. 5. Performance of the FCF on 256 × 256 Lena image contaminated by Gaussian noise with $\mu = 0, \sigma^2 = 400$: (a) without impulsive noise and (b) with (2.5%, 2.5%) impulsive noise.

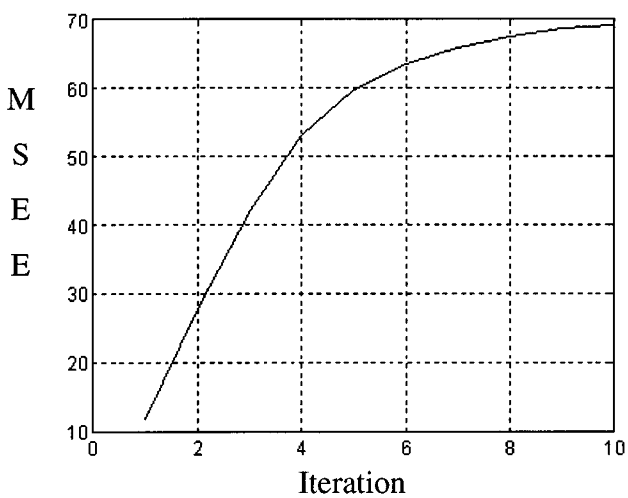


Fig. 6. Performance deterioration of the FCF on the Lena image.

Fig. 9 shows the results for two variations of the EPS filter [25].

Fig. 10 shows the restoration created by two versions of the ENHANCE filter [22].

Fig. 11 shows the restoration created by two versions of the FCF. Here we can see that the FCF image seems to be better after four iterations of the algorithm. We will quantify this effect in Table II. From Figs. 5 and 6 we know that increasing the number of iterations has two different effects—one good and one bad.

Fig. 7. Noisy version of Fig. 3.

Table II summarizes the behavior of various filters on the image in Fig. 7. The FCF has excellent performance on edge preservation. This is highly important, especially for complex images. On the other hand, it sometimes suffers from relatively poor performance on noise removal from simple images. This problem will be addressed in the next section.

V. Improved Smoothing

We will next consider two modifications to the FCF. The purpose of these modifications is to improve its performance in smoothing noisy images.

Modification 1: To make the FCF more insensitive to Gaussian noise, the rule R0 in (1) is replaced with the following rule:

$$R'0\text{: ELSE IF}(\mathbf{more}' \text{ of } x_i \text{ are } \mathbf{Z}) \text{ THEN } y \text{ is } ave(x_i) \qquad (7)$$

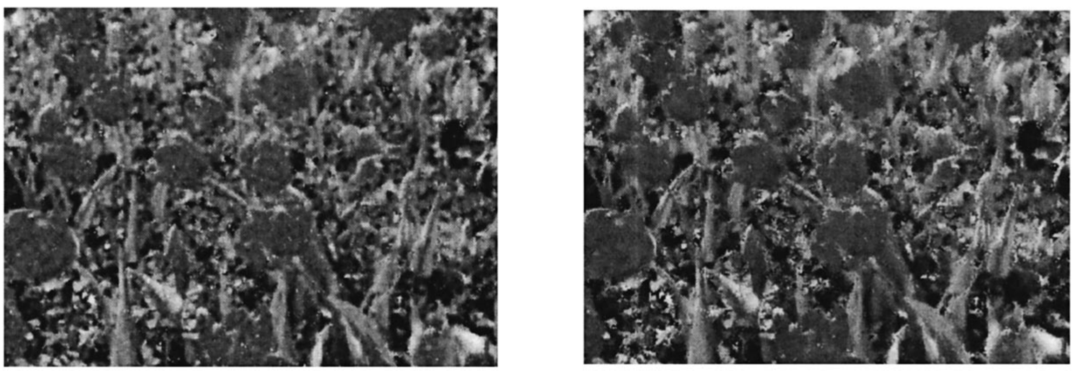
with

$$ave(x_i) = \text{average}(x_i\colon x_i \in \text{support}(\mathbf{Z})) \qquad (8)$$

where the linguistic term “**more**’ is shown in Fig. 12. This is a smoothed version of the **more** function. The α and β parameters have been adjusted so that the function is approximately linear over a wider input range. This tends to provide a smoothing effect.

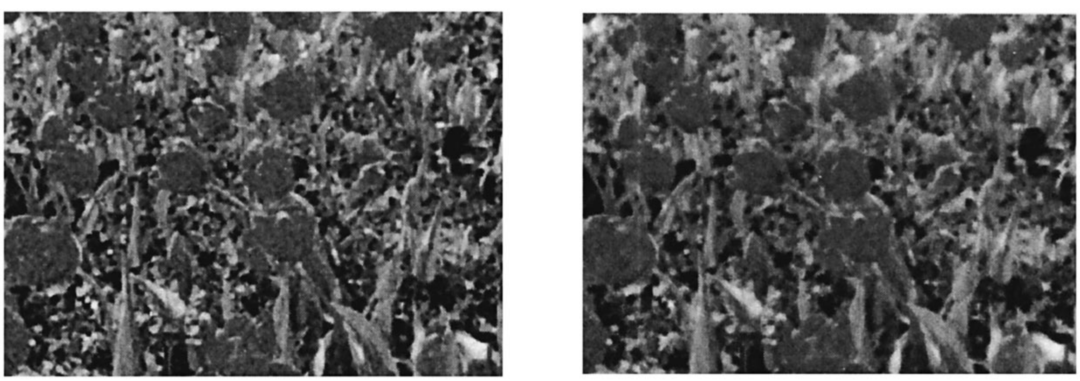
(a) (b)

Fig. 8. Image restored by (a) 3 × 3 median filter and (b) FWM filter [23].



(a) (b)

Fig. 9. Image restored by (a) 5 × 5 EPS filter and (b) 7 × 7 EPS filter [25].



(a) (b)

Fig. 10. Image restored by (a) 3 × 3 ENHANCE filter and (b) 5 × 5 ENHANCE filter [22].

The output y is calculated by

$$y = k.ave(x_i) + (1-k).\sum_{i=1}^{6} C_i\lambda_i \tag{9}$$

where

$$k = \mu_{\text{more}'}\left(\frac{\text{number of } x_i \text{ which } x_i \in \text{support}(Z)}{\text{total number of } x_i}\right). \tag{10}$$

Modification 2: Replace the min operator in (3) with the median operator. This restores the original image in just one iteration.

We will refer to this modified filter as the smoothing fuzzy control filter (SFCF). To see how the modified filter works, we consider the following experiments.

VI. Experiments with the SCFC

In this section we will show additional experiments to demonstrate the capabilities of the SFCF algorithm. We will also investigate the sensitivity of various algorithms to Gaussian and impulsive noise.

Experiment 6—Performance of the SFCF on Experiments 1 and 5: In this experiment we use the image from Experiment

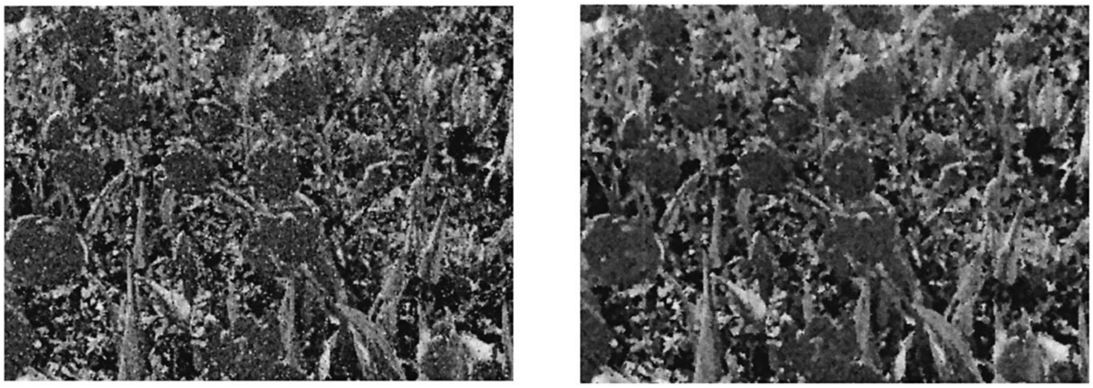


Fig. 11. Image restored by (a) FCF after one iteration and (b) FCF after four iterations.

TABLE II
RESULTS OF EXPERIMENT #5

Filter Type	MSE
median 3×3	529.1
median 5×5	907.6
FWM	427.8
EPS 5×5	460.3
EPS 7×7	488.5
ENHANCE 3×3	430.9
ENHANCE 5×5	588.0
FCF 3×3 (after 1 iteration)	734.1
FCF 3×3 (after 4 iterations)	461.1

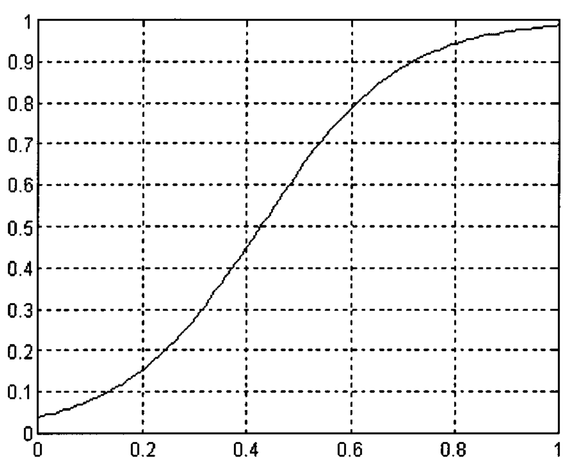


Fig. 12. A typical membership function of fuzzy function "**more**."

Fig. 13. Image restored by the SFCF.

TABLE III
PERFORMANCE OF THE SFCF ON EXPERIMENTS 1 AND 5 IMAGES

Filter Type	Experiment 1 MSEE	Experiment 5 MSE
median 3×3	610	529.1
median 5×5	1682	907.6
FWM	506	427.8
EPS 5×5	847	460.3
EPS 7×7	1053	488.5
ENHANCE 3×3	577	430.9
ENHANCE 5×5	1102	588.0
FCF 3×3 (after 1 iteration)	76	734.1
FCF 3×3 (after 4 iterations)	359	461.1
SFCF 3×3	421	359.6

5 [Fig. 7(b)] as the input to the SFCF. The result is depicted in Fig. 13.

Table III summarizes the behavior of the SFCF on the images from Experiments 1 and 5. (Recall that Experiment 1 tests edge preservation, and Experiment 5 tests noise removal.) For example, for the Experiment 5 image the MSE of the restored image is 359.6. It is clear that the SFCF restores the complex image [Fig. 7(b)] better than the other filters. The same trend is apparent for the Experiment 1 image. This justifies the modifications presented in the previous section. We have a modified filter that is capable of image enhancement for complex images.

Experiment 7—Effect of Variance-Lena Image/Gaussian Noise: In this experiment we will show how the noise variance affects the performance of the SFCF. Here again we use the Lena image corrupted by zero mean Gaussian noise with different variances ($\sigma^2 = 0, 100, 200, 300, 400$). Fig. 14, which shows the MSE of the restored images as a function of Gaussian noise variance, compares the performance of the SFCF with the performances of the FWM, EPS, and ENHANCE filters. These results show that the SFCF (modified filter) is better than the other filters for all noise levels. This is also demonstrated by Table IV, which compares the performance of the SFCF with other filters for case where $\sigma^2 = 400$.

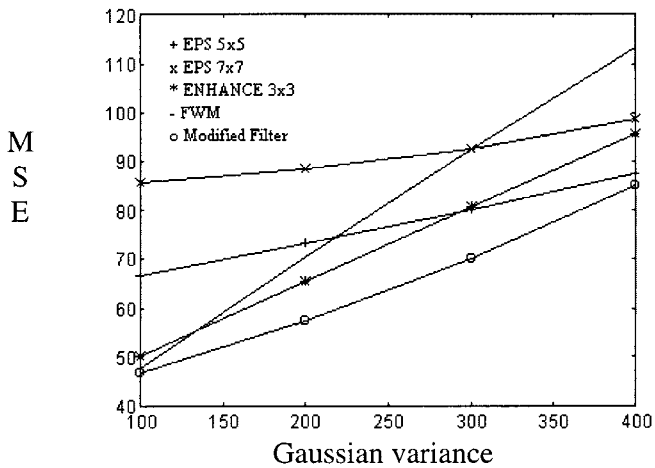


Fig. 14. MSE as a function of variance of Gaussian noise computed for the Lena image.

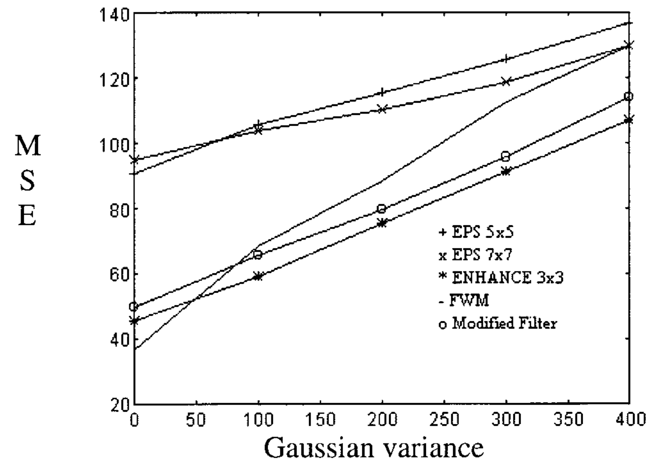


Fig. 15. MSE of restored images of different filters for the Lena image corrupted by mixed noise [Gaussian and (2.5%, 2.5%) impulsive noise].

TABLE IV
PERFORMANCE OF THE SFCF ON THE LENA IMAGE WITH GAUSSIAN NOISE ($\sigma^2 = 400$)

Filter Type	MSE
median 3×3	111.1
median 5×5	127.1
FWM	113.4
EPS 5×5	87.61
EPS 7×7	98.67
ENHANCE 3×3	96.12
ENHANCE 5×5	102.4
FCF 3×3 (after 1 iteration)	200.5
FCF 3×3 (after 4 iterations)	104.1
SFCF 3×3	85.11

TABLE V
PERFORMANCE OF THE SFCF ON THE LENA IMAGE WITH IMPULSIVE AND GAUSSIAN NOISE ($\sigma^2 = 400$)

Filter Type	MSE
median 3×3	127.9
median 5×5	134.0
FWM	130.3
EPS 5×5	136.9
EPS 7×7	129.7
ENHANCE 3×3	107.6
ENHANCE 5×5	110.8
FCF 3×3 (after 1 iteration)	541.2
FCF 3×3 (after 4 iterations)	146.4
SFCF 3×3	113.8

Experiment 8—Effect of Variance-Lena Image/Mixed Noise Case: We next test the behavior of the SFCF as the variance of Gaussian noise changes in a mixed noise environment. The Lena image is mixed with (2.5%, 2.5%) impulsive noise and used as an input to our modified filter. The results of image restoration, shown in Fig. 15, demonstrate that the SFCF also performs well in mixed noise environments.

Table V compares the performance of the SFCF with other filters for the $\sigma^2 = 400$ case. Here again, the SFCF performs very well.

Experiment 9—Effect of Variance—Fig. 7/Gaussian Noise: In this experiment we wish to show how the SFCF works for complex noisy images. Here we consider the image given in Fig. 7 corrupted by zero mean Gaussian noise with different variances ($\sigma^2 = 0, 100, 200, 300, 400$). The performance of the SFCF is shown in Fig. 16. The SFCF has better image restoration than other filters, such as FWM and ENHANCE.

Experiment 10—Effect of Variance—Fig. 7/Mixed Noise: The purpose of this experiment is to illustrate how the SFCF behaves for complex, mixed-noise images. The image in Experiment 9, mixed with (2.5%, 2.5%) impulsive noise, is used here. Fig. 17 demonstrates the results of image restoration. Here we can also see the improvements achieved by the SFCF.

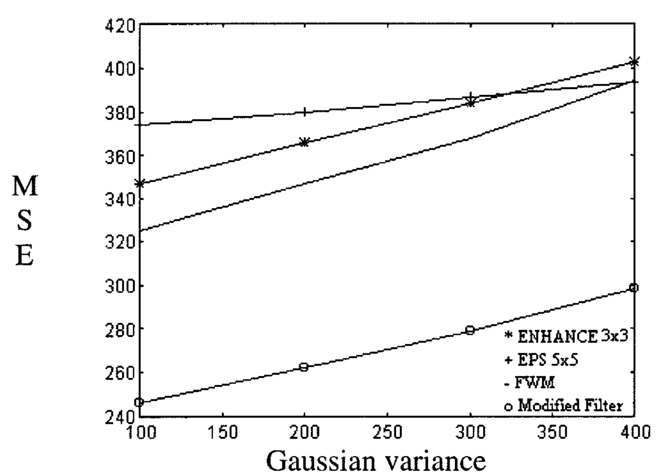


Fig. 16. MSE as a function of variance of Gaussian noise computed for Fig. 7.

Experiment 11—Speed Comparison: This last experiment with the SFCF demonstrates the computational efficiency of the algorithm. Table VI shows the computation time for various algorithms on a typical image. (All filters are implemented on a PC AT Pentium-166 with BorlandC 4.5 for Windows.) We can see that the SFCF algorithm is faster than other algorithms that have comparable image enhancement characteristics.

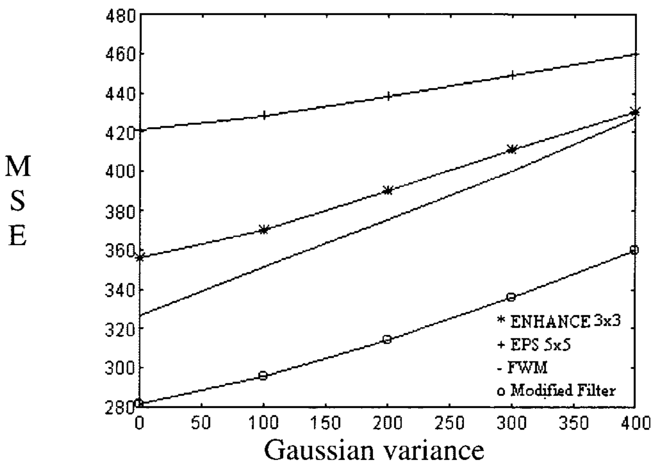


Fig. 17. MSE of restored images of different filters for Fig. 7 corrupted by mixed noise [Gaussian and (2.5%, 2.5%) impulsive noise].

TABLE VI
SPEED COMPARISON

Filter Type	Time (sec)
median 3×3	1
median 5×5	4
FWM	440
EPS 5×5	78
EPS 7×7	151
ENHANCE 3×3	30
ENHANCE 5×5	110
FCF 3×3 (after 1 iteration)	10
FCF 3×3 (after 4 iterations)	40
SFCF 3×3	15

VII. IMAGE SHARPENING

Noting that edge sharpening and noise filtering are two conflicting tasks, we now develop a set of additional fuzzy rules to produce sharper image edges without noise amplification. Using the same general structure as previous rules, we have developed the following two rules for image sharpening:

R′1: IF $(\mathbf{more}$ of x_i are $\mathbf{Z})$ AND $(\mathbf{notfew}$ of x_i are $\mathbf{A1})$
THEN y is $\mathbf{B1}$

R′2: IF $(\mathbf{more}$ of x_i are $\mathbf{Z})$ AND $(\mathbf{notfew}$ of x_i are $\mathbf{A2})$
THEN y is $\mathbf{B2}$. (11)

In the above, $\mathbf{A1}$, $\mathbf{A2}$, $\mathbf{B1}$, $\mathbf{B2}$ are the fuzzy functions shown in Fig. 18, and the fuzzy function **notfew**, shown in Fig. 19, is defined by

$$\mu_{\text{notfew}}(z) = \frac{1}{1+e^{-(\alpha_3 z - \beta 3)}}. \tag{12}$$

The activation degree of R′1 is calculated as

$$\begin{aligned}\lambda_1' = {} & \min\{\mu_{A_1}(x_i): \mu_{A_1}(x_i) > \mu_Z(x_i)\} \\ & \times \mu_{\text{more}}\left[\frac{\#\text{ of } x_i \text{ for which } \mu_Z(x_i) > \mu_{A_1}(x_i)}{\text{total number of } x_i}\right] \\ & \times \mu_{\text{notfew}}\left[\frac{\#\text{ of } x_i \text{ for which } \mu_{A_1}(x_i) > \mu_Z(x_i)}{\text{total number of } x_i}\right]\end{aligned} \tag{13}$$

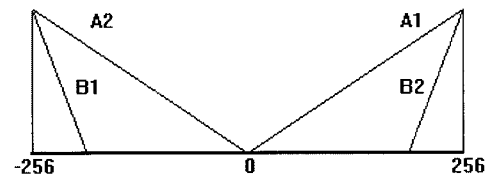


Fig. 18. Fuzzy membership functions A1, A2, B1, and B2.

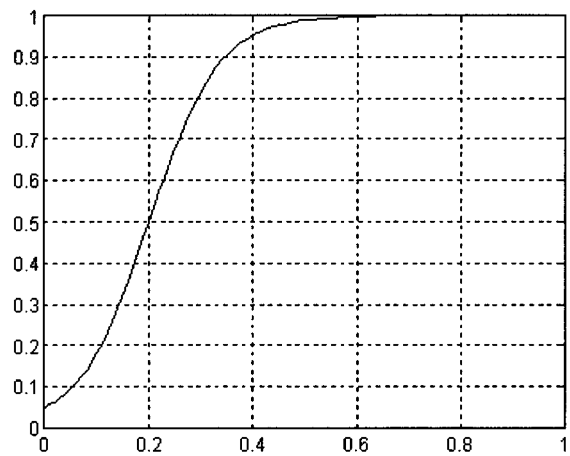


Fig. 19. Fuzzy function for **notfew**.

and the output y is computed by

$$y = k.ave(x_i) + (1-k).\left(\sum_{i=1}^{6} C_i\lambda_i + \text{SC}.\sum_{i=1}^{2} CB_i\lambda_i'\right) \tag{14}$$

where CB_i is the central point of B_i and SC represents the sharpening coefficient.

The rules R′1 and R′2 are designed so that they are fired only in edge regions (the regions consisting of two or more different areas). This ensures that only the edges become sharper. We will identify this modified filter as the sharpening and smoothing fuzz control filter (SSFCF).

VIII. EXPERIMENTS WITH THE SSFCF

In order to demonstrate the behavior of the SSFCF, we consider the image given in Fig. 20(a). This figure represents a test image contaminated by Gaussian noise with $\mu = 0$ and $\sigma^2 = 100$. The results of image restorations with the SSFCF (for two different sharpening coefficients) are shown in Fig. 20(c) and (d). As we can observe from these figures, the sharpening ability of the SSFCF is remarkable. To provide a basis for comparison, we also applied the method given in [19] to the test image shown in Fig. 20(a). The resulting processed image is shown in Fig. 20(b).

In order to quantify the performances of the SSFCF, we computed the local variances in background (BV) and in detailed (DV) areas of the image as defined in [33]. These values for Fig. 20 are listed in Table VIII. Noting that smaller values for BV indicate less noise amplification while larger values for DV imply higher sharpening, we can see in Table VII that SSFCF performance is remarkably high. For example, the SSFCF with

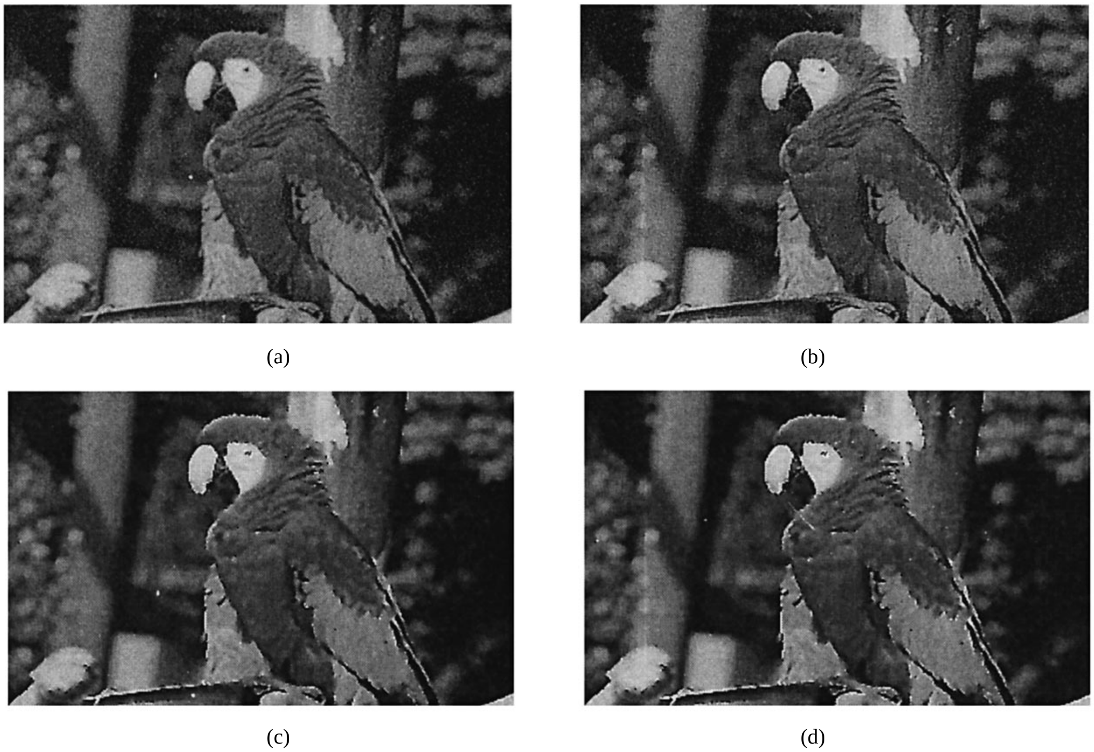


Fig. 20. (a) Test image contaminated by Gaussian noise with $\mu = 0, \sigma^2 = 100$; (b) the result of method in [19]; and (c), (d) the results of the SSFCF with SC $= 1$ and SC $= 2$, respectively.

TABLE VII
PERFORMANCE ON THE IMAGE IN FIG. 20(a)

Image	BV	DV
Original Noisy Image	143	1146
Processed with Filter Proposed in [19]	203	2307
Processed with SSFCF with SC=1	48	2670
Processed with SSFCF with SC=2	61	3621

TABLE VIII
PERFORMANCE ON THE LENA IMAGE

Image	BV	DV
Original Noisy Image	99	1002
Processed with FIRE enhancement in [19]	129	2075
Processed with unsharp masking in [34]	504	2484
Processed with FIRE enhancement (II) in [19]	146	2515
Processed with SSFCF with SC=2	53	3171
Processed with SSFCF with SC=1	42	2332

SC $= 1$ gives little noise magnification (BV value of 48, which is smaller than that of the original noisy image) and a much higher sharpening in the detailed areas (with DV of 2670).

To further test the SSFCF, we consider again the Lena image contaminated by Gaussian noise with $\mu = 0$ and $\sigma^2 = 50$. For this image, Table VIII lists the BV and DV values for the SSFCF and for the methods presented in [19] and [34]. Table VIII confirms the results presented in Table VII. In short, for noisy images the SSFCF performs much better than the methods given in [19] and [34], with less noise amplification and significant sharpening of details.

IX. CONCLUSION

In this paper we presented three new filtering methods based on the use of fuzzy logic control. The goal of the filtering process was to simultaneously satisfy the three tasks of image enhancement: edge preservation, impulsive noise removal, and smoothing of nonimpulsive noise. The first proposed filter (the FCF) was only successful in performing the first two tasks. It was modified (the SFCF) to improve its ability to smooth Gaussian noise. We then performed several different experiments to demonstrate its effectiveness. The performance of the SFCF on several different types of images was compared with the performance of a number of well-known filters. These comparisons demonstrate that

1) Computation time for the SFCF is less than that for other filters.
2) When compared with other methods, the SFCF has excellent performance on edge preservation.
3) SFCF is capable of image restoration in noisy environments.

Finally, we suggested a modification to the SFCF (termed the SSFCF) to sharpen image edges without noise magnification. Several experiments demonstrated the improved image sharpening of the SSFCF.

REFERENCES

[1] I. Pitas and A. N. Venetsanopoulos, *Nonlinear Digital Filters: Principles and Applications*. Norwell, MA: Kluwer, 1990.
[2] R. M. Haralick and L. G. Shapiro, *Computer and Robot Vision*. Reading, MA: Addison-Wesley, 1992, vol. 1.
[3] G. A. Mastin, "Adaptive filters for digital image noise smoothing: An evaluation," *Comput. Vis., Graph, Image Process*, vol. 31, pp. 103–121, 1985.
[4] B. Kosko, *Neural Networks and Fuzzy Systems*. Englewood Cliffs, NJ: Prentice-Hall, 1992.
[5] J. C. Bezdeck and S. K. Pal, Eds., *Fuzzy Models for Pattern Recognition*, New York: IEEE Press, 1992.
[6] S. K. Pal, "Fuzzy sets in image processing and recognition," in *Proc. 1st IEEE Int. Conf. Fuzzy System*, 1992, pp. 119–126.
[7] R. Krishnapuram and M. Keller, "Fuzzy sets theoretic approach to computer vision: An overview," in *Proc. 1st IEEE Int. Conf. Fuzzy Systems*, 1992, pp. 135–142.
[8] J. S. Kim and H. S. Cho, "A fuzzy logic and neural network approach to boundary detection for noisy imagery," *Fuzzy Sets Syst.*, vol. 65, pp. 141–159, Aug. 1994.
[9] F. Russo and G. Ramponi, "Edge detection by FIRE operators," in *Proc. 3rd IEEE Int. Conf. Fuzzy System*, 1994, pp. 249–253.
[10] ——, "Combined FIRE filters for image enhancement," in *Proc. 3rd IEEE Int. Conf. Fuzzy Systems*, 1994, pp. 261–264.
[11] M. Mancuso, R. Poluzzi, and G. Rizzotto, "A fuzzy filter for dynamic range reduction and contrast enhancement," in *Proc. 3rd IEEE Int. Conf. Fuzzy Systems*, 1994, pp. 264a–267.
[12] K. Arakawa, "Digital signal processing based on fuzzy rules," in *Proc. 5th IFSA World Congr.*, 1994, pp. 1305–1308.
[13] B. T. Chen, Y. Chen, and W. Hsu, "Image processing and understanding based on the fuzzy inference approach," in *Proc. 3rd IEEE Int. Conf. Fuzzy Systems*, 1994, pp. 279–283.
[14] X. Yang and P. S. Toh, "Adaptive fuzzy multilevel median filter," *IEEE Trans. Image Processing*, vol. 4, pp. 680–682, May 1995.
[15] F. Russo and G. Ramponi, "Fuzzy operator for sharpening of noisy images," *IEEE Electron Lett.*, vol. 28, pp. 1715–1717, Aug. 1992.
[16] F. Russo, "A user-friendly research tool for image processing with fuzzy rules," in *Proc. 1st IEEE Int. Conf. Fuzzy Systems*, 1992, pp. 561–568.
[17] F. Russo and G. Ramponi, "Nonlinear fuzzy operators for image processing," *Signal Processing*, vol. 38, pp. 429–440, Aug. 1994.
[18] ——, "A noise smoother using cascaded FIRE filters," in *Proc. 4th IEEE Int. Conf. Fuzzy System*, vol. 1, 1995, pp. 351–358.
[19] ——, "An image enhancement technique based on the FIRE operator," in *Proc. 2nd IEEE Int. Conf. Image Processing*, vol. 1, 1995, pp. 155–158.
[20] ——, "Removal of impulsive noise using a FIRE filter," in *Proc. 3rd IEEE Int. Conf. Image Processing*, vol. 2, 1996, pp. 975–978.
[21] ——, "A fuzzy filter for images corrupted by impulse noise," in *IEEE Signal Processing Lett.*, vol. 3, 1996, pp. 168–170.
[22] Y. Choi and R. Krishnapuram, "A robust approach to image enhancement based on fuzzy logic," *IEEE Trans. Image Processing*, vol. 6, no. 6, pp. 808–825, June 1997.
[23] A. Taguchi, "A design method of fuzzy weighted median filters," in *Proc. 3rd IEEE Int. Conf. Image Processing*, vol. 1, 1996, pp. 423–426.
[24] P. T. Yu and R. C. Chen, "Fuzzy stack filters—Their definitions, fundamental properties, and application in image processing," *IEEE Trans. Image Processing*, vol. 5, pp. 838–854, June 1996.
[25] M. Muneyasu, Y. Wada, and T. Hinamoto, "Edge-preserving smoothing by adaptive nonlinear filters based on fuzzy control laws," in *Proc. 3rd IEEE Int. Conf. Image Processing*, vol. 1, 1996, pp. 785–788.
[26] R. Sucher, "A self-organizing nonlinear filter based on fuzzy clustering," *IEEE Int. Symp. Circuits Systems, ISCAS'96*, vol. 2, pp. 101–103, 1996.
[27] M. Doroodchi and A. M. Reza, "Fuzzy cluster filter," in *Proc. 3rd IEEE Int. Conf. Image Processing*, vol. 2, 1996, pp. 939–942.
[28] ——, "Implementation of fuzzy cluster filter for nonlinear signal and image processing," in *Proc. 3rd IEEE Int. Conf. Image Processing*, vol. 3, 1996, pp. 2117–2122.
[29] J. H. Wang and M. D. Yu, "Image restoration by adaptive fuzzy optimal filter," in *Proc. 1995 IEEE Int. Conf. Systems, Man, Cybernetics, Intelligent Systems 21st Century*, vol. 1, 1995, pp. 845–848.
[30] C. L. Chen, C. S. Lee, and Y. H. Kuo, "Design of high speed weighted fuzzy mean filters with generic LR fuzzy cells," in *Proc. 3rd IEEE Int. Conf. Image Processing*, vol. 2, 1996, pp. 1027–1030.
[31] C. S. Lee, Y. H. Kuo, and P. T. Yu, "Weighted fuzzy mean filters for heavy-tailed noise removal," in *Proc. 3rd Int. Symp. Uncertainty Modeling Analysis Annual Conference North American Fuzzy Information Processing Society*, 1995, pp. 601–606.
[32] S. Peng and L. Lucke, "A hybrid filter for image enhancement," in *Proc. 2nd IEEE Int. Conf. Image Processing*, vol. 1, 1995, pp. 163–166.
[33] A. Vanzo, G. Ramponi, and G. L. Sicuranza, "An image enhancement technique using polynomial filters," in *Proc. 1st IEEE Int. Conf. Image Processing ICIP'94*, 1994, pp. 477–481.
[34] A. K. Jain, *Fundamentals of Digital Image Processing*. New York: Prentice-Hall, 1989.

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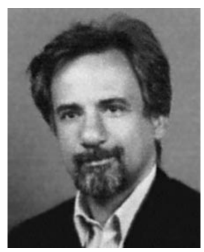

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