RESEARCH NOTE

A NEW ITERATIVEFUZZY-BASED METHOD FOR IMAGE ENHANCEMENT

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(Received: Feb. 13, 1998 - Accepted in Final Form: January 2, 2000)

Abstract This paper presents a new filtering approach based on fuzzy-logic which has high performance in mixed noise environments. This filter is mainly based on the idea that each pixel is not allowed to be uniformly fired by each of the fuzzy rules. In the proposed filtering algorithm, the rule membership functions are tuned iteratively in order to preserve the image edges. Sveral test experiments were performed in oreder to hlight the merit of the proposed method. The results are very promising and indicating the high performance of the proposed filter in image restoration compared with those of the filters which have been recently cited in the image processing literature.

Key Words Image Filtering, Fuzzy Logic, Image Enhancement

چکیده در این مقاله روش جدیدی برای فیلترسازی تصویر مبتنی بر منطق فازی برای حذف (و یا کاهش) نویزهای گوسی و ایمپالسی معرفی شده است. ایده اصلی در این فیلتر آنست که قوانین فازی بطور یکسان بر روی نقاط تصویر فعال نگردند. فیلتر طراحی شده بصورت تکراری به تصویر اعمال می گردد و به منظور حفظ لبه های تصویر در هر تکرار شکل توابع عضویت تغییر می کند. عماکرد بالای این فیلتر در کاهش نویز در مقایسه با آلگوریتمهای دیگر فیلترسازی تصویر با آزمایشات مختلف آورده شده قابل اثبات می باشد.

INTRODUCTION

As an important task in image enhancement, noise filtering can be viewed as replacing the gray-level value of each 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 is worth being determined by averaging neighboring pixels values. On the other hand, if the local region contains edge 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 performing reasoning with vague and uncertain information; this is a clear justification for fuzzy logic common usage [1-3].

In this paper, we propose a new filter, based on fuzzy logic control [4], which can efficiently restore images in the mixed noise environments (i.e. impulsive and Gaussian noise). The filter is mainly based on the idea that each pixel is not allowed to be uniformly fired by each of the fuzzy rules. In the proposed filtering algorithm, the rule membership functions are tuned iteratively in order to preserve the image edges.

THE PROPOSED METHOD (IFF)

This section presents the architecture of our proposed rule-based image processing system acronymed by Iterative Fuzzy Filter , IFF. In this system, we adopt the general structure of fuzzy if-then-else rule mechanism originally proposed by Russo in his papers [5-13]. In contrast to Russo's technique, our approach is mainly based on the idea of not letting each point in the area of concern being uniformly fired by each of the basic fuzzy rules. This idea is widely used in fuzzy control applications [4]. To furnish this goal, the following fuzzy rules and membership functions given in Figure 1 are proposed for image filtering:

R1:IF (**more** of x_i are **NB**) THEN y is **NB**
R2:IF (**more** of x_i are **NM**) THEN y is **NM**
R3:IF (**more** of x_i are **NS**) THEN y is **NS**
R4:IF (**more** of x_i are **PS**) THEN y is **PS**
R5:IF (**more** of x_i are **PM**) THEN y is **PM**
R6:IF (**more** of x_i are **PB**) THEN y is **PB**
R0:ELSE y is **Z** (1)

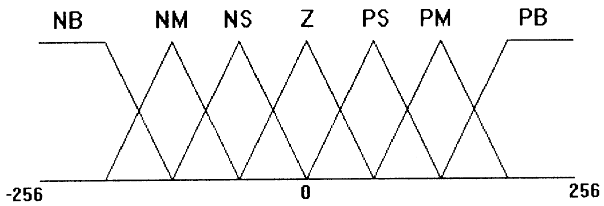

Figure 1. Membership functions.

Where NB,NM,NS,PS,PM,PB,Z are fuzzy functions in which N stands for negative, P for positive, B for big, M for medium, S for small and Z for zero as depicted in Figure 1.

In the above, x_i's are the luminance differences between neighboring pixels, P_i (located in a window of size NxN), 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 S-type fuzzy function and may be described by the following formula:

$$\mu_{more}(z) = \begin{cases} 0 & z \le a \\ .5\left\{1 - \cos\left[\dfrac{\pi(z-a)}{b-a}\right]\right\} & a < z < b \\ 1 & z \ge b \end{cases} \quad (2)$$

Where the range of parameters a and b are depended to the variable z and desired considerations.

The rule degree's activity calculation

The activity degree of R1 , λ_1, is computed by the following relationship (the other if-then rules degree of activities are computed similarly)

$$\lambda_1 = \min\{\mu_{NB}(x_i) : \mu_{NB}(x_i) > 0\} \times \mu_{more}\left[\frac{\text{number of } x_i \text{ which } \mu_{NB}(x_i) > 0}{\text{total number of } x_i}\right] \quad (3)$$

and for the ELSE rule, R0, we may apply the following formula to evaluate the degree of activation:

$$\lambda_0 = Max\{0, 1 - \sum_{i=1}^{6} \lambda_i\} \quad (4)$$

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

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

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

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

$$y = \sum_{i=1}^{6} C_i \lambda_i \quad (6)$$

EXPERIMENTAL RESULTS

Experiment 1: In order to demonstrate the performance of the filter in a Gaussian noise environment, we consider the Lena image as a case study. This image is first contaminated by Gaussian noise with zero mean and variance 400. Then, it is applied to the proposed filter. The result of filtering process is depicted in Figure 2, labeled (b). We can easily observe from this figure that as the number of iterations increases, a better image restoration in the sense of Mean Square Error (MSE) is obtained. To show the performance of the filter in the mixed noise case, we take the image considered in this experiment, added by [%2.5, %2.5] impulsive noise. The result is also shown in Figure 3; in this case the plot is labeled by (a). From these two results, cases of Gaussian noise and mixed noise, we may conclude that the proposed filter has good ability in image restoration as the number of iteration increases.

Experiment 2: The aim of this experiment was to show how the noise variance affects performance of the proposed filter. Here again we use the Lena image corrupted by zero mean Gaussian noise with different variances ($\sigma^2 = 100, 200, 300, 400$).

Figure 3, which shows the MSE of the restored images as a function of the variance of Gaussian noise, compares the performance of the proposed filter with that of the Fuzzy Weighted Median, FWM, (proposed in [14]) & Edge Preserving Smoothing, EPS, (proposed in [15]) with two window size 5×5 and 7×7 filters. These results are encouraging and indicate the satisfactory performance of our proposed method.

Experiment 3: This experiment aims to show how the proposed filter would behave as the variance of Gaussian noise changes in a mixed noisy environment. The image in experiment 2 is mixed by [%2.5, %2.5] impulsive noise and used as an input to our proposed filter. The results in image restoration shown in Figure 4 demonstrate that the proposed filter in mixed noise has the best performance among the filters listed in Table 1.

Experiment 4: To show the performance of the proposed method in a mixed noisy environment, we consider the image given in Figure 8(b) which is actually the image given in Figure 8(a) corrupted by Gaussian noise with $\mu=0$, $\sigma^2=400$ and [%2.5, %2.5] impulsive noise. The result of our method and those of the other filters listed in Table 1, are depicted in Figures 8(c)-(h). The behaviors of these filters in the sense of MSE are reported in Table 1, column 3. From this Table, it can be easily observed that the proposed method compared with the other methods given in Table 1 works much better in a mixed noisy environment.

THE MODIFIED IFF (MIFF)

Unfortunately, as observed from several test experiments, in each iteration the output image edges get a little blurred. Therefore, increasing the iteration numbers makes the image more unsharp. Especially for low noise cases, this makes the image, after a few iterations, become more degraded instead of getting enhanced. To resolve this problem, in each step we tune the **more** function in a way that it becomes sharper at the boundaries as shown in Figure 5. The reason behind this is the filter has been enforce to become more active when as needed. On the other hand, the goal was to make the filter become less active on those areas in which the parts of image is not needed more changes.

By sharpening the shape of **more** function in each iteration, as shown in Figure 5, its range of activity becomes less; this makes the rules R1-R6 fire only in those regions in which they have higher possibility of firing. Thus, after a few iterations the rules are not activated for most image pixels. This feature allows us to rise the number of iterations without having any edge blurring problem. By referring to the previous section, we may enhance the filtering property of the proposed filter by inceasing the number of itertions without losing edge information.

This modification can also be employed as a stopping criterion for our algorithm which is explained as follows. When the number of pixels, for which at least one of the rules R1-R6 is activated, becomes less than a certain threshold value (which can be set to a low percent of the total pixels in the image), there is no use of running more iterations to have better image enhancement. Consequently, it is worth terminating the algorithm at this moment.

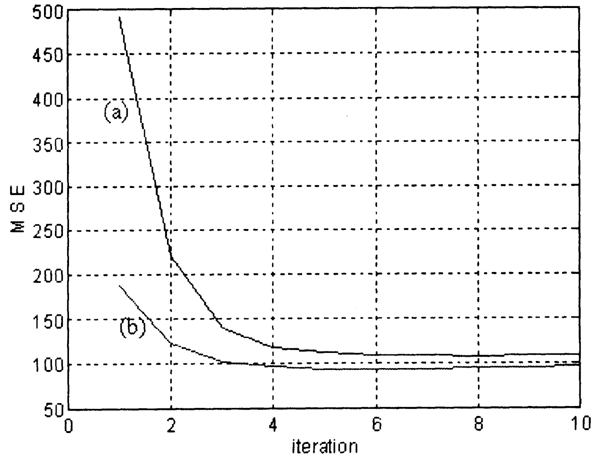

Figure 2. Performance of the proposed filter on 256x256 Lena image contaminated by Gaussian noise with var=400 and a) [%2.5, %2.5] impulsive noise; b) without impulsive noise.

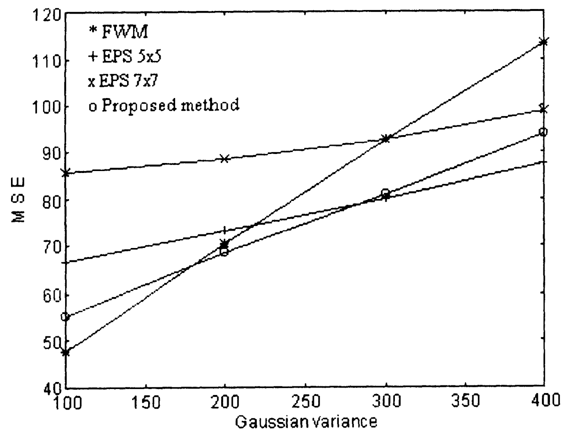

Figure 3. MSE as a function of variance of Gaussian noise computed for the Lena image.

The comparison of the proposed and modified filters are depicted in Figures 6-8 and Table 1. Figures 6 and 7 show the better performance of the modified filter especially in low noise cases. We can further observe that the modified filter outperforms in edge preserving by comparing Figures 8(h) & 8(i).

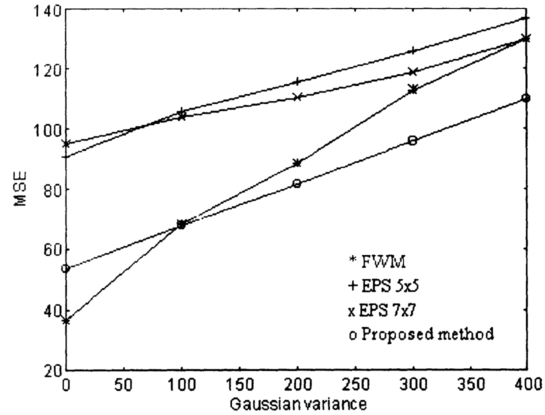

Figure 4. MSE of restored images of different filters for the Lena image corrupted by mixed noise (Gaussian and [%2.5, %2.5] impulsive noise).

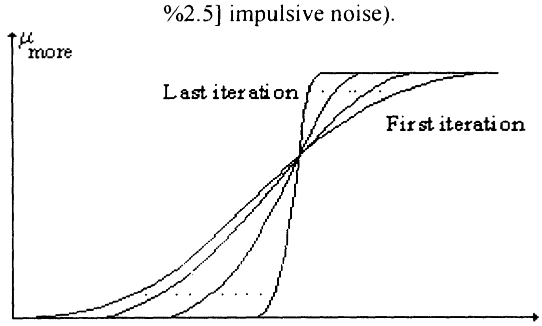

Figure 5. Different shapes of more function.

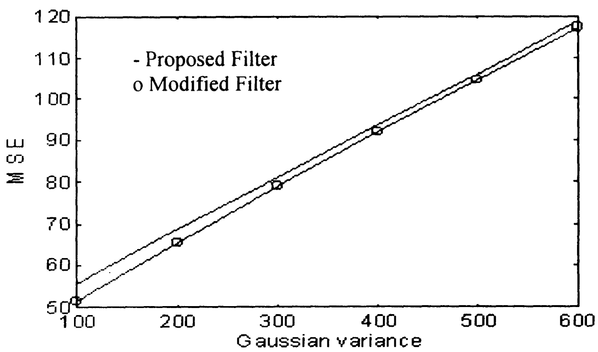

Figure 6. MSE as a function of variance of Gaussian noise computed for the Lena image for IFF and MIFF filters with 3x3 window size.

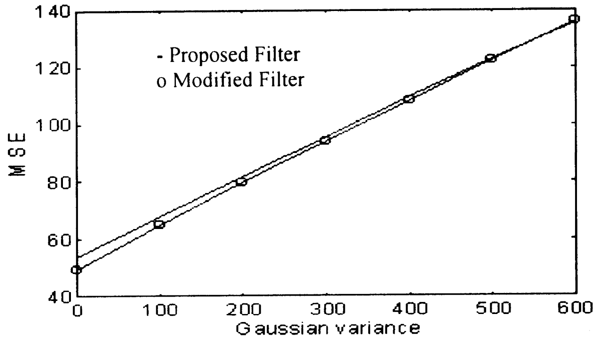

Figure 7. MSE of restored images of IFF and MIFF filters with 3x3 window size for the Lena image corrupted by mixed noise (Gaussian and [%2.5, %2.5] impulsive noise).

TABLE 1. The Behaviors of Filters in the Sense of MSE for Different Images.

	Image 1	*Image 2*	*Image 3*
Median 3×3	127.9	115.7	111.1
Median 5×5	134	122.5	127.1
FWM	130.3	108.3	113.4
EPS 5×5	136.9	119.5	87.61
EPS 7×7	129.7	109.3	98.67
IFF 3x3 (after 1 iteration)	491.6	450.8	187.8
IFF 3x3 (after 6 iterations)	109.8	101.4	93.61
MIFF 3x3 (after 10 iterations)	108.4	97.52	92.17

Image 1: The Lena image with 256 gray levels which is contaminated by [%2.5, %2.5] impulsive noise and Gaussian noise with $\mu=0$, $\sigma^2=400$.
Image 2: Figure 8(b).
Image 3: The Lena image which is contaminated by Gaussian noise with $\mu=0$, $\sigma^2=400$.

CONCLUSION

In this paper we presented a new iterative filtering method based on fuzzy logic control, called IFF, to image enhancement. To make the filter more efficient, the modified IFF, acronymed by MIFF, is then introducd. In this technique, we tune the rule membership functions in each iteration in order to have better edge preserving property. We performed several different experiments in order to demonstrate the effectiveness of the proposed filtering approach. The results of the proposed filter were compared with those filters listed in Table 1. From this Table and Figures 2-8, it can be concluded that the proposed filters possess high capability of image restoration in noisy environments.

NOMENCLATURE

MSE	Mean Squar Error
min	minimum
NB	Negative Big
NM	Negative Medium
NS	Negative Small
PB	Positive Big
PM	Positive Medium
PS	Positive Small
Z	Zero
Ci	Central point of the membership function for the ith rule
Wi	Width of the membership function for the ith rule
λ_i	Activation degree of the ith rule
$\mu_\alpha(.)$	Membership function of fuzzy set α
IFF	Iterative Fuzzy Filter
MIFF	Modified Iterative Fuzzy Filter

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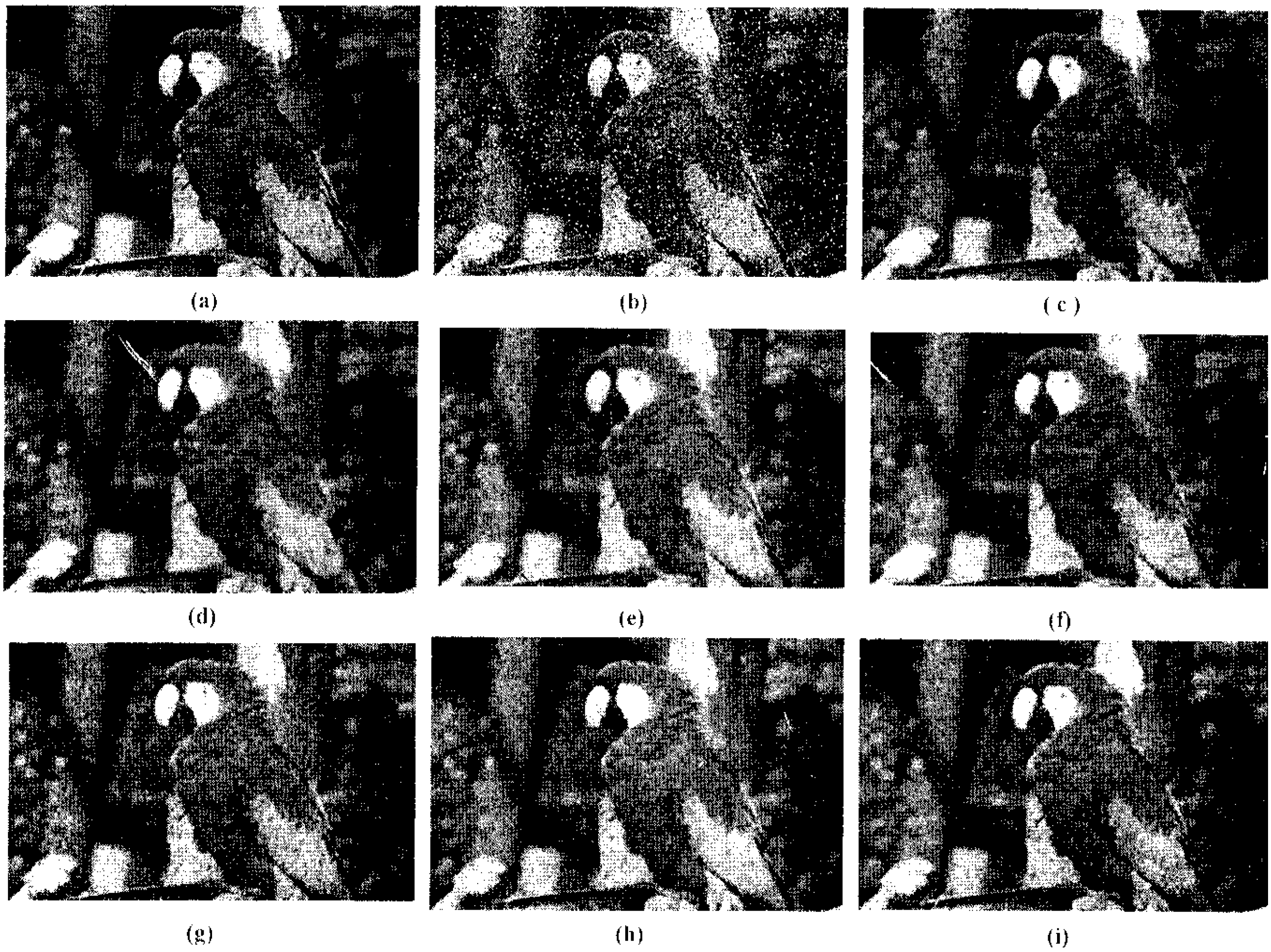

Figure 8. a) A 320x200 test image with 256 gray levels; b) the image corrupted by Gaussian noise with $\mu = 0$, $\sigma^2 = 400$ and [%2.5, %2.5] impulsive noise; c) restored by median 3x3; d) restored by median 5x5; e) restored by EPS 5x5; f) restored by EPS 7x7; g) restored by FWM; h) restored by the proposed IFF filter after six iterations; i) restored by the MIFF filter after ten iterations.