Fuzzy Multipass Filter for Impulse Noise Removal in Digital Images

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Abstract: This paper presents a fuzzy multipass filter that effectively removes impulse noise in digital images. The proposed fuzzy inference mechanism is partly based on the well-known Fuzzy Inference Ruled by Else-action (FIRE) reasoning strategy, coupled with a newly introduced pseudo fuzzy rulebase that is represented by a set of simple logical operations. The FIRE mechanism is adopted to perform strong noise cancellation when impulses are detected, whereas the pseudo fuzzy rulebase conveniently simplifies the complicated computation and evaluation of a complex-structured rulebase in fuzzy filtering. Additionally, the proposed filter uses two inter-related fuzzy membership functions to increase its adaptiveness towards local noise statistics, which in turn has improved its restoration performance. Simulation results demonstrate the effectiveness and feasibility of the proposed fuzzy multipass filter.

Key–Words: Impulse noise, pseudo fuzzy rulebase, fuzzy filter, nonlinear filter, image denoising, image restoration

1 Introduction

Visual information from digital images plays a pivotal role in image processing as multimedia become more widespread from day to day with the advancement in computing. Unfortunately, digital images are subjected to the contamination of noise during image acquisition, transmission, storage, and/or retrieval [1]. One of the common types of noise is the impulse noise. This kind of noise affects many image processing applications and has been widely addressed in literature. The main problem of impulse noise is the alteration of pixel gray values so that they no longer exhibit a luminance compatibility with the local neighboring pixels. Such changes in pixels intensities significantly degrade the visual quality of the digital image.

In the last few years, impulse noise filters have been developed using various approaches, leading to a varied collection of methods in the literature [2]−[7]. Generally, a good impulse noise filter is characterized by its capability to distinguish between useful information (e.g., image details, edges, and textures) and the unwanted noise in order to preserve the fidelity of image data [8]. In other words, an effective filter should possess filtering strategy that could mimic human decision-making to accurately classify noise and noise-free pixels. Such a filter can be designed by applying a branch of artificial intelligence theories, called the fuzzy logic, to its filtering mechanism. Over the last decade, fuzzy logic has successfully entered many application domains in science and engineering, projecting itself as a competitive alternative over classical methods, particularly in the field of image noise reduction [9]−[12].

In this paper, we propose a novel filter for impulse noise removal, called the fuzzy multipass (FM) filter, that is capable to perform detail-preserving impulse noise smoothing. In the next section, we provide a detailed discussion on the fuzzy multipass filter. The characteristics of the two inter-related fuzzy sets adopted are explained in detail, and the concept of pseudo fuzzy rulebase is introduced. Moreover, an appropriate correction estimate is also formulated by evaluating the pseudo fuzzy rulebase. Simulation results by the proposed filter are presented and compared to those of some existing filters in Section 3. Finally, we conclude this work in Section 4.

2 The Fuzzy Multipass Filter

The FM filter performs impulse denoising by raster-scanning the noisy image with a 3×3 search window as shown in Fig. 1. Each element in the search window is treated as a fuzzy input variable that is defined by:

$$\widehat{w_x} \;=\; w_x - w_c \;:\; x = 1, 2, 3, \ldots, 8, \quad (1)$$

w_1	w_2	w_3
w_4	w_c	w_5
w_6	w_7	w_8

Figure 1: The 3×3 search window.

where w_c is the center reference pixel in the search window, w_x is the neighboring pixels of w_c, $\widehat{w_x}$ is the relative gradient value between w_x and w_c, and x is the index number for the neighboring pixels in the 3×3 search window. For a grayscale digital image with L gray levels, this search window will be applied recursively on the noisy image.

2.1 The Choice of Fuzzy Sets

The fuzzy input variables w_x and $\widehat{w_x}$ are used in the fuzzification process, whereby the first fuzzy set *average* $\mu_A(w_x)$ takes on the neighboring pixels w_x. This trapezoid-shaped fuzzy set is controlled by two predefined parameters a_1 and a_2 [10], as shown in Fig. 2. It is mathematically defined by (2) to (7):

$$\mu_A(w_x) = \begin{cases} \frac{w_x}{a_1-a_2} + C_1 & : \quad 0.0 \le w_x < W_1, \\ 1.0 & : \quad W_1 \le w_x < W_2, \\ \frac{-w_x}{a_1-a_2} + C_2 & : \quad W_2 \le w_x < W_{max}, \\ 0.0 & : \quad \text{otherwise}, \end{cases} \tag{2}$$

where:

$$W_{max} = L - 1, \tag{3}$$

$$W_1 = 0.5W_{max} - a_2, \tag{4}$$

$$W_2 = 0.5W_{max} + a_2, \tag{5}$$

$$C_1 = \frac{a_1 - 0.5W_{max}}{a_1 - a_2}, \tag{6}$$

$$C_2 = \frac{a_1 + 0.5W_{max}}{a_1 - a_2}. \tag{7}$$

The fuzzy set *average* is used to deal with long-tailed impulse noise for pixel intensity in the medium range (i.e., 20 to 150). Any pixel in this range that is affected by impulsive intensities will be smoothed by this fuzzy set.

The ability to suppress impulses are further improved by the inclusion of a second fuzzy set *high*

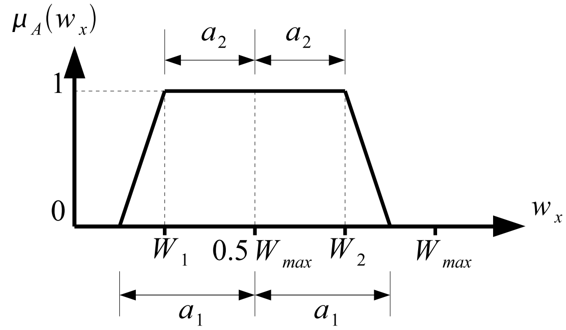


Figure 2: The fuzzy set *average*.

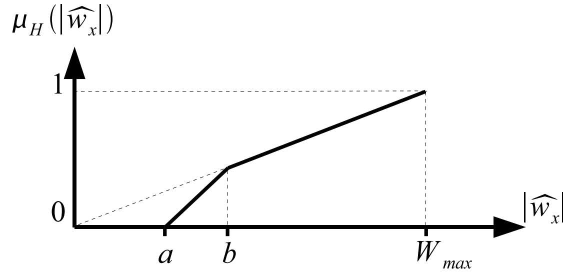


Figure 3: The fuzzy set *high*.

$\mu_H(|\widehat{w_x}|)$. This fuzzy set is shown in Fig. 3, and it is related to the first fuzzy set *average* through the relation

$$a = b \times \mu_A(w_x), \tag{8}$$

where a and b define the shape of the second fuzzy set *high*.

The fuzzy set *high* helps to exhibit good characterization in fine image details preservation. Implicitly, it is controlled by the first fuzzy set *average* according to (8). Mathematically, the fuzzy set *high* is defined by

$$\mu_H(|\widehat{w_x}|) = \begin{cases} 0.0 & : \quad 0.0 \le |\widehat{w_x}| < a, \\ \frac{b(|\widehat{w_x}|-a)}{W_{max}(b-a)} & : \quad a \le |\widehat{w_x}| < b, \\ \frac{|\widehat{w_x}|}{W_{max}} & : \quad b \le |\widehat{w_x}| \le W_{max}. \end{cases} \tag{9}$$

Interpreting (9), the center reference pixel w_c is retained if its relative gradient $\widehat{w_x}$ falls within the range $0 \le |\widehat{w_x}| < a$ because the intensity difference between w_x and w_c is small. Such action avoids disturbing fine details in the image. In an attempt to further cultivate the detail-preserving characteristic of the FM filter, the parameter a is adaptively varied according to the local image contents. Then, within the range $b \le |\widehat{w_x}| \le W_{max}$, a higher membership value is assigned to neighboring pixel when the relative gradient $\widehat{w_x}$ is large, which signals the likely presence of

ISBN: 978-1-61804-081-7

impulsive pixel in the neighborhood and, therefore, a strong cancellation is required.

Note that the input variable for the fuzzy set *high* is the absolute of the relative gradient $|\widehat{w_x}|$. For an image with intensities that fall in the dynamic range $[0, L-1]$, $\widehat{w_x}$ varies within the range $[-L+1, L-1]$. However, only the absolute value is considered in the fuzzification process as the proposed fuzzy rulebase structure is capable of handling the symmetrical requirement to address positive and negative impulses. Here, positive impulse appears when the center reference pixel w_c is brighter than its neighboring pixels w_x. On the other hand, a negative impulse is produced when w_c is darker than w_x.

2.2 The Pseudo Fuzzy `IF-THEN-ELSE` Rulebase Structure

Based on the original idea introduced by Zadeh [13], a new approach to capture human knowledge with fuzzy rules is outlined by Negnevitsky in [14]. The most basic form of fuzzy rule is the `IF-THEN` conditional statements:

`IF` *antecedent clause* is . . .
`THEN` *consequent clause* is . . .

where the antecedent clause is the condition to be evaluated, and the consequent clause is the action taken if the condition of the antecedent clause is met. In many cases, as is shown in [9]−[11], the flexibility provided by fuzzy reasoning can be expanded by incorporating the `ELSE` statement into the fuzzy rule in the form

`IF` *input* is . . .
`THEN` *output* is . . .
`ELSE` *output* is . . .

where the consequent clause of the `ELSE` statement is an additional action that caters for a more robust outcome in the decision-making process.

In this paper, the rulebase is constructed as a set of symmetrical fuzzy rules. It consists of a series of rules that is capable in handling positive and negative impulses. These fuzzy rules are represented by a set of pseudo fuzzy rulebase, which is a newly introduced rulebase structure using logical operations. The importance of the pseudo fuzzy rulebase is largely in simplifying the tedious process in evaluating complex-structured fuzzy rulebase, which is a common problem for many fuzzy filters particularly the class of FIRE filters [9]−[11]. In this framework, instead of using the conventional `IF-THEN-ELSE`

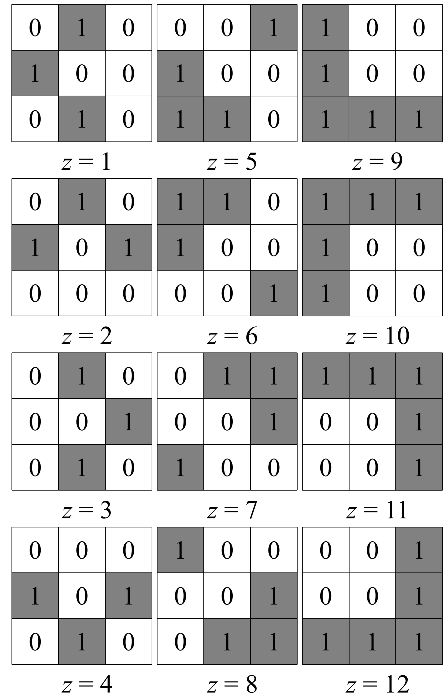


Figure 4: The 3×3 binary windows representing the pseudo fuzzy rulebase.

fuzzy structure to "fire" a rule, logical (Boolean) operations are used to keep track on the execution of any rule.[1] These pseudo rules are indexed by the set z ($z = 1, 2, 3, \ldots, 12$), in which each z represents a pattern in the 3×3 binary window, as shown in Fig. 4.

The patterns represented by binary 1's in the z binary windows are determined heuristically, and each "1" represents an antecedent clause for evaluating the noisy image. These patterns take into consideration the possibilies of textural orientations that might contain in a 3×3 search window. The presence of impulsive pixel will interrupt the patterns, and thus, it can be detected and removed. Moving forward, the logical operations that evaluate the pseudo fuzzy rulebase is formulated.

2.3 The Fuzzy Inference Mechanism

Once the fuzzification process with the aid of the pseudo fuzzy rulebase in Fig. 4 is completed, the fuzzy inference mechanism will determine an estimate to correct the noise pixel. The decision whether the center reference pixel requires a correction fully

[1]The word "pseudo" is used to describe the fact that fuzzy rules are represented and evaluated by logical operations, which involve either logic "0" or "1", unlike the conventional fuzzification process that produces membership values in the range $[0.0, 1.0]$ for fuzzy reasoning.

ISBN: 978-1-61804-081-7

b_1	b_2	b_3
b_4	b_c	b_5
b_6	b_7	b_8

zth window

Figure 5: The general representation of the zth fuzzy rule.

depends on the fuzzy inference mechanism to be discussed here.

The fuzzy rules represented by the z binary windows is dictated by the logical operation

$$\psi(t) \quad = \quad \psi(t-1) \cdot \rho(x), \tag{10}$$

where t is the number of times (10) is executed in the zth window (i.e., $t \leq 8$). Then, the polarity function $\rho(x)$ is defined as

$$\rho(x) = \begin{cases} 0 & : \quad \widehat{w_x} < 0, \\ 1 & : \quad \widehat{w_x} \geq 0. \end{cases} \tag{11}$$

In (10), $\psi(t)$ is used to detect positive or negative impulses. If the relative gradient is positive, $\rho(x)$ takes on logic "1" to indicate a positive impulse is present. Otherwise, $\rho(x)$ is assigned with logic "0" to indicate the presence of a negative impulse. Before we venture forth, the pseudo fuzzy rulebase in Fig. 4 is generalized with a general window as shown in Fig. 5. The central bit is the binary variable b_c while its neighboring bits are represented by b_x. Again, the neighboring bits of b_c are indexed by x.

Initially, $\psi(0)$ is initialized as logic "1". During the filtering phase, $\psi(t)$ is applied repeatedly if $b_x = 1$ in the zth window. It is worth noting that $\psi(t)$ is not executed when $b_x = 0$. Clearly, b_x is used to represent the rules in the pseudo fuzzy rulebase, and given the absolute relative gradient $|\widehat{w_x}|$, the final value of $\psi(t)$ is solely determined by the variable $\rho(x)$. After each zth window is evaluated, the final value of $\psi(t)$ is used to decide on the appropriateness for a correction estimate.

The correction estimate $\widehat{c}$ is adopted from the one used in FIRE filter due to its elegant simplicity. It is defined by:

$$\widehat{c} \quad = \quad W_{max} \cdot (c_+ - c_-), \tag{12}$$

where

$$c_+ = \max\{\min\{\mu_H(|\widehat{w_x}|) : \psi(t) = 1\} z = 1, \ldots, 12\}$$

and

$$c_+ = \max\{\min\{\mu_H(|\widehat{w_x}|) : \psi(t) = 0\} z = 1, \ldots, 12\}.$$

Although $\psi(t)$ in (10) is seen to favor the c_- term, but this is not the case because the selection of the fuzzy sets would automatically handle impulsive pixels appropriately. Finally, the correction estimate $\widehat{c}$ is added to the center reference pixel w_c to yield the final output

$$\widetilde{w_c} \quad = \quad w_c + \widehat{c}. \tag{13}$$

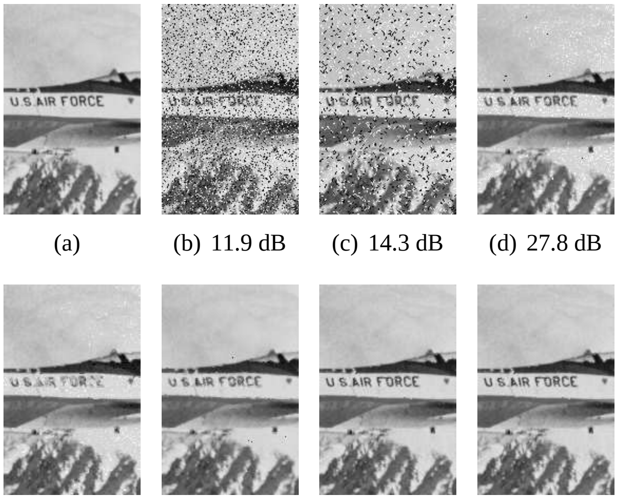
When none of the pseudo fuzzy rules is activated, both c_+ and c_- will be nil and, in this case, the center reference pixel w_c is retained.

3 Experimental Results

In this section, simulation results by the proposed FM filter are presented. They are compared to the simulation results by some state-of-the-art impulse noise filters, namely, the histogram-based efficient detail-preserving (HEDP) [3], efficient detail-preserving algorithm (EDPA) [5], FIRE [10], and the adaptive fuzzy switching (AFS) [2] filters. Note that these filters, like the FM filter, employ fuzzy techniques in their filtering mechanisms, and thus, they belong to the class of fuzzy filters.

Here, two widely used test images ("Jet" and "Pentagon") of size 512×512 are artificially inflicted with 10% to 50% impulse (salt-and-pepper) noise in 10% noise step. These test images are denoised by the abovementioned filters and their restored images are evaluated, both numerically and visually. The peak signal-to-noise ratio (PSNR) image quality metric is used to quantitatively compare the restoration results. Visual inspection on the filtered images is also performed to subjectively evaluate the quality of the filtered images. Then, the choice for parameters selection is reported at the end of this section.

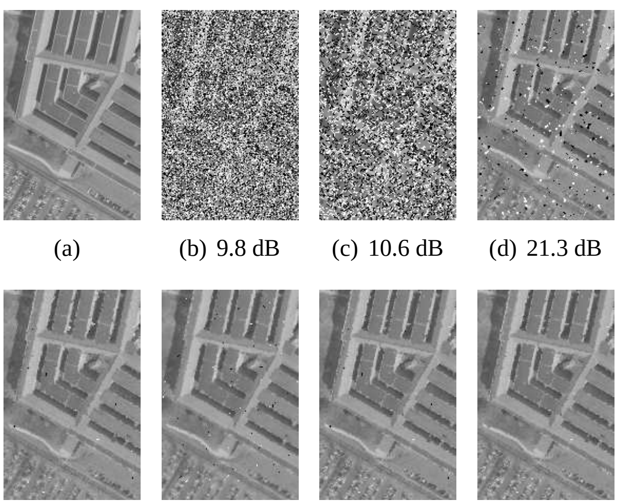
Simulation results using the "Jet" test image corrupted with 20% of impulse noise are shown in Fig. 6. The "Jet" test image is chosen because of the similarity between the object and background, which are difficult to distinguish except by their salient features. The object is mainly identified by its textures which are separated by sharp edges, whereas the background is characterized by the nonuniform surfaces. These characteristics make the "Jet" test image suitable for testing the denoising power, as well as the detail-preserving ability, of the filters. At 20% noise level, the HEDP filter fails to perform as most of the impulse noise still appear in its filtered image. The EDPA filter leaves behind white dots scattered across the sky regions with bright intensities. The FIRE and AFS filters both able to remove impulsive pixels, but at the cost of damaging minute details, such as the



(a) (b) 11.9 dB (c) 14.3 dB (d) 27.8 dB

(e) 30.5 dB (f) 32.7 dB (g) 34.7 dB (h) 35.4 dB

Figure 6: (a) A portion of the original "Jet" image. (b) "Jet" image corrupted with 20% impulse noise. The filtered images using the (c) HEDP [3], (d) EDPA [5], (e) FIRE [10], and (f) AFS [2]. The restored images using the proposed filter with (g) one, and (h) two iterations.



(a) (b) 9.8 dB (c) 10.6 dB (d) 21.3 dB

(e) 26.8 dB (f) 27.0 dB (g) 28.1 dB (h) 33.9 dB

Figure 7: (a) A zoomed segment of the original "Pentagon" image. (b) "Pentagon" image corrupted with 40% impulse noise. The filtered images using the (c) HEDP [3], (d) EDPA [5], (e) FIRE [10], and (f) AFS [2]. The restored images using the proposed filter with (g) one, and (h) two iterations.

graphemic letters on the plane. Conversely, the proposed FM filter outperforms other filters by producing the highest PSNR values, at the same time, it suppresses impulse noise and preserves fine image details.

Table 1: The PSNR (dB) of Iteratively Restored "Jet" Image by the Fuzzy Multipass Filter.

Impulse Noise Density	**Noisy PSNR**	**After 1 iteration**	**After 2 iterations**
10%	14.9	39.1	39.5
20%	11.9	34.7	35.4
30%	10.2	31.3	32.5
40%	8.9	28.0	29.7
50%	7.9	25.3	26.6

Table 2: The PSNR (dB) of Iteratively Restored "Pentagon" Image by the Fuzzy Multipass Filter.

Impulse Noise Density	**Noisy PSNR**	**After 1 iteration**	**After 2 iterations**
10%	15.8	37.5	37.6
20%	12.8	33.6	33.9
30%	11.1	30.9	31.4
40%	9.8	28.1	33.9
50%	8.8	25.3	26.6

The "Pentagon" test image corrupted with 40% of impulse noise is shown in Fig. 7. It is a high altitude aerial image, representing images often obtained from applications such as remote sensing or satellite images. It is made up of sharp corners, edges, and abundant of small details. The simulation results show that the HEDP and EDPA filters fail to remove noise, with the latter having a better performance than the former. The FIRE and AFS filters leave behind some black dots disguised as image details in the filtered images. Again, the proposed FM filter yields the highest PSNR, and its performance is further improved by performing one additional iteration without jeopardizing the content of the image data.

The overall filtering results by the FM filter, using one and two iterations, are numerically summarized in Tables 1 and 2 for for the "Jet" and "Pentagon" test images, respectively. From Tables 1 and 2, it is found that images corrupted with higher density of impulse noise (i.e., 30 to 50%) would require an additional iteration to further improve its denoising performance. The second iteration would remove any remaining noise unfiltered during the first iteration, while keeping image details, edges, and textures undisturbed. For lower noise densities (i.e., 5 to 25%), additional iterations are not required as one iteration is sufficient to remove most of the impulses.

We now comment on the computational complexity of the proposed FM filter based on its runtime, and

ISBN: 978-1-61804-081-7

later compare it with the runtime of the HEDP, EDPA, FIRE, and AFS filters. All the algorithms are coded in C++ using a Dell laptop with 1.66 GHz Intel Centrino Duo processor. The HEDP and EDPA filters consume about 0.12 s and 0.14 s, respectively, to denoise a 512×512 image. It takes about 0.25 s for the AFS filter to process images of the same dimension, while the FIRE filter has the slowest runtime with approximately 0.60 s. On the other hand, the proposed FM filter only takes about 0.05 s to denoise an image of size 512×512. The simplicity for fuzzy rulebase evaluation and generation speeds up the runtime of the FM filter, and this underscores the importance of the proposed pseudo fuzzy rulebase. Furthermore, the proposed method does not require the computation or estimation of complex parameters. These significantly improve the computing time of the FM filter.

Finally, the optimization of the fuzzy sets parameters is performed using the “hill-climbing” approach. The test image “Jet” corrupted with 10% of impulse noise is used for tuning and optimization purposes. Initially, the parameters a_1 and b are set to 127, while a_2 is made varying from 0 to 255. Here, the value of a_2 with the highest PSNR is chosen. Then, by keeping a_1 and a_2 constant, b is made varying from 0 to 255 and the value corresponds to the highest PSNR value is chosen. The process is repeated for a_1. Using this procedure, it is found that $a_1 = 127$, $a_2 = 117$, and $b = 143$ could yield optimal restoration results even when the FM filter is applied to images other than the “Jet” test image. Once these parameters are optimized, the FM filter is applicable without needing to tune its parameters.

4 Conclusion

This paper presents a novel fuzzy multipass filter for the removal of impulse noise. It is capable of suppressing high density of impulse noise, at the same time, preserving fine details, edges, and textures in the underlying image. A new pseudo fuzzy inference mechanism that utilizes simple logical operations to evaluate and represent complex fuzzy rulebase is also proposed. Simulation results, which are comparable to the state-of-the-art fuzzy filters, show that the proposed filter has a relatively fast runtime. This makes the proposed algorithm practically useful for real applications.

Acknowledgements: This research was supported by the Universiti Sains Malaysia under a Fundamental Research Grant Scheme, Ministry of Higher Education, Malaysia, titled “Investigation of New Color Image Illumination Estimation Concept for Development of New Color Correction Techniques,” Postgraduate Fellowship Scheme, and Postgraduate Research Grant Scheme (USM-RU-PRGS 1001/PELECT/8032052).

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