Genetic Fuzzy Filter Based on MAD and ROAD to Remove Mixed Impulse Noise

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ABSTRACT:

In this paper, we propose a genetic fuzzy image filtering based on rank-ordered absolute differences (ROAD) and median of the absolute deviations from the median (MAD). The proposed method which is consisted of three components, including fuzzy noise detection system, fuzzy switching scheme filtering, and fuzzy parameters optimization use genetic algorithms (GA) to perform efficient and effective noise removal. Our idea is to utilize MAD and ROAD as measures of noise probability of a pixel. Fuzzy inference system is used to justify the degree of which a pixel can be categorized as noisy. Based on the fuzzy inference result, the fuzzy switching scheme that adopts median filter as the main estimator is applied to the filtering. The GA training aims to find the best parameters for the fuzzy sets in the fuzzy noise detection. Based on the experimental results, the proposed method has successfully removed mixed impulse noise in low to medium probabilities, while keeping the uncorrupted pixels less affected by the median filtering. It also surpasses the other methods, either classical or soft computing-based approaches to impulse noise removal, in MAE and PSNR evaluations.

KEYWORDS: Fuzzy Filters; Genetic Algorithm; MAD; ROAD; Mixed Impulse noise.

1. INTRODUCTION

Images are required as sources of information for interpretation and analysis by many applications. Impulse noise can contaminate digital images in many cases, especially when they are transferred or converted from one form to another. The main characteristic of impulse noise is that only parts of pixels are corrupted while the others remain free from noise [1]. The quality of input images plays a key role in image-based measurement. Many image enhancement techniques exist due to the needs of noiseless and highly defined images for better interpretation & analysis. The goal of image enhancement is to improve the image quality so that the processed image is better than the original image for a specific application or a set of objectives such as analysis, detection, segmentation, and recognition. Enhancing image quality can be done by removing noise, amplifying image contrast and amplifying the level of a detail [2].

This paper presents a new approach to remove mixed impulse noise [3] that applies the concept of fuzzy filtering [4]. It employs two statistical properties of the image, including MAD [5] and ROAD [6], and it works only on spatial domain. Our idea is to utilize MAD and ROAD as measures of noise probability of a pixel. Fuzzy inference system is used to justify the degree of which a pixel can be categorized as noisy. Based on the fuzzy inference result, the fuzzy switching scheme that adopts median filter as the main estimator is applied to the filtering.

In section 2-6, we describe the theoretical background needed in this paper. Section 7 describes our new approach in removing mixed-type impulse noise. The experiment results and discussions are presented in section 8 to simulate the performance of our new method. Finally the conclusions are drawn in Section 9.

2. FUZZY AND GENETIC ALGORITHMS IN IMAGE ENHANCEMENT

Soft computing has become a new computing paradigm which is very relevant for pattern recognition and image analysis because of its tolerance to imprecision, uncertainty, approximate reasoning, and partial truth. Although soft computing is mostly applied in classification and recognition tasks, it can also be applied in image enhancement [7]. Some soft computing methods that have been implemented in

image enhancement are neural network, cellular neural network, pulse coupled neural network, rough set, fuzzy filter, genetic algorithms, and the hybrids of those methods: fuzzy-GA, fuzzy network [8].

Genetic algorithms have been applied to image enhancement by several authors. Various tasks in image processing solved by genetic algorithms range from basic image contrast and level of detail enhancement, to complex filters and deformable models parameters. Genetic algorithms are used to construct new filters, to optimize parameters of existing filters, and to look for optimal sequence of existing filters. The approach of genetic algorithm for each problem is unique, with different information encoding types, reproduction and selection schemes [2]. In his paper, Cho employed evolutionary image enhancement (EIE) to optimize a set of proper filters for noise reduction in images [9]. Petrović et al. implemented genetic programming to detect mixed impulse noise in an image [3].

Fuzzy filters are also an active research area of soft computing in image enhancement. Some fuzzy filters methods that have been implemented so far are the "fuzzy inference ruled by else-action" filters, the "fuzzy control based" filters, and the GOA filters [10]. Schulte S. et al. [4] proposed fuzzy random impulse noise reduction method that consists of a fuzzy detection mechanism and a fuzzy filtering method to remove random-valued impulse noise from corrupted images. Lee's weighted fuzzy mean filter (WFM) is proven to be effective in removing impulsive noise, especially in high noise probability [11]. It has been improved as adaptive weighted fuzzy mean filter to yield better results in low noise environment [12]. Further enhancement of this method applies genetic algorithm to optimize the parameters of the fuzzy inference systems [13]. It can remove salt-and-pepper noise very well while preserving edges and other image details.

3. MIXED IMPULSE NOISE

Salt-and-pepper noise is the most popular impulse noise model where corrupted pixels are replaced with maximum or minimum intensity values [1]. Abreu et al. introduce random-valued impulse noise of which noise intensities randomly range from the minimum to the maximum intensity values, that is 0 to 255 for 8-bit grayscale images [14]. A new model of impulse noise proposed by Petrović incorporates both aforementioned impulse noise models [3]. Half of the corrupted pixels are contaminated by the salt-and-pepper noise, the other half are contaminated by noise in random amplitudes, while the rest is free from noise. Let x_{ij} be an image pixel containing mixed impulse noise,

$$x_{ij} = \begin{cases} n_{ij}^{unif}, with \ probability \quad \frac{p}{2} \\ n_{ij}^{snp}, with \ probability \quad \frac{p}{2} \\ f_{ij}, \ with \ probability 1-p \end{cases}$$
(1)

Where $n_{ij}^{unif} \in [L_{\min}, L_{\max}]$ is uniform impulse noise which has random value ranging from the lowest the highest intensity to values, and $n_{ii}^{snp} \in \{L_{\min}, L_{\max}\}$ is salt-and-pepper noise. Also, f_{ij} denotes a noise-free image pixel at the location (i, j). This type of noise model is claimed to be more realistic because the impulse noise occurs as a result of disturbances induced by noise signals with random amplitudes. The amplitudes of the impulse noise can fall into the allowed dynamic range, it can also fall out of the range. The noise will be saturated to the maximum or minimum value if it is out of the range. Otherwise, it will appear as uniform impulse noise (when it is within the dynamic range). Therefore, this noise model is more suitable for evaluating the performance of impulse noise filters.

4. MEDIAN ABSOLUTE DEVIATION (MAD)

Median of the absolute deviations from the median, a robust estimator of the variance, was used to separate noisy pixels from image details [15]. MAD can be successfully used for the estimation of local image variance in the presence of impulse noise [5]. Let x_{ij} denote pixels with coordinates (i, j) in noisy image, and X_{ij} denote the set of pixels in $(2K+1)\times(2K+1)$ neighborhood window W centered at x_{ij} .

$$X_{ij} = \{x_{i-K,j-K}, \cdots, x_{ij}, \cdots, x_{i+K,j+K}\}$$
The median of the image is defined as
(2)

m = median(X)

$$m_{ij} - mean(X_{ij}) \tag{5}$$

(2)

The deviation image is the absolute difference between the noisy and its median image. It is defined by

$$d_{ij} = \left| x_{ij} - m_{ij} \right| \tag{4}$$

MAD presents the median of absolute deviations from the median. It is defined by

$$MAD_{ij} = median\left(\left|X_{ij} - median\left(X_{ij}\right)\right|\right)$$
(5)

Fig. 1 and Fig. 2 show the deviation image (d) and the median of the absolute deviations (MAD) from 256×256 Lena image corrupted by 20% mixed impulse noise.

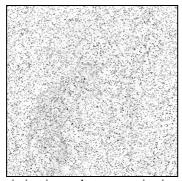


Fig. 1. Deviation image between noisy image xij and its median image

Sharp dots visible in Fig. 1 depict the noise removed by median filter, while the softer dots indicate fine details lost because of the median filtering. As can be seen from Fig. 2, despite the impulse noise in the image, MAD can retain the details information of the image very well. We can exploit MAD to distinguish noisy and noise-free pixels in an image. We can exploit MAD to distinguish noisy and noise-free pixels in an image.



Fig. 2. MAD image of the noisy Lena image for 5×5 window size

5. RANK-ORDER ABSOLUTE DIFFERENCES (ROAD)

Rank-ordered absolute differences (ROAD) is an image statistic for detecting random-valued impulse noise [6]. Let X_{ij}^{0} denote the set X_{ij} with x_{ij} excluded. We define D_{ij} as the absolute difference between the gray-level values in X_{ij} and x_{ij} .

$$D_{ij} = \left| X_{ij}^{0} - x_{ij} \right| \tag{6}$$

Let r_{ij}^{k} be the *k*th smallest value in D_{ij} when D_{ij} values are sorted in ascending order. Then:

$$ROAD_{ij}^{m} = \sum_{k=1}^{m} r_{ij}^{k}$$
⁽⁷⁾

Where $2 \le m \le (2K+1)^2 - 2$. If the noise ratio is higher than 25%, it is suggested that we use the 5-by-5 windows and m = 12. Otherwise, use 3-by-3 windows and m = 4 [16].

6. SWITCHING SCHEME FILTERING

Median filter is one of the most popular approaches for impulse noise removal where every pixel in an image is replaced by its median of certain window size [1]. In median filter, all pixels are treated in the same way, either they are noisy or not. It has been proven as a powerful method to remove impulse noise, but at the same time it removes edges and other details in uncorrupted pixels. Adaptive median filter, weighted median filter, center weighted median filter, etc. are some modifications to median filter to minimize the detail loss caused by the filtering [17].

One of the strategies to preserve edges and details is the switching scheme. Let x_{ij} and y_{ij} denote the pixels with coordinates (i,j) in a noisy and a filtered image, respectively. The switching filter concept is defined by

$$y_{ij} = M_{ij} \cdot \xi(x_{ij}) + (1 - M_{ij}) \cdot x_{ij}$$
(8)

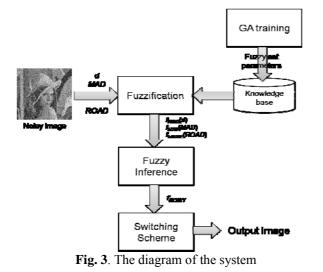
Where $\xi(x_{ii})$ is the estimated value of the

corrupted pixel x_{ij} , and M_{ij} is the binary noise map, with 1's indicate noisy pixels on respected coordinates. The filter removes noise in two steps: detecting impulse noise in an image and replacing the detected pixels with estimated values. The noise-free pixels are kept unfiltered. Therefore, excessive filtering that removes edges and details can be avoided. Generally, the detection employs some local statistics of the neighborhoods around the processed pixels, such as median, weighted median, rank-order thresholding, normalized mean, fuzzy reasoning, or neural networks [15].

7. THE PROPOSED METHOD

We propose a fuzzy switching scheme filtering method based on MAD and ROAD statistical properties. The parameters included in the fuzzy inference system are optimized using genetic algorithm. This filter is designed to remove mixed impulse noise, which means that it can also be used to remove salt-and-pepper and uniform impulse noise. We define three main processes in this method: fuzzy inference system, fuzzy switching scheme filtering, and fuzzy parameters optimization. Fig. 3 depicts overall process of our method.

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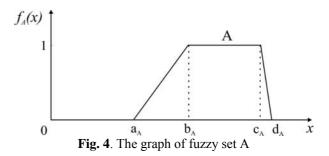


7.1. Fuzzy Noise Detection System

In order to avoid excessive filtering that can cause detail loss in images, noisy and noise-free pixels should be treated differently. If a pixel is detected as noisy, its value will be replaced by an estimate; otherwise, it will be left as is. We use fuzzy inference system to determine whether a pixel can be categorized as noisy. The detection system yields the pixels' degree to be categorized as noisy, which ranges from 0 to 1.

The first step in detecting the noise is extracting the value of MAD and ROAD from a noisy image. We will also use the deviation image *d* in this process. To obtain *ROAD* $_{ij}^{4}$ we use 3-by-3 windows and m = 4 [16]. Fuzzification process maps MAD_{ij} into LOW, d_{ij} into HIGH, and $ROAD^{4}_{ij}$ into LARGE fuzzy sets. In this process, the trapezoidal membership function is chosen to define the fuzzy sets. Equation (9) denotes the membership function $f_A(x_{ij})$ of fuzzy set A [18]. Fig. 4 illustrates trapezoidal fuzzy membership functions A which has a parameter set A = $[a_A, b_A, c_A, d_A]$.

$$f_{A}(x_{ij}) = \begin{cases} 0, & x_{ij} < a_{A} \\ \frac{(x_{ij} - a_{A})}{(b_{A} - a_{A})}, & a_{A} \leq x_{ij} < b_{A} \\ 1, & b_{A} \leq x_{ij} < c_{A} \\ \frac{(d_{A} - x_{ij})}{(d_{A} - c_{A})}, & c_{A} \leq x_{ij} < d_{A} \\ 0, & x_{ij} \geq d_{A} \end{cases}$$
(9)



Although noisy pixels tend to have d and ROAD value higher than noise-free pixels do, there's no fixed threshold value to distinguish the noisy pixels amongst all pixels in an image. Lower value on d mostly came from the image details loss caused by median filtering. MAD value is highly related to the details in an image. The MAD value of noisy image is not much different from the original one. It can retain details and edges information from an image although the image becomes noisy until certain degree. Its value is relatively low regardless the noise conditions. MAD and d are incorporated to detect the noise and leave the details of an image [15]. If a pixel has high d value, it is most probably a noisy pixel. But if a pixel has low MAD value, it can be considered as an image details that we do not want to filter. This information can be translated into a fuzzy rule:

IF ((d_{ij} is HIGH) AND (MAD_{ij} is LOW)) OR ($ROAD_{ij}^4$ is LARGE) THEN x_{ij} is NOISY

The new fuzzy set $f_{NOISY}(x_{ij})$, which has values in [0,1], derived from the above inference system is the noise detector. Higher value of $f_{NOISY}(x_{ij})$ indicates the higher probability of x_{ij} becoming noisy pixel. The degree of this noise probability determines the effects of median filtering applied to the respective pixel.

7.2. Fuzzy Switching Scheme Filtering

Adopting the switching scheme filtering [5] and the noise detection result, the filtered image yij is defined as follows

$$y_{ij} = f_{NOISY}(x_{ij}) \cdot m_{ij} + (1 - f_{NOISY}(x_{ij})) \cdot x_{ij} \quad (10)$$

A pixel x_{ij} will be replaced with its median if it is detected as noisy ($f_{NOISY}(x_{ij}) = 1$). If the pixel x_{ij} is not detected as noisy, it will be kept at its original value. The pixels will be filtered proportional to the value of $f_{NOISY}(x_{ij})$.

7.3. Fuzzy Parameters Optimization Using GA

In this section we apply the genetic algorithms to find the best parameter for fuzzification process explained in the previous section. Defining a fixed threshold of d, MAD, and ROAD to differentiate noisy

pixels from the noise-free ones is not trivial. For noise in low amplitudes, the value of d, MAD, and ROAD are relatively similar to their values for noise-free pixels in edges or small details.

Fig. 5 illustrates the genetic learning process. The genes represent 12 parameters of trapezoidal membership functions in fuzzy sets HIGH, LOW, and LARGE. To maintain meaningful fuzzy membership functions, the following restrictions on the parameters are applied.

$$a_{HIGH} \le b_{HIGH} < c_{HIGH} \le d_{HIGH}$$
$$a_{LOW} \le b_{LOW} < c_{LOW} \le d_{LOW}$$
(11)

$$a_{LARGE} \le b_{LARGE} < c_{LARGE} \le d_{LARGE}$$

We use special representations and operators to maintain feasible solutions in the GA [19]. The genes are coded using integer codification because all the possible values of d, MAD, and ROAD are integers and it is easier to implement the restrictions mentioned by equation (11).

Parents for producing new offsprings are chosen using roulette wheel method. The crossover operator is single-point crossover, which means a crossover site is randomly chosen within the gene length. The mutation is done by adding or subtracting the gene values with small numbers [20].

Applying GA operators may cause the genes fall into unfeasible solutions. To maintain feasible solutions, we apply repair algorithm that make changes to unfeasible individuals so that the gene values are kept in the allowed values [19].

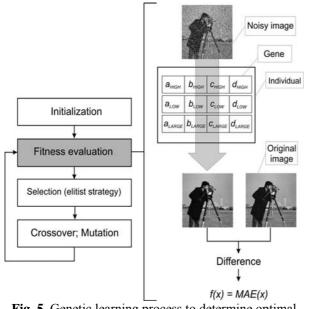


Fig. 5. Genetic learning process to determine optimal parameters of fuzzy filtering

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The mean absolute error (MAE) is adopted to evaluate the fitness of individuals. Equation (12) shows the fitness function to be minimized.

$$f(x) = MAE(x) \tag{12}$$

The image used in the training process is not necessarily the same as the one that will be filtered. Once the results obtained, they can be used many times for filtering by saving them in a knowledge base.

8. RESULTS AND DISCUSSION

A set of experiment has been done to test the performance of the proposed method. The popular 256×256 8-bit grayscale Lena image was used in the experiment. Mixed impulse noise model was employed to simulate the impulse noise. The impulse noise added ranged in 0.1-0.5 probabilities, with 0.1 increments. The mean absolute error (MAE) and peak signal-to-noise ratio (PSNR) as well as subjective evaluation were used to assess the performance of the proposed method. The performance was compared to the other soft computing methods in image enhancement such as GFIF [13], WFM [12], FRINR [4], EIE [9] as well as two classical approaches in image filtering, average and median filters in 3×3 and 5×5 window size.

Fuzzy set parameters were trained using 256×256 8bit grayscale cameraman image. The GA training parameters were 100 generations, 20 population size, 2 elite counts, 0.8 crossover fractions, and 0.01 mutation probabilities. The final training results are shown in table I. The training results are the parameters of the fuzzy sets HIGH, LOW and LARGE.

The parameters from the training results are used to filter the noisy images. Fig. 6 shows the comparison among the original image, noisy image, median 5×5 filtered noisy image, and the noisy image filtered by the proposed method. The effect of median filter in 5×5 windows is obvious. The noise is removed, but the image also lost many of its details. We can see that our detection can selectively replace noisy pixels with its median, while keeping the rest less affected by the median filter. The complete comparison of filtering results among the methods can be seen in Figure 9.





(b)



Fig. 6. (a) 128×128 8-bit grayscale Lena image, (b) image corrupted by 0.1 mixed impulse noise, (c) the noisy image filtered by median filter in 5×5 windows, and (d) the noisy image filtered by the proposed method.

This method also outranked the other methods in MAE and PSNR evaluation. The graphs of MAE and PSNR values of the method are shown in Fig. 7 and Fig. 8. It gained the lowest MAE and the highest PSNR for every noise probability tested.

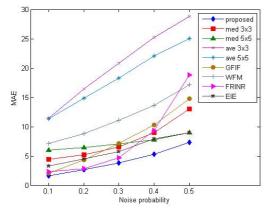


Fig. 7. MAE curves comparison

(a)

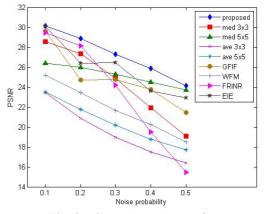


Fig. 8. PSNR curves comparison

9. CONCLUSION

In this paper, a fuzzy image filtering based on ROAD and MAD has been presented. The proposed method consists of three components, including fuzzy noise detection system, fuzzy switching scheme filtering, and fuzzy parameters optimization using GA to perform efficient and effective noise removal. The noise are detected by the fuzzy noise detection system, then filtered using fuzzy switching scheme filtering to minimize degrading effect of median filtering on noisefree pixels. The GA training aims to find the best parameters for the fuzzy sets in fuzzy noise detection.

From the experimental results, we observe that PSNR and MAE value of the proposed method achieve the most effective results than the other approaches, including median filters, average filters, EIE, WFM, GFIF, and FRINR. Subjective evaluation on the filtering results also show its superior performance on removing mixed impulse noise in low to medium noise probabilities.

Table 1. 674 training result for the fuzzy sets parameters											
a _{HIGH}	$\mathbf{b}_{\mathrm{HIGH}}$	$\mathbf{c}_{\mathrm{HIGH}}$	$d_{\rm HIGH}$	a_{LOW}	b_{LOW}	c_{LOW}	d_{LOW}	a _{LARGE}	b _{LARGE}	c _{LARGE}	d _{LARGE}
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(b)

Table 1. GA training result for the fuzzy sets parameters

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(h)

Fig. 9. Noisy 256x256 8-bit grayscale Lena image corrupted by 0.2 mixed impulse noise filtered by: (a) the proposed filter, (b) 3x3 average filter, (c) 5x5 average filter, (d) 3x3 median filter, (e) 5x5 median filter, (f) EIE, (g) WFM, (h) GFIF, and (i) FRINR.

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