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IMPULSE NOISE REMOVAL USING IMPROVED PARTICLE SWARM OPTIMIZATION

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ABSTRACT— The fuzzy filter based on particle swarm optimization is used to remove the high density image impulse noise, which occur during the transmission, data acquisition and processing. The proposed system has a fuzzy filter which has the parallel fuzzy inference mechanism, fuzzy mean process, and a fuzzy composition process. In particular, by using no-reference Q metric, the particle swarm optimization learning is sufficient to optimize the parameter necessitated by the particle swarm optimization based fuzzy filter, therefore the proposed fuzzy filter can cope with particle situation where the assumption of existence of "ground-truth" reference does not hold. The merging of the particle swarm optimization with the fuzzy filter helps to build an auto tuning mechanism for the fuzzy filter without any prior knowledge regarding the noise and the true image. Thus the reference measures are not need for removing the noise and in restoring the image. The final output image (Restored image) confirm that the fuzzy filter based on particle swarm optimization attain the excellent quality of restored images in term of peak signal-to-noise ratio, mean absolute error and mean square error even when the noise rate is above 0.5 and without having any reference measures.

Keywords — Fuzzy filter, Particle Swarm Optimization (PSO), Structural Similarity, Singular Value Decomposition.

I. INTRODUCTION

Digital images are often corrupted by impulsive noise during data acquisition, transmission, and processing. Here the turbulent particle swarm optimization (PSO) (TPSO)-based fuzzy filtering (or TPFF for short) approach to remove impulse noise from highly corrupted images.

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The proposed fuzzy filter contains a parallel fuzzy inference mechanism, a fuzzy mean process, and a fuzzy composition process. To a certain extent, the TPFF is an improved and online version of those genetic-based algorithms which had attracted a number of works during the past years. As the PSO is renowned for its ability of achieving success rate and solution quality, the superiority of the TPFF is almost for sure. Therefore, the proposed fuzzy filter can cope with practical situations where the assumption of the existence of the "ground-truth" reference does not hold. The experimental results confirm that the TPFF attains an excellent quality of restored images in terms of peak signal-to-noise ratio, mean square error, and mean absolute error even when the noise rate is above 0.5 and without the aid of noise-free images.

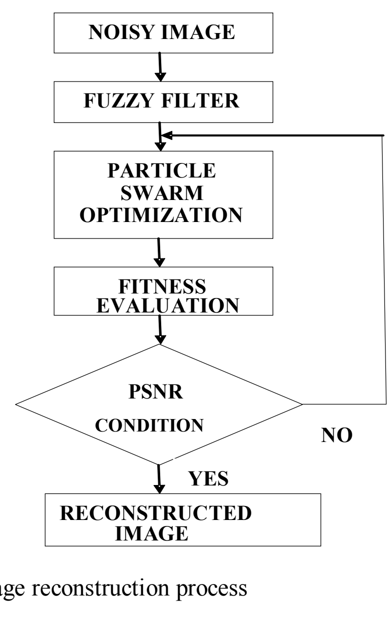

Fig.1. Image reconstruction process

The Fig.1 shows the process for reconstructing the noisy image. The process consist of the input image which is a highly corrupted image, fuzzy filter, the output

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of the fuzzy filter is given to the PSO, then the PSNR value is checked, if the PSNR value is satisfied then the output image(reconstructed image) is obtained. If the PSNR value is not satisfied then the particles values are changed by the PSO techniques, this process is repeated until the expected PSNR value reached, Once the PSNR value satisfies our expected value then the output image will obtained.

II MATERIALS AND METHODS

The fuzzy set technique serves as an important ingredient in the development of information technologies. In the field of information systems, the fuzzy set plays a role in the development of intelligent systems and the storage of imprecise linguistic information.

Applications can be found in many areas such as control systems, fuzzy time series forecasting, artificial intelligence and image processing[7]. In particular, fuzzy image filters have the advantage of being easy to realize by simple fuzzy rules that characterize a particular noise. Over the past years, a huge amount of fuzzy-based noise reduction methods were developed. The noise adaptive fuzzy switching median filtering mechanism [1] employed fuzzy reasoning to handle uncertainty presented in the extracted local information introduced by noise. The fuzzy impulse noise detection and reduction method dealt with the images corrupted by fat-tailed noise.

Particle swarm optimization (PSO) is a decade-old concept in the global optimization domain. It is a popular computational technique developed by Eberhart and Kennedy, based on the social behavior of birds flocking for food searching. The PSO was generally found to outperform other evolutionary algorithms (such as GAs, mimetic algorithms, ant-colony optimization, and shuffled frog-leaping algorithm) in terms of success rate and solution quality while being second best in terms of processing time. To provide quantitative data on the fidelity of rendered images, quality metrics are of paramount importance for the PSO.

These metrics can be typically divided into two main categories, namely, full reference and no reference. Full-reference metrics need a complete reference image, and what they calculate is the similarity between the target and reference images. Metrics such as the classical peak signal-to-noise ratio (PSNR), MSE, MAE, and the structural similarity (SSIM) belong to this category. Unfortunately, the full-reference metrics are hardly applicable due to the unavailability of the reference images in most practical applications. To overcome the deficiency, researchers thus turned their attention to the parameter optimization problem of the field (i.e., no reference) using the generalized cross-validation, L-curve method, Stein's unbiased risk estimate (SURE), etc. In recent years, the SURE gradually became popular as it provided an efficient means for an unbiased estimation of the MSE without the reference image. However, the performance of the SURE is barely acceptable for Gaussian noise, and an accurate estimation of the noise variance is still necessary.

In fact, an ideal no-reference measure that is useful for the parameter optimization problem should take both noise and blur conditions into account. Recently, Xiang and Milanfar proposed a no-reference image quality metric based upon the singular value decomposition (SVD) of the local image gradient matrix and provided a quantitative measure of true image content.

III. PROPOSED METHOD

In a scenario where an image (M × N) is corrupted by impulsive noise, let xij be the 8-b gray level of the noisy pixel at location (i, j) and $1 \leq i \leq M, 1 \leq j \leq N$

$$X_{ij} = \begin{cases} n_{ij}, \text{ with probability } p \\ \varphi_{ij}, \text{with proability } 1-p \end{cases} \quad (1)$$

where φ_{ij} denotes a noise-free image pixel and n_{ij} denotes a noisy impulse at the location (i, j) with a noise corruption rate p. The simplest and most frequently used impulse noise model is the salt-and-pepper noise, where noisy pixels take either the minimal or maximal value, i.e., $n_{ij} \in$ {Lmin, Lmax} with Lmin and Lmax, respectively representing the lowest and highest pixel luminance values within the dynamic range.

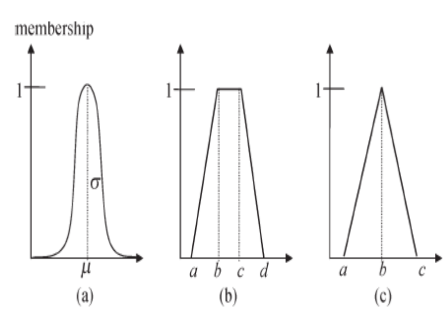

Fig.2. Examples of membership function

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Moreover, the uniform impulse noise model can often be found in the contemporary literature too, where the noisy pixel can have any value within the dynamic range with equal probability. Membership functions for fuzzy sets can be defined in any number of ways as long as they follow the rules of fuzzy sets. Three examples of frequently used membership functions for calculating the fuzzy number are shown in Fig. 2.

However, it is hard to say which membership function is the best one. The choice of the membership function depends on the subjective aspect of fuzzy logic, which allows the desired values to be interpreted appropriately. Bigand and Colot had demonstrated the design of a robust fuzzy filter using certain membership functions, and we also obtain similar results with triangle and trapezoid membership functions.

It is thus straightforward for us to employ the triangle membership functions for simplifying the tuning procedure of filter parameters. The membership function fA(x) with the fuzzy set A denoted by A = [aA, bA, cA] is given in Fig.2(c)

$$f_A(x)=\begin{cases} 0, & x < a_A \\ \frac{x-a_A}{b_A-a_A}, & a_A \le x < b_A \\ \frac{c_A-x}{c_A-b_A}, & b_A < x < c_A \\ 0, & x \ge c_A \end{cases} \qquad (2)$$

A fuzzy set allows its members to have different degrees of membership. Here, we define S ($S \geq 3$) fuzzy sets for a gray-level image. Suppose that the image can be classified into "very dark" (VD), "dark" (DK), "medium" (MD), "bright"(BR), and "very bright" (VB), as shown in Fig. 3. The membership functions of fuzzy sets VD, DK, MD, BR, and VB are denoted as VD = [a_{VD}, b_{VD}, c_{VD}], DK = [a_{DK}, b_{DK},c_{DK}],M = [a_{MD}, b_{MD}, c_{MD}], B = [a_{BR}, b_{BR}, c_{BR}], and VB = [a_{VB}, b_{VB}, c_{VB}], respectively.

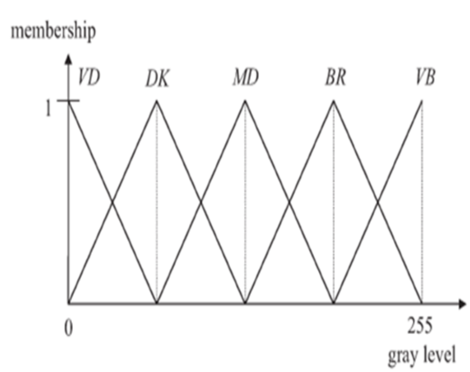

Fig. 3. Membership function

The architecture of the fuzzy filtering process for impulsive noise removal is shown in Fig. 4.

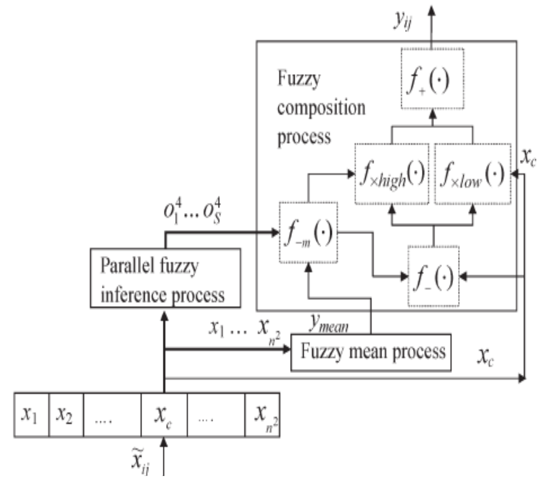

Fig. 4. Architecture of fuzzy filtering process

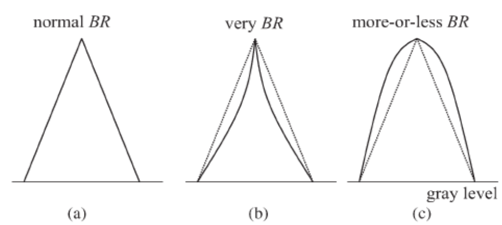

Fig. 5. Linguistic term

A. Parallel Fuzzy Inference Process

Here, the linguistic modifier λ is adopted to modify the membership functions to fit the linguistic characterization. Equation defines the computing mechanism of the fuzzy inference vector through the linguistic modifier. Two of the most well-known modifiers are the erosion corresponding to "very" (λ = 2) and the dilation corresponding to "more-or-less" (λ = 0.5). Fig. 5 shows the graphic representations of three specific linguistic terms, including normal bright (λ=1), very bright (λ=2), and more-or-less bright (λ=0.5).

$$O^3_{AS} = \begin{cases} ((f_{AS}(x_{rl}))^2 \ , \text{ if "very"(} \lambda=2) \\ ((f_{AS}(x_{rl})) \ , \text{ if "normal" } (\lambda=1) \\ ((f_{AS}(x_{rl}))^{0.5}, \text{if "more or less } (\lambda=0.5) \end{cases} \qquad (3)$$

where $1 \le r \le n2$, $1 \le s \le S$, $1 \le l \le S$. Finally, the fuzzy inference rules are denoted as follows:

Fuzzy Rule LS :

If (x_1 is LS) AND (x_2 is LS) AND . . . AND (x_9 is LS) THEN o_s^4 is LS, where LS ∈ {VDK, DK, MD, BR, VBR}.

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Equation (4.4) shows the computing mechanism for the output of the aforementioned rules

$$o_j^4 = \begin{cases} \dfrac{\sum_{r=1}^{n^4}\left(x_{r1} \times o_{Ar}^3(x_{r1})\right)}{\sum_{r=1}^{n^3}\left(o_{Ar}^3(x_{r1})\right)}, & if\left(\sum_{r=1}^{n^3}\left(o_{Ar}^3(x_{r1})\right)\right) > 0 \\ 0, & otherwise \end{cases} \quad (4)$$

B. Fuzzy Mean Process

The fuzzy mean process aims at deriving a fuzzy mean of the processing windows. The process is carried out using a trapezoidal membership function of four parameters, i.e., A = [a_A, b_A, c_A, d_A], shown in Fig. 2(c). Equation specifies the computing process with the fuzzy interval F_mean for the fuzzy mean process. Moreover, the fuzzy function F_mean for the fuzzy mean process is shown in Fig. 6.

$$y_{mean} = \begin{cases} \dfrac{\sum_{r=1}^{n^4}\left(f_{F-mean}(x_r) \times x_r\right)}{\sum_{r=1}^{n^3} f_{F-mean}(x_r)}, & if\left(\sum_{r=1}^{n^3} f_{F-mean}(x_r)\right) > 0 \\ 0, & otherwise \end{cases} \quad (5)$$

Where

$$f_{F-mean}(x) = \begin{cases} x/\alpha, & 0 \le x < \alpha \\ 1, & \alpha \le x < \beta \\ (255 - x)/(255 - \beta), & \beta \le x \le 255 \end{cases} \quad (6)$$

and the fuzzy set F_mean = [0, α, β, 255].

C. Fuzzy Composition Process

The core concept of the fuzzy filter is to pick out an adequate inference drawn from different linguistic sets along with the output of the fuzzy mean process and then merge these two probable informative sources by fuzzy weighting.

V.SIMULATION RESULTS

The Simulation results of the proposed method is as given below.

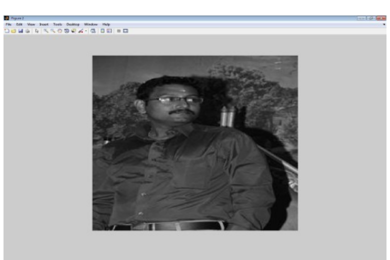

Fig. 6. Actual image (Before noise)

Fig.6. shows the input image which is the actual image before adding noise. Fig.7. shows the noisy image with noise rate of 0.6

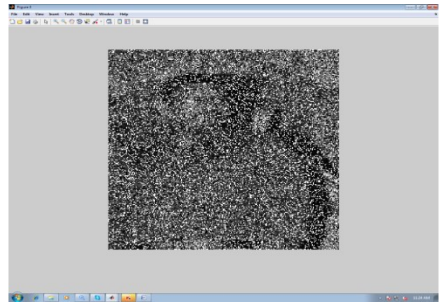

Fig. 7. Noisy image (noise rate 0.6)

Fig.8. shows the Restored image which is obtained by applying the proposed technique to give a noise free image

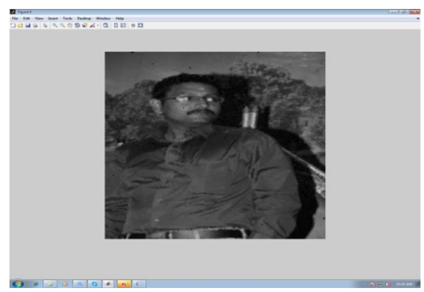

Fig. 8. Restored image (noise free image)

TABLE I

COMPARISON OF NOISE AND PSNR

S.No	Noise Density	Fuzzy PSNR	Fuzzy-PSO PSNR
1.	0.4	32.674	33.474
2.	0.5	30.913	31.567
3.	0.6	28.167	29.786
4.	0.7	23.757	24.589
5.	0.8	19.322	21.543

Table I shows the values of Fuzzy PSNR and Fuzzy-PSO PSNR for different values of Noise Density. The Proposed Fuzzy-PSO PSNR is able to outsmart the Fuzzy PSNR with larger values proving its reliability.

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VI. CONCLUSION

As the PSO has several desirable properties such as fewer parameters, easier implementation, low computational cost, and faster convergence to the optimal solution, the superiority of the fuzzy filter based on PSO is almost for sure. The no-reference image quality Q metric adopted here can reflect the extent of both blurriness and randomness of images without any prior knowledge.

Using the fuzzy filter based on PSO the high impulse noise in the image was restored without having any reference measures, any trial and error.

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