Impulse Image Noise Reduction Using Fuzzy-Cellular Automata Method

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Abstract—This paper proposes an algorithm to lessen the impacts of variety of distortions occurred in aerial images. The proposed algorithm detects the noisy pixels in a given image using fuzzy logic based technique in an iterative manner, then the noisy image is corrected based on the cellular structure modeling to filter out the noise. Our solution for noise reduction overcomes the difficulties of cellular automaton (CA) model in noise estimation and finds the accurate noisy mask by providing a fuzzy technique. Simulation results of the proposed algorithm show the accuracy and effectiveness of this algorithm for image with high percentage of pepper and salt noise.

Index Terms—Noise reduction, fuzzy logic, cellular automata, aerial images.

I. INTRODUCTION

Image reconstruction of radio astronomy, radar imaging, meteorology and oceanography are a few examples of the applications of noise reduction [1], [2]. Satellite images are inevitably distorted by noise during acquisition and transmission processes. However noise makes an image imperceptible and difficult to analyze. Therefore, it is important to suppress noise in images before other image processing and analysis activities.

The main concern in all image de-noising techniques is to remove noise while keeping the structure of image intact. As noise is random-unwanted variation of brightness, finding an ideal technique for noise cancellation is hardly achieved. All algorithms for noise restoration intend to improve the existing approaches based on some assumptions such as additive noise, white Gaussian, single noise source etc.

Noise reduction process comprises of two main steps. The first one is to find a statistic model of the additive noises and the second step is the application of digital filters to remove the noise [3], [4]. Since many images are degraded by the additive noise [5], [6], the assumptions of additive noise will simplify the noise reduction process. Linear filters are one of the efficient tools for additive Gaussian noise reduction. However, the nonlinear and adaptive filters have been developed to deal with non-additive or non-Gaussian noises. They include unsharp masking [7], discrete wavelet transforms (DWT) [8], histogram equalization based approaches [9] and adaptive filtering techniques have been proposed.

The recent research involves fuzzy algorithms in noise reduction. Fuzzy filtering has been used in medical images,

satellite images, industry and signal processing. Several fuzzy filters have been introduced, e.g. well-known FIRE filter, weighted fuzzy mean filter [10], and iterative fuzzy control based filter [11]. Fuzzy filters detect a correct value for each pixel, mainly based on its luminance difference between some patterns of neighboring pixels and act as smoothing filters. Our proposed technique uses a fuzzy noise reduction technique to detect noisy pixels in an image, which is an enhancement of that in the literature [6]. The noisy image is then corrected based on the Cellular Automaton (CA) model. A suggested way of combining the cellular spaces based technique with the fuzzy logic has been introduced for the first time in [5]. Comparing with [5], in this paper, we detect the noisy mask with a completely different fuzzy algorithm introduced which detects the noise with higher performance. Furthermore, the introduced algorithm can work iteratively and works better on the edges. In addition, the neighbor pixels can be detected as noisy pixels with higher ratio in this paper. Implementations show the accuracy and effectiveness of this technique for image with high percentage of pepper and salt noise.

II. METHODOLOGY

The introduced method starts with a fuzzy filtering operator, which identifies noise by analyzing and evaluating a pixel of interest, with its neighbors. Then, we calculate a correction value for the noisy pixel based on a dynamic CA modeling approach. The flowchart of the proposed method is shown in Fig. 1.

Fig. 1. Proposed method flowchart

Fig. 2. Neighbor pixels around pixel of interest

Like most noise detection techniques, a 3×3 sub-image is employed as a search window [12]. Within the window, pixels directly adjacent to the pixel of interest are defined as the first layer neighbors. As schematically described in Fig. 2, the center pixel number 0 is the one under study, and the pixels {1, 2, 3, 4, 5, 6, 7, 8} constitute its first layer neighbors.

We define the gradient values, $\nabla f(x, y)$ and $\tilde{\nabla} f(x, y)$, of a pixel at (x, y) in a direction as

$$\nabla_{(i,j)}^{(k)} f(x, y) = f^{(k)}(x+i, y+j) - f^{(k)}(x, y) \quad (1)$$

$$\tilde{\nabla}_{(i,j)}^{(k)} f(x, y) = f_{New}^{(k)}(x+i, y+j) - f^{(k)}(x, y) \quad (2)$$

where k is an iteration counter, $f^{(k)}(x, y)$ and $f_{New}^{(k)}(x, y)$ are the old and new gray values of the pixel at (x, y) location in the k^{th} iteration (for example, to calculate the gradient value of pixel 0, the pixels {1, 2, 3, 4} calculated earlier and have the new gray values). A pair of index (i, j) represents one of the eight neighbors that can accept values -1, 0 and 1.

We also define the difference in intensity between a pixel of interest (i.e. pixel 0) and its neighbor pixels, $I_{(i,j)} = \nabla_{(i,j)}^{(k)} f(x, y)$, as the input of our fuzzy system. As operator scans (starting from NW then N, then NE, then W and so on) the image in the X and Y directions, the updated value of pixels is used for an input whenever available. In fact when the operator is applied at pixel (x, y) , it has already operated on the pixel $(\tilde{x}, \tilde{y})$ where $\tilde{x} < x$ and $\tilde{y} < y$. Thus the input of fuzzy operator is defined as:

$$I_{(i,j)} = \begin{cases} \nabla_{(i,j)}^{(k)} f(x, y) & \lambda < 0 \\ \tilde{\nabla}_{(i,j)}^{(k)} f(x, y) & \lambda > 0 \end{cases} \quad (3)$$

where $\lambda = i + 2j$.

For example, consider the pixel (pixel 0) in column 50 and row 50, which has gray value of $f(50, 50)$. The difference in intensity for neighbors located in NW (North West) and S (South) of our studied pixel can be calculated as:

$$I_{(-1,-1)} = \tilde{\nabla}_{(-1,-1)}^{(k)} f(50, 50) = f_{New}^{(k)}(50-1, 50-1) - f^{(k)}(50, 50)$$

and

$$I_{(0,1)} = \nabla_{(0,1)}^{(k)} f(50, 50) = f^{(k)}(50, 50+1) - f^{(k)}(50, 50),$$

respectively.

Equation (3) is used to calculate the intensity of a pixel with all neighbors (NW, N, NE, W, E, SW, S and SE) and then these values are used to identify noisy neighbors. Each of these 8 values passes through a fuzzy system to generate the

output, O , based on the Fuzzy reasoning Positive and Negative luminance. To implement the Fuzzy reasoning Positive and Negative luminance, difference fuzzy sets are defined by their respective membership functions which have triangular shape, shown in Fig. 3.

Fig. 3. Membership functions of positive and negative luminance differences (L is the Gray levels of input image)

III. FUZZY RULES

Fuzzy rules are defined in a way that each set of rules only deals with a particular pattern of pixels. For each pattern of pixels there are two complementary rules which are fixed [6]. For example consider the following two rules defined on the set: $H_1 = \{I_{(0,-1)}, I_{(0,1)}, I_{(1,0)}\}$

IF $(I_{(0,-1)}, POS)$ AND $(I_{(0,1)}, POS)$ AND $(I_{(1,0)}, POS)$ (4)
THEN (O, POS)

IF $(I_{(0,-1)}, NEG)$ AND $(I_{(0,1)}, NEG)$ AND $(I_{(1,0)}, NEG)$ (5)
THEN (O, NEG)

where POS means positive, NEG means negative and O is the output of the fuzzy operator. These two rules try to find if the pixel under the test is different from its neighboring pixels 2, 5 and 7 or not.

Defining the other 13 sets, $H_\alpha, \alpha = 1, 2, 3, \dots, 12, 13$, we have a total of 26 fuzzy rules. These sets are shown in Fig. 4.

Fig. 4. Various patterns of neighboring pixels used to detect noisy pixels

These rules have been defined to study as many as possible sets, where neighboring sets of noise pixels happen.

Next step is to generate and check the output of the fuzzy operator. If the studied pixel is identified as a noisy one, its neighborhoods should be reevaluated.

IV. GENERATING NOISY MASK AND OUTPUT

The output value of the fuzzy operator is the error value of the studied pixel. This value determines whether the pixel is noisy or not. This output value can be calculated by the following fuzzy inference process [13], [6]:

$$\beta_1 = \max\{\min\{M_{POS}(I_{(i,j)}); (i,j) \in H_\alpha\}; i, j = -1, 0, 1\} \quad (6)$$

$$\beta_2 = \max\{\min\{M_{NEG}(I_{(i,j)}); (i,j) \in H_\alpha\}; i, j = -1, 0, 1\} \quad (7)$$

$$\beta = \max\{0, 1 - \beta_1 - \beta_2\} \quad (8)$$

$$E = (L - 1) \frac{(\beta_1 - \beta_2)}{(\beta_1 + \beta_2 + \beta)} \quad (9)$$

Here L is the image gray levels, E is the fuzzy output of the studied pixel, and M_{POS} and M_{NEG} are membership functions of positive and negative luminance differences, respectively.

Now if the error is larger than a threshold, it means the studied pixel is noisy. Noisy mask is a matrix with the same size of the input image and it includes zeros and ones. It can be calculated as follows:

$$Noisy\ Mask(x, y) = \begin{cases} 1 & E(x, y) \geq Threshold \\ 0 & E(x, y) < Threshold \end{cases} \quad (10)$$

where threshold value has been set on 40 for our simulations. Threshold Choice depends on each image that how much noisy it is.

Now we have an estimation of likely noise level at each pixel. Next is to reduce the noise in affected pixels. In this paper, we propose a cellular space based method to restore the degraded pixel. The Cellular automaton (CA) model, also called cellular structure or tessellation structure, is a multi-dimensional grid structure of cells at certain finite value of states. The updated value of states is generated based on the current state of the cell and the states of its neighboring cells, and comply with a fixed mathematical updating rule. An image can be considered as a two-dimensional cellular structure. Each pixel forms one cell and the state of the cell is the gray-scale value of the pixel in the image from 0 to 255. Two most popular types of neighborhood are the Moore neighborhood and the von Neumann neighborhood (see in Fig. 5). The Moore neighborhood consists of square shape neighboring cells surrounding the center cell (x, y) . The von Neumann neighborhood usually contains four orthogonal cells adjacent to the center cell (x, y) , and can be extended by different radius. In the following, we use the Moore neighborhood with radius of 2 and the random majority Cellular automata update rule [14] as the state transition rule. For the noisy pixels at the boundary of the image, we map the existing neighbors into their mirrored side to form a complete

neighborhood, so that the update rule can be applied. However, one problem of the cellular based noise reduction techniques is that a reference image is required to locate the noisy pixels. Hence, we further involve the fuzzy logic in the proposed method to solve this problem.

Fig. 5. (a) Moore neighborhood (b) Von Neumann neighborhood

V. ITERATIONS

The algorithm may be iterated several times to remove more impulse noises. After each iteration, the value of a pixel affected by its immediate neighbors is used as an input for the next iteration. It can be seen that after some iterations there would be clusters of impulse noise distributed around the image that cannot be removed by the algorithm. This is due to the fact that there had been no adequate valid noise free pixels next to these noisy clusters.

VI. RESULTS AND COMPARISON

In the previous sections, the structure and methodology of our proposed method called Improved Fuzzy-Cellular Automata were described. In this section, the proposed method is applied to a sample of aerial image [15] and the famous test image –Lena [15] to clean up the impulse noise. And then results are compared.

The proposed method has been implemented to show its performance. Improved Fuzzy-Cellular Automata method for the second iteration (IFCA2) is compared with other noise reduction methods such as Median Filter with a 3×3 mask, Adaptive Wiener (with mask 3×3) as (AW3), Fuzzy-Cellular Automata (FCA) [5], and Fuzzy-Filter by Russo (FFR) [6]. Fig. 6 and Fig. 7 show the subjective visual measure for de-noised results of the noisy images with the noise ratio of 40 percent.

Fig. 6. Performance comparisons of various methods for 40% noise added

Fig. 7. De-noising a satellite image with 40% noise added

In addition to the visual of the comparison, we use Peak Signal-to-Noise Ratio (PSNR),

$$PSNR = 20 \log_{10} \left(\frac{255}{\sqrt{MSE}} \right) \quad (11)$$

to compare the performance of our improved technique with the other methods mentioned, in which the Mean Squared Error (MSE) in Eq. 6 can be calculated from

$$MSE = \frac{1}{N \times M} \sum_{x=1}^M \sum_{y=1}^N (F_{Noisy}(x, y) - F_{Denoise}(x, y))^2 \quad (12)$$

where $F_{Noisy}(x, y)$ is the gray value of the original noisy image, and $F_{Denoise}(x, y)$ is that of the de-noise image in the pixel specified by X and Y coordinates. M and N are the size of the image.

The tables below summarize the quantitative measure of different algorithms. Table I is the Mean Squared Error (MSE) values of several different methods applied to Lena's Image, and Table II is the PSNR values for restoration results of the selective methods for the same image. Fig. 6 shows graphically the performance comparisons of these methods. Also, the proposed method has been applied to a satellite image with 40% noise added and Fig. 7 shows the performance improvement of IFCA2 method.

TABLE I: THE MEAN SQUARE ERROR (MSE) FOR LENA'S IMAGE

Method	% of Noise Added		
	10	40	80
Noisy	1763.6	7186	14285
SMF3	50	844.49	9379.2
AW3	373.25	984.47	2094.1
FFR	29.65	214.89	4285.9
FCA	20.22	954.32	5054.3
IFCA2	19.81	842.78	4051.1

TABLE II: THE POWER OF SIGNAL TO NOISE RATIO (PSNR) FOR LENA'S IMAGE

Method	% of Noise Added		
	10	40	80
Noisy	15.67	9.57	6.6
SMF3	31.14	18.86	8.41
AW3	22.41	18.20	14.92
FFR	33.41	24.80	11.81
FCA	34.11	18.33	11.09
IFCA2	35.16	18.87	12.05

VII. CONCLUSION

This paper has introduced a powerful algorithm based on

fuzzy technique and cellular automata to detect and remove the impulsive noise from satellite and aerial images. Firstly, in order to find an accurate noisy mask this paper used the fuzzy noise detection process in an iterative manner, then removes noisy pixels by gaining effectiveness of cellular automata. The experiment result clearly shows that the improved algorithm yields better result compared with other techniques.

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