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Spatial Domain Image Enhancement using Cloud Model for Suppressing Impulse Noise

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Abstract: Impulse noise corrupts the image when it is sensing from a malfunctioning camera, storing in a fault memory or sending through a noisy channel. As images are giving useful information in every field, image denoising plays a key role in image processing. Median filters are preferred for removal of impulse noise. Existing methods suppress noise randomly without considering whether the pixel is "noisy" or not. This paper proposes a method for effective noise suppression by understanding uncertainties in noisy image. There are two stages in this method. First stage identifies the corrupted pixels via uncertainty based detector where as second stage suppresses the noise candidates by using weighted fuzzy mean filter compared with the traditional switched hashing filters. The proposed method provides good results subjectively and objectively. As the proposed filter can restore the image with good detail preservation at a high noise level, great improvement results in image denoising.

keywords: Cloud model (CM), image denoising, impulse noise, median filter, weighted fuzzy mean filter, uncertainties, peak signal to noise ratio(PSNR).

1. INTRODUCTION

Noisy images have blurred or damaged details due to noise added by the sensors or cameras. As noisy pixels values are of maximum, noise is said to be impulse noise. Images are al socorrupted by noise while storing the image in faulty memo ry,or during the transmission of image via noisy channel. I mage denoising is the most important task to restore the orig inal image details from a noisy image. The impulse noise da mages the image details by corrupting pixels. Impulse noise is suppressedby grasping the noise characteristics of the ima ge. Noise is to be distributed randomly in the image. So that the uncertainties are the most important features to c onsider for suppressing the impulse noise, unfortunately the impulse noise is similar to uncertainties. The uncertainties t hat are involved in the impulse noise are randomness and fu zziness. These are two importantfeatures. In the previous d enoising techniques, filters consider only the randomness. Among these, the effective filters arethe median filter and they unconditionally process each p ixel without considering the pixel is corrupted or not, so th at's why uncorrupted pixels are also altered. At high noise le vels, image details are damaged. This paper presents a nove l effective filter based on the cloud model (CM) for supervi sing impulse noise, so that typeof filter is called CM filter .T hats why, the experimental results shows that even if the noi se level is close to 95% in the image,CM filter can able to r estore the images with good detailed preservation compared with the traditional switching filters.

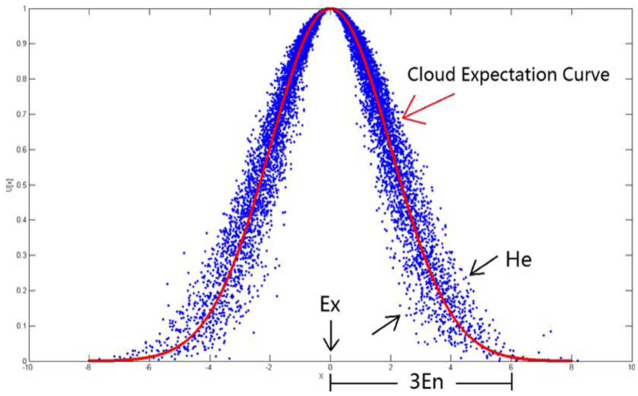
II. CLOUD MODEL

A . CM and its Digital Characters

The CM combines the fuzziness and randomness and then it forms an inter mapping between the qualitative and quantitative information .Let U be a universal set expressed by the exact numbers. C is the quantitative concept associated with U. the certainty degree of x for C i.e., μ(x) □ [0, 1] .the random realization of concept C if number x□U exist

$$\mu : U \rightarrow [0,1] \ \forall \chi \in U \qquad (1)$$

Each x is called a drop; the distribution of x on U is called the cloud. The three parameters that are used to characterize the cloud are expected value, entropy En and hyper entropy He. Ex points out which drops can best represents the concept and reflects the distinguished feature of the concept, Ex represents expectation of the cloud drops .En represents the uncertainty measurement of the quantitative concept .these can be determined by using both randomness and fuzziness. He represents uncertainty measurement of expectation of cloud drops i.e, En. the noise pixels are the usually distributed on the both sides of the cloud, and the uncorrupted pixels are located near the central region of the cloud. The red square regions represent the certainty degrees of the uncorrupted pixels, and the blue square regions show the certainty degrees of the noise pixels. the noise pixels are usually set to the maximum or minimum values in the range.



He is the uncertainty measurement of En.

B . Contribution of Cloud Drops to the Concept

The cloud is formed due to the drops. The certainty degrees and the contribution degrees of the drops are increasing when the drops are approaching ex. The drops will be located within the domain of [Ex-3En, Ex+3En] take up to 99.99% of the whole quantity .but the drops which are located out of the domain [Ex-3En, Ex+3En], their

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contribution to the concept can be neglected. This is known as "3En rule"

C . Cloud Expectation Curve

The uncertainty degree of each drop is a probability distribution rather than a fixed value in the normal cloud generator .so that the certainty degree of each drop is a random value in a dynamic range. A curve is composed by using all the drops and their expectations of certainty degrees and that curve is known as cloud expectation curve (CEC).

III. CM FILTER

A . Noise Model

During the transmission of data through the noisy sensors or communications channels. Create some errors in the data, so that causes frequent corruption of the digital Image by impulse noise, the noise pixels are set to the maximum and minimum values in a dynamic range.

Let $x_{i,j}$ for (i,j) € Ωbe the gray value of image x at pixel location (i,j). the dynamic range of x is [S_{min} , S_{max}]. y be the noisy image then gray level at location (i,j) is given by

$$y_{i,j} = \begin{cases} S_{min}, & \text{with probability } p \\ S_{max}, & \text{with probability } q \\ X_{i,j}, & \text{with probability } 1-p-q \end{cases}$$

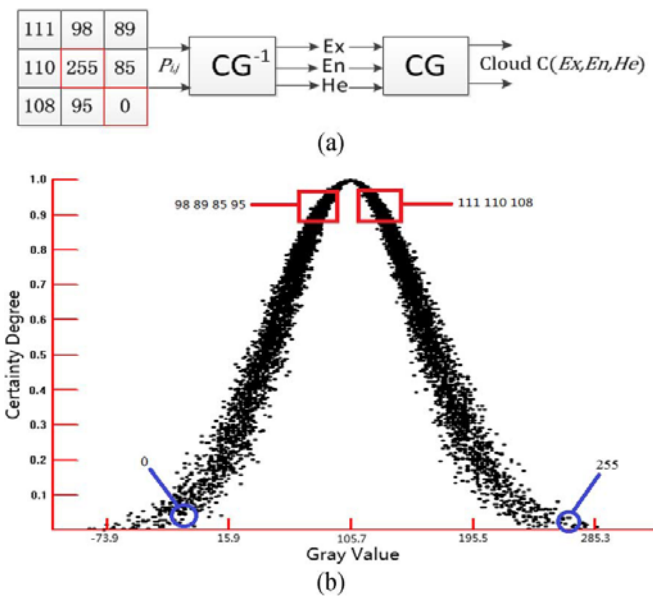

Fig.2 (a) Calculated the cloud that represents the observed neighborhood. (b) Cloud C (105.7, 44.9, 47.8) represents the neighborhood in (a).

B. Noise Detection

Detection window contains the difference between the noise pixels and the mean of all the pixels are larger than the others in the same window because usually the noise pixels are set to the maximum or minimum values in the range .the CM consist of all the pixels in the window as a set, the contribution degrees for the noise pixels are usually lower than the others. By using the features, the distinguishing between the noise pixels from the uncorrupted ones is done. the above fig.2(a) shows the noise detection in the image . the values 0 and 255 are the noise pixels. each pixel is treated as a cloud drop and input them into the backward CM generator CG^{-1} .

TABLE I
CERTAINTY DEGREE OF EACH PIXEL

s.no	*Gray Value*	*Certainty Degree*
1.	***111***	***0.99298***
2.	***98***	***0.98555***
3.	***89***	***0.93352***
4.	***110***	***0.99536***
5.	***255***	***0.00400***
6.	***85***	***0.89963***
7.	***108***	***0.99865***
8.	***95***	***0.97222***
9.	***0***	***0.06297***

Therefore, three parameters of cloud C are produced at the output of CG-1.they are forwarded into the CG then finally, cloud C is formed and comes as a output of the CG. The table I shows that the certainty degrees of noise pixels.

Take a window $W_{i,j}^{2N+1}$ of size (2N+1)X(2N+1) centered at location (i,j) and the gray value of the pixel at location (i,j) is $x_{i,j}$, The maximum and minimum gray values in the noise image could be S_{max} and S_{min} respectively. Then $W^{2N=1}_{i,j}$ denotes the maximum and minimum values in $W_{i,j}^{2N+1}$.

$$W_{i,j}^{2N+1} = \{(i+s, j+t) | -N \leq s,\ t \leq N\}$$

Algorithm I

1. Initialize $N = 1$ and threshold δ (δ is a positive integer), denote n as the number of uncorrupted pixels in $W_{i,j}^{2N+1}$, and initialize $n = 0$.

2. Calculate Ex of all the pixel in $W_{i,j}^{2N+1}$, i.e.,

$$\mathrm{Ex} = \frac{1}{n} \sum_{x_{i+s,i+t} \in W_{i,j}^{2N+1}} x_{i+s,j+t}. \tag{2}$$

3. Calculate En, i.e.,

$$\mathrm{En} = \sqrt{\frac{\pi}{2}} \times \frac{1}{n} \sum_{x_{i+s,j+t} \in W_{i,j}^{2N+1}} |x_{i+s,j+t} - \mathrm{Ex}|. \tag{3}$$

4. Calculate $W_{\max}^{2N+1}$ and $W_{\min}^{2N+1}$, respectively, i.e.,

$$W_{\max}^{2N+1} = \mathrm{Min}(S_{\max}, \mathrm{Ex} + 3\mathrm{En})$$
$$W_{\min}^{2N+1} = \mathrm{Max}(S_{\min}, \mathrm{Ex} - 3\mathrm{En})$$

where Min and Max are the extreme operations to recover the smallest and the largest of the two values, respectively.

5. If $W_{\min}^{2N+1} < x_{i,j} < W_{\max}^{2N+1}$, then $x_{i,j}$ is an uncorrupted pixel; otherwise, go to step 6.

6. Identify if the other pixels in $W_{i,j}^{2N+1}$ are the noise pixels or not. For pixel $x_{i+s,j+t}$, if $W_{\min}^{2N+1} < x_{i+s,j+t} < W_{\max}^{2N+1}$, then $x_{i+s,j+t}$ will remain, and $n = n + 1$.

7. If $W_{\min}^{2N+1} \geq x_{i,j}$ or $x_{i,j} \geq W_{\max}^{2N+1}$, with $n < \delta$, then set $N = N + 1$, and go to step 2; otherwise, $x_{i,j}$ is a noise candidate.

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Compared with the traditional detectors, the proposed detector has mainly three major differences. First, the proposed detector uses all pixels in the window to detect noise pixels. However, the traditional filters consider the extreme values, median value. Second, the traditional filters usually remove the extreme values in the detection window .All the pixels that are set to the maximum and minimum values are not the noise pixels. Third, The proposed detector identifies if the pixel is a noise pixel or not and then removes all the noise pixels in $W_{i,j}^{2N+1}$ at a same instant of time.

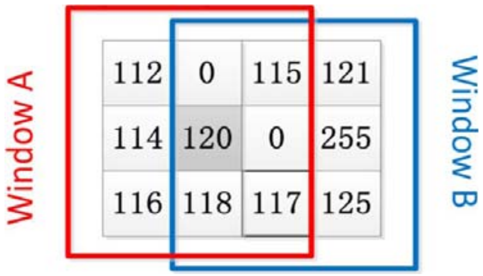


Fig. 3. Pixel in different windows has different characters.

C. WFM Filter

The traditional switching methods are two-stage filters, they identifies the noise pixels and then recorded the information of the noise pixels by using a noise map. Finally, based on the map, The filters suppress the Noise pixels one by one .These filters will increase the memory sp a-
ces and also decreases the computational efficiency.In order to overcome this drawback, the CM filter suppresses the noise pixel immediately after the pixel had been detected as a corrupted one. Therefore, the CM filter uses noise detector and post filter in same windows.

$$W_{i,j}^{2N+1} = \{(i+s, j+t) | -N \le s,\ t \le N\}.$$

Algorithm II

1. Calculate Ex of each uncorrupted pixel in $N_{i,j}^{2N+1}$, i.e.,

$$\mathrm{Ex} = \frac{1}{n} \sum_{x_{i+s,j+t} \in N_{i,j}^{2N+1}} x_{i+s,j+t}. \qquad (4)$$

2. Calculate En, i.e.,

$$\mathrm{En} = \sqrt{\frac{\pi}{2}} \times \frac{1}{n} \sum_{x_{i+s,j+t} \in N_{i,j}^{2N+1}} |x_{i+s,j+t} - \mathrm{Ex}|. \qquad (5)$$

3. Calculate weights for $x_{i+s,j+t}$, i.e.,

$$w_{i+s,j+t} = \exp\left(-(x_{i+s,j+t} - \mathrm{Ex})^2 / 2\mathrm{En}^2\right). \qquad (6)$$

4. Calculate the weighted mean, i.e.,

$$y_{i,j} = \sum_{x_{i+s,j+t} \in N_{i,j}^{2N+1}} w_{i+s,j+t} x_{i+s,j+t}. \qquad (7)$$

IV. RESULTS AND DISCUSSION

A. Configuration

The grayscale images of size 512×512 of lena and bridge are selected for the simulations. These images are corrupted equally probability “salt” (with value 255) and “pepper”(with value 0) noise . For the comparison purposes, The minimum-maximum exclusive mean(MMEM) filter, The Adaptive Median (AM) Filter. The median-type noise detectors and detail-preserving regularization (AM-EPR) filter, The fast median (FM) filter, The boundary discriminative noise detection detection (BDND) filter are tested. At high noise levels, The above filters can be used to suppress the salt-and-pepper noise. In many cases, The noise level exceeds 60% so that the CM filter can effectively restore the original image details with good quality even at high noise level.

B . Noise Detection Performance

The accuracy of noise detection is important because it will influence directly on the qualities of the restored images. Table II lists the information about the accuracies of five filters. These filters are compared by using two parameters namely; The number of noise pixels that are identified as noiseless pixels, Other one is the number of false alarms (FA) i.e., The number of uncorrupted pixels that are identified as noise pixels.

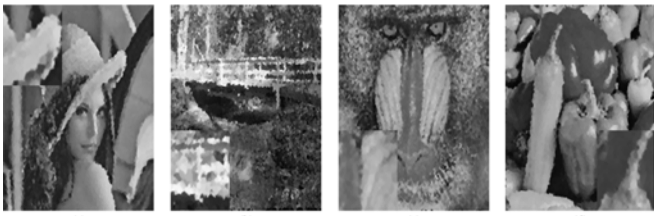
C . Restoration Performance

The restoration performance of six filters are evaluated by using the peak signal-to-noise ratio (PSNR) restoration performance can be quantified.

$$\mathrm{PSNR} = 10 \log_{10} \frac{255^2}{\frac{1}{MN} \sum_{i,j} (y_{i,j} - x_{i,j})^2} \qquad (8)$$

Where $y_{i,j}$ and $x_{i,j}$ denote the pixel values of the restored image and the original image, respectively.

Fig. 4. Restoration results of different filters. (a) Corrupted Lena image with 80% salt-and-pepper noise (6.42 dB). (b) Original image. (c) CM filter (28.66 dB).(d) MMEM filter (27.66 dB). (e) AM filter (24.89 dB). (f) BDND *filter (27.67 dB). (g) FM filter (23.08 dB). (h) AM-EPR filter (27.23 dB).*



(a) (b) (c) (d)

Fig. 5. Images with the noise level of 95% restored by the CM filter. (a) Lena (24.97 dB). (b) Bridge (20.05 dB). (c) Peppers (24.45 dB). (d) Baboon (19.08 dB).

D . Computational Complexity

The runtimes of the filters are compared in table v, Computational complexity is the most advantage feature for the Cm filter. In order to make a reliable comparison. Each filter is run 20 times in the same running environment. The table II lists the average runtimes in milliseconds for various filters.

TABLE II
AVERAGE RUN TIME (MILLI SECONDS)

Filter	Noise Density (%)			
	10	20	30	40
CM	546	577	640	655
BDND	12324	12308	12386	12168
AM	187	203	203	218
MMEM	421	421	359	312
FM	187	172	187	187
AMEPR	90168	119481	165922	203346
Filter	Noise Density (%)			
	50	60	70	80
CM	546	577	640	655
BDND	12324	12308	12386	12168
AM	187	203	203	218
MMEM	421	421	359	312
FM	187	172	187	187
AMEPR	90168	119481	165922	203346

V. CONCLUSION

The traditional switching filter having three aspects in image denoising that merit our attentions. First, in noise detection, accuracy is important factor. The denoising performance of the filter is improved by increasing the detec ti-on accuracy .Second, Computational efficiency is another important factor for the denoising filters. The filters with less computational efficiency may not obtain the satisfactory results. Finally, By improving the knowledge about the uncertainties exist in the noise will help to improve the qualities of the restored images. In the proposed method, A filter is provided to suppressing the impulse noise effectively. Based on the cloud model, the uncertainties are represented clearly, which is helpful in identification and suppressing noise. The experimental results shows that the CM filter is the best one compared with others .In noise identification, press er-vation of image details and performance even in the noise levels also these filter can restore the texture, the details and the edges of the images with good visual effect.

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