COGNITION MODEL BASED ADAPTIVE MULTILEVEL FILTER FOR REMOVAL OF IMPULSE NOISE

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Abstract—Image denoising is an important image processing task, both as a process itself, and as a component in other processes. The main properties of a good image denoising model are that it will remove noise while preserving edges. This paper presents a novel adaptive multilevel filter based on the cloud model (CM) to remove impulse noise; CM is an uncertain cognitive model called the CM filter. First, an uncertainty-based detector identifies the pixels corrupted by impulse noise. Then, a weighted multilevel arithmetic mean filter is applied to remove the noise candidates. Compared with the traditional filters, the CM filter makes a great improvement in image denoising.

Index terms—Cloud model (CM), image denoising, impulse noise, median filter.

I. INTRODUCTION

Image denoising is the recovery of a digital image that has been contaminated by additive white Gaussian noise. Among the uncertainties involved in impulse noise, the randomness and the fuzziness are the two most important features. The randomness mainly shows in two aspects, i.e., the pixels are randomly corrupted by the noise and the noise pixels are randomly set to the maximum or minimum value. The fuzziness focuses on the pixels with the extreme values whether they belong to the noise or not. Not all of the pixels, which are set to the extreme values, will be the noise pixels. In early denoising techniques, the filters only think about the randomness. Among these filters, the famous ones are the median (MED) filter ([1], [2]). They unconditionally fulfill on each pixel without considering whether the pixel is “bad” or not., since the uncorrupted pixels are altered, they damage many image details in the high noise levels; A novel effective filter based on the cloud model (CM) for impulse noise removal is presented, called the CM filter. The experimental results show that, compared with the traditional filters, the CM filter has the better performance in image denoising.

II. CM FILTER

A. *Preprocessing*

The gray values of the pixels are usually lower than in the other areas. The images restored by the CM filter basically keep the same gray levels with the original images. Then the impulse noise is added. In the model, the observed gray level at location (i.j) is given by,

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

B. *Uncertainty Detector*

The CM is a natural-language cognitive model with uncertainty. It combines the fuzziness and the randomness, and forms an inter mapping between the qualitative and quantitative information.

$$\mu : U \rightarrow [0,1] \; \forall x \in U \quad x \rightarrow \mu(x)$$

Then the distribution of x on U is called the cloud, and each x is called a drop [15]. The cloud can be characterized by three parameters, i.e., the expected value Ex, entropy En, and hyper entropy He. Ex is the expectation of the cloud drops’ distribution in the domain En is the uncertainty measurement of the qualitative concept, which is determined by both the randomness and the fuzziness of the concept.

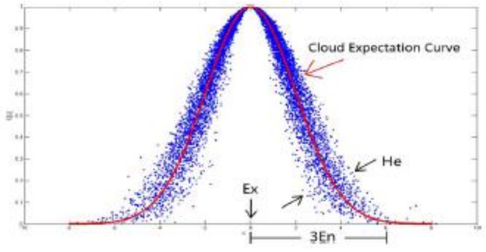

Fig. 1 Cloud C (0, 2, 0.3).

The cloud employs its three parameters to represent the qualitative concept. For example, cloud Ex En He is shown in Fig. 1. The drops compose the cloud. When the drops are approaching ex, the certainty degrees and the contribution degrees of the drops are increasing. Therefore, in the cloud, the drop communities contribute to the concept with the different contribution degrees.

According to the normal cloud generator (CG), the certainty degree of each drop is a probability distribution rather than a fixed value. It means that the certainty degree of each drop is a random value in a dynamic range. If He of the cloud is 0, then the certainty degree of each drop will change to be a fixed value. The fixed value is the expectation value of the certainty degree.

In fact, the value is also the unbiased estimation for the average value of the certainty degrees in the range. All the drops and their expectations of certainty degrees can compose a curve, and the curve is the cloud expectation curve (CEC). For example, the red curve is the CEC of cloud (see Fig. 1). Thus, the noise pixels are usually distributed on the both sides of the cloud, and the uncorrupted pixels are located near the central region of the Cloud.

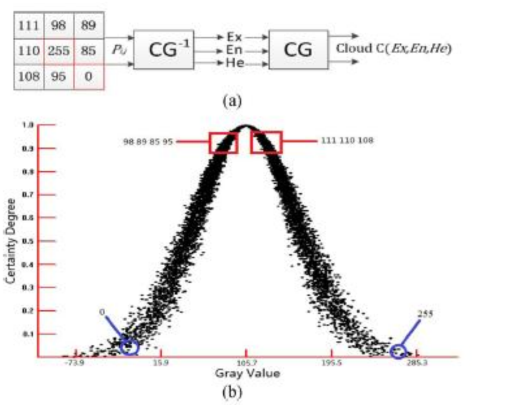

Fig. 2 (a) Calculated the cloud that represents the observed neighborhood. (b) Cloud C (105.7, 44.9, and 47.8) represents the neighborhood in (a).

TABLE 1
CERTAINTY DEGREE OF EACH PIXEL

Gray Value	Certainty Degree
111	0.99298
98	0.98555
89	0.93352
110	0.99536
255	**0.00400**
85	0.89963
108	0.99865
95	0.97222
0	**0.06297**

Where r=p+q defines the noise level.

The contribution degrees and the certainty degrees are usually lower than the others. The certainty degree of each pixel is shown in Table 1. It is how we can distinguish the noise pixels from the uncorrupted ones, e.g., there is an observed neighborhood (the left square region of Fig. 2(a); 0 and 255 are the noise pixels) and if cloud exists, which can represent the neighborhood.

Let each pixel be a cloud drop and input them into the backward CM generator CG^{-1}. The outputs of CG^{-1} are the three parameters of cloud. Then, we input Ex, En, and He into the forward CG. Finally, cloud comes out as the output of the CG.

C. Noise Removal

The impulse noise is removed from the image. Calculate Ex and En. The filter replaces the noise pixel by using the weighted mean of the remaining pixels, and their weights are the certainty degrees of them. In the cloud, the certainty degree of each drop is a random value.

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.,

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

3. Calculate En, i.e.,

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

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.

Algorithm II

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

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

2. Calculate En, i.e.,

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

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

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

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

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

However, in the cloud, the certainty degree of each drop is a random value. Thus, to increase the computational efficiency and the robust stabilization of the CM filter, the filter also uses the CEC to calculate the certainty degree for each pixel.

D. *Weighted Multilevel Arithmetic Mean filter*

Once the CM filter identifies a pixel as a "good" one, the pixel naturally keeps its original value. Only the corrupted candidates are replaced, which is the same to the traditional filters. However, many switching methods are two-stage filters. They identify the noise pixels first and then use a noise map to record the information of the noise pixels, such as the pixel locations. Finally, according to the map, the filters remove the noise pixels one by one. Thus, they scan the noise image twice. Those filters not only increase the memory spaces but also decrease the computational efficiency. To overcome this drawback, the CM filter removes a pixel immediately after the pixel has been identified as a corrupted candidate. Therefore, in the CM filter, the noise detector and the post filter use the same windows. It means that the window size of the post filter is the one that is used by the noise detection at the last time. For example, in a 3x3 window, the CM filter cannot identify if a pixel is "good" or "bad." Then, the window size will be adaptively increased. Until in the 7x7 window, the pixel is identified as a corrupted candidate, and the CM filter removes the pixel in the same 7x7 window immediately. Many denoising methods are also switching median filters. It means that the filters try to identify the noise pixels and then replace the noise pixel by the median value.

III. RESULTS AND DISCUSSION

A. *Configuration*

Two commonly tested 512x512 8-bit grayscale images, Lena and Bridge are selected in the simulations. The images are corrupted by equal probability "salt" (with value 255) and "pepper" (with value 0) noise. For comparative purposes, the adaptive median (AM) filter [3], the minimum–maximum exclusive mean (MMEM) filter, the median-type noise detectors and detail-preserving regularization (AM-EPR) filter [12], the boundary discriminative noise detection (BDND) filter, and the fast median (FM) filter [14] are also tested. These filters can remove the salt-and-pepper noise in the high noise levels. However, when the noise level is higher than 60%, the other filters ([8], [5]) cannot remove the noise with good image qualities. For an in-depth study in the denoising performance of the selected filters, the simulations are divided into multiple stages. First, the filters apply on the noise images in a wide range of noise levels varying from 10% to 80% with increments of 10%. It focuses on two aspects, the accuracy of the noise detection and the quality of the restored image. Therefore, only the filters that can restore the images without noise and distortion will enter the next stage. Second, the filters that passed the first stage will be applied on the noisy images with the highest noise level (90%). The experiment aims to study the detail-preserving abilities of the filters when the images are affected by a severe noise. Finally, the CM filter with different values applies on the noise image in a wide range of the noise levels varying from 10% to 90% with increments of 10%.

The main objective is to characterize the robustness to the threshold parameter .The FM filter directly regards all pixels whose values are set0 and 255 in a fixed-size (3x3) detection window as the corrupted pixels and then uses the median values or the left neighborhood values to replace the noise pixels. The MMEM filter discards all pixels whose values are equal or similar to the maximum or minimum values in 3x3 or 5x5 windows and then calculates the average value (AVG) of the remaining pixels or the four neighboring pixels. Finally, if (is the detected pixel), then the detected pixel is a noise pixel, and it will be replaced by AVG. The AM filter uses an adaptive size window to identify the noise pixels and then replaces the noise pixels by the median values. To detect the noise patches and filter out the noise, the maximum window size should be chosen such that it increases with the noise level. Therefore, set in all our simulations. The AM-EPR filter combines the AM filter and a variation method. It uses the AM detector to identify the noise pixels and then replaces the noise pixel by using the variation method to preserve the image details. Thus, for the AM-EPR filter, we also set in all our simulations. In addition, we choose as the edge-preserving function, if most of the noise is suppressed, but staircases appear. If, the fine details are not seriously distorted, but the noise cannot be fully suppressed. Another parameter of the AM-EPR filter is the pertinent choice factor. In tests, the AM-EPR filter is very robust with respect to. Thus, we fix in all our simulations. The BDND filter uses two size windows (3x3 and 21x21) to identify the noise and then uses a noise map to recorder all noise pixel addresses. Finally, it uses an adaptive window to remove the noise. In order to avoid severe blurring of image details at high-noise-density cases, the maximum window size of the adaptive window is limited to 7x7 in all our simulations. In addition, to increase the computational efficiency of the CM filter, the detection threshold is always 1 in the first-stage simulations, and to increase the qualities of the restored images, changes to 3 in the second stage.

B. Noise Detection Performance

The denoising performances of the switching filters are usually higher than the standard median filter and its varieties, because the switching filters only remove the noise without altering the uncorrupted pixels. Therefore, the noise detection plays a key role in image denoising. However, with the noise level sharply increased, the noise patches will be formed. The pixels in the noise patches are easy to be identified as the "good" ones, which often results in detection errors. Thus, the accuracy of the noise detection can directly influence the qualities of the restored images.

C. Restoration Performance

The restoration performances are quantified by the peak signal to-noise ratio (PSNR)

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

It denotes the pixel values of the restored image and the original image, respectively. When the noise level is lower than 60%, the performance of the CM filter is similar to the BDND filter and the AM-EPR filter. However, with the noise level sharply increased, many noise patches will be formed. This fact causes many detection errors and makes, the differences between each filter result more and clearer. The FM filter creates many stripe regions because it often replaces the corrupted pixel by the left neighborhood pixel.

Fig.3 Restoration results of different filters. (a) Corrupted Lena image with 80% salt-and-pepper noise (6.42 dB). (b) Original image. (c) CM filters (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)

Although having the same noise detector as the AM filter, the AM-EPR filter makes a great progress in the post filtering. The AM filter cannot preserve the edges well at the high noise level [see Figs. 4(e) and 5(e)], because it is a switching median filter. To overcome this drawback, the AM-EPR filter combines the AM filter and a variation method to preserve the image details. Thus, the qualities of the images restored by the AM-EPR filter are usually better than the AM filters.

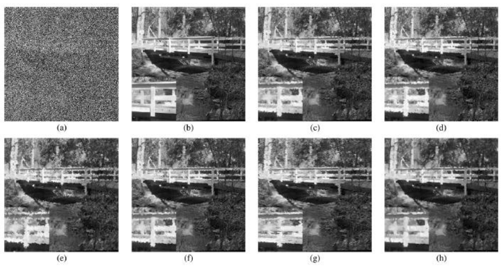

Fig.4 Restoration results of different filters. (a) Corrupted Bridge image with 80% salt-and-pepper noise (6.22 dB). (b) Original image. (C) CM filters (22.63 dB). (d) MMEM filters (21.66 dB). (e)

AM filter (20.21 dB). (f) BDND filters (21.82 dB). (g) FM filters (20.24 dB). (h) AM-EPR filter (21.70 dB)

Therefore, the images restored by the AM-EPR filter appear to have many speckles, particularly in the regions of the Lena hair and the bottom right corner of Bridge. In the images, these regions are the highest activity regions, in which the gray values of the pixels are usually lower than in the other areas. It means that the differences between the pixel and its neighborhood pixels are smaller than the others. These two reasons reduce the sensitivity of the detail-preserving method and cause the qualities of the image restored by the AM-EPR to decrease. Different outcomes between two filters are represented by difference images. The difference images are derived from the absolute value error images by using both original and restored images after filtering.

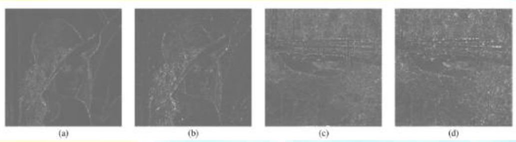

Fig.5 (a) Difference image of Lena using the CM filter at the 80% noise level. (b) Difference image of Lena using the AM-EPR filter. (c) Difference image of Bridge using the CM filter at the 80% noise level. (d) Difference image of Bridge using the AM-EPR filter.

However, at the edges of the Lena hair, the color of Fig. (a) is darker than that of Fig. (b), i.e., in these high activity regions, the edge-preserving ability of the CM filter is better than that of the AM-EPR filter.

Fig.6 Restoration results of different filters. (a) Lena with the noise level of 90% (5.90 dB). (b) Original image. (c) CM filters (26.85 dB). (d) BDND filters (25.45 dB).

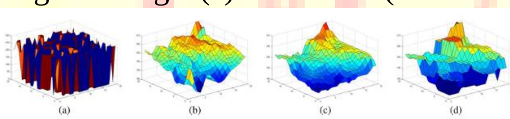

Fig.7 Local restoration results (Lena) of different filters. (a) Noise image. (b) Original image. (c) CM filter. (d) BDND filter.

Fig.8 Restoration results of different filters. (a) Bridge with the noise level of 90% (5.71 dB). (b) Original image. (c) CM filter (21.30 dB). (d) BDND filters (20.13 dB).

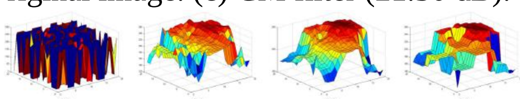

Fig.9 Local restoration results (Bridge) of different filters. (a) Noise image. (b) Original image. (c) CM filters. (d) BDND filters.

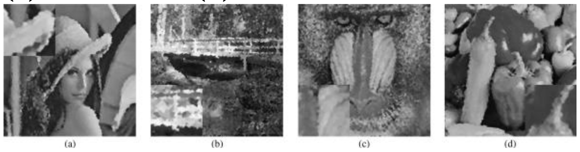

Fig.10 Images with the noise level of 95% restored by the CM filter. (a) Lena (24.97 dB). (b) Bridge (20.05 dB). (c) Baboon (24.45 dB). (d) Peppers (19.08 dB).

IV. CONCLUSION

A novel filter with uncertainty for impulse noise removal has been proposed. It represents the uncertainties of the noise perfectly by using the CM, which is helpful in detecting and removing the noise. In addition, the proposed filter identifies the noise pixel without needing to sort the pixel gray values, which immensely increases the computational efficiency in noise detection. The experimental results show the CM filter is the best one among the tested filters, compared with the traditional filters, the CM filter makes a great improvement and has the higher performances. Even if the noise level closes to 95%, the texture, the details, and the edges of the images restored by the CM filter are preserved with good visual effect. In sum, the CM filter is a moderately fast denoising filter with good detail preservation. Although the CM filter can only detect the fixed-valued impulse noise, and at the 95%noise level, the restored images have some blurring edges in some local areas. This paper presents a novel adaptive multilevel filter based on the cloud model (CM) to remove impulse noise. An uncertainty-based detector identifies the pixels corrupted by impulse noise. A weighted multilevel arithmetic mean filter is applied to remove the noise candidates. The experimental results show that, compared with the traditional filters, the CM filter makes a great improvement in image denoising. However, we can further improve the CM filter by using different noise detectors or restoration methods to solve it.

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