REMOVAL OF IMPULSE NOISE IN IMAGE USING CLOUD MODEL FILTER

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***Abstract*—**

The major inherent feature of impulse noise is Uncertainty. Understanding the uncertainties can improve the performance of image denoising. This paper presents a novel adaptive detail-preserving filter based on the cloud model (CM) to remove impulse noise. It is called the CM filter. First, an uncertainty-based detector identifies the pixels corrupted by impulse noise. Then, a weighted fuzzy mean filter is applied to remove the noise candidates. The experimental results show that, compared with the traditional switching filters, the CM filter makes a great improvement in image denoising. Even at a noise level as high as 95%, the CM filter still can restore the image with good detail preservation.

***Keywords*—**Cloud model (CM), image denoising, impulse noise, median filter.

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I. INTRODUCTION

IMAGE denoising plays a key role in image processing, be-cause impulse noise often corrupts the image pixels. There fore, grasping the noise characteristics is helpful to remove the noise. Uncertainties are inherent features [1] and are unfortu-nately similar to impulse noise. This fact makes image denoising a difficult task. Understanding the uncertainties can improve the performance of image denoising.

Among the uncertainties involved in impulse noise, the ran-domness 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. On the other hand, 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 me-dian (MED) filter and its varieties [2]–[5]. They uncondition-ally fulfill on each pixel without considering whether the pixel is “bad” or not. As a result, since the uncorrupted pixels are al-tered, they damage many image details in the high noise levels.

With the development of fuzzy theory, the fuzziness attracts people’s attention gradually. Some people introduce the membership and present a novel solution, i.e., the switching filters [6]–[18]. They try to identify the noise pixels before the noise removing. Although the experimental results show that, com-pared with the MED and its varieties, the switching filters make a great improvement in image denoising, these filters create many detection errors and smear the image details in the high noise levels because of not understanding the uncertainties of the noise completely

To represent the uncertainties better and resolve the afore-mentioned problems, this paper presents a new effective filter based on the cloud model (CM) for impulse noise removal. It is called the CM filter. The CM is an uncertain cognitive model. After several years of development and perfection, it is success-fully applied in data mining [19]–[21], image processing [22], [23], and other fields [24]. The experimental results show that, compared with the traditional switching filters, the CM filter has the better performance in image denoising across a wide range of noise levels. Even if the noise level is close to 95%, the

CM filter can restore the images with good detail preservation

II. CM

AA. CM and its Digital Characters

T 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.

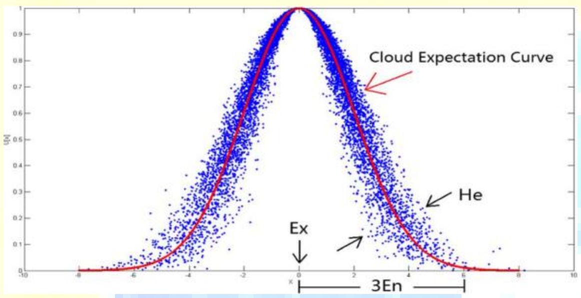

Fig. 1. Cloud

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 [24]. It points out which drops can best represent the concept and reflects the distinguished feature of the concept. En is the uncertainty measurement of the qualitative concept, which is determined by both the randomness and the fuzziness of the concept [23]. It represents the value region in which the drop is acceptable by the concept, while reflecting the correlation of the randomness and the fuzziness of the concept. He is the uncertainty measurement of En [21].

The cloud employs its three parameters to represent the qualitative concept. For example, cloud Ex En He is shown in Fig. 1.

B. Contribution of Cloud Drops to the Concept

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. In fact, the drops located within take up to 99.99% of the whole quantity and contribute 99.74% to the concept.

Thus, the drops are located out of domain , and then, their contributions to the concept can be neglected. This is “the 3En rule.”

C. CEC

According to the normal cloud generator (CG) [20], 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 (Fig. 1).

III. CM FILTER

A. Noise Model

The noisy sensors or communication channels create some errors in the data transmission, which cause the frequent corruption of the digital image by impulse noise [26]. Thus, the noise pixels are usually set to the maximum and minimum values in a dynamic range.

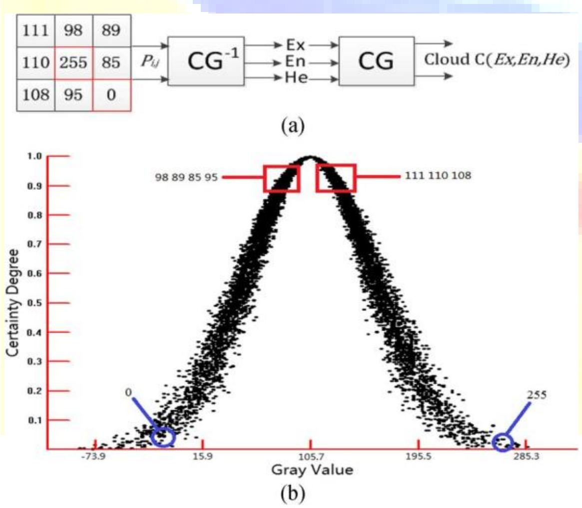

Fig. 2. (a) Calculated the cloud that represents the observed neighborhood. (b) Cloud (105.7, 44.9, 47.8) represents the neighborhood in (a)

B. Noise Detection

As previously described, the noise pixels are usually set to the maximum or minimum values in the range. Therefore, the differences between the noise pixels and the mean of all the pixels are larger than the others in the same detection window. We regard all the pixels in the window as a set and use a CM to represent it. Then, for the noise pixels, the contribution degrees and the certainty degrees are usually lower than the others. 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 [see Fig. 2(b)], 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 are the three parameters of cloud . Then, we input Ex, En, and He into the forward CG [25]. Finally, cloud comes out as the output of the CG. Table I shows that the certainty degrees of the noise pixels are far less than that of the uncorrupted pixels (the certainty degree of each pixel, which is calculated through the CEC). 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 [see Fig. 2(b)]. 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 [in online version, see Fig. 2(b)].

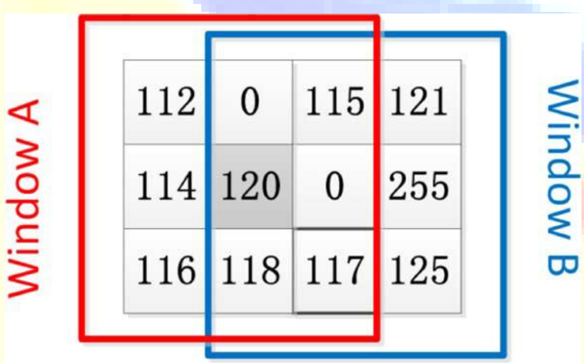

Fig. 3. Pixel in different windows has different characters.

The proposed detector has three major differences with the traditional detectors. First, the proposed detector uses all the pixels in the window to detect the pixel. Second, the traditional filters usually discard the extreme values in the detection window. However, not all of the pixels that are set to the maximum or minimum values will be the noise pixels. For example, 120 is obvious an uncorrupted pixel, if only 0 and 255 are the noise (see Fig. 3). For the traditional filters, 120 is easy to be identified as a noise pixel in window A and it must be an uncorrupted pixel in window B Obviously, discarding the extreme value directly, this often creates the detection errors and causes some useful information loss. Thus, the membership degrees of the pixels must not always be 0 or 1, which is so "hard." They must be the "soft" values, just like the certainty degrees of the pixels in the proposed detector. Third, the proposed detector identifies if the detected pixel is a noise pixel or not and discards all the noise candidates in at the same time. It is a pretreatment to increase the computational efficiency of the post processing

C. WFM Filter

Once the CMfilter 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 switching 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

In addition, 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 or its variants. However, in the high noise levels, those median filters cannot preserve the image details well, particularly the edges. Because of only focusing on the median value, they ignore the contributions of the other remained pixels. To resolve this problem, the CM filter uses a weighted fuzzy mean (WFM) filter to replace the noise pixel and restore the images

The WFM filter replaces the noise pixel by using the weighted mean of the remaining pixels, and their weights are the certainty degrees of them. However, it is noteworthy that, 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 WFM filter also uses the CEC to calculate the certainty degree for each pixel.

IV. 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 AM filter [7], the MMEM filter [9], the AM-EPR filter [16], the BDND filter [17], and the fast median (FM) filter [18] 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 ([6], [8], [10]–[15]) 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

B. Noise Detection Performance

The denoising performances of the switching filters are usually higher than the standard median filter and its varieties, be cause 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.

The noise detection accuracy of the AMfilter can replace that of the AM-EPR filter, because the AM filter and the AM-EPR filter have the same noise detector. The images restored by the MMEM filter, many noise pixels remain, and the detail preservation is compromised. In addition, although MD of the AM filter is zero, its FA is larger than the others resulting in a restored mage of poor visual quality. It will sharply decrease the detail-preserving ability of the filters and the qualities of the restored images. On the other hand, the FM and CM filters have the same MD and FA, and their detection accuracies are higher than the BDND filter. However, the FM filer detects the noise pixels by artificially discarding the pixels whose gray values are 0 or 255. In sum, the CM filter is the best one among them in noise detection.

C. Restoration Performance

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

The FM filter creates many stripe regions [see Figs. 4(g)], because it often replaces the corrupted pixel by the left neighborhood pixel. . In addition, the window size of the FM filter is too small, and it is not large enough to detect the noise patches. If the FM filer does not artificially discard the pixels with gray value 0 or 255, then many noise pixels will remain in the restored images.

In the first-stage simulations, the CM filter [see Figs. 4(c)] and the BDND filter [see Figs. 4(f)] always restore the images without noise.

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).

D. Computational Complexity

At the end of this section, to show the advantage of the CM filter in computational complexity, the runtimes of the filters are compared. To make a reliable comparison, each filter is run 20 times in the same running environment; it is C#.Net (Framework 4.0) on a personal computer equipped with the 3.2-GHz CPU and 2 GB of random access memory. Table I lists the average runtimes in milliseconds for each filter operating on the Lena

TABLE I

COMPARISON OF CPU TIME IN MILLISECONDS

Filter	Noise Density (%)							
	10	20	30	40	50	60	70	80
CM	546	577	640	655	686	702	764	920
BDND	12324	12308	12386	12168	12074	11825	11544	11341
AM	187	203	203	218	250	312	452	780
MMEM	421	421	359	312	312	296	328	343
FM	187	172	187	187	187	187	172	187
AM-EPR	90168	119481	165922	203346	243750	288195	326743	368410

The CMfilter is the third slowest one among the filters. However, it is not like the AM-EPR and BDND filters, its runtimes always keep from 500 to 1000 ms in the simulations. For the BDND filter, its runtime is about 22 times and 12 times that of the CM filter with the noise levels of 10% and 80%, respectively. The noise level of 80%, the runtime of the AM filter is only less than the 140-ms CM filter, because the AM filter identifies that the noise also needs to iterate many times, just like the CM filter. Moreover, the AM filter is a switching median filter, and it replaces the noise pixel by using the median value. Thus, the AM filter is faster than the CM filter. On the other hand, The CM filter identifies the noise pixel without needing to sort the pixel gray values, which is not similar to the traditional switching filters. This makes the filter decrease the computational complexity and increase the computational efficiency in noise detection. In sum, to obtain the same qualities of the restored images, the CM filter is the fastest one among the tested filters.

V. CONCLUSION

For the switching filter, there are three aspects in image denoising that merit our attentions. First, the accuracy of the noise detection is a very important factor, because it will directly influence the results of the image denoising. Thus, increasing the detection accuracy can improve the denoising performance of the filter. Second, the computational efficiency is also an important factor to the denoising filters because, in the real-time work, the filters with lower computational efficiency may not obtain the satisfactory results. Finally, large uncertainties exist in the noise. Thus, understanding the uncertainties can completely help to improve the qualities of the restored images.

In this paper, 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. The experimental results show the CM filter is the best one among the tested filters, compared with the traditional switching filters. No matter whether, in noise detection, the image details preservation or computational complexity, 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.

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