An Adaptive Weighted Fuzzy Mean Filter Based on Cloud Model

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Abstract: *This research proposes an Adaptive Weighted Fuzzy Mean Filter (AWFMF) based on Cloud Model (CM) to remove the salt and pepper noise in the digital images. Also, the performance of the proposed filter is compared with existing variants of median and switching filters using peak signal to noise ratio (PSNR) and quality index. The proposed filter is able to remove salt and pepper noise even at 90% noise level with good detail preservation.*

Keywords: *Image denoising, salt and pepper noise, CM.*

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1. Introduction

Digital images are corrupted by various noises due to the errors in sensors [1] and/or communication channels. They change the pixel values which do not reflect the original scene. Impulse noise is one amongst them which degrades the quality of the digital image. A large number of algorithms have been reported to remove the additive impulse noise. Most of these algorithms use median filters and its modifications. Standard Median Filter (SMF) is implemented by moving a finite length of window throughout the image that replaces the centre pixel of the window with the median value of the pixels in that window [8]. This implementation modifies both noisy and noise-free pixels. Thus, SMF removes the lines and corners in the image while suppressing the noise. To overcome this difficulty, several variations of the SMF have been proposed. The Weighted Median Filter (WMF) is one of the variations to median filter which assigns uneven weights to the pixels in the window [2, 20] by accounting the local characteristics of each pixel in the window [4]. This provides some degree of control to the smoothing behaviour but these uneven weights introduce complexity in design and implementation of WMF. The extension of WMF is the Centre Weighted Median Filter (CWMF) [6, 10, 11], which assigns weight to the central value of the window only to reduce the complexity in the design [9]. The CWMF filter performs well when the noise is low and fails if noise is high. To overcome this, Adaptive Median Filter (AMF) with variable window size is introduced. AMF is robust in removing the impulse noise while preserving the details even though the noise is high [10]. The filters discussed above use only the randomness associated with impulse noise. They replace unconditionally each pixel with median value of the window without checking whether the pixel is good or bad. As a result, they damage many image details by replacing good pixels at high noise levels.

With the development of Fuzzy, the use of switching filters to remove impulse noise has attracted more research recently [3, 13, 17, 19, 23]. These filters employ an impulse detector to determine the presence of impulses in the image. Only these impulses will be filtered by switching filters. The Progressive Switching Median Filter (PSMF) is one of the switching filters in which both impulse detector and noise filter are applied progressively in iterative manner to obtain better results [19]. These progressive iteration increases the time complexity of the filter. To minimize the time complexity, Fast Median Filter (FMF) was proposed. In FMF, the impulses are replaced by either the median pixel or neighbourhood pixel [17]. The median value may be an impulse at higher noise level. At that situation, neighbourhood pixels are used for impulse replacement.

Even though switching filters perform better than median and its variant filters, they are not able to recover the original image at high noise level. It is necessary to understand the randomness and fuzziness completely to recover original image at high noise level. To understand randomness and fuzziness associated with the impulse noise, this paper proposes Adaptive Weighted Fuzzy Mean Filter (AWFMF) based on Cloud Model (CM). The experimental results show that the proposed filter has better performance than SMF, AMF, PSMF and FMF in terms of Peak Signal to Noise Ratio (PSNR) and Quality Index (QI) across a wide range of noise level from 10% to 90%.

2. Cloud Model

To remove the impulse noise in digital images, it is necessary to grasp impulse noise characteristics. Uncertainties are inherent features of impulse noise. So, understanding and applying uncertainties in a better way can improve the performance of impulse removing filter. Uncertainties in impulse noise exist through the randomness and the fuzziness. When the pixels are randomly corrupted and randomly set to the maximum extreme value '255' or minimum value '0', then the impulse noise is said to be salt and pepper noise. This shows the randomness whereas not all of the extreme value pixels are impulses shows the fuzziness associated with impulse noise. This relation between randomness and fuzziness was established by CM [22]. CM is a model of the uncertainty transformation between quantitative representation and qualitative concept based on normal distribution and bell shaped membership function. CM has been successfully applied to data mining [5, 18], image classification [14], image segmentation [15, 16] and optimization [7].

Let U be a quantity domain expressed with accurate numbers and C be a quality concept related to U. If here is a quantity value, $x \in U$ which realizes the quality concept C, then the certainty degree of x for C is $\mu(x)$ and it lies between [0, 1]. It is the membership degree in the fuzzy set and has distribution of probability. It is the random number which has the steady tendency.

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

The distribution of x on U is called cloud and each x is called a cloud drop. The cloud can be characterized by three parameters, i.e., the expected value E_x, entropy E_n and hyper entropy H_e [5, 12, 14, 15, 16, 18, 22]. E_x is the mathematical expectation of the cloud drop distributed in the universal set. E_n is the uncertainty measurement of the qualitative concept, which is determined by both randomness and the fuzziness. It represents the value of the region in which the drop is acceptable by the concept, while reflecting the correlation of randomness and fuzziness. H_e is the uncertainty measurement of E_n. It is the second order entropy of the entropy. In image processing applications, image and pixels represent the cloud and cloud drops. The pixels are given as input to the backward CM generator CG^{-1}. Backward cloud generator is a conversion model which can convert quantity numbers to a quality concept. The outputs of CG^{-1} are E_x, E_n and H_e. These three parameters can be applied to the forward CG to generate the cloud. Forward CG is the mapping from quality to quantity. This is shown in Figure1.

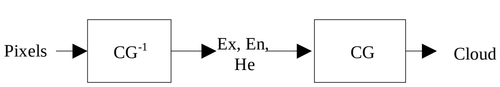
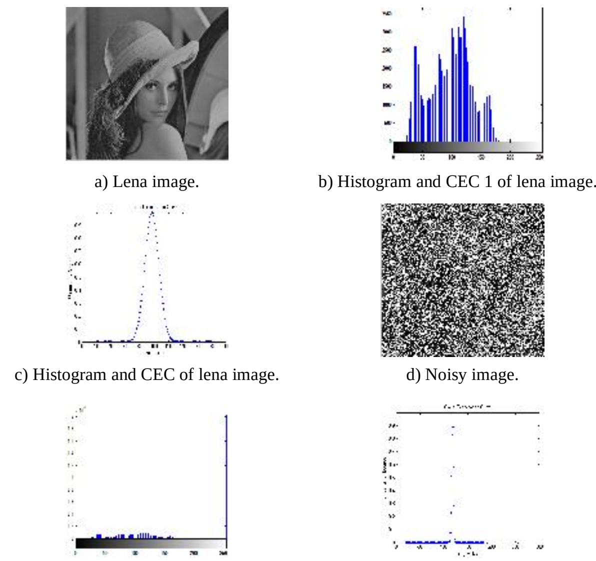


Figure 1. Forward and backward cloud generator.

The drops in the cloud contribute to the concept with the different contribution degrees [22]. When the drops are approaching the mean value E_x, their certainty and the contribution degrees are increasing. Within the one dimensional universal domain U, the cloud drops lies in the interval [E_x-3E_n, E_x+3E_n] take up to 99.99% of the whole quantity and contribute 99.74% to the concept C. So, the cloud drops located out of the domain [E_x-3E_n, E_x+3E_n] contribute very less to the concept and their contributions can be neglected. This is "3 E_n rule." According to the forward CG, the certainty degree of each drop is a random value in a dynamic range. If H_e 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. A curve called Cloud Expectation Curve (CEC) is constructed by plotting all the drops in X-axis and their expectations of certainty degrees in Y-axis. The histogram and CEC of Lena image and noisy Lena image at 70% of noise level are shown in the Figure 2.



a) Lena image. b) Histogram and CEC 1 of lena image.

c) Histogram and CEC of lena image. d) Noisy image.

e) Histogram and CEC 1 of noisy image. f) Histogram and CEC 2 of noisy image.

Figure 2. Histogram and CEC of noise-free and noisy image.

3. Adaptive Weighted Fuzzy Mean Filter

The proposed AWFM Filter is a double stage filter, where the first stage is the impulse detector and the second one is impulse replacement filter. When pixels are randomly corrupted by two fixed extreme values, 0 and 255, with the same probability, the impulse is said to be salt and pepper. When these salt and pepper noisy pixels are detected in the first stage, they are subjected to next filtering stage. Otherwise, noise-free pixels are retained without any filtering action to preserve the image details and textures in the original image.

3.1. Noisy Pixel Detector

Similar to other impulse detection algorithm, this Noisy Pixel Detector (NPD) uses prior information about the salt and pepper noise with the following assumptions:

- Only the proportions of image pixels are corrupted while other pixels are noise-free.
- Noisy pixels take a very large value as positive impulse or a very small value as negative impulse.

Normally, the salt noise takes the pixel value of 255 and pepper noise takes the pixel value of 0. These two values are used to identify the noisy pixels in the image. The NPD checks the value of every pixel in the image. If the value of pixel value ‘0’ or ‘255’, then the pixel will be replaced by ‘0’. Otherwise, the pixel is left unchanged.

$$x(i,j)=\begin{cases}0, & if\ p(i,j)=0\ or\ 255\\ p(i,j), & otherwise\end{cases} \qquad (2)$$

Where p is the input image to NPD and x is the output image.

3.2. Noisy Pixel Replacement Filter

The Noisy Pixel Replacement Filter (NPRF) replaces the noise pixel marked with $x(i, j)$=0 by the weighted fuzzy mean value of the remaining pixels in the square filtering window $W_{i,j}^{2N+1}$ of size $2N+1$, where:

$$W_{i,j}^{2N+1}=\left\{x_{i+s,j+t}\right\}, where\ \ s,t\in(-N,...,0,...,N)$$

- *Step* 1: Set the window size by initializing N=1. Then, the number of noise- free pixels in the filtering window $W_{i,j}^{2N+1}$ is counted. If the current filtering window does not have any noise-free pixel, then the filtering window size is increased by incrementing the value of N by one. Else, E_x of all noise-free pixels in $W_{i,j}^{2N+1}$ is calculated using the formulae:

$$E_x=\frac{1}{n}\sum_{x_{i+s,j+t}\in W_{i,j}^{2N+1}} x_{i+s,j+t} \qquad (3)$$

- *Step* 2: En is calculated using the following formulae:

$$E_n=\sqrt{\frac{\text{®}}{2}}\times\frac{1}{n}\sum_{x_{i+s,j+t}\in W_{i,j}^{2N+1}}\left|x_{i+s,j+t}-E_x\right| \qquad (4)$$

- *Step* 3: Weight for each and every noise free pixel in the window is calculated using the formulae:

$$w_{i+s,j+t}=exp(-(x_{i+s,j+t}-E_x)^2/\,2E_n^2) \qquad (5)$$

- *Step* 4: The weighted mean is calculated as:

$$y_{i,j}=\sum_{x_{i+s,j+t}\in W_{i,j}^{2N+1}} w_{i+s,j+t}x_{i+s,j+t}\Big/ w_{i+s,j+t} \qquad (6)$$

- *Step* 5: Finally, the noisy pixel $x(i, j)$ is replaced by the weighted mean value $y_{i,j}$.

4. Simulation Results

In this section, the performance of proposed AWFM Filter is compared with SMF, AMF, PSMF and FMF. For simulation, twelve gray scale images (baboon, barbara, barco, boat, cameraman, fingerprint, house, lena, medical, penguins, peppers and pout) with different image conditions are taken and salt and pepper noise is added with noise level varying from 10% to 90% in increments of 10%. Various filters are applied to these noisy images and the filtered images are evaluated using quantitative measures PSNR and QI [21]. The restoration results of proposed AWFM Filter at 90% noise level are shown in Figure 3. From the results, it is inferred that AWFM Filter is able to produce reconstructed images with good image detail preservation.

a) Original image. b) Noisy image. c) Restored image.

Figure 3. Restoration results of proposed AWFM filter.

Figures 4 and 5, shows the performance of SMF, AMF, PSMF, FMF and AWFM Filters in terms of PSNR and QI at different noise levels varying from 10% to 90% in increments of 10%. This figure proves that the proposed AWFM Filter has a better noise suppression ability in terms of PSNR and QI also.

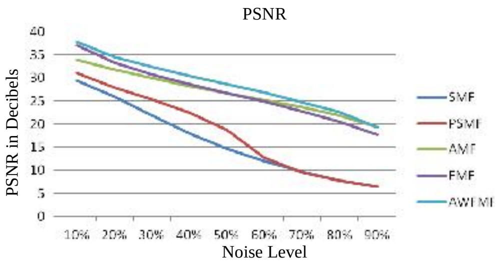


Figure 4. PSNR comparison of various filters at different noise levels.

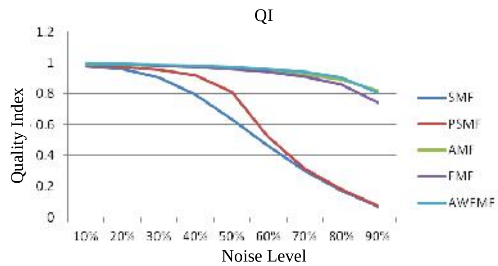


Figure 5. QI comparison of various filters at different noise levels.

Table 1 presents the processing time of proposed AWFM Filter for various images at different noise levels varying from 10% to 90% in increments of 10%. In general, the proposed filter has a relatively higher processing time as compared to the other filters implemented. This higher processing time can be compensated by the better filtering results in terms of qualitative and quantitative results.

Table 1. Processing time (in seconds) of proposed AWFM filter for various images at different noise levels.

Image	Noise Level								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Baboon	0.75191	0.96966	1.3791	1.8287	2.98716	3.23417	3.530467	4.25287	4.9004
Barbara	0.52434	0.99371	1.4146	2.18437	2.5412	2.615068	3.8421	3.94428	4.22906
Barco	0.54287	0.96008	1.4158	2.3004	2.50991	3.168867	3.42727	3.8384	4.38189
Boat	0.52046	0.9819	1.8036	1.9629	2.20012	2.571621	3.46024	3.60449	4.4321
Cameraman	0.69395	1.3587	1.48196	1.8249	2.36345	3.641341	4.21475	5.54342	5.7853
Fingerprint	0.52305	0.98505	1.9129	2.1888	2.22522	2.623606	3.44354	4.15893	4.2288
House	0.5368	1.46283	2.0804	2.2435	2.588871	3.2355	3.89043	4.61397	4.8176
Lena	0.54033	0.97627	1.8125	2.157	3.029238	3.35332	3.52886	4.40474	5.1409
Medical	0.72095	0.98684	1.4407	2.2273	3.02758	3.19486	3.20009	3.76136	3.8508
Penguins	0.53253	0.98107	1.4047	1.8435	2.19109	3.512191	3.69909	4.4728	4.8119
peppers	0.58537	1.29176	1.4525	1.8023	2.5914	2.694667	3.45504	3.64331	4.1871
Pout	0.74211	1.17949	1.4615	2.5154	3.059177	3.09408	4.52252	5.4049	6.16947
Average	0.6012225	1.093946667	1.588355	2.0899225	2.609534667	3.07827425	3.684533083	4.3036225	4.74461

5. Conclusions

In this research, an AWFM Filter is proposed and implemented to remove the salt and pepper noise in the digital images effectively. The proposed filter is able to remove salt and pepper noise even at 90% noise level and yields exemplary and comprehensible results in terms of PSNR and QI than many of the other median filters. At the same time, it preserves the image details such as thin lines, edges and textures. In addition, this filter does not require any threshold, tuning and optimization parameters. So, it is concluded that the proposed AWFM Filter is simple to implement for good filtering results with efficient processing time.

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