A Highly Effective Adaptive Switching Mean Filter Algorithm for Salt and Pepper Noise Removal

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ABSTRACT
This paper presents an efficient three-stage adaptive switching mean filter to remove salt-and-pepper impulse noise from highly corrupted images. Firstly, the noise detection stage is to detect pixels as “noise pixels” and “noise-free pixels”. The detected “noise pixels” will then be subjected to the second stage which is the noise cancellation, while “noise-free pixels” are retained and left unchanged. The method adaptively changes the size of the filtering window based on the number of the “noise-free pixels” in the neighborhood. For the filtering, only “noise-free pixels” in the window are considered to find the mean value. If this value is not available in the maximum window size, the last processed pixel value is used as the replacement. In the third stage, this algorithm utilizes previously processed neighboring pixel values to get better image quality as the really processed noise pixel used as a noise –free pixel for the next noisy pixel processing. Experimental results clearly show that the proposed algorithm outperforms many of the existing methods in terms of visual quality and quantitative measures. The advantage of the proposed method is that it works well for high-density salt & pepper noise even up to a noise percentage of 95%.

General Terms
Image processing, Image filtering, Noise reduction.

Keywords
salt-and-pepper noise, mean filter, adaptive filter, switching filter

1. INTRODUCTION
Images often get corrupted by impulse noise during the acquisition or transmission. An important type of impulsive noise is salt & pepper noise. In salt & pepper corrupted images, noisy pixels take either maximum or minimum value degrading the image quality. Removal of salt & pepper is an important pre-processing step because it can influence the subsequent phases in image processing such as segmentation, edge detection and recognition [1].

The Standard Median Filter (SMF) is one of the most widely used non-linear noise filtering techniques to remove this noise, due to its denoising capability and computational efficiency. The main drawback of (SMF) is that it processes all pixels in the image equally, including the “noise free pixels” .Thus, it is effective only for low noise densities and at high noise densities, it often exhibits blurring for large window sizes and insufficient noise suppression for small window sizes [2].Many variations and improvements of median filter have been introduced such as weighted median filter [3], center weighted median filter[4] and recursive weighted median filter [5] .Anther type of the median based methods is the switching method, which is constructed from two stages. The first stage is to detect the “noise-pixels”. The second stage is to remove only the “noise-pixels” while the “noise-free pixels” are kept unchanged.

The common drawback among all of these filtering techniques is that the noisy pixels are replaced without taking into account local features such as the presence of edges and the noise level. Hence details of the images and edges are not recovered satisfactorily, especially when the noise level is high. So, adaptive median filter is improved in many literatures such as [6] and [7].The classic adaptive median filter algorithm [7] aims to reduce noise density by expanding the window size .However, it has two drawbacks: (1) The original noisy pixel is kept unchanged when failing to find the median value in the maximum window size; (2) The noisy pixels are considered in the calculation of median operation.

In this paper, an efficient adaptive switching mean filtering algorithm for salt and pepper noise removal is proposed. Switching mean filter framework is used in this algorithm in order to speed up the process and allow local details in the image to be preserved because only the noise pixels are filtered .Thus, it takes a decision whether the pixel under test is corrupted or not before applying the filtering which applied only to the detected “noise pixels “in the input image. This method adaptively changes the size of the filter based on the number of the “noise-free pixels” in the neighborhood. For the filtering, only “noise-free pixels” are considered for the finding of the average value of noisy pixel. This algorithm utilizes previously processed neighboring pixel values to get better image quality. The experimental results demonstrate that the proposed technique is effective for removing noise and preserving fine details than other existing denoising methods .The rest of this paper is organized as follows , in section 2 a related work is introduced. The proposed algorithm is presented in section 3. The implementation result and comparison are provided in section 4. Finally, conclusion is presented in section 5.

2. RELATED WORK
Haidi et.al. [8] (SAMF) which presents a simple adaptive median filter for the removal of impulse noise from highly corrupted images, which comprises two stages: noise detection and noise cancellation. The first stage is to detect the impulse noise in the image as “noise-free pixel” and “noise pixel”. Then, the second stage is to eliminate the impulse noise from the image and only the “noise-pixels” are processed, while “noise-free pixels” are copied directly to the output image. The size of the median filter changes adaptively based on the number of the “noise-free pixels“in the

neighborhood. For the filtering, only "noise-free pixels" are considered for the finding of the median value .For each noisy pixel, the number of "noise-free pixels" ,contained in the filtering window, must be larger than or equal to eight pixels .If this condition is not met ,the size of the filter will be increased by two .This procedure is repeated until the condition is met then the central noisy pixel is replaced with the median value. Further, Srinivasan and Ebenezer [9] have proposed a new fast and efficient decision-based algorithm (DBA) for removal of high-density impulse noises .This algorithm is proposed for restoration of images that are highly corrupted by impulse noise. It processes the corrupted image by first detecting the impulse noise. The detection of noisy and noise-free pixels is decided by checking whether the value of a processed pixel element lies between the maximum and minimum values that occur inside the selected window. This is because the impulse noise pixels can take the maximum and minimum values in the dynamic range (0, 255). If the value of the pixel processed is within this range, then it is an uncorrupted pixel and left unchanged. If the value does not lie within this range, then it is a noisy pixel and is replaced by the median value of the window or by its neighborhood values. For obtaining the new value of the processed pixel, the method depend on the median, maximum, and minimum pixels values within the selected window. Pei-Yin Chen and Chih-Yuan Lien [10] have proposed an efficient edge-preserving algorithm for removal of salt-and-pepper noise from corrupted images. It can preserve edges very well while removing impulse noise. This algorithm is composed of two components: efficient impulse detector and edge preserving filter. The former determines which pixels are corrupted by fixed-valued impulse noise. The latter reconstructs the noisy pixels by observing the spatial correlation and preserving the edges efficiently. For each noisy pixel, the image filter detects edges in six directions first and estimates the intensity value of the pixel accordingly. In addition, S. Esakkirajan et.al. [11] have proposed a modified decision based unsymmetrical trimmed median filter algorithm for the restoration of gray scale, and color images that are highly corrupted by salt and pepper noise. This algorithm replaces the noisy pixel by trimmed median value when other pixel values, 0's and 255's are present in the selected window and when all the pixel values are 0's and 255's then the noise pixel is replaced by mean value of all the elements present in the selected window. Xiao Kang et.al. [12] have proposed a novel adaptive switching median filter for laser image based on local salt and pepper noise density .This algorithm for Laser image which often mixes with salt and pepper noise when obtained and transmitted by image sensor. Pixel points are divided into salt and pepper noise points and signal points according to two level detection mechanisms firstly, then, local salt and pepper noise density is introduced here to determined filter window of every noise point, only noise points are filtered by different size window adaptively whereas signal points are kept unprocessed finally.

3. THE PROPOSED METHOD

The proposed adaptive switching mean filtering algorithm includes three stages: (1) Noise Detection, (2) Noise Cancellation, (3) Noisy Image and Detection Map Update.

3.1 Noise Detection

In this method, switching mean filter framework is used in order to speed up the process because only the noise pixels are filtered. In addition, it also allows local details in the image to be preserved.

In this stage, the processing pixel is checked whether it is noisy or noisy free. That is, if the processing pixel lies between maximum and minimum gray level values then it is noise free pixel, it is left unchanged. If the processing pixel takes the maximum or minimum gray level then it is noisy pixel which is processed by the filtering operation.

Assuming that the two intensities $P_{i,j}$ that present "salt and pepper noise" are the maximum (K) and the minimum (0) values of the image's dynamic range. Considering this

$$d_{i,j} = \begin{cases} 1, \text{if } \mathrm{P_{i,j}} = K \vee \mathrm{P_{i,j}} = 0 \\ 0, \ otherwise \end{cases} \qquad (1)$$

assumption, a binary value is assigned to each elements $d_{i,j} \in D$ of the detection map D. The detection map is computed from the noisy image as follows:

The entries of "1" and "0" in the detection map D represent the noisy and the noise-free pixels, respectively.

3.2 Noise Cancellation

This stage is applied only to the detected noise pixels in the input image. Adaptive filter framework is used in order to enable the flexibility of the filter to change its size accordingly based on the number of the "noise-free pixels" in the neighborhood.

For each detected 'noise pixel' $P_{i,j}$,the size of the filtering window (W×W) is initialized to 3×3 and an array R with length LR is populated with noise-free-pixels contained in the window. The length of array, depending upon the noise density within the window, varies from zero to eight. The minimum length zero shows all pixels in the window are noisy, whereas the maximum length eight indicates all eight pixels are noise-free. To estimate the value of noisy pixel, we emphasize noise-free pixels and a constraint of minimum three noise-free pixels in the array R (i.e. $L_R \geq 3$). If this condition is satisfied, then the central noisy pixel is replaced with the mean of R as

$$Avg_R = mean(R) \qquad (2)$$

If the current filtering window does not have a minimum number of three "noise-free pixels" (i.e. $L_R < 3$) and the filter size is less than the maximum size W_{Max}=7, then the filtering window will be expanded by two in its size (W=W+2). This procedure is repeated until the criterion of ($L_R \geq 3$) is met. We prefer to use W=7 as a maximum filter size because the larger size window may not be too efficient and effective and the correlation between pixels decreases as pixels are separated apart. Moreover, the larger window may also remove the edges and fine image details.

Considering this possibility, the search for "noise-free pixels" is halted when the detected "noise-free pixels" are less than three (L_R<3) and at the same time, the filtering window has reached a size of 7×7. In this case, we replace the central noisy pixel with the last processed pixel. If the current W×W window doesn't meet the condition and its size can't be increased by two as it reached to its maximum size especially the boundary pixels, in this exception we also replace the central pixel with the last processed pixel in the neighborhood.

3.3 Noisy Image and Detection Map Update:

If the noisy pixel is replaced with the average estimated, then the detection map is also updated by changing the entries at the corresponding location in the detection map from "1" to "0" as

$$d_{i,j} = \begin{cases} 0, \; if \; d_{i,j} = 1 \wedge L_R \geq 3 \\ d_{i,j} \; , otherwise \end{cases} \quad (3)$$

In this stage, the algorithm utilizes previously processed neighboring pixel values to get better image quality as the really processed noise pixel used as a noise –free pixel for the next noisy pixel processing.

The proposed method is summarized by the following algorithm, For each pixel location (i,j) with di,j=1 (i.e noise pixel) :

Step 1: Initialize the filtering window size to W=3, where $W_{Max} = 7$.

Step 2: Assign the number of "noise –free pixels" contained in the filtering window to L.

Step 3: If L<3, go to step 6.

Step4: Calculate the average (Avg) based on the "noise-free pixels" contained in W×W window.

Step5: Replace the central noisy pixel with the average value and go to step 7.

Step6: If $W \leq W_{Max}$, then the filtering window will be increased by two (i.e. W =W+2) and return to step 2 ,else replace the central pixel with the last processed pixel in the neighborhood.

Step 7**:** Update the input noisy image and the detection map D to use the processed pixel as a noise-free pixel for the next processed pixel.

In the proposed algorithm, the filter performs denoising iteratively for each noise pixel until all the corrupted pixels in the noisy image are eliminated (see figure 1).

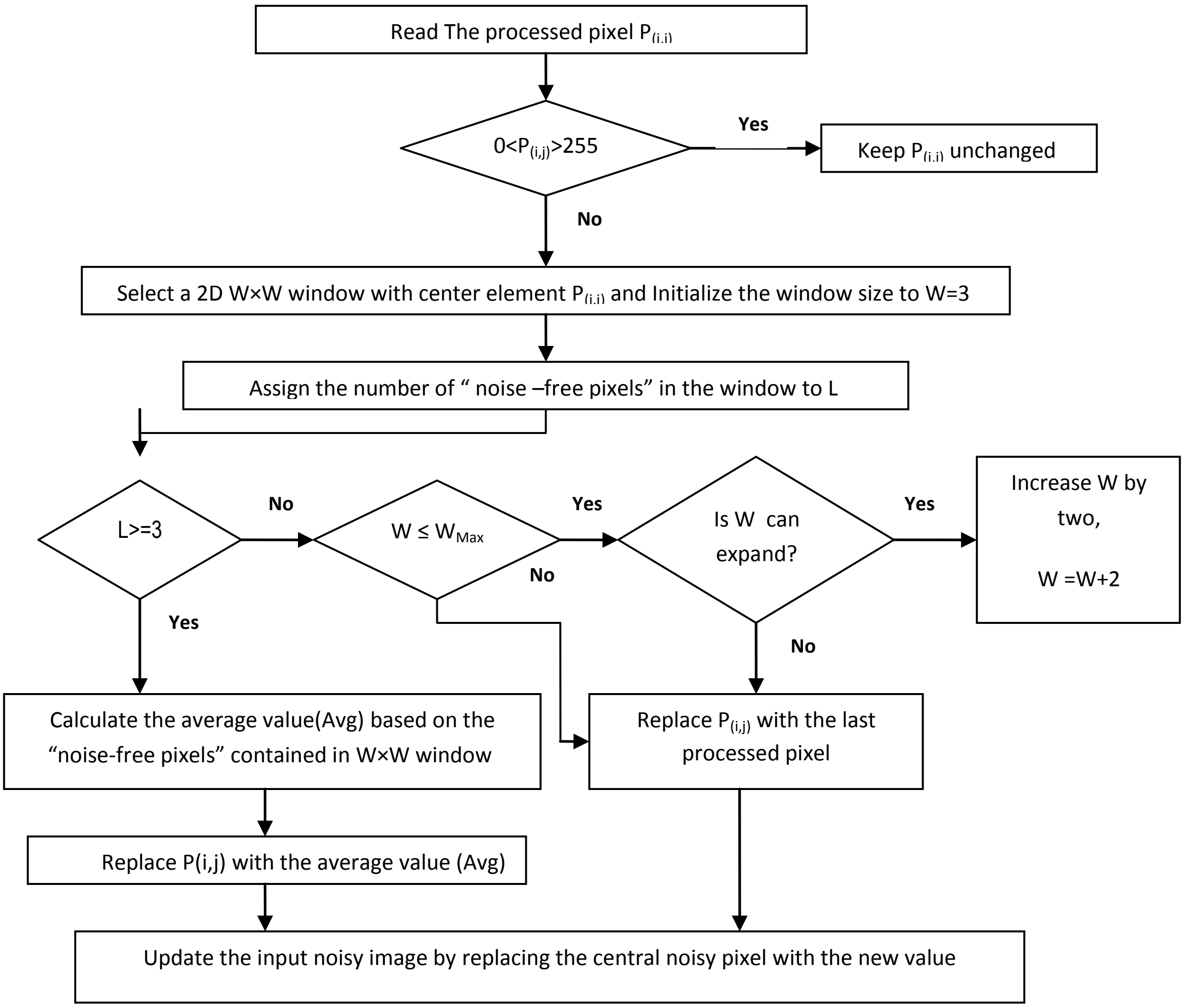


Fig 1: The flowchart of the proposed algorithm

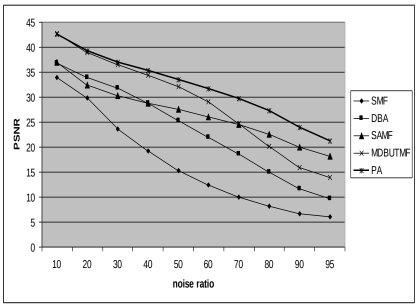
4. RESULTS AND DISSUCTION

In the paper, several experiments are carried out to analyze the performance of the proposed scheme with dynamic range of values (0, 255). The simulation results of four standard images of Lena, Baboon, Boat, and Bridge are reported. These images of size 512×512 are corrupted with varying level of noise density (ND) from 10 % to 95 % using the salt-and-pepper noise. The simulation results obtained from the proposed scheme are compared with other salt-and-pepper noise filtering algorithms: Standard Median Filter (SMF) , Decision-Based Algorithm(DBA) [9],Simple Adaptive Median Filter (SAMF) [8], and Modified Decision Based Unsymmetric Trimmed Median Filter (MDFUTMF) [11].We used the peak signal-to-noise ratio (PSNR) measure as a quantative evaluation to assess quality of the restored image and to compare the results quantitatively with previous filtering algorithms. The PSNR measure is defined as:

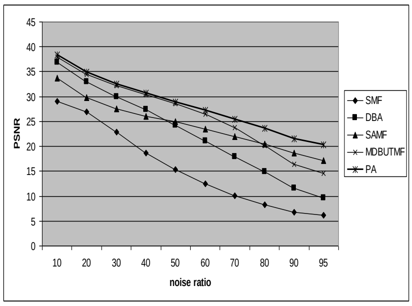
$$PSNR = 10\log_{10}\frac{(255)^2}{MSE} \qquad (4)$$

$$MSE = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(X_{i,j} - G_{i,j})^2 \qquad (5)$$

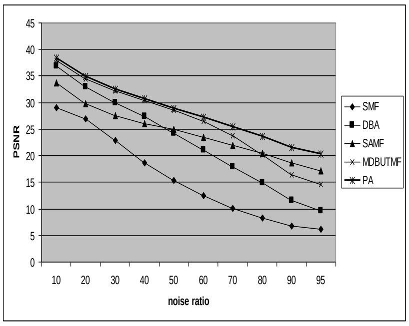
Where $X_{i,j}$ is the original noise-free image, $G_{i,j}$ is the restored image, MSE is the mean square error and $M\times N$ indicates the size of pixels of the original and the restored images .The PSNR value of the proposed algorithm is compared against the existing algorithms by varying the noise density from 10% to 95% (see Table 1). It is observed that our proposed algorithm (PA) provided the best PSNR at high noise densities. A plot of PSNR against noise densities for Lena , Baboon, Boat ,and Bridge images are shown (see figure 2) and the PSNR curves demonstrate that the Proposed Algorithm (PA) is the best in performance. The qualitative analysis of the proposed algorithm at different noise densities for Lena, Baboon and Boat images are shown respectively (see Figure 3, 4 and 5). It shows that the proposed algorithm is capable of removing salt-and-pepper noise more effectively, while preserving the fine image details and edges.



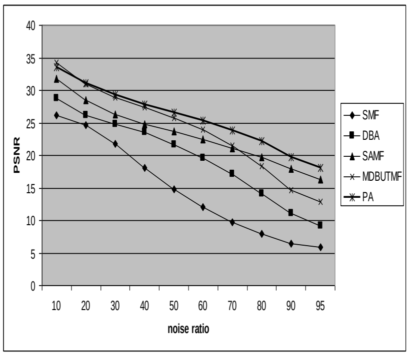
(a)



(b)



(c)



(d)

Fig 2 . Comparison graph of PSNR at different noise densities for (a) Lena image, (b) Baboon image, (c) Boat image, (d) Bridge image

5. CONCLUSION

This paper presents an efficient technique to remove salt and pepper impulse noise from highly corrupted images. It is actually a hybrid of the adaptive filter with the switching filter based on the arithmetic mean operation. The advantages of this method are that it solves the drawbacks of the classic adaptive median filter algorithm. In addition, it utilizes previously processed neighboring pixel values to get better image quality .further, it does not need a threshold parameter and the training stage is not required. The performance of the algorithm has been tested at different of noise densities. Even at high noise density levels the proposed algorithm gives better results in comparison with other existing algorithms.

6. REFERENCES

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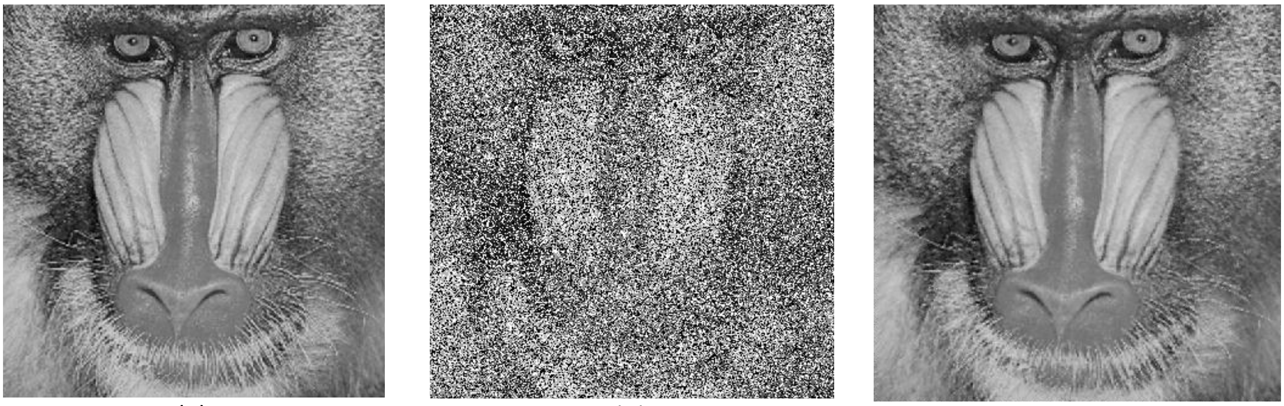
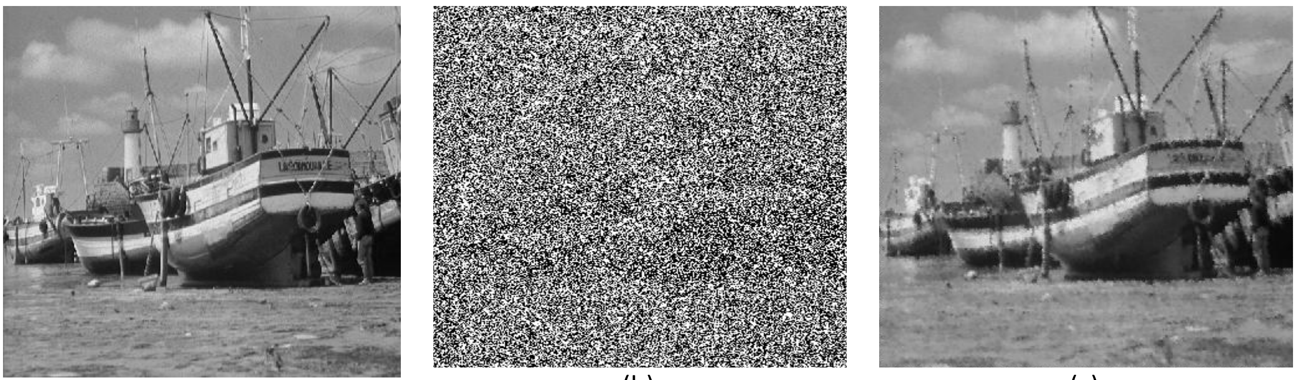
(a) (b) (c)

Fig 3. (a) Original 'Lena' image , (b) 'Lena' image corrupted with 30% ,(c) Output of the proposed method .



(a) (b) (c)

Fig 4. (a) Original 'Baboon' image,(b) 'Baboon' image corrupted with 50% , (c) Output of the proposed method



(a) (b) (c)

Fig 5. (a) Original 'Boat' image , (b) 'Boat' image corrupted with 80%, (c) Output of the proposed method

Table 1: Comparison of PSNR values of different algorithms for Lena , Baboon, Boat , and Bridge images respectively

Lena Image										
	10%	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**95%**
SMF(3×3)	33.9085	29.8645	23.7039	19.2248	15.2628	12.4080	10.0528	8.1563	6.6618	6.0190
DBA[9]	36.8199	33.9044	31.7456	28.7360	25.2938	21.9672	18.5844	15.0147	11.5929	9.6391
SAMF[8]	36.9998	32.3841	30.3480	28.8118	27.5963	26.0609	24.5417	22.5338	20.0325	18.1604
MDBUTMF [11]	42.7136	38.9992	36.5897	34.4640	32.1538	29.0257	24.6871	20.2110	15.9809	13.9076
PA	42.6193	39.2878	37.0283	35.2349	33.5170	31.6340	29.6914	27.3335	23.9264	21.1758
Baboon Image										
	10%	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**95%**
SMF(3×3)	29.0304	26.9441	22.8935	18.7009	15.3300	12.4360	10.1332	8.3259	6.8122	6.1895
DBA[9]	36.8536	32.9135	29.9838	27.3456	24.1648	21.0440	17.8447	14.8783	11.5854	9.6895
SAMF[8]	33.7263	29.7970	27.4912	26.0124	24.9142	23.4256	21.9704	20.4616	18.6262	17.1973
MDBUTMF [11]	37.9596	34.4987	32.2676	30.3322	28.6624	26.4979	23.7418	20.2399	16.4650	14.6120
PA	38.3650	34.9011	32.5624	30.7441	28.9354	27.2518	25.4844	23.6458	21.5895	20.2653
Boat Image										
	10%	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**95%**
SMF(3×3)	29.8434	27.4584	22.9733	18.8340	15.2372	12.3124	10.0013	8.1886	6.6741	6.0641
DBA[9]	37.4227	33.4271	30.6414	27.8768	24.8093	21.4992	18.2477	14.7737	11.5432	9.5521
SAMF[8]	35.2379	31.0923	29.1111	27.3610	26.0618	24.7122	23.0723	21.4012	19.2694	17.5934
MDBUTMF [11]	38.8632	35.2889	32.9842	31.1049	29.2432	26.7922	23.7151	19.8872	15.9324	13.9802
PA	38.4782	35.2436	33.1749	31.4639	29.9930	28.4434	26.7038	24.5981	21.8175	19.6119
Bridge Image										
	10%	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**95%**
SMF(3×3)	26.1467	24.6778	21.7219	18.0625	14.7791	11.9923	9.7422	7.9266	6.4196	5.8246
DBA[9]	28.7159	26.2283	24.8345	23.6061	21.6307	19.5556	17.0765	14.0652	11.0497	9.1878
SAMF[8]	31.7723	28.4675	26.2552	24.8321	23.6480	22.4487	21.0629	19.7286	17.9016	16.3522
MDBUTMF [11]	34.2869	30.9936	28.9683	27.3740	25.8155	23.9065	21.4947	18.3041	14.6965	12.9211
PA	33.6413	31.0781	29.2796	27.8117	26.5177	25.3105	23.8365	22.2070	19.7655	18.1343