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Adaptive Switching Weight Mean Filter for Salt and Pepper Image Denoising

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Abstract

We propose Adaptive Switching Weight Mean Filter (ASWMF) to remove the salt and pepper noise. Instead of using median or mean, ASWMF assigns value of a switching weight mean (SWM) to grey value of the centre pixel of an adaptive window. SWM is evaluated by eliminating all noisy pixels from the adaptive window and putting a low weight for pixels on the diagonals and a high weight for pixels outside the diagonals. ASWMF can remove noise with various noise levels effectively. It not only successes for low-density denoising, but also removes medium-density and high-density noise impressively. In experiments, we compare denoising results with other similar denoising methods. According to intuition as well as error metrics such as the peak signal-to-noise ratio and the structure similarity, ASWMF outperforms other methods.

Keywords: Image Denoising; Salt and Pepper; Image Restoration; Filter; Image Noise

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1. Introduction

In many problems of image processing [1], image denoising [2, 3, 4, 5, 6] is a common and important problem to improve digital image quality. Because digital noise usually destroys image structures and decreases efficiency of postprocessing tasks such as image segmentation [7, 8], image analysis, histopathological image processing [9], pattern recognition [10] etc., we must remove them. Noise is usually added to digital images during being captured by digital cameras, CT/X-Ray/MRI scanners, microscopies, etc. There are some popular types of noises: Gaussian noise [11, 12, 13], Poisson noise [14, 15], impulse noise [16, 4] and speckle noise [17]. The salt and pepper (SnP) noise is a simple type of the impulse noise [4, 3, 18, 19].

The SnP noise can appear by sharp and sudden disturbances in the image signal [4]. The SnP noise has only two grey values: the white pixel (the maximum grey value) and the black pixel (the minimum grey value). The white pixel is called to be a salt pixel and the black pixel – a pepper pixel.

To eliminate the SnP noise, there are many approaches such as median filters, mean filters, wiener filters, wavelet analysis, regularization, Principal Component Analysis (PCA) and machine learning. Filters based on median filters [20, 16, 21] is an effective approach to treat the SnP noise. The first Median Filter (MF) is introduced in the work of Lim [21]. Although, MF removes low-density SnP noise effectively, it works badly on medium-density and high-density noises. During removing medium-density and high-density noises, MF usually creates many defects. To remove this drawback, Adaptive Median Filter (AMF) [22] and Adaptive Centre-Weighted Median Filter (ACWMF) [16] were proposed. Although AMF and ACWMF work more effectively than MF, they are still ineffective for removing medium-density and high-density noises. In recent years, the Based Pixel Density Filter (BPDF) [23] developed by Erkan et al. is another effective filter for SnP noise. However, for the cases of medium-density noise and high-density noises, BPDF creates a raindrop effect. The effect destroys edges, details and image structures.

Regularization is a well-known approach that has achieved many achievements in recent years. Regularization is very effective to remove complex-structure noises such as the Gaussian, Poisson, speckle and Gaussian-Poisson noises. There are several works of regularization approach developed for removing the impulse noise, including the SnP noise. Hemant et al. proposed Generalized Synthesis and Analysis Prior Algorithms [24] (GSAP). Chan and Esedoglu proposed a SnP denoising method based on total variation with L^1 norm [25] (TVL1).

In this paper, we propose Adaptive Switching Weight Mean Filter (ASWMF) to remove the SnP noise. We consider adaptive windows with a fixed size of every pixel of a noisy image. If the centre pixel is a noisy candidate, we eliminate all noisy pixels from its own adaptive window. After that, we put a low weight for pixels of the diagonals and a high weight for pixels outside the diagonals of the adaptive window to evaluate a mean value. We called the mean value to be a switching weight mean. The switching weight mean value will be assigned to grey value of the centre pixel. In the experiments, we test the proposed denoising filter on various images of the UC Berkeley dataset and the MIRIAD dataset with various noise levels. Denoising quality is evaluated according to the full reference image quality assessments such as the Peak signal-to-noise ratio (PSNR) and the Structural similarity (SSIM) metrics. Otherwise, we also compare the denoising results of ASWMF with ones of other similar denoising methods such as MF, ACWMF, GSAP, BPDF and TVL1.

The rest of the paper is structured as follows. Section II presents the proposed denoising method. Section III presents experimental results and comparison of denoising quality of the methods. Finally, Section IV concludes.

2. Proposed Image Denoising Method

2.1. Definition, Notions and the Salt and Pepper Noise Model

Let $[u^*_{ij}]_{m\times n}$, $[u_{ij}]_{m\times n}$ $[v_{ij}]_{m\times n}$ be an original (ground truth), a restored and a corrupted (noisy) grayscale images, respectively; where m, n are number of pixels by the image height and the image width.

Definition 1. We denote $[\delta_{min}, \delta_{max}]$ for a dynamic range of grey values of an image. For an 8-bit grayscale image, $\delta_{min} = 0$, $\delta_{max} = 255$. The SnP noise model can be designated as:

$$v_{ij} = \begin{cases} \delta_{min}\,, & with\ probability\ p \\ \delta_{max}\,, & with\ propability\ q \\ u_{ij}^*\,, & with\ probability\ 1-(p+q) \end{cases}, \quad (1)$$

where $0 \le p + q \le 1$ is the SnP level. If the noise level is an even number, $p = q$.

Definition 2. Let $w \in \mathbb{N}^* = 1,2,\ldots$. An adaptive window with size $(2w + 1)$ centred at a pixel location (i,j) is defined as follows:

$$S_{ij}(w) = \{(i^*, j^*): |i^* - i| \le w, |j^* - j| \le w\}. \quad (2)$$

Definition 3. Switching weight mean of an adaptive window $S_{ij}(w)$ of an image $[u]_{m\times n}$ is defined as follows:

$$S_{ij}^{swmean}(w) = \sum_{k=1}^{3} \omega_k \Psi(\mathcal{D}_k) \Bigg/ \sum_{k=1}^{3} \omega_k |\mathcal{D}_k|\,, \quad (3)$$

where $\mathcal{D}_1$ is a set of all noise-free pixels of the main diagonal of the window, $\mathcal{D}_2$ is a set of all noise-free pixels of the second diagonal of the window, $\mathcal{D}_3$ is a set of all noise-free pixels outside two diagonals of the window. Operator $|\cdot|$ is the set cardinality (number of elements of a set). Notion $\Psi(\mathcal{D}_k) = \sum_{(i^*,j^*)\in\mathcal{D}_k} u_{i^*j^*}$, i.e., a sum of grey values of all pixels in $\mathcal{D}_k$. Parameters ω_i are weights. In experiments, we set $\omega_1 = \omega_2 = 1$ and $\omega_3 = 10$.

In this paper, we denote $S_{ij}^{min}(w), S_{ij}^{max}(w)$ for the minimum grey value and the maximum grey value of a window with the size $(2w + 1)$ centred at a pixel (i,j), respectively.

2.2. Proposed Denoising Method

Detail of the proposed SnP images denoising method is presented in Algorithm 1. Because we only consider a small size of the adaptive window with the size of 7×7, evaluation processes in the adaptive window do not cost much. Hence, complexity of the proposed algorithm is $O(49 \times m \times n) \approx O(m \times n)$ when m, n are large enough.

Algorithm 1. Adaptive Switching Weight Mean Filter (ASWMF).

Input: The input noisy images v.
Output: The restored images u.

Function $u = \boldsymbol{Denoise}(v)$

Initialize $u \leftarrow v, w \leftarrow 3, \omega_1 \leftarrow \omega_2 \leftarrow 1, \omega_3 \leftarrow 10$.

For each pixel (i,j) of the image u

Evaluate $S_{ij}^{min}(w), S_{ij}^{max}(w)$.

If $u_{ij} \le S_{ij}^{min}(w)$ **OR** $u_{ij} \ge S_{ij}^{max}(w)$ **Then**

Find out sets $\mathcal{D}_1, \mathcal{D}_2, \mathcal{D}_3$.

Evaluate $\Psi(\mathcal{D}_1), \Psi(\mathcal{D}_2), \Psi(\mathcal{D}_3)$, $|\mathcal{D}_1|$, $|\mathcal{D}_2|$, $|\mathcal{D}_3|$.

Evaluate $S_{ij}^{swmean}(w)$.

Set $u_{ij} \leftarrow S_{ij}^{swmean}(w)$.

End

End

End.

Let us explain how the proposed algorithm works. Firstly, we consider all pixels of the noisy image. For each pixel (i,j) of the noisy image, we define an adaptive window $S_{ij}(w)$ centred at a pixel (i,j). We must notice that, we only consider a window with the size of 7×7. Of course, we can consider other windows such as $3 \times 3, 5 \times 5$ etc. However, for small windows, the denoising performance is not high, especially for medium-density and high-density noises. For larger windows, the speed of algorithm slows down, and they can cause blurry edges. The size of 7×7 is ideal for the adaptive window. We also can use the dynamic windows to improve accuracy of the denoising results. However, it also influences the evaluation speed.

Secondly, in the adaptive window, we search the maximum and the minimum grey values. The centre pixel (i,j) will be considered as a noise-free candidate if its grey value belongs to the open interval of the minimum and the maximum grey values, i.e., $S_{ij}^{min} < u_{ij} < S_{ij}^{max}$. Otherwise, the centre pixel is a noisy candidate. If the centre pixel is a noisy candidate, we find out the sets $\mathcal{D}_1, \mathcal{D}_2, \mathcal{D}_3$ of the adaptive window. Next, we evaluate the switching weight mean. The mean value will be assigned to grey value of the centre pixel of the adaptive window.

As we can see, in the switching weight mean, we put a low weight for pixels on the diagonals and a high weight for pixels outside the diagonals. Let consider the following example to understand the reason. Suppose that the adaptive window has the following form:

156	159	158	155	158	156	159
160	154	157	158	157	159	158
156	159	158	155	158	156	159
160	154	157	**158**	157	159	158
156	153	155	159	159	155	156
155	155	155	157	156	159	152
156	153	157	156	153	155	154

156	255	0	255	0	255	159
255	0	0	255	157	255	158
255	159	255	255	158	0	159
160	0	157	**255**	157	0	0
156	255	155	159	255	155	156
155	255	155	255	156	255	152
255	0	0	156	255	255	154

The left window stands for an original image, the right window stands for a corresponding noisy image with the noise level of 50%. The centre pixel is marked in bold. The switching weight mean with the same weight (i.e., $\omega_1 = \omega_2 = \omega_3 = 1$) is 171. The switching weight mean with the selected weights (i.e., $\omega_1 = \omega_2 = 1, \omega_3 = 10$) as in Algorithm 1 is 159. As can be seen, the new grey value (i.e., 159) evaluated by ASWMF with different weights is closer to grey value (i.e., 158) of the original centre pixel than the grey value (i.e., 171) evaluated by ASWMF with the same weight. Hence, the proposed method with the different weights denoises better than the case of the same weight. Although $\omega_1 = \omega_2 = 1, \omega_3 = 10$ may not be optimal values, in many experiments, we see that with this setting, ASWMF gives excellent denoising results.

3. Experimental Results and Discussions

We implement the proposed SnP denoising method on MATLAB 2018b. The computing system configuration is Windows 10 pro, 4GB RAM, CPU Intel core i5. We must notice that, in ASWMF, we set parameters as follows: $w = 3, \omega_1 = \omega_2 = 1, \omega_3 = 10$.

3.1. Image Quality Assessment Metrics

To compare image denoising quality, it is necessary to assess image quality after denoising based on error metrics. The Peak signal-to-noise ratio (PSNR) and the Structure Similarity (SSIM) are the most popular full reference image quality assessment metrics [12, 6, 26]. The PSNR is defined as follows:

$$PSNR = 10\log_{10}\left(\frac{u_{max}^2}{MSE}\right) dB \tag{4}$$

where

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(u_{ij}^{*} - u_{ij}\right)^2 \tag{5}$$

is the mean squared error, u_{max} denotes the maximum value, for e.g. for 8-bit images $u_{max} = 255$; u_{ij} and u_{ij}^{*} are grey values of u and u^{*} at each pixel (i, j), respectively. The higher PSNR (measured in decibels – dB), the better image quality.

Structural similarity (SSIM) is a better error metric for comparing the image quality and it is in the range [0, 1] with value closer to one indicating better structure preservation. This metric based on characteristics of the human vision. The SSIM value is computed between two images ω_1, ω_2 as follows:

$$SSIM = \frac{\left(2\mu_{\omega_1}\mu_{\omega_2} + c_1\right)\left(2\sigma_{\omega_1\omega_2} + c_2\right)}{\left(\mu_{\omega_1}^2 + \mu_{\omega_2}^2 + c_1\right)\left(\sigma_{\omega_1}^2 + \sigma_{\omega_2}^2 + c_2\right)}, \tag{6}$$

where μ_{ω_i} is the average value of ω_i, $\sigma_{\omega_i}^2$ – the variance value of ω_i, $\sigma_{\omega_1\omega_2}$ – the covariance value, and c_1, c_2 are numerical stabilizing parameters, $c_1 = (K_1L)^2, c_2 = (K_2L)^2, K_1 = 0.01, K_2 = 0.03$; and $L = 255$ for an 8-bit image.

3.2. Image Dataset

We test denoising methods on images of the UC-Berkeley dataset[†] and the MIRIAD dataset[‡]. The UC-Berkeley dataset contains 200 grayscale images stored in JPEG format. We select 20 images with the same size of 481×321 pixels to test as in Figure 1. The MIRIAD dataset contains 124 grayscale images of volumetric MRI brain-scans of Alzheimer's sufferers and healthy elderly people. All images have the same size 256×256 pixels.

In experiments, we use the built-in *imnoise* function of MATLAB to generate the SnP noise with various noise levels. This method is necessary to assess image quality after denoising, because to evaluate PSNR and SSIM values, we need noise-free images (ground truth). We consider 4 cases with the noise levels varying in 20%, 40%, 60% and 80%. Otherwise, we also compare denoising results with the ones of denoising methods such as MF, ACWMF, TVL1, GSAP and BPDF.

Fig. 1. Several images of the UC-Berkeley dataset.

[†] *https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/BSDS300/ html/dataset/images.html*

[‡] *https://www.ucl.ac.uk/drc/research/methods/minimal-interval-resonance-imaging-alzheimers-disease-miriad*

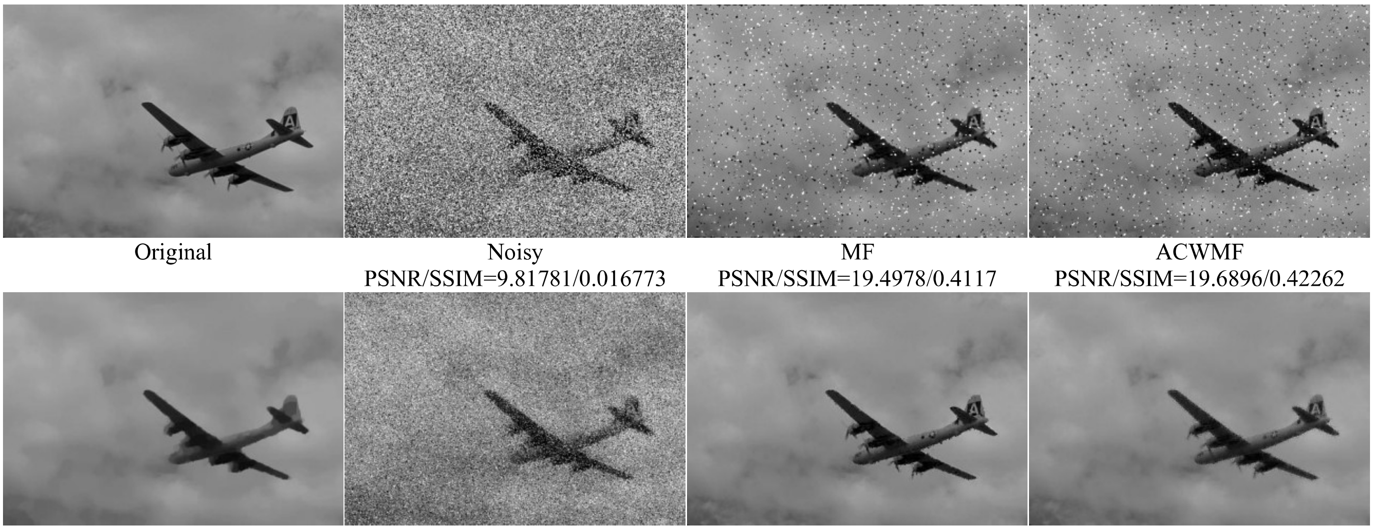
3.3. Experimental Results and Discussion

For the first test case of the noise level of 20%, we test on the plane image with ID 3096. Denoising results are presented in Figure 2. For the low noise level of 20%, MF and ACWMF work well. There is just a little noise on the restoration results. GSAP removed noise completely, but it made the plane to be blurred. TVL1 also removed noise completely, but many details such as the propellers, the letter A on the tail are lost. BPDF removed noise excellently for this noise level. ASWMF also removed noise excellently. Denoising result by ASWMF is slightly smoother than one by BPDF. The PSNR value and the SSIM value of the denoising result by BPDF is the highest (PSNR/SSIM=40.5446/0.99261) and followed by the denoising result of ASWMF (PSNR/SSIM=38.8721/0.98706).

Original | Noisy PSNR/SSIM=12.8115/0.036684 | MF PSNR/SSIM=30.8882/0.92333 | ACWMF PSNR/SSIM=32.3993/0.94041

TVL1 PSNR/SSIM=35.134/0.9685 | GSAP PSNR/SSIM=31.9488/0.94188 | BPDF PSNR/SSIM=40.5446/0.99261 | Proposed PSNR/SSIM=38.8721/0.98706

Fig. 2. Denoising results with the noise level of 20% for the plane image.



Original | Noisy PSNR/SSIM=9.81781/0.016773 | MF PSNR/SSIM=19.4978/0.4117 | ACWMF PSNR/SSIM=19.6896/0.42262

TVL1 PSNR/SSIM=33.2179/0.96066 | GSAP PSNR/SSIM=14.6072/0.045906 | BPDF PSNR/SSIM=35.5334/0.97885 | Proposed PSNR/SSIM=35.5382/0.96995

Fig. 3. Denoising results with the noise level of 40% for the plane image.

For the second case of the noise level of 40% for the same above image, denoising results are presented in Figure 3. GSAP removed noise ineffectively. There is a lot of noise in the denoising result. MF and ACWMF also works ineffectively. Although MF and ACWMF removed noise better than GSAP, there is still a lot of noise on their denoising results. As the above case, TVL1 removed noise completely, but many small details are lost. BPDF removed noise effectively, but it preserved edges not well. This can be seen clearly on the tail and the propellers. However, denoising result by BPDF overall looks good. ASWMF removed noise effectively. However, it has smoothed edges. This is a reason making the SSIM score lower than one of denoising result of BPDF. The PSNR value of denoising result by ASWMF is the highest (35.5382), but the SSIM value of denoising result by ASWMF (0.96995) is a little lower than one of denoising result of BPDF (0.97885).

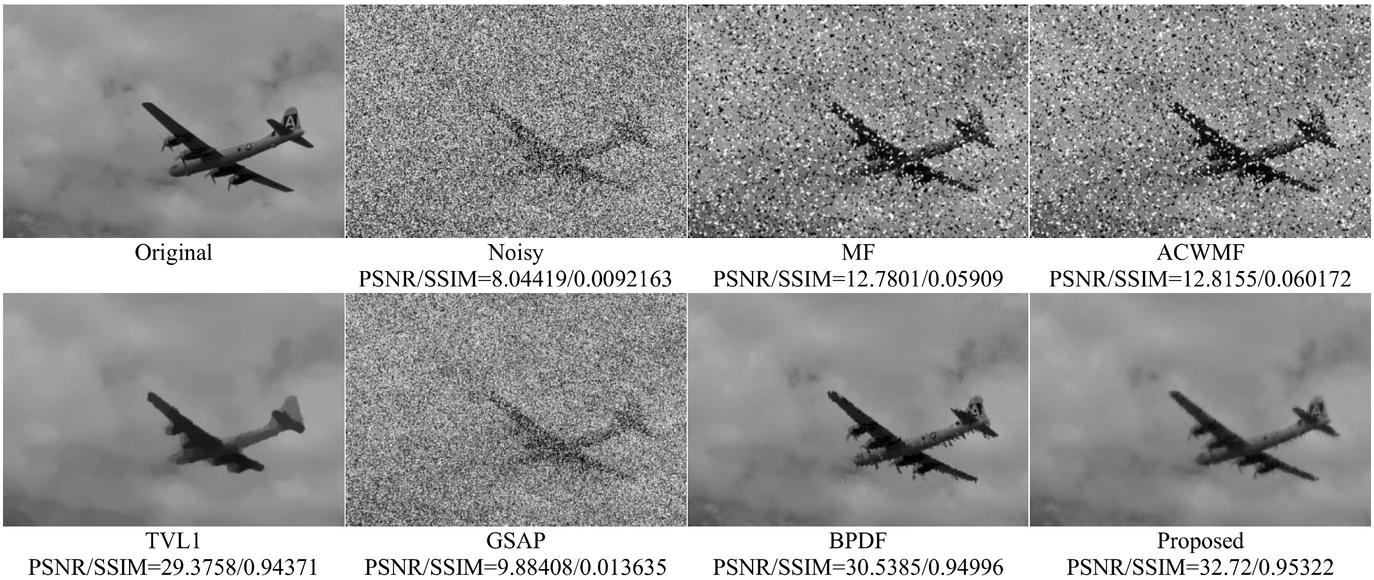


Fig. 4. Denoising results with the noise level of 60% for the plane image.

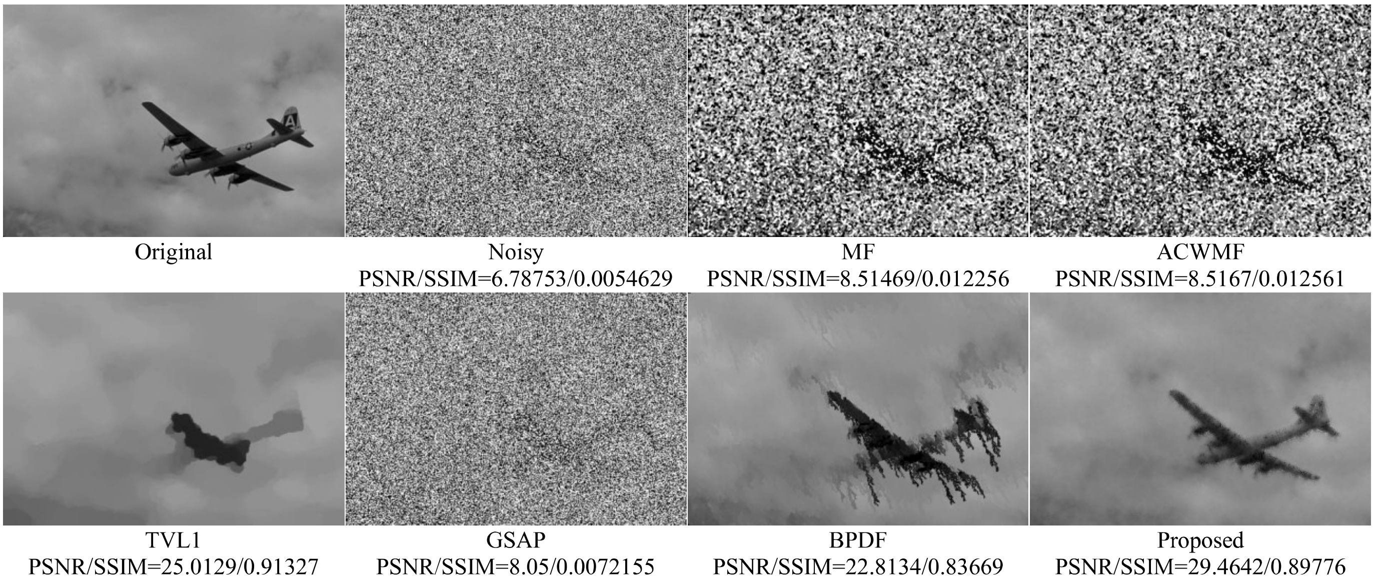


Fig. 5. Denoising results with the noise level of 80% for the plane image.

For the third case of the noise level of 60%, the denoising result for the plane image are presented in Figure 4. As the above case, GSAP removed noise badly. MF and ACWMF worked better, but a lot of noise still remains. For the high-density noise level, BPDF begins to cause raindrop effects. This defect can be seen clearly on edges of the plane. ASWMF removed noise effectively. Although there are some small defects on edge of the plane, but the denoising result overall looks very good. The PSNR and SSIM values of the denoising result of ASWMF are the highest (32.72/0.95322).

For the fourth case of the noise level of 80%, denoising results for the plane image are presented in Figure 5. This is a case of a very high noise level. GSAP, MF and ACWMF gave meaningless restoration results. We cannot see anything. TVL1 removed noise completely, but all main details are lost. It is very hard to recognize the plane in the denoising result. The raindrop effect became stronger and destroyed all image structures in the denoising result of BPDF. Denoising result by the proposed method is the best. Noise was removed completely. All details are also preserved well. The PSNR and SSIM values of ASWMF are the highest (29.4642/0.89776).

Table 1 presents the average PSNR values for various noise levels (20%, 40%, 60% and 80%) of denoising results of the methods for 20 images of the UC Berkeley dataset. Table 2 are for the average SSIM values. With the noise level of 20%, the average PSNR value and the average SSIM value of denoising result of ASWMF are only lower than ones of BPDF. For the noise level of 40%, the average PSNR value of denoising result of ASWMF is the highest, but the average SSIM value is still lower than the result of BPDF. For other high noise levels such 60% and 80%, the average PSNR values and the average SSIM values of the proposed method are the highest. We can confirm that ASWMF works more effectively for the medium-density and high-density noise than other methods. The average PSNR value and the average SSIM value of all noise levels of ASWMF are also the highest.

Table 1. The average PSNR values of denoising results of the methods for 20 images of the UC Berkeley dataset.

Name	20%	40%	60%	80%	Average
Noisy	12.2538	9.2431	7.4902	6.242	8.8073
MF	25.9562	18.1532	12.035	7.9469	16.0228
ACWMF	27.6506	18.265	11.9957	7.9115	16.4557
TVL1	24.4657	23.4177	22.0523	20.2058	22.5354
GSAP	26.3273	15.6779	9.4136	7.4209	14.7099
BPDF	**32.0131**	27.6186	24.0032	18.3523	25.4968
Proposed	30.863	**27.8368**	**25.6253**	**23.077**	**26.8505**

Table 2. The average SSIM values of denoising results of the methods for 20 images of the UC Berkeley dataset.

Name	20%	40%	60%	80%	Average
Noisy	0.1205	0.0544	0.0278	0.013	0.0539
MF	0.8045	0.4394	0.1159	0.029	0.3472
ACWMF	0.8923	0.4729	0.1261	0.0308	0.3805
TVL1	0.6751	0.6367	0.5916	0.5369	0.6101
GSAP	0.7749	0.1558	0.0379	0.0158	0.2461
BPDF	**0.9530**	**0.8813**	0.7641	0.5321	0.7826
Proposed	0.9387	0.8696	**0.7791**	**0.641**	**0.8071**

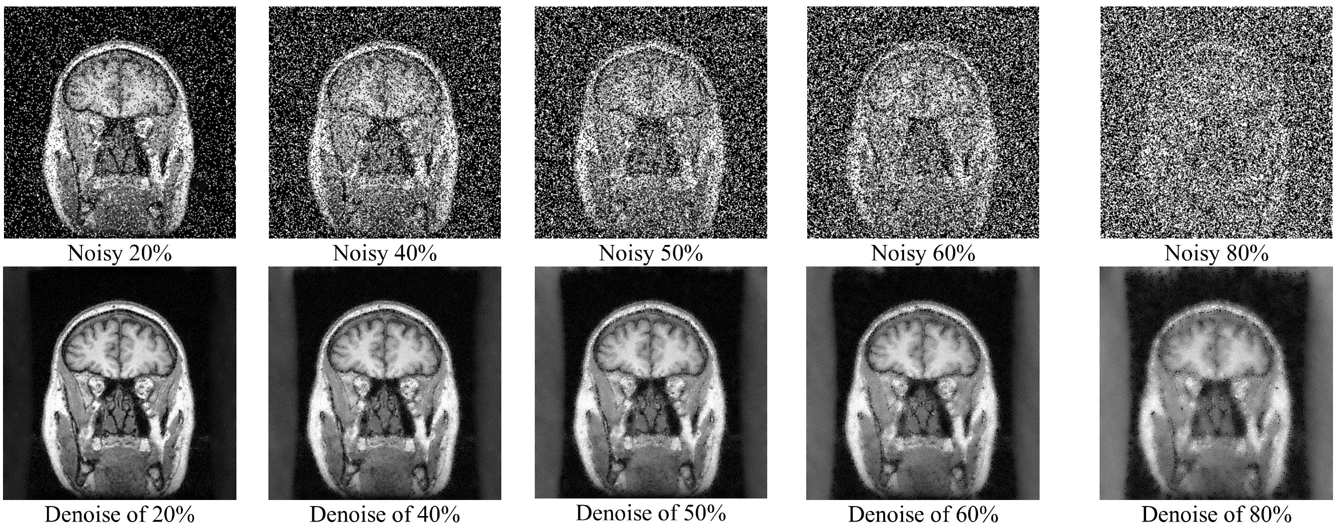


Fig. 6. Denoising results on images of the MIRIAD dataset with various noise levels.

For the last case, we test ASWMF on images of the MIRIAD dataset. We must notice that the images have absolutely black/white regions, i.e., their grey values are 0 and 255. The proposed method can remove noise with various noise levels very well. The denoising results are showed in the Figure 6. The average PSNR and average SSIM values of ASWMF are presented in Table 3.

Table 3. The average PSNR and average SSIM values of denoising results of ASWMF for images of the MIRIAD dataset.

Metric	20%	40%	50%	60%	80%	Average
PSNR	24.4112	19.7394	18.0163	16.5299	13.7764	18.4946
SSIM	0.6696	0.5829	0.5303	0.4682	0.2978	0.5098

About execution time, TVL1 and GSAP remove noise the most slowly. MF and ACWMF works very fast. The difference of execution time of BPDF and ASWMF is very small. They take around 2 seconds to remove noise for an image of the UC Berkeley dataset.

4. Conclusions

In this paper, we have proposed Adaptive Switching Weight Mean Filter (ASWMF) to remove the salt and pepper noise. ASWMF only considers an adaptive window with the size 7×7 and eliminates noisy pixels in the window from evaluating new grey value for the centre pixel. ASWMF does not consider the same weight for all pixels, but it puts a low weight for pixels of the diagonals and a high weight for other pixels of the window. Therefore, ASWMF can remove noise from low density to high density effectively. For medium-density and high-density noise, ASWMF outperforms other compared denoising methods.

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