An Improved BPDF Filter for High Density Salt and Pepper Denoising

Dang N. H. Thanh [1], Le Thi Thanh [2], V. B. Surya Prasath [3, 4, 5, 6], Ugur Erkan [7]
[1] Department of Information Technology, Hue College of Industry, Hue 530000 VN
dnhthanh@hueic.edu.vn
[2] Department of Basis Sciences, Ho Chi Minh city University of Transport, Ho Chi Minh 700000 VN
thanh.le@ut.edu.vn
[3] Division of Biomedical Informatics, Cincinnati Children's Hospital Medical Center, Cincinnati, OH 45229 USA
[4] Department of Pediatrics, University of Cincinnati, OH USA
[5] Department of Biomedical Informatics, College of Medicine, University of Cincinnati, OH 45267 USA
[6] Department of Electrical Engineering and Computer Science, University of Cincinnati, OH 45221 USA
surya.prasath@cchmc.org, prasatsa@uc.edu
[7] Department of Computer Engineering, Karamanoglu Mehmetbey University, Karaman 70200, Turkey
ugurerkan@kmu.edu.tr

***Abstract*— The BPDF (based on pixel density filter) is an effective filter to remove the salt-and-pepper noise, but it only can work on low and medium noise levels. In this paper we propose an improved version of the BPDF to remove the high-density salt-and-pepper noise. Our proposed method can work effectively on high and very high noise levels (above 90%). In the experiment, we compare the denoising result of the proposed method with the denoising results by BPDF filter and DAMF filter to prove effectiveness of the proposed method. The denoising quality is assessed by the peak signal-to-noise ratio and the structure similarity metrics.**

Keywords—Denoising, Salt and Pepper, Image restoration, Image processing, Image quality assessment, high density noise.

I. INTRODUCTION

In many electronics imaging systems, the acquired digital image always contains noise [1, 2, 3, 4, 5, 6]. Noise will reduce image quality [3, 7, 8]. The salt-and-pepper noise is a simple type of noise that has important characteristics: there are only two densities – the highest density pixel that called to be a salt pixel (white pixel) and the lowest density pixel that called to be a pepper pixel (black pixel) [9]. The salt-and-pepper noise can be caused by sharp and sudden disturbances in the image signal [9]. The task to detect the corrupted pixels in the case of salt-and-pepper noise is easier than other noises, because we can estimate the corrupted pixels based on their intensities values. However, the high-density noise removal is still hard problem.

There are a lot of approaches were applied to solve the high-density salt-and-pepper denoising problem, such as the partial differential equations (PDEs) [10], the regularization [9, 5], the stochastic methods etc. Among them, methods based on the filters, such as mean filters, median filters, Wiener filters are also highly assessed because of their advantages. The most important advantage of the filters: the execution speed is very fast, but the accuracy is still very high. Ekran et al. proposed the BPDF [11] filter that is very good to remove the salt-and-pepper noise for the low and medium noise levels. This filter can process noise on image with very high speed. However, it cannot work on high-density noise. In our tests, with high-density noise, the BPDF filter causes the raindrop effects. On images with very high-density noise, the BPDF absolutely failed. We cannot see anything on the acquired denoised image.

In this paper, we propose an improved BPDF filter to remove the high-density salt-and-pepper noise. In the proposed method, we add more a new procedure to the BPDF. This procedure will process the noise on the highest and the lowest considered clipping windows: 3x3 and 7x7. By the support of this middle stage, the BPDF can work more effectively on the high-density noise.

In the experiments, we use the open dataset of real images and generate the salt-and-pepper noise with various noise levels to make the noisy images. For the high-density noise, we only take the noise levels from 60% up to 95%. We also test the proposed method on super-high-density noise: 98% and 99% to prove the impressive noise removal potential of the proposed method. In the experiment, we also handle the comparison with other salt-and-pepper denoising methods, such as BPDF and DAMF [12]. The DAMF is a state-of-the-art filter that remove the high-density salt-and-pepper noise effectively.

The rest of the paper is organized as follows. Section II presents the proposed salt-and-pepper denoising method. Section III presents experimental results for salt-and-pepper denoising with various noise levels and the comparison. Finally, Section IV concludes.

II. THE PROPOSED SALT AND PEPPER DENOISING METHOD

Let $u_0(x), v(x), u(x) \in \mathbb{R}$ – be original image (reference image), noisy image and reconstructed image, respectively, where $x = (i,j) \in \Omega \subset \mathbb{R}^2, \Omega = \{1 \leq i \leq m, 1 \leq j \leq n\}$ – pixels. The goal of the denoising problem by filtering is to restore the corrupted pixels based on the neighbor uncorrupted pixels. So, the denoising problem by filtering always starts from

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the considered clipping windows. The clipping window with radius d centered at pixel (i,j) is defined:

$$W_d(i,j) = \{(k,l), |k-i| \le d, |l-j| \le d\}.$$

Because we only consider the clipping window centered at every corrupted pixel, if the corrupted pixels lay on the outer edge of image, we need to extend the image to top, bottom, left and right more d rows/columns pixels.

The BPDF filter will consider the clipping windows, but their sizes are not fixed. The sizes of clipping windows will be extended to guarantee that there is at least an uncorrupted pixel in the considered clipping windows. For the proposed method, we add an additional procedure to reduce the noise on the 3x3 and 7x7 clipping windows. So, the noise density will be reduced significantly before applying the BPDF filter.

In this paper, we will also cover the BPDF filter shortly before proposing the improved version of BPDF. The detail of the BPDF filter is presented in algorithm 1.

Algorithm 1. The BPDF filter to remove the low and medium density salt-and-pepper noise.

Input: The corrupted image v.
Output: The restored image u.

Function u = BPDF(v)

Initialize $d_m, u \leftarrow v$.
For every pixel (i,j) in noisy image u
Set $d \leftarrow 1$.
If pixel (i,j) is a noisy
  Repeat
  If (there is at least an uncorrupted pixel in $W_d(i,j)$)
    If (there is at least pixel in $W_d(i,j)$ that belongs to interval $(0,10) \cup (245,255)$)
      M ←Maximum repetitive pixels values.
      $u(i,j) \leftarrow median\{M\}$.
    Else
      $d \leftarrow d+1$.
    End.
  Else
    $d \leftarrow d+1$.
  End.
  Until $(d > d_m)$.
End.
End.
End.

The proposed improved BPDF filter to remove the high-density salt-and-pepper noise is presented in algorithm 2.

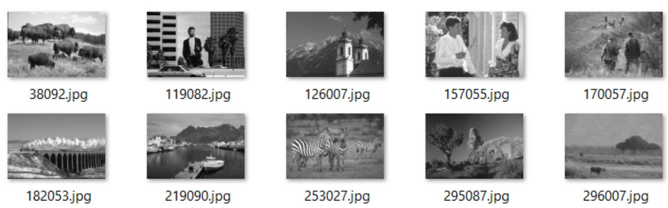

Fig. 1. The original images without noise for test cases.

As can be seen, the proposed method is performed via two stages: first stage – reducing noise on 3x3 clipping window and 7x7 clipping window; second stage – reducing noise by BPDF filter. The way to reduce noise on two stages is different. On first stage, we evaluate value to fill the corrupted pixel by evaluating median of all uncorrupted pixel in the considered clipping windows. However, on the second stage, by the BPDF, the evaluation based on the maximum repetitive pixels values.

Algorithm 2. The proposed improved BPDF filter to remove the high-density salt-and-pepper noise.

Input: The corrupted image v.
Output: The restored image u.

Function u = IBPDF(v)

Initialize $u \leftarrow v$.
For every pixel (i,j) in noisy image u
  If (pixel (i,j) is noisy)
    If (there is at least an uncorrupted pixel in $W_1(i,j)$)
      M ←Eliminate corrupted pixels from $W_1(i,j)$.
      $u(i,j) \leftarrow median\{M\}$.
    Else If (there is at least an uncorrupted pixel in $W_3(i,j)$
      M ←Eliminate corrupted pixels from $W_3(i,j)$.
      $u(i,j) \leftarrow median\{M\}$.
    End.
  End.
End.
$u \leftarrow$ **BPDF**(u).
End.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

We handle the experiments of the proposed parameter estimation method for the salt-and-pepper denoising on MATLAB. The configuration of the computing system is Windows 10 Pro with Intel Core i5, 1.6GHz, 4GB 2295MHz DDR3 RAM memory.

A. The Image Quality Assessment Metrics

To quantitatively test the restoration performance, we utilize the following error metrics that are widely used in the image processing literature [13, 14, 15, 4, 16, 17, 18]:

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

where

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(u^{(ij)} - u_0^{(ij)}\right)^2$$

is the mean squared error with u_0 is the original (latent) image, $u^{(ij)}$ and $u_0^{(ij)}$ are intensities of u and u_0 at the pixel (i,j), u_{max} denotes the maximum value, for e.g for 8-bit images $u_{max} = 255$. Note that a difference of 0.5dB is clearly visible and higher PSNR (measured in decibels – dB) indicate better quality image. Structural similarity (SSIM) is a proven to be 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. The SSIM is computed between two windows and of common size $N \times N$,

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

where μ_{ω_i} – the average of ω_i, $\sigma_{\omega_i}^2$ – the variance of ω_i, $\sigma_{\omega_1\omega_2}$ – the covariance, and c_1, c_2 stabilization parameters. The mean value of SSIM (MSSIM) is taken as the single value of quality indicating the structural similarity of the two images compared. For image denoising, in the synthetic noise added case, the original noise-free (e.g. ground-truth) and restored image is compared to find out how much structures are preserved by the restored method while removing noise.

Fig. 2. Denoising result for image 157055 with noise level 60%.

Fig. 3. Denoising result for image 157055 with noise level 75%.

B. Synthetic Images and Test Cases

We test the denoising performance of the proposed method with following cases: on two images with various noise levels and on multiple selected images of dataset with two very high noise level.

Figure 1 shows the selected images of the UC Berkeley dataset that we use for the tests. We choose 10 images. All images are stored in JPEG, grayscale and size 481x321 pixels. The images IDs is under their thumbnails.

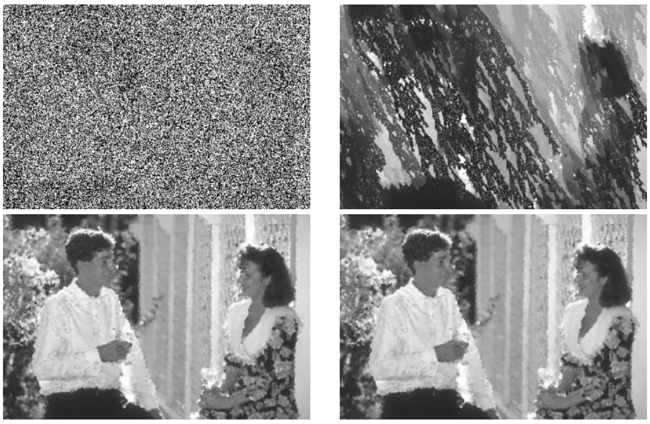

Fig. 4. Denoising result for image 157055 with noise level 85%.

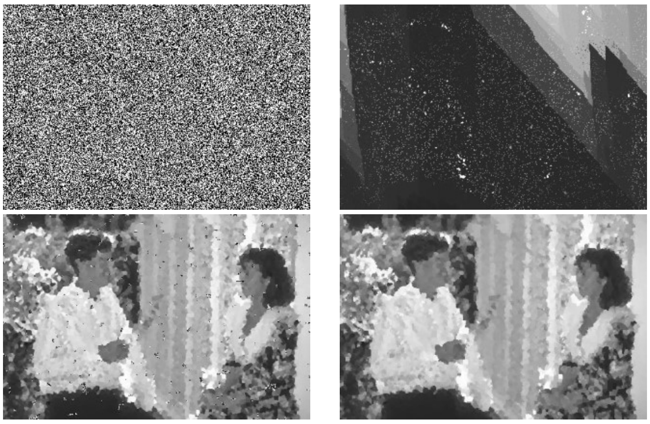

Fig. 5. Denoising result for image 157055 with noise level 95%.

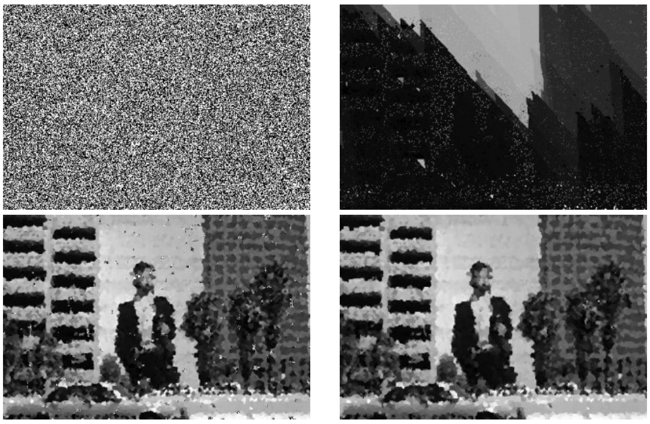

Fig. 6. Denoising result for image 119082 with noise level 95%.

Fig. 7. Denoising result by the proposed method for image 157055 with noise levels 98% and 99%.

(a) *The first case*: we implement the proposed method on two images: the "man and woman" (ID 157005) and the violist (ID 119082) of open dataset with various noise levels: 60%, 75%, 85% and 95%. In this case, we will evaluate the image quality metrics PSNR/SSIM after denoising. The original images are taken from the open dataset of the UC Berkeley <u>*https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/BSDS300/html/dataset/images.html*</u>. We will generate the salt-and-pepper noise by using the built-in function *imnoise* of MATLAB for the tests.

TABLE 1. IMAGE QUALITY METRICS **PSNR/SSIM** OF DENOISED IMAGES IDs 119082/157005 WITH VARIOUS NOISE LEVELS.

	IDs	Metric	60%	75%	85%	95%
Noisy	119082	PSNR	6.8967	5.9339	5.371	4.8992
		SSIM	0.0471	0.0262	0.0148	0.006
	157005	PSNR	7.2794	6.286	5.7417	5.2804
		SSIM	0.0335	0.01821	0.0121	0.0071
BPDF	119082	PSNR	19.4224	15.5939	10.5662	8.5747
		SSIM	0.6552	0.4662	0.25729	0.2052
	157005	PSNR	22.0688	18.6481	10.5383	7.5014
		SSIM	0.7433	0.5661	0.2419	0.1699
DAMF	119082	PSNR	23.0143	21.1104	19.6263	15.968
		SSIM	0.8075	0.7213	0.6237	0.4086
	157005	PSNR	25.9131	24.0569	22.4696	18.1116
		SSIM	0.8686	0.8022	0.7222	0.5061
Proposed	119082	PSNR	**23.028**	**21.1933**	**19.7636**	**17.1332**
		SSIM	**0.8079**	**0.7247**	**0.6312**	**0.4488**
	157005	PSNR	**25.9191**	**24.1196**	**22.6376**	**20.0271**
		SSIM	**0.8687**	**0.8034**	**0.7252**	**0.5616**

TABLE 2. IMAGE QUALITY METRICS **PSNR** OF DENOISED IMAGES WITH NOISE LEVEL 85%.

Image IDs	Corrupted	BPDF	DAMF	Proposed
119082	5.371	10.5662	19.6263	**19.7636**
126007	5.9785	16.7956	24.8488	**24.9736**
157055	5.7417	10.5383	22.4696	**22.6376**
170057	6.3635	16.4035	26.1796	**26.3127**
182053	6.0278	14.6069	20.6892	**20.8526**
219090	5.9781	15.9962	22.7878	**22.9376**
253027	6.2536	13.2988	19.0979	**19.1023**
295087	5.9468	17.3486	24.17	**24.3791**
296007	6.5168	19.0277	29.1871	**29.4287**
38092	5.6804	11.2752	22.437	**22.6367**

The denoising results for the "man and woman" with the noise levels 60%, 75%, 85% and 95% are presented in figures 2, 3, 4 and 5, respectively. The first image is the noisy image, the second one – denoised image by BPDF, the third one – by DAMF and the last one – by the proposed. As can be seen, the BPDF filter causes the raindrop effect in the case of high noise density. From the noise level 75% up to 95%, the defect is very clearly visible. Especially, if the noise level is very high (around 95%), the BPDF absolutely failed. For the DAMF filter, the result is better a lot. Only for the very high noise level (around 95%), the DAMF works ineffectively. There are some defects on the denoised images. This also can be clearly visible on the figure 6 with the violist image. In all cases, our proposed method works very effectively. With the very high noise level (up to 99%), our proposed method also works well. The denoising results by the proposed method on the "man and woman" image with the noise levels 98% (the first image) and 99% (the second image) are presented in figure 7. Table 1 presents the denoising quality by PSNR and SSIM metrics for the violist and the "man and woman" images with various noise levels. We can see that our proposed method gives the best result in all cases. The higher noise level, the clearer difference.

(b) *The second case*: the proposed method will be compared to other salt-and-pepper denoising methods. The dataset is like above. In this case, we only use the salt-and-pepper noise levels 85% (high) and 95% (very high) for all the tests.

The values of PSNR and SSIM metrics for the case of noise level 85% are presented in tables 2 and 3. The values of PSNR and SSIM metrics for the case of noise level 95% are presented in tables 4 and 5. It is very explicit to recognize that our proposed method gives the best denoising result in both cases.

TABLE 3. IMAGE QUALITY METRICS **SSIM** OF DENOISED IMAGES WITH NOISE LEVEL 85%.

Image IDs	Corrupted	BPDF	DAMF	Proposed
119082	0.014754	0.25729	0.62374	**0.6312**
126007	0.0076611	0.56535	0.78417	**0.78844**
157055	0.012065	0.24185	0.72216	**0.72516**
170057	0.0074641	0.38743	0.77173	**0.77196**
182053	0.014537	0.44791	0.71811	**0.72207**
219090	0.0105	0.4594	0.70675	**0.71362**
253027	0.01902	0.26828	0.66498	**0.66881**
295087	0.0077135	0.42198	0.6943	**0.70135**
296007	0.005945	0.54132	0.77666	**0.78307**
38092	0.011879	0.33376	0.65606	**0.66297**

TABLE 4. IMAGE QUALITY METRICS **PSNR** OF DENOISED IMAGES WITH NOISE LEVEL 95%.

Image IDs	Corrupted	BPDF	DAMF	Proposed
119082	4.8992	8.57465	15.968	**17.1332**
126007	5.5063	13.299	20.0429	**22.4379**
157055	5.2804	7.50144	18.1116	**20.0271**
170057	5.8848	15.3871	20.4472	**23.3241**
182053	5.5395	12.8351	17.3804	**18.6129**
219090	5.4763	14.3158	18.5099	**20.616**
253027	5.7504	11.4917	16.05	**16.9625**
295087	5.4668	13.625	19.6187	**22.3694**
296007	6.0319	17.0963	22.4744	**27.2497**
38092	5.1925	8.61608	18.5525	**20.2166**

TABLE 5. IMAGE QUALITY METRICS **SSIM** OF DENOISED IMAGES WITH NOISE LEVEL 95%.

Image IDs	Corrupted	BPDF	DAMF	Proposed
119082	0.0060205	0.20516	0.40857	**0.44882**
126007	0.0045439	0.44856	0.59949	**0.68314**
157055	0.0071278	0.16985	0.5061	**0.56156**
170057	0.005009	0.3883	0.55251	**0.60825**
182053	0.0072764	0.38826	0.52666	**0.59913**
219090	0.0053391	0.41161	0.51959	**0.60166**
253027	0.0065872	0.23951	0.46012	**0.50851**
295087	0.0049044	0.33621	0.51034	**0.58432**
296007	0.0044123	0.49937	0.60776	**0.6885**
38092	0.0060257	0.26172	0.46824	**0.52127**

In all tests, our proposed method can work very fast. It only takes up to 4 seconds to remove noise. This result is really impressive to compare to PDEs-based [10], regularization-based [19, 6, 20] methods.

IV. Conclusions

In this paper, we proposed an improved BPDF filter. The proposed method works effectively on various noise levels and with very high noise levels – up to 99%. This denoising result is really impressive to compare to other state-of-the-art denoising methods, such as DAMF. Otherwise, our proposed method can work fast enough to process noise on large and/or high-resolution images that requires a vast of computations.

In future works, we would like to extend this method to apply for the impulse denoising problem. This kind of noise is very popular in images created by electronics devices. Otherwise, we would like to compare our result with other method based on machine learning [21, 22].

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