Image Thresholding-based Switching Filter for Salt & Pepper Noise Removal

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***Abstract*—Switching filter is a popular kind of image salt & pepper noise removal techniques in recent years. Unfortunately, noise detection schemes in existing switching filters are usually unsuitable for dealing with those images containing a certain number of noise-free pixels with gray levels 0s or 255s. To alleviate this issue, a new noise detection scheme is proposed, which can be regarded as a generalization of MDBUTMF's (modified decision based unsymmetric trimmed median filter) scheme. The proposed detection scheme innovatively utilizes image thresholding results obtained by gray level extremes 0 and 255 to further exclude fake noise pixels. And MDBUTMF's noise restoration scheme is adopted to restore our detected noise pixels. A series of simulations demonstrate that the proposed algorithm has higher noise detection accuracy and better restoration effect with higher PSNR values.**

Keywords-salt & pepper noise; switching filter; median; mean

I. INTRODUCTION

Impulse noise in images is usually generated by bit errors in transmission or introduced during image signal acquisition [1-2]. There are two common types of impulse noise, i.e., salt & pepper noise and random valued noise. Salt & pepper noise is one of the main factors causing image contamination and quality degradation, and corrupted (noise) pixels take gray level extremes, 0 or 255, for an 8-bit image. Dramatic gray level changes of salt & pepper noise to its neighbors bring the same large gradient value as an image edge pixel, which causes great difficulty for image analysis, especially for edge detection.

Median filter is a widely used nonlinear filter for salt & pepper noise removal in terms of its good noise suppression ability and high computational efficiency. Standard median filter is prone to damage image details such as thin lines and sharp corners due to its undiscriminating median replacement operation on each pixel. In addition, selection of appropriate filtering window size is also a difficult problem. Increment of filtering window size will enhance noise suppression ability, but lead to the loss of image details simultaneously. To alleviate these issues, many modified median filters have been developed. Among them, switching median filters were widely concerned recently for its easy implementation and effectiveness.

Switching filters divide the whole noise removal process into two relatively independent stages. The first stage aims to detect corrupted (noise) pixels from a noisy image. The second stage is to restore those detected noise pixels. Researchers usually think that the difficulty of noise detection is how to distinguish real edge pixel from noise pixel as both of them have similar gray level characteristic in their own local windows, especially when noise density is high. Many schemes have been suggested to improve detection accuracy, such as boundary discriminative noise detection algorithm (BDND)[3] , highly effective impulse noise detection algorithm (HEND)[4], directional weighted median filters (DWMF[5] and MDWMF[6]) and modified decision based unsymmetric trimmed median filter (MDBUTMF)[7]. Unfortunately, these algorithms are unsuitable for those images containing noise-free pixels with gray levels 0s or 255s. To improve noise detection accuracy and restoration effect on this type of images, an image thresholding-based switching filter for noise removal is presented in this paper. The proposed algorithm improves noise detection of MDBUTMF and follows MDBUTMF's noise restoration scheme. Extensive simulations demonstrate the effectiveness of the proposed algorithm.

The rest of this paper is organized as follows: Section II discusses noise model, drawbacks of several existing noise detection schemes and our improvement. Section III describes the proposed algorithm. Simulation results on some images are arranged in Section IV. Conclusions are drawn in Section V.

II. NOISE DETECTION

A. Noise Model

Salt & pepper noise is a common impulse noise. Image pixels are randomly corrupted by two fixed gray level extremes, 0 and 255, with the same probability for an 8-bit gray level image. Assuming that $x_{i,j}$ and $f_{i,j}$ are gray levels of image pixel with coordinate (i, j) in original noise-free image and the corrupted image respectively, the probability density function of $f_{i,j}$ is

$$P(f_{i,j}) = \begin{cases} p/2, & \text{for } f_{i,j} = 0 \\ 1-p, & \text{for } f_{i,j} = x_{i,j} \\ p/2, & \text{for } f_{i,j} = 255 \end{cases} \tag{1}$$

where p denotes noise density.

B. Noise Detection and Our Improvement

Noise detection aims at identifying all corrupted (noise) pixels from a noisy image. When noise detection stage is over,

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a two-dimensional binary decision map, namely *BM*, is obtained, where 0 and 1 indicate noise-free pixel and noise one respectively.

In the opinion of most people, difficulty of noise detection origins from the easy confusion of real edge pixel and noise pixel. Hence, most researchers focused on distinguishing edge pixels from noise ones. For example, BDND[3] adopts two-stage detection with different filtering window sizes to identify noise pixels. Unfortunately, its second stage also called validation stage lacks statistical significance due to too small filtering window, dramatically weakening effect of validation. To resolve this issue, HEND[4] utilizes directional gray level differences to improve effect of validation stage. DWMF[5] and MDWMF[6] use directional weighted gray level differences to identify noise pixels. The starting point of HEND, DWMF and MDWMF is that edge pixel has certain direction, but noise pixel has no direction.

In practice, if an image contains a certain number of noise-free pixels (edge or non-edge pixels) with gray levels 0s or 255s, those non-edge noise-free pixels also cause great difficulty for noise detection. For this type of images, existing algorithms usually suffer serious miss detection (i.e., the number of noise pixels being misclassified as noise-free ones) or false alarm (i.e., the number of noise-free pixels being misclassified as noise ones). As compared with the above other algorithms, the advantages of MDBUTMF are that: 1) there is no miss detection as it regards all the pixels with levels 0s or 255s as noise pixels; 2) it has high computational efficiency due to its simple noise detection scheme. Of course, when dealing with an image containing noise-free pixels with levels 0s or 255s, its obvious disadvantage emerges. In this case, MDBUTMF faces serious false alarm, as all noise-free pixels with levels 0s or 255s are misclassified as noise pixels.

To alleviate the issue, a modified noise detection scheme using image thresholding results is presented. Its noise detection process is as follows:

(1) Initialize all the elements of a two-dimensional binary decision map *BM* to be 0s.

(2) Find the coordinates of all the pixels with gray levels 0s or 255s, and set corresponding elements of *BM* to be 1s. The mathematical formulation is

$$BM_{\forall p_{i,j}}(i,j)=1, \quad f_{i,j}\in\{0,255\} \tag{2}$$

where $f_{i,j}$ is the gray level of image pixel with coordinate (i, j).

(3) Estimate *SNR* value of the image by our algorithm in Ref. [8] as a rough estimation for noise density.

(4) If $SNR>1.5$, continue the following steps; otherwise, the process stops.

(5) Acquire image thresholding result seg_0 obtained by threshold 0. Its mathematical formulation is

$$seg_0(i,j)=\begin{cases}1, & if\ \ f_{i,j}=0\\ 0, & otherwise\end{cases} \tag{3}$$

where 1 and 0 denote object pixel and background one, respectively.

(6) Search object pixels in seg_0, find out the connected components composed of object pixels under 8-connected graph topology, and calculate the number of pixels in each connected component. We convert those object pixels in connected components whose pixel numbers are over 20 to be noise-free pixels, i.e., setting corresponding *BM* elements to be 0s.

(7) Similarly, acquire image thresholding result obtained by threshold 255. The mathematical formulation is

$$seg_{255}(i,j)=\begin{cases}1, & if\ \ f_{i,j}=255\\ 0, & otherwise\end{cases} \tag{4}$$

(8) Search object pixels in seg_{255}, find out the connected components, and convert those object pixels in connected components whose pixel numbers are over 20 to be noise-free pixels.

(9) Acquire final binary decision map *BM* representing noise detection result.

In fact, the steps (1) and (2) constitute MDBUTMF's noise detection scheme. Therefore, our scheme is a generalization of MDBUTMF's. Our motivation is that: when noise density is low, the number of white noise pixels adhered to each other should be small, as salt & pepper noise is uniformly distributed in the whole image. Similarly, the number of black noise pixels adhered to each other also should be small. On the contrary, real white and black image regions composed of noise-free pixels with levels 0s or 255s usually have more image pixels. Hence, when the pixel number of a connected component in seg_0 or seg_{255} is larger than 20, the probability of being real image region is higher than that of being noise region. In this case, the component is regarded as real image region, and its image pixels should be noise-free ones.

III. THE PROPOSED ALGORITHM

After combining the new noise detection scheme with MDBUTMF's noise restoration, a new switching median filter is presented in this paper. The steps of the proposed algorithm are as follows:

Step 1	Detect noise pixels in an image via the proposed scheme in Section II.
Step 2	For any one of detected noise pixels, $p_{i,j}$, acquire its 3×3 local window and form a gray level set Ω.
Step 3	If Ω only contains the elements with 0s or 255s, then restored gray level of $p_{i,j}$ is taken as the mean value of Ω.
Step 4	If Ω contains some elements with gray levels except 0 or 255, then eliminate those elements of 0s or 255s and replace $p_{i,j}$ with the median value of remaining elements.
Step 5	Repeat steps 2 to 4 until all the detected pixels in the whole image are processed.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of 4 algorithms (i.e., BDND[3], HEND[4], MDBUTMF[7]and the proposed algorithm) on salt &

pepper noise detection, we applied them to three gray level images, namely Block, Couple and Gearwheel, shown in Figure 1. All of them are 8-bit images with resolution of 256×256. Accuracy of noise detection is quantitatively measured by two common criteria, i.e., false alarm (FA) and miss detection (MD). FA represents the number of noise-free pixels being misclassified as noise ones. MD indicates the number of noise pixels being misclassified as noise-free ones. In addition, PSNR (peak signal-to-noise ratio)[3] is chosen as a measure for quantitative comparison of restoration results. Its formula is

$$\mathrm{PSNR}=10\log_{10}\frac{255^2}{\frac{1}{N}\sum_{i,j}(r_{i,j}-x_{i,j})^2}, \qquad (5)$$

where N is the total number of image pixels, $r_{i,j}$ and $x_{i,j}$ denote the gray levels of $p_{i,j}$ in the restored image and the original noise-free one, respectively. The higher PSNR is, the better the quality of the restored image. In HEND[4], parameters T_1 and T_2 are set to be 5/255 and 1/255, respectively.

Figure 1. Original noise-free testing images: Block, Couple and Gearwheel.

To compare accuracy of noise detection, we applied 4 algorithms to noisy images of varying noise density from 10% to 50% with incremental step 10%. We repeat the noise adding and detection procedures 5 times independently for each noise density and take the average as the final result. To make all the methods be able to implement on the whole image region, we extend each of the four boundaries of the testing images through mirror-reflecting by enough pixels. Tables I to VI list average false alarm and miss detection values by applying 4 algorithms to three testing samples respectively. From these tables, one can observe that: 1) when noise density>30%, our noise detection scheme is degraded to be MDBUTMF's scheme. The reason is that the condition of noise density>30% usually corresponds to that of SNR≤1.5. When the condition is established, our image thresholding-based noise validation stage composed of steps 5 to 8 in section II stops, and only MDBUTMF's noise detection composed of steps 1 and 2 is implemented. 2) When noise density≤30%, the proposed algorithm has smallest false alarm and largest miss detection. However, the sum of its false alarm and miss detection is obviously smaller than those of the counterparts.

After quantitative comparison of noise detection, we now focus on noise restoration. There are 4 noise detection schemes from BDND, HEND, MDBUTMF and the proposed algorithm. To demonstrate influence of noise detection on noise removal, we combine all detection schemes with MDBUTMF's restoration to remove salt & pepper noise. These combinations are still called BDND, HEND, MDBUTMF and OUR. Tables VII to IX list average PSNR values of restored images when noise density varies from 10% to 50% under 5 repeated tests. These tables clearly show that the proposed algorithm has the best restoration effect when noise density≤30%. HEND and MDBUTMF have similar effect, and both of them are better than BDND. The conclusions can also be demonstrated by the visual restoration results in Figures 2 to 4. We only give the results corresponding to noise densities 10%, 20% and 30%, as our result is the same as MDBUTFM's result when noise density>30%.

TABLE I. AVERAGE FA COMPARISON FOR BLOCK

Noise density	BDND	HEND	MDBUTMF	OUR
10%	3705	1602	1459	319
20%	2901	1507	1372	305
30%	2338	1418	1294	254
40%	1971	1322	1222	1222
50%	1718	1232	1137	1137

TABLE II. AVERAGE MD COMPARISON FOR BLOCK

Noise density	BDND	HEND	MDBUTMF	OUR
10%	1	0	0	52
20%	11	0	0	129
30%	62	0	0	278
40%	218	0	0	0
50%	477	0	0	0

TABLE III. AVERAGE FA COMPARISON FOR COUPLE

Noise density	BDND	HEND	MDBUTMF	OUR
10%	15007	11420	13294	325
20%	13743	12093	12598	12598
30%	12676	11792	11925	4984
40%	11628	11140	11166	11166
50%	10808	10497	10506	10506

TABLE IV. AVERAGE MD COMPARISON FOR COUPLE

Noise density	BDND	HEND	MDBUTMF	OUR
10%	0	0	0	182
20%	2	0	0	0
30%	13	0	0	449
40%	57	0	0	0
50%	167	0	0	0

TABLE V. AVERAGE FA COMPARISON FOR GEARWHEEL

Noise density	BDND	HEND	MDBUTMF	OUR
10%	12020	3616	3431	966
20%	9018	3433	3247	856
30%	6891	3245	3073	2105
40%	5339	3049	2893	2893
50%	4228	2841	2699	2699

TABLE VI. AVERAGE MD COMPARISON FOR GEARWHEEL

Noise density	BDND	HEND	MDBUTMF	OUR
10%	0	0	0	150
20%	7	0	0	351
30%	43	0	0	308
40%	188	0	0	0
50%	417	0	0	0

TABLE VII. AVERAGE PSNR COMPARISON FOR BLOCK

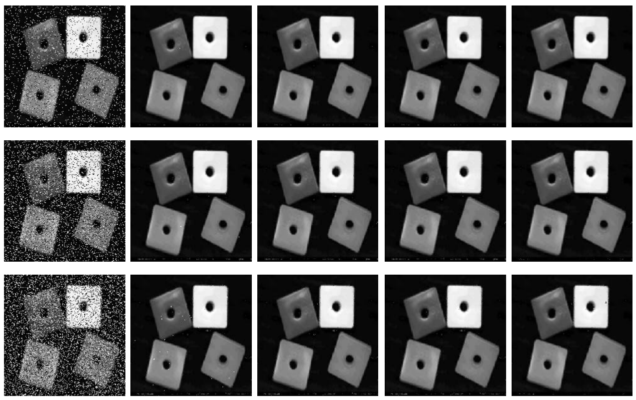
Noise density	BDND	HEND	MDBUTMF	OUR
10%	41.664	41.853	41.872	46.852
20%	35.484	37.03	37.037	40.592
30%	30.235	33.834	33.836	34.845
40%	25.964	31.149	31.15	31.15
50%	22.489	27.862	27.862	27.862

TABLE VIII. AVERAGE PSNR COMPARISON FOR COUPLE

Noise density	BDND	HEND	MDBUTMF	OUR
10%	26.442	26.508	26.508	32.524
20%	23.612	23.645	23.645	23.645
30%	21.399	21.471	21.471	23.796
40%	19.278	19.455	19.455	19.455
50%	17.551	17.909	17.909	17.909

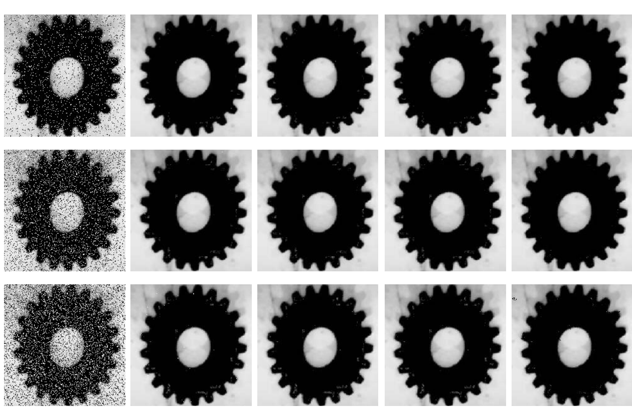
TABLE IX. AVERAGE PSNR COMPARISON FOR GEARWHEEL

Noise density	BDND	HEND	MDBUTMF	OUR
10%	38.342	38.464	38.501	42.83
20%	33.923	34.215	34.225	37.839
30%	30.398	31.292	31.297	31.835
40%	26.541	28.66	28.662	28.662
50%	23.777	25.976	25.977	25.977



(a) noise image (b) BDND (c) HEND (d) MDBUTMF (e) OUR
Figure 2. Image restoration results for Block: the up row for noise density 10%, the middle row for density 20% and the button row for density 30%.

(a) noise image (b) BDND (c) HEND (d) MDBUTMF (e) OUR
Figure 3. Image restoration results for Couple: the up row for noise density 10%, the middle row for density 20% and the button row for density 30%.



(a) noise image (b) BDND (c) HEND (d) MDBUTMF (e) OUR
Figure 4. Image restoration results for Gearwheel: the up row for noise density 10%, the middle row for density 20% and the button row for density 30%.

V. CONCLUSIONS

Existing noise detection algorithms mainly focuses on distinguishing real edge pixel from noise pixel. In practice, if an image contains a certain number of noise-free pixels (edge or non-edge pixels) with gray levels 0s or 255s, those non-edge noise-free pixels also cause great difficulty for noise detection. This makes existing algorithms unsuitable for dealing with this type of images. To solve this problem, on the basis of MDBUTMF, an innovative image thresholding-based noise detection scheme is proposed, and a noise removal algorithm is developed after integrating with MDBUTMF's restoration scheme. We utilize connectivity of object regions in image thresholding results obtained by 0 or 255 to exclude fake noise pixels. The exclusion operation is only performed when noise density is low. Hence, our algorithm is a generalization of MDBUTMF. Extensive simulations on a series of images demonstrate the effectiveness of the proposed algorithm.

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