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LETTER

Modified switching median filter with one more noise detector for impulse noise removal

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Abstract

In this paper, the switching median filter is modified by adding one more noise detector to improve the capability of impulse noise removal. The proposed impulse noise detector is established based on the rank order arrangement of the pixels in the sliding window. The original switching median filter cannot detect the noise pixel whose value is close to its neighbors if the threshold is designed for emphasizing the detail preservation. Therefore, it is hard to recognize a noise-like pixel as a noise or a noise-free pixel in the sliding window. The proposed impulse noise detector overcomes the above weakness such that the switching median filter is much effective in impulse noise removal.

Keywords: Image processing; Impulse noise; Median filter; Switching median filter; Rank order

1. Introduction

Images are frequently corrupted by impulse noise due to the errors generated in noisy sensors and communication channels [1]. The subsequent image processing procedures such as edge detection, image segmentation and object tracking etc. might get worse performances if the noise exists in the input image with high noise density. Therefore, detecting noise and replacing the noise pixel with an appropriate value is an important work for image processing.

The median (MED) filter [1] is a well-known nonlinear filter to eliminate the noise in the smooth regions in image. But in the detail regions such as edge and texture, MED might smear the detail. The MED based impulse noise filters have been proposed in [2–6] already to solve this problem. The switching MED filters I and II (SWM-I and SWM-II) [2] determine the difference between the current pixel and the MED in the corresponding sliding window and then use a threshold to determine whether the current pixel is noise. To preserve the detail, the center weighted median filter (CWM) [1] is added into SWM-I as the tri-state median filter (TSM) [3]. TSM uses two thresholds to determine whether the current pixel should be replaced by the original value, the outputs of MED or of CWM. The filter proposed in [4] modifies TSM with more thresholds to reach the better performance. In the filter proposed in [5], the detail is detected and preserved by using the Laplacian edge detector. The filter proposed in [6] modifies SWM-I with a much stricter condition for noise detection. The noise is detected only when the current pixel and neighbors are much different. In this paper, SWM is modified with one more process by using the concept of rank order to improve the noise removal capability. The simulations results show that the proposed modified SWM (MSWM) has the better noise removal capability than the other filters.

The remainder of this paper is organized as follows: Section 2 reviews SWM-I and SWM-II. Section 3 introduces the

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main algorithm of the proposed MSWM. Section 4 presents how to select the parameters of MSWM in different noise density. The simulations and experimental results are listed in Section 5. Finally, a brief conclusion is given in Section 6.

2. Reviews of SWM-I and SWM-II

Let $\{x_{i-L,j-L}, \ldots, x_{i,j}, \ldots, x_{i+L,j+L}\}$ represent the input sample in the $(2L+1)\times(2L+1)$ sliding window where $x_{i,j}$ is the current pixel locating at position (i, j) in the image. The output of SWM is defined as

$$y_{i,j} = \begin{cases} x_{\text{med}}, & \Delta x \geqslant T_i, \\ x_{i,j}, & \Delta x < T_i, \end{cases} \tag{1}$$

where $\Delta x = |x_{i,j} - x_{\text{med}}|$, x_{med}=MED$\{x_{i-L,j-L}, \ldots, x_{i,j}, \ldots, x_{i+L,j+L}\}$ in SWM-I and x_{med}=MED$\{x_{i-L,j-L}, \ldots, w\Diamond x_{i,j}, \ldots, x_{i+L,j+L}\}$ in SWM-II, $w\Diamond x_{i,j}$ denotes that $x_{i,j}$ multiplies w times, T_i is a threshold and $y_{i,j}$ is the filtered pixel locating at position (i, j). $\Delta x \geqslant T_i$ means that the current pixel is much more different from its neighbors and can be treated as a noise. $\Delta x < T_i$ denotes the current pixel to be regarded as a noise-free pixel. In fact, the impulse noise value is uniformly distributed, once its value is rather close to its neighbors such that $\Delta x < T_i$ happens, the noise pixel cannot be detected by SWM. Hence, this noise pixel cannot be filtered unless the threshold is lowered down. The lower threshold is used, the more noise pixels are detected, but less detail pixels are preserved. In other words, there is a trade-off between noise detection and detail preservation on tuning the threshold.

3. The proposed modified SWM

Now the proposed MSWM modifies SWM by adding one more process when $\Delta x < T_i$ happens. Arrange the input samples in ascending order such as $x^1 \leqslant x^2 \leqslant \cdots \leqslant x^{(2L+1)\times(2L+1)}$. The superscript of the sorted x represents its rank order denoted by $R(x)$. Then, the one more noise detection process under the case $\Delta x < T_i$ is shown as

$$y_{i,j} = \begin{cases} x_{\text{med}}, & \Delta R \geqslant T_{\text{r}}, \\ x_{i,j}, & \Delta R < T_{\text{r}}, \end{cases} \tag{2}$$

where $\Delta R = |R(x_{i,j}) - R(x_{\text{med}})|$, and T_{r} is another threshold. The case $\Delta R \geqslant T_{\text{r}}$ means that the rank order of the current pixel $x_{i,j}$ is larger than the corresponding MED with T_{r}-order. It denotes that $x_{i,j}$ is a noise pixel and must be filtered since the pixel close to the MED has the less probability to be corrupted by impulse noise and the pixel close to one of two ends of the sorted samples is very possible an impulse noise . The proposed MSWM is summarized in the flowchart of Fig. 1.

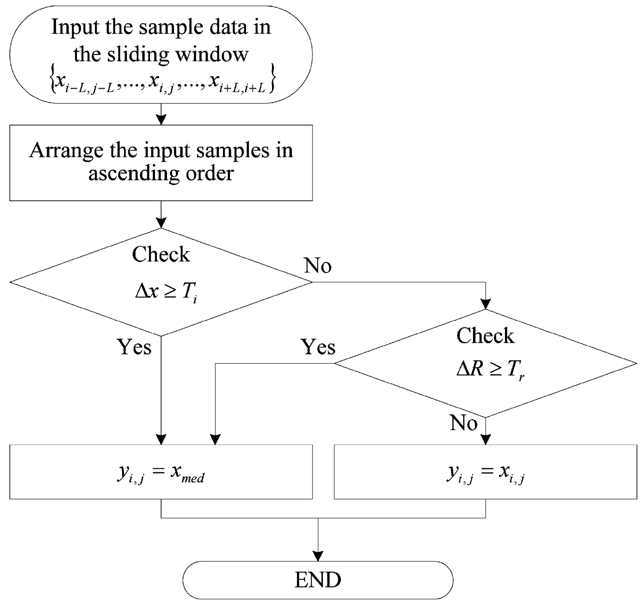


Fig. 1. The flowchart of MSWM.

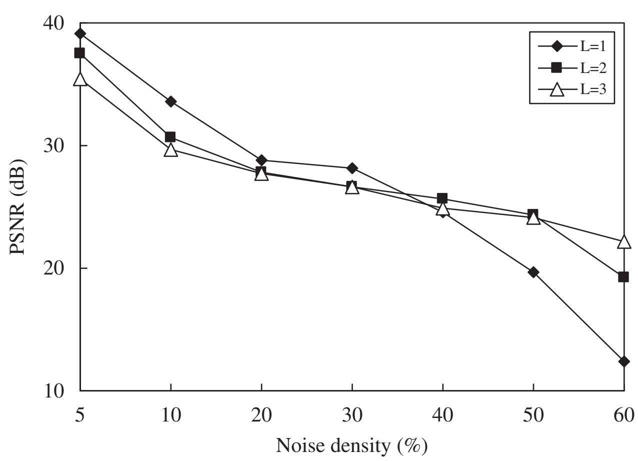


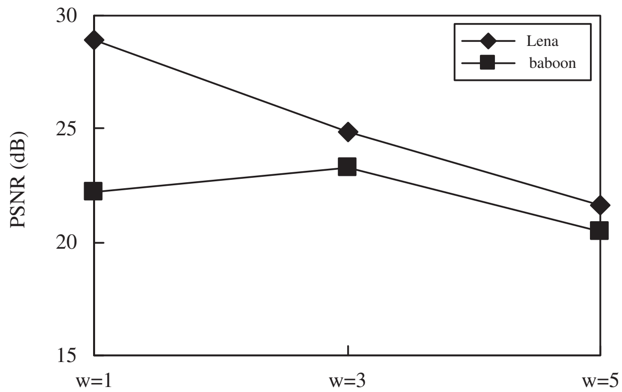
Fig. 2. The noise removal capabilities of MED with different sliding window sizes in "Lena" images with different noise densities.

4. The selections of the parameters

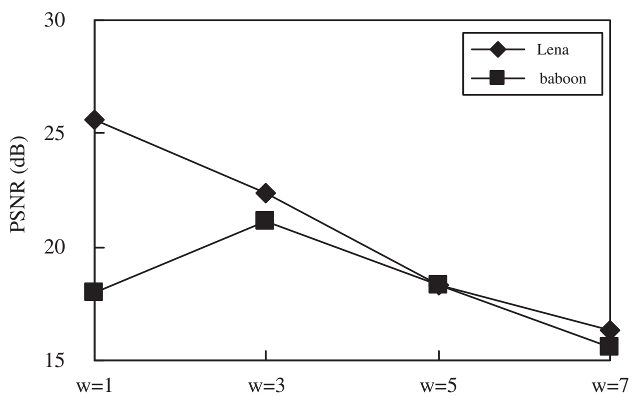
In practical applications, the selections of L, w, T_i and T_{r} depend on the noise density and the specific of each image. Consequently, selection strategy for these parameters is discussed. Generally speaking, the lower the noise density is, the smaller the sliding window is used. Fig. 2 shows the PSNR values for the "Lena" image by MED, where the random-value impulse noise is with noise densities $p \in \{5\%, 10\%, 20\%, 30\%, 40\%, 50\%, 60\%\}$ and $L \in \{1, 2, 3\}$. The random-value impulse noise is uniformly distributed in the range $0, 255$. It can be obviously seen that the relatively high PSNR values are obtained by using $L = 1$ while $p \in \{5\%, 10\%, 20\%, 30\%\}$, using $L=2$ while $p \in \{40\%, 50\%\}$, and using $L=3$ while $p=60\%$. Therefore, we suggest that the size of the sliding window is set as shown in Table 1.

Table 1. The suggested size of the sliding window for different noise densities

Noise density	Suggested size of sliding window	L
$0\% \leqslant p < 40\%$	3×3	1
$40\% \leqslant p < 60\%$	5×5	2
$p \geqslant 60\%$	7×7	3

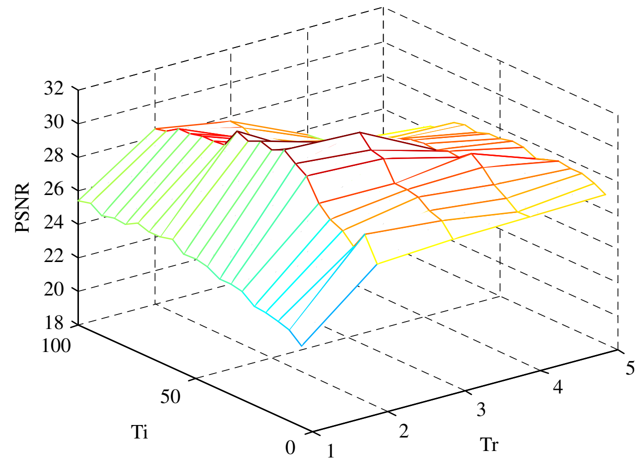


(a)

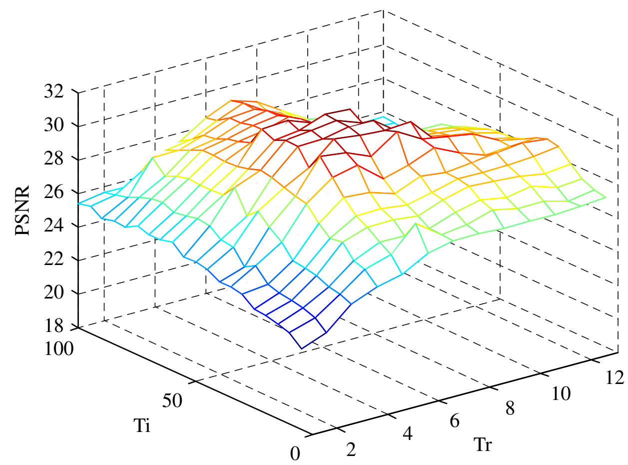


(b)

Fig. 3. The noise removal capabilities of SWM with different weights $w$in "Lena" and "baboon" images by using the window sizes (a) $L=1$; (b) $L=2$.



(a)



(b)

Fig. 4. The noise removal capabilities of MSWM with different T_i and T_r by using the window sizes (a) $L=1$; (b) $L=2$.

To determine the value w, the corrupted "Lena" and "baboon" images with $p \in \{20\%, 40\%\}$ are used. "Lena" is a smooth image while "baboon" is a complicated image. Fig. 3(a) shows the PSNR values for both "Lena" and "baboon" images with $p=20\%$ by using SWM with $L=1$, $T_i=50$ and $w \in \{1,3,5\}$. Fig. 3(b) shows the PSNR values for both "Lena" and "baboon" images with $p=40\%$ by using SWM with $L=2$, $T_i=50$ and $w \in \{1,3,5,7\}$. We can see that "Lena" image performs relatively high PSNR when $w=1$ and "baboon" image performs relatively high PSNR when $w=3$. Therefore, we suggest that w is set as 1 for processing the smooth image and w is set as 3 for processing the complicated image.

In SWM, the threshold T_i is suggested to set as 50. The threshold T_i in MSWM is set the same as SWM. The other threshold $T_r$is set as an integer that is most close to $0.5(4L^2+4L+w)\cdot p(1-p)$, where $(4L^2+4L+w)$ is the number of the sorted sample data including the current pixel $x_{i,j}$ which multiplies w times, since the noise density in the entire image is identical to the noise density in the sliding window, theoretically. For example, if $p=40\%$ and $w=1$, then T_r is set as 3 in the 3×3 sliding window. However, if the noise density is unknown and there is not efficient noise density estimation method provided in advance, the parameters L, w, T_i and T_r cannot be selected appropriately and theoretically. Therefore, we adopt seven well-known images "airplane", "bridge", "building", "cameraman", "peppers", "Lena" and "baboon" with $p \in \{10\%, 20\%, 30\%, 40\%\}$, to be the test images. Let them go through a series of simulations using MSWM with $w=1$, where T_i is tuned from 0 to 100; T_r is tuned from 1 to 5 in 3×3 sliding window and is tuned from 1 to 13 in 5×5 sliding window. The mean values of PSNR for 28 test images (seven images with four noise densities) plotted with different T_i and T_r are shown in Fig. 4(a) with $L=1$ and Fig. 4(b) with $L=2$. We can see that MSWM has

Table 2. PSNR for the corrupted image “Lena” with various filters

Method	$p = 10\%$ (dB)	$p = 20\%$ (dB)	$p = 30\%$ (dB)	$p = 40\%$ (dB)
SWM-I	32.33	28.91	25.82	22.92
SWM-II	30.94	24.86	20.56	17.93
TSM	38.13	32.97	27.78	23.91
Ref. [4]	36.88	33.31	28.83	24.90
Ref. [5]	33.44	28.76	24.95	22.13
ERID	35.74	29.44	24.59	21.43
DRID	33.53	27.48	23.18	20.39
MSWM	**38.17**	**34.18**	**29.82**	**26.06**

Table 3. PSNR for the corrupted image “peppers” with various filters

Method	$p = 10\%$ (dB)	$p = 20\%$ (dB)	$p = 30\%$ (dB)	$p = 40\%$ (dB)
SWM-I	37.12	33.12	28.65	25.31
SWM-II	36.95	29.86	29.06	25.14
TSM	38.12	36.18	30.17	27.31
Ref. [4]	37.65	35.77	31.96	28.46
Ref. [5]	37.01	34.29	27.58	24.65
ERID	37.14	35.16	27.65	24.91
DRID	36.45	32.18	27.26	23.55
MSWM	**38.63**	**36.82**	**32.30**	**28.85**

Table 4. PSNR for the corrupted image “baboon” with various filters

Method	$p = 10\%$ (dB)	$p = 20\%$ (dB)	$p = 30\%$ (dB)	$p = 40\%$ (dB)
SWM-I	27.10	24.83	22.97	21.13
SWM-II	27.67	23.25	20.19	17.95
TSM	26.31	25.05	23.53	21.68
Ref. [4]	25.24	24.23	23.14	21.67
Ref. [5]	**27.71**	24.98	22.83	20.95
ERID	25.78	24.24	22.37	20.41
DRID	26.35	24.03	21.74	19.70
MSWM	26.68	**25.17**	**23.59**	**21.93**

Table 5. PSNR for the corrupted image “building” with various filters

Method	$p = 10\%$ (dB)	$p = 20\%$ (dB)	$p = 30\%$ (dB)	$p = 40\%$ (dB)
SWM-I	31.08	28.41	24.89	22.64
SWM-II	29.95	23.95	22.37	21.43
TSM	33.58	30.47	26.58	23.49
Ref. [4]	32.93	29.62	25.76	24.15
Ref. [5]	32.30	30.06	23.21	22.04
ERID	31.93	27.58	23.64	20.61
DRID	29.36	26.32	22.43	20.16
MSWM	**34.27**	**30.93**	**26.92**	**24.73**

good performance while $40 \leqslant T_i \leqslant 60$, $T_r \in \{2, 3\}$ in 3×3 sliding window and $5 \leqslant T_r \leqslant 10$ in 5×5 sliding window. Hence $T_i = 50$, $T_r = 2$ for $L = 1$; and$T_r = 7$ for $L = 2$ are selected in the simulations of the proposed MSWM.

5. Experimental results

To check the noise removal capability of the proposed MSWM, MSWM ($T_i = 50$, $T_r = 2$, $L = 1$ and $w = 1$, for

$p \in \{10\%, 20\%, 30\%\}$; $T_i = 50$, $T_r = 7$, $L = 2$ and $w = 1$, for $p \in 40\%$) is compared with seven methods including SWM-I from [2] ($T_i = 50$), SWM-II from [2] ($T_i = 30$, $w = 3$), TSM from [3] ($T = 20$, $w = 3$), the methods proposed in [4] ($[\delta_0, \delta_1, \delta_2, \delta_3]$=[40, 25, 10, 5], $s = 0.3$) and [5] ($T = 100$), ERID ($\Theta = 15$, $s = 2$) from [6] and DRID ($\Theta = 5$, $s = 2$) from [6]. The "Lena", "peppers", "baboon" and "building" images are used as the test images, where "Lena" and "peppers" are smooth images, but "baboon" and "building" are complicated images. Tables 2–5 list the PSNR values of restored images with $p \in \{10\%, 20\%, 30\%, 40\%\}$ for "Lena", "peppers", "baboon" and "building" images, respectively. MSWM outperforms other filters except the "baboon" image with $p = 10\%$. Fig. 5 shows the corrupted "Lena" image with $p = 20\%$ random-value impulse noise and the corresponding restored images filtered by SWM-I, SWM-II, TSM, the filters of [4,5], ERID, DRID and the proposed MSWM, respectively. Fig. 6 shows the simulations for "building" image with $p = 40\%$ random-value impulse noise. The threshold T or T_i, and/or other parameters w and s, etc. are the best values suggested in the corresponding papers [2–6], respectively.

The proposed MSWM detects the noise when either pixel value or rank order deviates from the MED, while ERID detects the noise when both pixel value and rank order deviate from the MED. The above two methods look very similar since both of them use the same measurements, Δx and ΔR, to determine whether the current pixel is noise. The criterion, which is to determine the current pixel as an impulse noise, of ERID is stricter than the criterion of MSWM such that the detection rate of ERID is higher than that of MSWM seemingly. Nevertheless, the selection of the threshold T_i in MSWM is different from the selection of Θ in ERID. ERID uses the low Θ, while MSWM uses the higher T_i which is the same as SWM. The noise detection criterion in MSWM is stricter than that in ERID instead if ΔR is not considered. It neutralizes the difference between the detection rates of MSWM and ERID. However, the probability of both $\Delta x \geqslant \Theta$ and $\Delta R \geqslant s$ are satisfied in ERID is much lower than the probability of either $\Delta x \geqslant T_i$ or $\Delta R \geqslant T_r$ is satisfied in MSWM. Hence, when the noise density is high, the noise pixel, which is not extremely close to one of two ends in the sorted samples, cannot be detected by ERID. Table 6 shows the noise detection rates of the "building" image corrupted with 10%, 20% and 40% impulse noises by using SWM-I, ERID and MSWM. The noise detection rate is defined as

$$\text{Noise detection rate} = 1 - \frac{\text{false alarm} + \text{missing detection}}{\text{the numbers of pixels in the entire image}}, \quad (3)$$

where false alarm means the numbers of "a noise-free pixel is detected as a noise" and missing detection means the numbers of "a noise is not detected as a noise". When $p \in \{10\%, 20\%\}$, the noise detection rates of MSWM are basically similar to those of ERID. But when $p = 40\%$, the noise detection rate of MSWM is higher than that of ERID.

Fig. 5. (a) The original "Lena" image; (b) corrupted with 20% random-value impulse noise; (c) SWM-I; (d) SWM-II; (e) TSM; (f) Ref. [4]; (g) Ref. [5]; (h) ERID; (i) DRID; (j) MSWM.

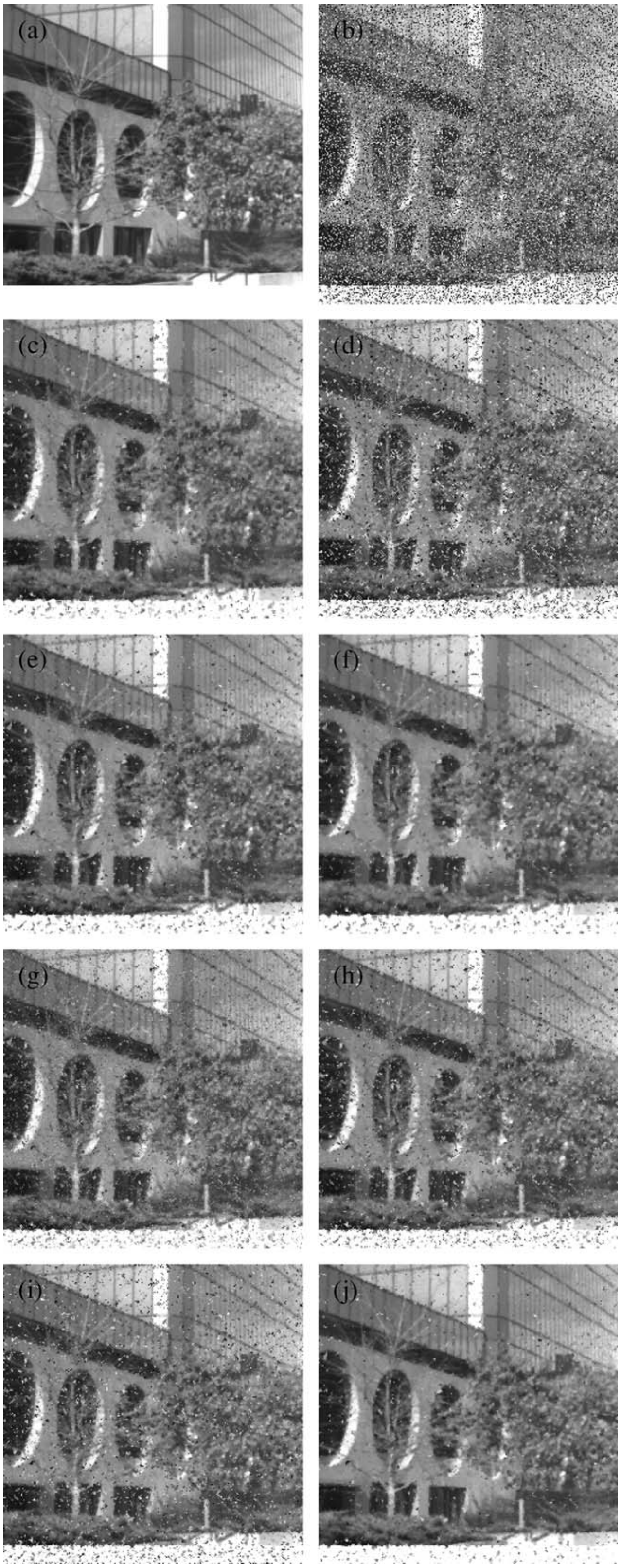


Fig. 6. (a) The original "building" image; (b) corrupted with 40% random-value impulse noise; (c) SWM-I; (d) SWM-II; (e) TSM; (f) Ref. [4]; (g) Ref. [5]; (h) ERID; (i) DRID; (j) MSWM.

Table 6. The noise detection rates of corrupted "building" image by using SWM-I, ERID and MSWM

Method	$p = 10\%$	$p = 20\%$	$p = 40\%$
SWM-I	77.76	65.14	43.37
ERID	91.43	84.66	60.32
MSWM	89.61	82.92	71.69

6. Conclusion

This paper has proposed a modified switching median filter (MSWM) based on the rank order arrangement to implement impulse noise removal. Without lowering down the threshold in SWM, MSWM modifies SWM with one more process in which the MED of the sliding window and the rank order of the current pixel are used to determine whether the current pixel is noise. The more noise pixels with values close to its neighbors are detected in MSWM. From the simulation results, we have seen that the proposed MSWM has a better performance than other existing filters.

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