A New Adaptive Switching Median Filter

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Abstract—**A new Adaptive Switching Median (ASWM) filter for removing impulse noise from corrupted images is presented. The originality of ASWM is that no *a priori* Threshold is needed as in the case of a classical Switching Median filter. Instead, Threshold is computed locally from image pixels intensity values in a sliding window. Results show that ASWM provides better performance in terms of PSNR and MAE than many other median filter variants for random-valued impulse noise. In addition it can preserve more image details in a high noise environment.**

Index Terms—**Detail-preserving, image restoration, impulse noise detection, switching median filter.**

I. Introduction

IMAGES are frequently corrupted by impulse noise due to camera sensors or transmission in noisy channels [1]. It occurs in bioluminescence imaging for which the image acquisition is disturbed by the presence of cosmic noise [2]. Cosmic noise can be considered to be an impulse noise. For this application in bioluminescence imaging, a step of filtering is needed as a preprocessing step before the deconvolution task [2].

The main approach for removing impulse noise is to use median-based filters (see, e.g., [1], [3]). However, since filters are usually implemented identically across the images, they tend to modify both noise and noise-free pixels. Consequently, some desirable details can be removed [1]. To overcome this problem, many modified forms of median filters were proposed among which are the weighted median filter [4] and the center weighted median (CWM) filter [5]. Those filters tend to work well with low noise level, but poorly for highly corrupted images. To solve this problem, the switching median (SWM) filter [6] was introduced. The main idea of the SWM is to use an impulse detector before filtering. This detector is based on an *a priori* Threshold value to decide if a median filter is to be applied or not. Next, many other approaches were proposed such as tri-state median (TSM) filter [7] and more recently, alpha-trimmed mean-based approach (ATMA) [8], directional weighted median (DWM) filter [9], and modified switching median (MSWM) filter [10].

All of these filters usually perform well in terms of Peak Signal-to-Noise Ratio (PSNR) and Mean Absolute Error (MAE). However, the principle drawback is that they have limited performance in terms of false and missed detections. Hence, they cannot preserve the image details and edges, especially when the noise is high.

To reduce these effects and improve impulse noise detection, we propose a new Adaptive Switching Median (ASWM) filter. The originality of ASWM is that no *a priori* Threshold is to be given as in the case of a classical SWM filter. Instead, the threshold is computed locally from image pixels intensity values in a sliding window using weighted statistics. Thus, it is expected that this new strategy will lead to better performances. The ASWM filter will be described and compared to other median filters using Monte-Carlo simulations.

This letter is organized as follows. In Section II, we review the impulse noise removal principle using SWM. The ASWM algorithm is described in Section III. Section IV gives simulation results using different test images to demonstrate the performances of the new approach. Finally, conclusions are noted in Section V.

II. Switching Median Filter (SWM)

The principle of the SWM filter is reminded. A SWM filter is a two steps procedure. First, a test decides whether or not a given pixel is contaminated by impulse noise: a pixel is contaminated if the absolute difference between the median value in its neighborhood and the value of the current pixel itself is greater than a given Threshold [6]. If contaminated, a classical median fitter is applied; if not, the current pixel is noise free and will be not modified. More precisely, consider X an image corrupted by an impulse noise and $X_{i,j}$ the grey level value at position i, j. Let W be a square window surrounding this pixel. This window is of size $(2L+1)\times(2L+1)$ where L is an integer greater than zero. The output $\hat{Y}_{i,j}$ of the switching median filter is given by

$$\hat{Y}_{i,j} = \begin{cases} m_{i,j}, & \text{if } |m_{i,j} - X_{i,j}| > Threshold, \\ X_{i,j}, & \text{otherwise} \end{cases} \tag{1}$$

where $m_{i,j}$ is the median value in the window W and *Threshold* is a fixed parameter.

The numerical Threshold value is defined *a priori* or chosen after many data dependant tests. The literature shows that an optimal threshold in the sense of the mean square error can be obtained for most real data [6], [7]. However, Threshold suitable for a particular image is not necessarily adapted to another one. In addition, an image is often non stationary and statistics in a region may be different in other part of the image.

The next section presents the new method that does not require *a priori* knowledge and automatically defines a local Threshold.

III. Adaptive SWM Filter (ASWM)

The proposed method has the same general structure as the SWM filter. The difference between the new method and SWM relies on the fact that Threshold is not an *a priori* choice but is

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computed locally from image pixels. For that reason, we called it the Adaptive SWM (ASWM) filter.

More precisely, the weighted mean value and the weighted standard deviation are estimated in the current window. The weights are the inverse of the distance between the weighted mean value of pixels in a given window and the considered pixel. A result is that impulse noise does not corrupt the determination of these statistics from which the Threshold is derived.

In each window, the weighted mean are first iteratively estimated. Then the weighted standard deviation is calculated and the Threshold is determined. This procedure is explained in the following.

Initialization: compute the weighted mean value M_w in a $(2\mathrm{L}+1)\times(2\mathrm{L}+1)$ window W surrounding the current pixel:

$$M_w(i,j)=\frac{\sum_{k,l}\omega_{k,l}\,X_{i+k,j+l}}{\sum_{k,l}\omega_{k,l}} \tag{2}$$

where $X_{i,j}$ is the grey level of the image X at pixel location (i,j) and $\omega_{k,l}$ the weights. These weights are all equal to 1 at *Initialization*. The index variation of k and l are in $[-\mathrm{L},\mathrm{L}]$.

Step 1: estimate the weights $\omega_{k,l}$ as

$$\omega_{k,l}=\frac{1}{|X_{i+k,j+l}-M_w(i,j)|+\delta}. \tag{3}$$

δ, a given small value, avoids possible division by zero. Then, a new weighted mean value $M_w(i,j)$ is obtained using (2).

Step 2: if $\left|M_w(i,j)^t-M_w(i,j)^{t-1}\right|<\varepsilon$, where ε is a given small value, then stop, else go to step 1 ($M_w(i,j)^t$ is the weighted mean value at iteration number t).

End.

Next, the weighted standard deviation $\sigma_w(i,j)$ is defined as

$$\sigma_w\,(i,j)=\sqrt{\frac{\sum_{k,l}\omega_{k,l}\,(X_{i+k,j+l}-M_w(i,j))^2}{\sum_{k,l}\omega_{k,l}}}. \tag{4}$$

Finally, ASWM can be summarized as follows:

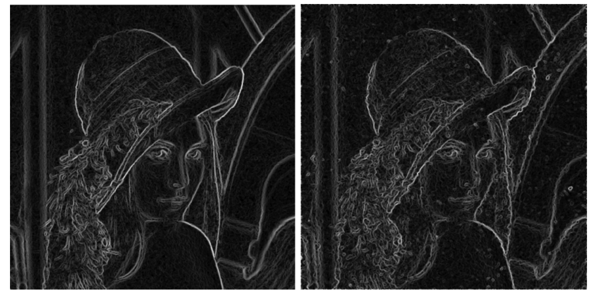
a) Compute the weighted mean $M_w(i,j)$ and the weighted standard deviation $\sigma_w(i,j)$ in the $(2\mathrm{L}+1)\times(2\mathrm{L}+1)\mathrm{W}$ window surrounding the current pixel as described above.
b) Use the following rule:

$$\hat{Y}_{i,j}=\begin{cases} m_{i,j}, & \text{if } |X_{i,j}-M_w(i,j)|>\alpha\times\sigma_w(i,j),\\ X_{i,j}, & \text{otherwise}\end{cases} \tag{5}$$

where $m_{i,j}$ is the median in the window $W_{i,j}$, α is a given parameter and $\alpha\times\sigma_w(i,j)$ represents the local threshold.

ASWM is applied recursively and iteratively. During the iterations, in each window, the threshold is decreased as proposed by Dong [9]. This is done by varying the α value. From simulations conducted on a broad variety of images, the following strategy for α yields satisfactory results, that is

$$\alpha_0=20,\ \text{and}\ \alpha_{\mathrm{n}+1}=\alpha_{\mathrm{n}}*0.8\ (\mathrm{n}\geq 0) \tag{6}$$



(a) (b)

Fig. 1. Values of σ_w for Lena image degraded respectively by (a) 30% of random-value impulsive noise and (b) 60% of random-value impulsive noise.

where α_0 is the initial α parameter and α_{n} the parameter in the nth step.

In Fig. 1, we show the values of σ_w across the "Lena" image degraded by (a) 30% and (b) 60% of random-value impulsive noise respectively. Here, we have chosen a 3×3 square window, $\delta=0.1$, $\varepsilon=0.01$ and 6 iterations were used (that means $\alpha_0=20$ and $\alpha_5=6.55$ [see (6)].

From the images of Fig. 1, we observed that σ_w is quite different depending on its location in the image: while σ_w is low in uniform regions, it shows high values in textured regions or in presence of edges. This adaptability is an important point to preserve image details. Besides, the noise percentage does not change this general behavior.

IV. Results

In this section, the restoration property, the noise detection capability of ASWM and the visual performances are evaluated and compared to a number of existing median-based filters used to remove random-valued impulse noise. Commonly, most authors use the peak signal-to-noise ratio (PSNR) and the mean absolute error (MAE) to quantify the restoration results. To complete comparisons, authors of [9] compute the number of missed noisy pixels and the number of noise-free pixels that are identified as noise to show the efficiency of their method. In the same aim, authors of [10] defined a noise detection rate. We will present such results in following Sections IV-A–IV-C.

A. Restoration Performance Measurements

Restoration performances are evaluated quantitatively by using PSNR and MAE, which are defined as in [3]. We compare ASWM to other well known median-based filters, which include the standard median SM [1] (with a 3×3 filtering window if noise percentage $\mathrm{p}<30\%$, and a 5×5 window otherwise), CWM filter [5] (w = 3), SWM filter [6] (T = 30), TSM filter [7] (T = 20), MSWM filter [10] ($\mathrm{T}_i=50$, and $\mathrm{T}_{\mathrm{r}}=2$), ATMA filter [8] ($\mathrm{s}=2$, $\mathrm{T}=12$, $\mathrm{N}=4$, $\mathrm{W}_l=5$, $\mathrm{W}_{\mathrm{u}}=30$, and $\text{iteration number}=2$ to 4), and DWM filter [9] (a 5×5 filtering window, $\mathrm{To}=512$, and $\text{iteration number}=5$ to 10). For ASWM filter, we have $\delta=0.1$, $\varepsilon=0.01$, and $\text{iteration number}=3$ to 10. For all tested methods, a 3×3 filtering window is used, unless mentioned otherwise.

As test images we adopted the well known images "Lena," "Boat," "Peppers," "Goldhill," and "Bridge." We have applied

TABLE I
PSNR (dB) AND MAE FOR A PROBABILITY OF 30% RANDOM-VALUED IMPULSIVE NOISEBEST RESULTS ARE BOLD PRINTED.

Filters		Lena	Bridge	Goldhill	Boat	Peppers
SM	PSNR	28.16	23.24	26.96	26.03	26.64
	MAE	4.63	10.17	6.16	6.62	5.26
CWM	PSNR	28.60	23.89	27.69	26.55	27.3
	MAE	3.75	8.33	4.95	5.42	4.24
SWM	PSNR	29.84	24.55	29.04	27.25	29.50
	MAE	2.75	6.14	3.31	3.91	2.81
TSM	PSNR	30.71	24.92	29.56	27.82	30.01
	MAE	2.35	6.03	3.06	3.57	2.44
MSWM	PSNR	30.68	24.11	28.95	27.45	28.35
	MAE	3.66	9.39	5.16	5.66	4.32
ATMA	PSNR	31.75	24.97	30.05	28.32	29.13
	MAE	2.12	6.68	3.02	3.52	2.47
DWM	PSNR	32.45	25.50	30.53	28.53	32.51
	MAE	2.03	5.34	2.81	3.32	1.99
ASWM (proposed)	PSNR	**32.91**	**25.62**	**30.87**	**28.75**	**33**
	MAE	**1.83**	**5.11**	**2.62**	**3.00**	**1.82**

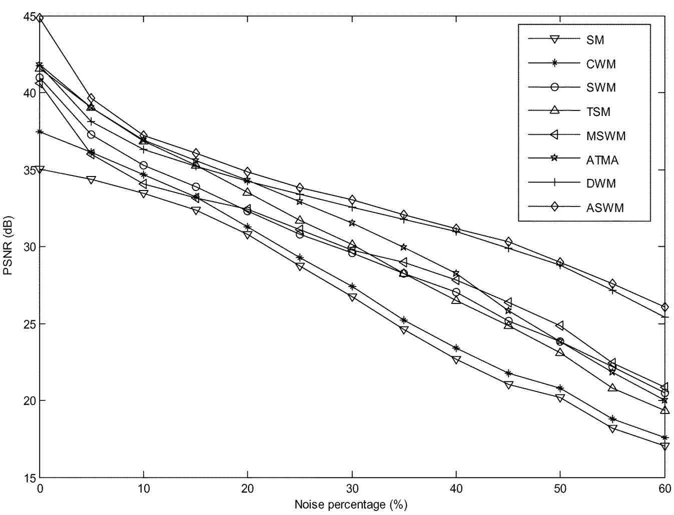


Fig. 2. Performance comparison of different methods for filtering the Peppers image degraded by various levels of random-value impulsive noise.

Monte Carlo simulations. Each image is 100 times degraded by a random impulse noise. The obtained mean PSNR and mean MAE are reported in Table I.

Results show that ASWM performs better than other considered methods and achieved the image quality with best PSNR and MAE for random valued impulse noise.

The performances of ASWM and other considered median-based filters for "Peppers" image in term of PSNR for random valued impulse noise with different noise densities are reported in Fig. 2.

Results show that ASWM performs well for the tested range data corrupted with various noise percentages up to 60%. Results are similar in term of MAE. This confirms that ASWM achieves good restoration in all range of noise percentage.

B. Noise Detection Performance Measurements

Here, we compare ASWM method with five recently proposed methods. Table II lists the number of missed noisy pixels.

TABLE II
THE NOISE DETECTION COMPARISON RESULTS FOR THE IMAGE "LENA" CORRUPTED BY RANDOM-VALUED IMPULSIVE NOISE. BEST RESULTS ARE BOLD PRINTED

"LENA" Image						
Methods	**10%**		**20%**		**30%**	
	Miss	False	Miss	False	Miss	False
SWM	2532	2439	5084	3030	6869	3739
	Sum = 4971		Sum = 8114		Sum = 10608	
TSM	2515	1855	5037	2510	6763	2628
	Sum = 4307		Sum = 7547		Sum = 9391	
MSWM	2953	108799	5674	98062	7674	87387
	Sum = 111752		Sum = 103736		Sum = 95061	
ATMA	2350	4916	4667	5502	6295	6337
	Sum = 7266		Sum = 10169		Sum = 12632	
DWM	2562	1364	5368	2901	7691	5061
	Sum = 3926		Sum = 8269		Sum = 12752	
ASWM (proposed)	**1594**	**1279**	**3019**	**4362**	**4083**	**4227**
	Sum = 2873		**Sum = 7381**		**Sum = 8310**	
Methods	**40%**		**50%**		**60%**	
	Miss	False	Miss	False	Miss	False
SWM	8333	4796	9484	6406	12612	9486
	Sum = 13129		Sum = 15890		Sum = 22098	
TSM	8167	3380	9190	4514	11612	9547
	Sum = 11547		Sum = 13704		Sum = 21159	
MSWM	8115	105859	8475	94844	10409	76817
	Sum = 113974		Sum = 103319		Sum = 87226	
ATMA	7469	7953	7922	10551	7577	14582
	Sum = 15422		Sum = 18473		Sum = 22159	
DWM	9567	7507	11035	7342	8084	11526
	Sum = 17074		Sum = 18377		Sum = 19610	
ASWM (proposed)	**4180**	**4735**	**4735**	**8613**	**4840**	**9453**
	Sum = 8915		**Sum = 13348**		**Sum = 14293**	

"Miss" term means a noisy pixel which is not detected as noise and "False" term means a noise free pixel detected as noise. For random-valued impulse noise, the noisy pixel values may not be so different from those of their neighbors. Therefore it is more likely for a noise detector to miss a noisy pixel or detect a noise-free pixel as noise [9], [11]. A good noise detector should be able to identify most of the noisy pixels. Its false alarm rate should be as small as possible.

Results for ASWM are of high quality. ASWM can still distinguish most of the noisy pixels, even when the noise level is as high as 60%.

C. Visual Performances

As a final illustration and in order to compare subjectively the methods, we give in Fig. 3, the "Goldhill" image with a 30% random value impulse noise restored by various methods.

ASWM exhibit excellent psycho-visual performances compared to other methods. Especially, the sketches of the houses are well restored using ASWM. This result is of high importance for impulse noise removal.

V. CONCLUSION

This letter proposes a new based switching median filter, called adaptive switching median (ASWM) filter. ASWM

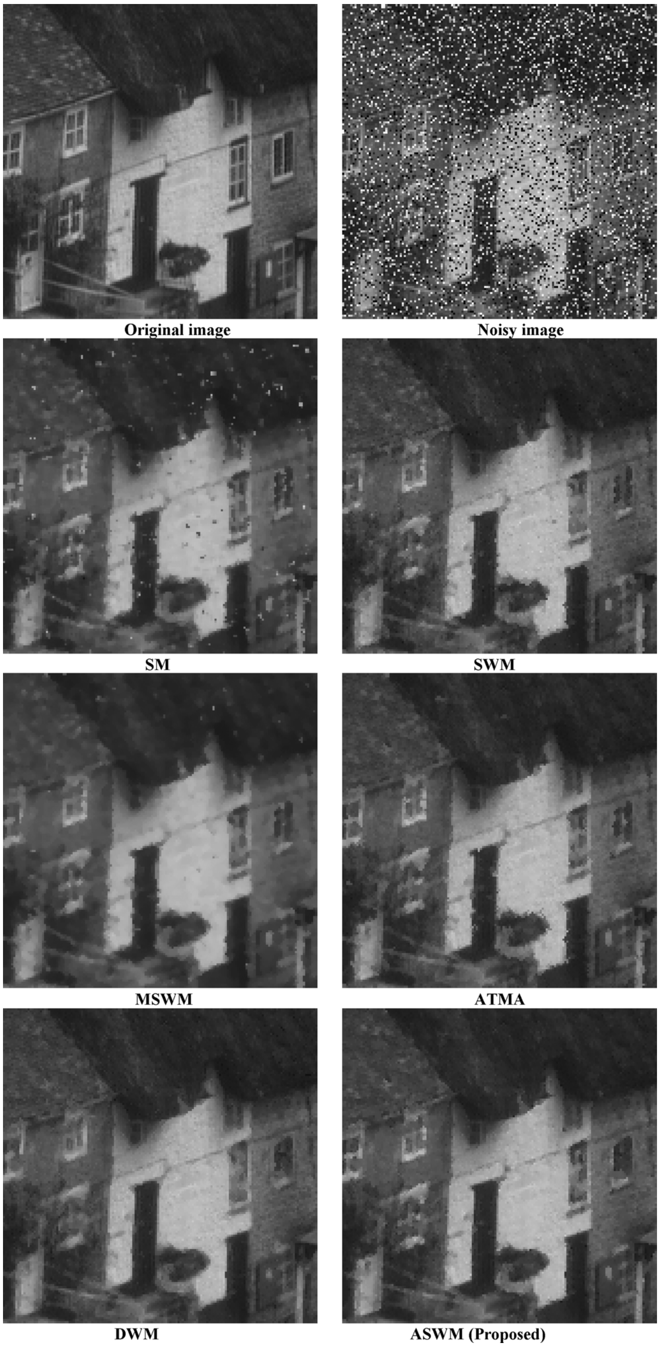


Fig. 3. Restoration performance comparison on the "Goldhill" image degraded by 30% random-value impulsive noise.

does not need an *a priori* Threshold as in the case in classical Switching Median filter to detect noisy pixels. Instead, Threshold is computed locally from image pixels grey values in a sliding window.

ASWM has shown high noise detection ability. Extensive simulations results indicate that ASWM performs significantly better than many other existing techniques. In addition, psychovisual results are of high quality.

Finally, ASWM will be used as pre processing to remove cosmic noise for an application in bioluminescence imaging [2].

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