Scientific Research and Essays Vol. 7(7), pp. 813-823, 23 February, 2012
Available online at http://www.academicjournals.org/SRE
DOI: 10.5897/SRE11.2056
ISSN 1992-2248 ©2012 Academic Journals

Full Length Research Paper

Random-valued impulse noise reduction in digital image using efficient nonparametric switching median filter

Mohd Helmi Suid and Nor Ashidi Mat Isa*

Imaging and Intelligent System Research Team (ISRT), School of Electrical and Electronic Engineering, Universiti Sains Malaysia, Engineering Campus, 14300 Nibong Tebal, Penang, Malaysia.

Accepted 10 February, 2012

Visual information plays an important role in modern applications as the usage of multimedia becomes more widespread from day to day. However, impulse noise is ubiquitous in real life and often distorts an image. This paper presents a new noise-filtering algorithm called efficient nonparametric switching median (ENPSM) filter, which is capable of reducing the effect of low level random-valued impulse noise up to 30% of the corruption rate in digital images. The proposed filter is composed of a nonparametric impulse noise detector and a recursive pixel restoration technique. Initiated with the impulse noise detector to determine any potential noise pixels, the filter will then replace the detected noise pixels with the median value of the surrounding pixels. Yet, only the noise-free pixels are considered, in order to determine the median value in a way that the filter is more efficient in the pixel restoration process. Based on the simulation results, it has been shown that the ENPSM method performs better than some of the existing state-of-the-art methods by giving better filtering performance, both in terms of qualitative and quantitative evaluations. Hence, this ENPSM filtering algorithm could possibly be used as a preprocessing module in the electronic imaging products.

Key words: Image processing, impulse noise, digital image, noise filtering, nonparametric switching median filter.

INTRODUCTION

With a lot of valuable information contained in them, the usage of digital images have gained much attention and they are widely used in many image processing applications such as in the geographical analysis and medical imaging analysis. Unfortunately, digital images are frequently subjected to the contamination of impulse noise due to the interferences generated during transmission, acquisition or storage through many electronic products. Of late, in accordance with the advancement in digital imaging technologies, the level of noise density in digital images has dropped significantly to the level that may be considered as low contamination rate, that is, less than 30% noise level (Toh and Mat-Isa, 2010). Nevertheless, it is still essential to remove impulse noise effect before carrying any subsequent image processing task, as the occurrences of noise can rigorously damage the information or data contained in the original image. Moreover, most of these subsequent tasks such as segmentation and edge detection etc. are largely affected by the quality of the filtered image (Dong et al., 2007; Toh et al., 2008).

*Corresponding author. E-mail: ashidi@eng.usm.my. Tel: +604 5996051. Fax: +604 5941023.

Abbreviations: ENPSM, Efficient nonparametric switching median filter; **SM**, standard median; **AM**, adaptive median; **CWM**, centre weighted median; **SWM**, switching median; **CWSWM**, centre weighted switching median; **LSM**, laplacian switching median filter; **ERID**, enhanced rank impulse detector; **MSM**, multi-state median; **TSM**, tri-state median; **MSWM**, modified switching median; **PSNR**, peak signal-to-noise ratio; **MSE**, mean-squared error; **MAE**, mean of absolute error.

Towards this, a denoising-based algorithm is known to be the most effective way to cater for the occurrence of impulse noise and for the improvement of the quality of the acquired image. Recently, a variety of nonlinear filtering techniques have been used to remove the impulse noise due to their impressive performance. One of the most classic nonlinear techniques is by windowing the noisy image with a standard median (SM) filter (Gonzalez and Woods, 1992). However, the SM filter often removes many desirable details and destroys fine textures while reducing noise, due to its filtering behavior that treats all noise and noise-free pixel uniformly. As the enhanced version, Hwang and Haddad (1995) and Sung and Yong (1991) have proposed the adaptive median (AM) filter and the centre weighted median (CWM) filter, respectively. Although they claim that these filters could preserve more details, yet again those filters are implemented invariantly across an image and this hasty smoothing property always tends to blur and smear the filtered images.

The aforementioned drawbacks have led to the emergence of various switching-based filters, for example, the switching median (SWM) filter along with the centre weighted switching median (CWSWM) filter (Sun and Neuvo, 1994), the Laplacian switching median (LSM) filter (Zhang and Karim, 2002), the enhanced rank impulse detector (ERID) (Aizenberg and Butakoff, 2004) and the multi-state median (MSM) filter (Chen and Wu, 2001), etc. Basically, this class of filtering scheme works based on the impulse detection mechanism which uses a fixed size filtering window and predefined threshold value to differentiate between noise and noise-free pixels. With the noise detector, these filters are shown to be more effective in terms of the detail and edge preservation compared to the uniformly applied conventional median filters. However, one disadvantage is that the switching rule is typically based on a fixed threshold for locally obtained statistics. This approach in certain circumstances tends to yield problem of pixel's misclassification and fails to replace the noise pixels.

As to obtain improved performances, numerous high-end methods based on the hybrid median-based filter have been developed by many researchers, recently. They have incorporated other order statistics (for example, rank order difference, alpha trimmed mean, etc.), image processing techniques and soft computing techniques into the median-based filters as part of their proposed filtering mechanisms. For example, the tri-state median (TSM) filter (Chen et al., 1999), is formed by the combination technique of CWM and SMF. Briefly, the TSM filter uses a set of two predefined thresholds in the impulse noise detection stage and its output will correspond to three possible states, namely the noise-free pixel (that is, which retains the original pixel value), the noisy pixel (that is, replaced by the output of SM) and the possibly noise-free pixel (that is, replaced by the output of CWM). In addition, Kang and Wang (2009) further modify the conventional SWM framework by adding a secondary impulse noise detection process. The proposed impulse noise detector is established based on the rank order arrangement of the pixels in the filtering window.

In general, the performance of filtering methods previously discussed is very much dependent on the predefined parameters. Such "inflexible" modeling under the parametric framework merely limits the performance of the filter as the responses towards varying noise density are dependent on the fixed parametric framework. Based on the above mentioned observation, we introduced a more flexible switching-based filter called efficient nonparametric switching median (ENPSM) filter, for detail-preserving restoration. The ENPSM filter is established based on the combination of local variance threshold in the impulse noise detection module and recursive restoration technique in the pixel restoration module.

MATERIALS AND METHODS

Impulse noise model

For an image stored as an 8-bit gray scale pixel resolution, the pixel intensities lie in the dynamic range [*Nmin*, *Nmax*], where *Nmin* and *Nmax* are the minimal and maximal intensities, respectively. Usually, a certain percentage of pixels is altered when images are contaminated by the impulse noise. For detail, let $x_{i,j}$ and $o_{i,j}$ be the gray level of the noisy image and the original image at location (*i*, *j*), respectively. Then, the impulse noise model with noise ratio *r* can be defined as:

$$x_{i,j} = \begin{cases} n_{i,j} : & \text{with probability } r \\ o_{i,j} : & \text{with probability } 1 - r \end{cases} \tag{1}$$

Where, $n_{i,j}$ is the gray level of the noisy pixel. There are two types of impulse noise model: the fixed-valued impulse noise (that is, salt-and-pepper) and random-valued impulse noise. For example, in an 8-bit gray scale image with 256 gray levels in the interval [0, 255], a salt-and-pepper noise is assumed to take the maximal and minimal intensities, that is, $n_{i,j} \in (0, 255)$.

Although many researchers have placed an emphasis on obtaining a good filter for removing salt-and-pepper noise (that is, which is the simplest form of noise) such as noise adaptive fuzzy SWM filter (Toh and Mat-Isa, 2010) and decision-based algorithm filter (Srinivasan and Ebenezer, 2007), this work takes one step further by focusing on the detection and suppression of random-valued impulse noise where $n_{i,j}$ can be distributed within the dynamic range, that is, $n_{i,j} \in [0, 255]$.

Efficient nonparametric switching median filter

A new version of the switching-based filter called the ENPSM filter is discussed and elaborated here. The proposed recursive double stage filter is particularly designed for images that are corrupted with a low level of random-valued impulse noise (that is, up to 30% noise level) and it can be divided into two modules. The first module involves the detection of impulse noise and its location based on a nonparametric framework. In this module, the predefined parameter (that is, threshold) for unscrambling the noise-free pixels from the noise pixels is flexible and not fixed in advance. The second module performs the recursive pixel restoration process. At this level, the 'noise' pixel is replaced by the estimated median value of the surrounding noise-free pixels. Otherwise, when a pixel is classified as 'noise-free', the pixel is retained and left unprocessed in order to avoid altering any details that are contained in the original image.

Impulse noise detection

The impulse noise detection can be carried out by analysing the local image statistics within a local window, based on the assumption that the intensity of an impulse noise pixel is significantly different from its surrounding pixels. For the process, the proposed ENPSM filter uses a square local window $W_{i,j}$ with odd dimensions (2N+1) × (2N+1) and is centered at $x_{i,j}$. It is given as:

$$W_{i,j} = x_{i-k,j-l},\ldots,x_{i,j},\ldots,x_{i+k,j+l} \;;\; \text{for } -N \le k,l \le N \quad (2)$$

The impulse noise detection process begins by sorting all pixels within the local window in ascending order as to find the median pixel $m_{i,j}$, which is defined by:

$$m_{i,j} = \text{med}\; x_{i-k,j-l},\ldots,x_{i,j},\ldots,x_{i+k,j+l} \quad (3)$$

Then, the median pixel $m_{i,j}$ is subtracted from all pixels in $W_{i,j}$ and the absolute luminance differences $d_{i\pm k,j\pm l}$ is computed by:

$$d_{i\pm k,j\pm l} = \left| x_{i\pm k,j\pm l} - m_{i,j} \right|; \quad \text{for } -N \le k,l \le N \quad (4)$$

Next, each value computed in $d_{i\pm k,j\pm l}$ is rearranged in ascending order. In order to increase the robustness of the proposed filter towards noise, the predefined threshold T_{ENPSM} is assigned as the median value in the sorted array. The term T_{ENPSM} is defined by:

$$T_{ENPSM} = \text{med}\; d_{i\pm k,j\pm l} \;|: -N \le k,l \le N \quad (5)$$

This is an attractive merit of the proposed ENPSM filtering scheme since it provides a variable T_{ENPSM} according to the local measurements of each local window. Based on the fact that different local windows have different local statistics, the selection of T_{ENPSM} to be the median of each local absolute luminance difference will ensure more accurate pixel classification results instead of using the fixed value threshold. Therefore, by employing this nonparametric concept, the possibility of pixel misclassification can be reduced significantly.

After T_{ENPSM} is obtained, the following process will create a noise mask $M_{i,j}$ to mark the locations of 'noise' pixels and 'noise-free' pixels. Thus, the process of generating noise mask can be grasped as:

$$M_{i,j} = \begin{cases} 1, & d_{i\pm k,j\pm l} > T_{ENPSM} \\ 0, & d_{i\pm k,j\pm l} \le T_{ENPSM} \end{cases} \quad (6)$$

Where $M_{i,j}$ = 1 signifies 'noise' pixel, while $M_{i,j}$ = 0 represents 'noise-free' pixel. The proposed impulse noise detection algorithm is elucidated in a step-by-step basis as follows:

Step 1: Select a two dimensional local window $W_{i,j}$ of size 3×3 from the noisy image. (The reason behind the selection of 3×3 window size is based on the fact that larger local window will blur the image's detail and edge).

Step 2: Sort all elements within $W_{i,j}$ in ascending order and calculate the median pixel $m_{i,j}$ using Equation 3.

Step 3: Compute the absolute luminance differences $d_{i\pm k,j\pm l}$ between $m_{i,j}$ and all pixels in $W_{i,j}$ according to Equation 4.

Step 4: Rearrange each value obtained in $d_{i\pm k,j\pm l}$ and set the predefined threshold T_{ENPSM} according to Equation 5.

Step 5: Generate the noise mask $M_{i,j}$ based on Equation 6. Slide $W_{i,j}$ to the next pixel and repeat Step 2 to 5 until the process is completed for the entire image.

To make it more comprehensible, Figure 1 shows the process of impulse noise detection as explained in Step1 to 5.

Noise filtering

After the detection stage is performed, the filtering process is carried out based on the noise mask obtained. 'Noise' pixels marked with $M_{i,j}$ = 1 will be replaced by the estimated median value; otherwise the 'noise-free' pixels will be left unprocessed. Again, a square filtering window $W_{filter\,i,j}$ with (2N_{filter}+1) × (2N_{filter}+1) dimensions will be used in this process and it is given as:

$$W_{filter\;i,j} = x_{i-k,j-l},\ldots,x_{i,j},\ldots,x_{i+k,j+l} \;;\; \text{where } -N_{filter} \le k,l \le N_{filter} \quad (7)$$

For every noise pixel detected, the estimated median value is counted using all 'noise-free' pixels in the current filtering window. It is computed by:

$$m_{estimated\,i,j} = \text{med}\; x_{i-k,j-l},\ldots,x_{i,j},\ldots,x_{i+k,j+l} \;\; \text{with } M_{i\pm k,j\pm l} = 0 \quad (8)$$

This procedure is carried out to avoid the noise pixels from influencing the determination of the real median value.

Finally, the correction term to restore a detected noise pixel is given here as:

$$y_{i,j^{ENPSM}} = \left[1 - M_{i,j}\right] . x_{i,j} + M_{i,j} . m_{estimated\,i,j} \quad (9)$$

As to enhance the filtering process, this algorithm is implemented recursively, where the estimation of the current pixel is dependent on the new values of previously processed pixels. An illustrative example on the ENPSM filter's impulse noise detection and filtering operation is shown in Figure 2.

RESULTS AND DISCUSSION

Here, the comparison of the performance between the proposed ENPSM filter and other related state-of-the-art impulse noise filters is demonstrated. A total of 100 standard grayscale test images of size 512 × 512 that were corrupted with random-valued impulse noise ranging from 10 to 30% were used in the simulation of the implemented filters. This set of test images was obtained from various online sources such as

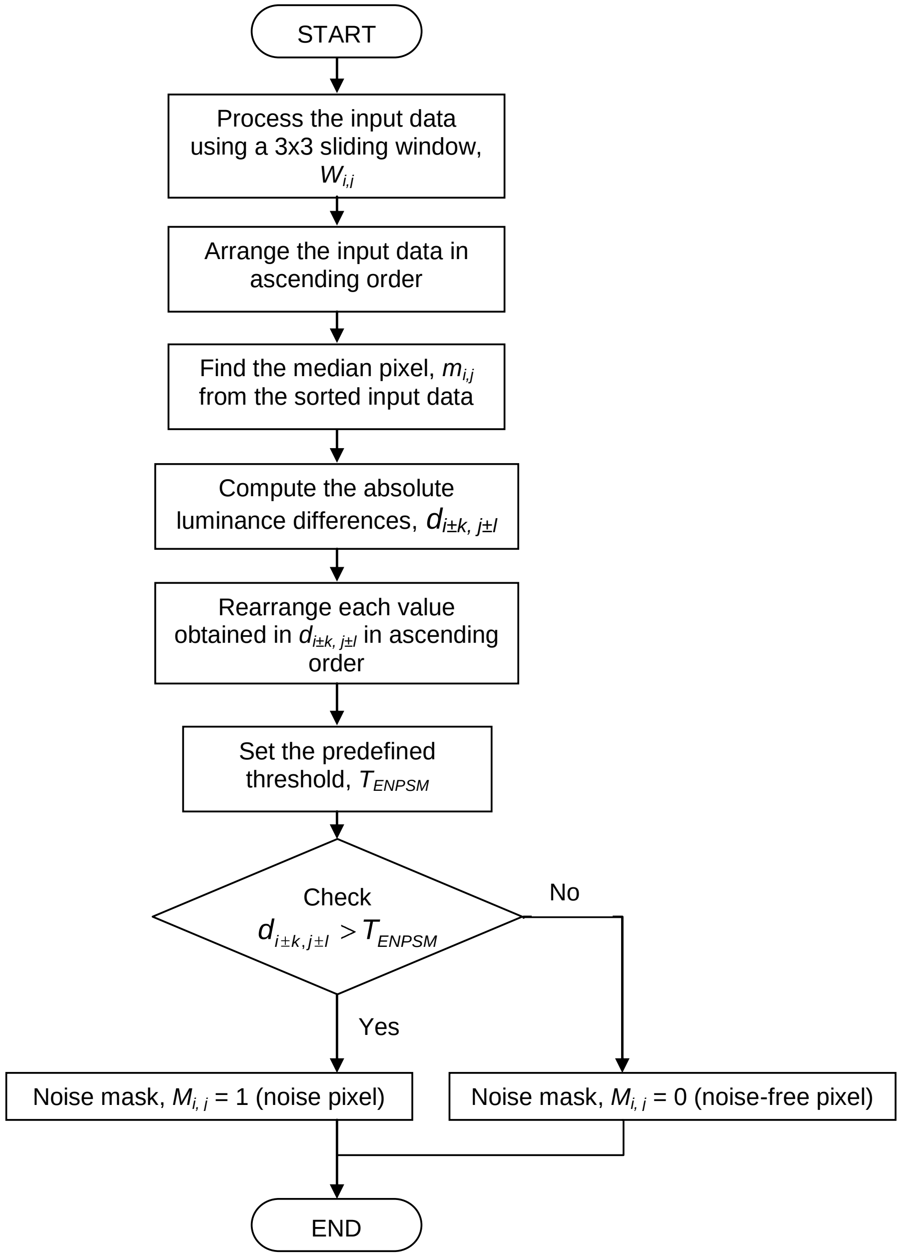


Figure 1. The flowchart of the ENPSM noise detection operation.

www.hlevkin.com, www.sipi.usc.edu and www.cipr.rpi.edu. These images were chosen because they contain fine image details and texture, which are suitable to evaluate the strengths and weaknesses of the implemented impulse noise filters.

The following conventional switching-based median filters with their suggested tuning parameters were used to compare with the proposed algorithm; the SWM filter (T = 50), centre weighted SWM filter (T = 30, w = 3), enhanced rank impulse detector (Θ = 15, s = 2), TSM filter (T = 20, w = 3) and modified SWM filter (T_1 = 30, T_2 = 3). In order to test the effectiveness and efficiency, simulation results of the implemented impulse noise filters were evaluated qualitatively and quantitatively.

Visual inspection quality

Providing visually pleasing output is imperative, since the quality of image is subjective to human eye. Therefore, a visual inspection was carried out in order to judge the filters' effectiveness in reducing impulse noise effect. As for the qualitative comparison, Figure 3 shows the restoration results of images named *Elaine*, *Pens* and

142	139	139
139	**165**	140
32	134	134

Selected 3×3 local window with $x_{i,\,j}$ = 165

↓

32	134	134	139	139	139	140	142	165

Sorted pixels in the filtering window with $m_{i,\,j}$ = 139

↓

107	5	5	0	0	0	1	3	26

Calculated absolute luminance differences, $d_{i\pm k,\, j\pm l}$

↓

0	0	0	1	3	5	5	26	107

Sorted elements of absolute luminance differences with T_{ENPSM} = 3

↓

1	1	1	0	0	0	0	0	1

Noise masking process, $M_{i,\,j}$
'noise' = $d_{i\pm k,\, j\pm l} > 3$
'noise-free' = $d_{i\pm k,\, j\pm l} \leq 3$

↓

0	0	0
0	1	0
1	1	1

3×3 filtering window, $W_{filter\ i,\,j}$
*since the centre pixel is equal to 1 (i.e. noise), it will be replaced by the estimated median value. Otherwise its original intensity will be retained.

↓

139	139	139	140	142

Estimated median value calculated based on 'noise-free' pixels;
$m_{estimated}$ = 139

↓

142	139	139
139	**139**	140
32	134	134

Result of the pixel restoration

Figure 2. The illustrated example on the ENPSM noise filtering operation.

Monarch corrupted with 10, 20 and 30% random-valued impulse noise, respectively. The qualitative evaluation has been carried out by analyzing the ability of the filters to produce the most appealing visual results. The analysis is conducted based on the feedback given by a panel of experts from Universiti Sains Malaysia. This panel consists of eight experienced researchers in the field of image processing. In all figures, a close-up view of each image was used for a clearer depiction.

As shown in *Elaine*, at 10% impulse noise density, all filters are found to be able to produce perceptibly reconstructed image. However, in *Pens*, we may notice that the proposed ENPSM filter gives better and clearer filtering result compared to the other conventional filtering

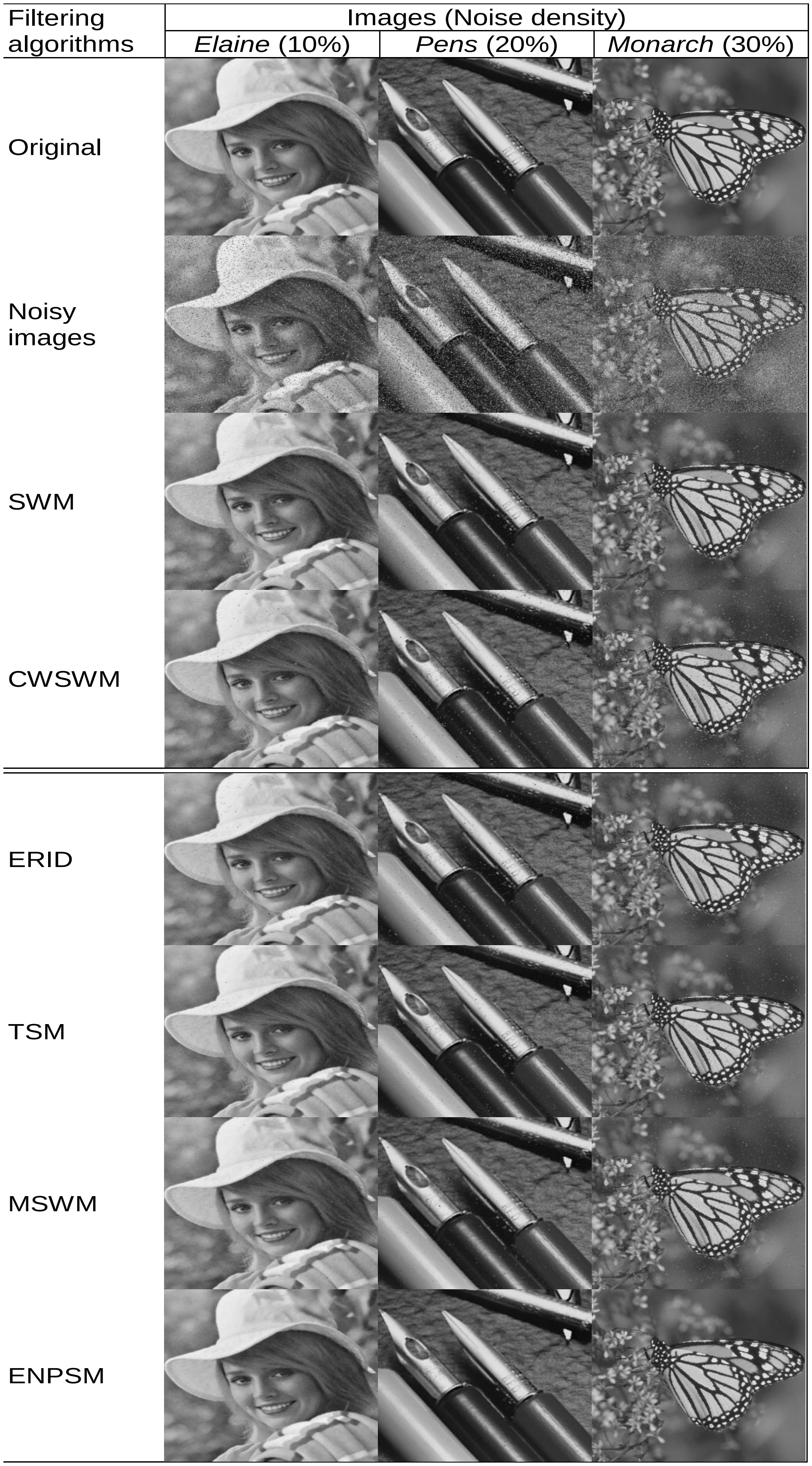


Figure 3. Simulation results of the standard grayscale test images.

algorithms. The noise particles and effects are significantly reduced and at the same time the image details are well preserved. On the other hand, some small noise patches have remained intact on the images produced by the other conventional filters (for example, see the *Pens'* body). This finding proves that these conventional filtering algorithms have failed to restore the noisy image properly.

Similar observations are obtained for the image named *Monarch*. For example, in the images restored by the conventional filtering algorithms, it can be seen that there is a great deal of noise contamination existed in the resultant images especially around the moth. These pictures' qualities are vastly inferior to the ones produced by the ENPSM filter. This observation indicates that the nonparametric concept introduced in the proposed filter works very well in distinguishing between the noise and the noise-free pixels. The concept really helps the proposed ENPSM filter to dexterously reduce the noise stain and further create less corrupted images. Meanwhile, the poor restoration results among the conventional filters can be attributed from their parametric impulse noise detection mechanisms which are inclined to highlight the problem of pixels' misclassification.

The zoomed *Elaine* and *Monarch* in Figure 3 are shown in Figure 4 as to demonstrate the filters' efficiencies in terms of details and edges' preservation. As obtained from *Elaine*, only the TSM filter and the proposed ENPSM filter are able to preserve the image's fine details (for example, refer to the eyelash at the left portion). However, the proposed ENPSM filter has a better noise suppression ability than the TSM filter since the filtered image does not have any visible noise patches. Moreover, as can be seen visually in *Monarch*, the ENPSM filter is also capable of preserving edges. Apparently, the robust nonparametric noise detection concept and the selection of median value among the noise-free pixels are found to be an ideal combination for yielding more idyllic restoration results. Conversely, the poor restoration results of the other conventional filters are due to their detection mechanisms which are less robust towards the contamination of random-valued impulse noise.

Quantitative analysis

In addition to the visual inspection of the restored images, the quality of the restored images is also evaluated quantitatively using the peak signal-to-noise ratio (PSNR). Mathematically, the PSNR for a digital image of the dimension $M \times N$ is defined as:

$$\text{PSNR} = 10\log_{10}\left(\frac{255^2}{\text{MSE}}\right)\ \text{dB} \tag{10}$$

Where MSE stands for the mean-squared error, given as:

$$\text{MSE} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\frac{\left[o_{i,j} - y_{i,j}\right]^2}{M \times N} \tag{11}$$

where $y_{i,\ j}$ is the filtered image and $o_{i,\ j}$ is the original noise-free image. Apart from the PSNR assessment, the mean of absolute error (MAE) has also been used in this analysis to characterize the filter's detail preservation behavior, one which is defined by:

$$\text{MAE} = \frac{1}{M \times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}|\, o_{i,j} - y_{i,j}\,| \tag{12}$$

Among the 100 test images, the numerical results for three commonly used standard grayscale test images *Elaine*, *Pens* and *Monarch* are shown in Tables 1 to 3, respectively. In all tables, the larger PSNR and smaller MAE values indicate better restoration results. The best results obtained are made bold.

As shown in Tables 1 to 3, the proposed filter consistently yields the highest PSNR and the lowest MAE values at all levels of random-valued impulse noise. These promising results are mostly resulted from the accurate noise detection and the efficient pixel restoration by the proposed ENPSM filter. In contrast, inconsistent performances have been shown by the conventional filters with their PSNR values to have decreased dramatically especially at 30% noise level. The larger MAE values as compared to the ENPSM filter also show that the conventional methods have been unable to cater for the occurrences of noise in a proper manner.

This study has further calculated the average PSNR for 100 tested images and the results are displayed in the graph shown in Figure 5. Apparently, the average PSNR curve for the ENPSM filter has the highest curve among all. This is followed by the average PSNR curve for the MSWM filter. Above 20% random-valued noise density, the two worst performing filters are the SWM and CWSWM filters. The result obtained in this additional analysis has clearly proven that the proposed ENPSM filter has outperformed the other conventional filters. It is evident that the ENPSM's filtering performance is tremendously consistent.

Meanwhile, the extrapolation of the average MAE curves has resulted from the various conventional filters in comparison and the proposed ENPSM filter is shown in Figure 6. It can be seen from the plot that the proposed ENPSM filter is able to outperform other recent conventional filters by having the lowest MAE curve, while the TSM and MSWM filters are trailing closely along it. Once again, this finding shows that the ENPSM filter is not only able to eliminate noise efficiently but it can also preserve the original appearance and shape of an image very well. The good detail and edge preservation of the ENPSM is a result emerging from the accurate noise

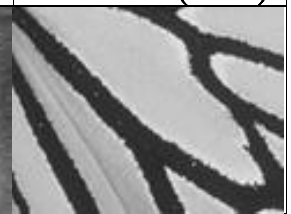
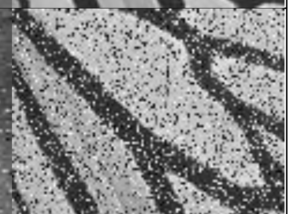
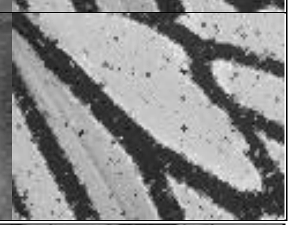
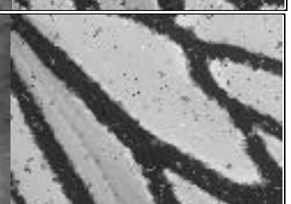
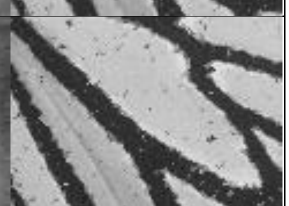
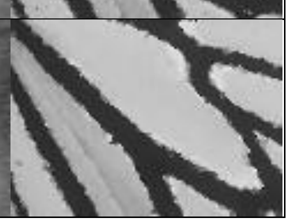
Filtering algorithms	Images (Noise density)	
	Elaine (10%)	*Monarch* (30%)
Original		
Noisy Images		
SWM		
CWSWM		
ERID		
TSM		
MSWM		
ENPSM		

Figure 4. The enlarged version of standard grayscale test images.

Table 1. Comparison of PSNR and MAE on different noise level restoration for '*Elaine*' (Test image).

Algorithm	10%	PSNR(dB) 20%	30%	10%	MAE 20%	30%
SWM	32.0452	28.6001	25.6460	1.3921	2.8822	4.6866
CWSWM	31.3360	27.5989	24.4272	1.2231	2.3885	4.8024
ERID	33.3793	29.0599	27.4424	1.8736	3.2301	4.8808
TSM	33.7649	30.3941	28.0509	1.1953	2.1763	3.3192
MSWM	32.6142	30.6292	28.1780	1.5318	3.0002	4.0422
ENPSM	33.9590	31.9943	30.6433	1.1541	2.0409	3.1856

Table 2. Comparison of PSNR and MAE on different noise level restoration for '*Pens*' (Test image).

Algorithm	10%	PSNR(dB) 20%	30%	10%	MAE 20%	30%
SWM	32.2993	28.4343	24.7552	1.2607	2.7565	5.0518
CWSWM	33.9389	27.9344	23.2054	1.1141	2.6225	5.7004
ERID	34.1186	29.5197	25.2547	1.0128	1.9589	4.0111
TSM	35.8175	30.9668	25.7629	0.9459	1.6345	3.7326
MSWM	35.9896	31.3970	26.5242	1.0502	2.4978	4.3571
ENPSM	36.1737	33.5591	30.6339	0.9207	1.4160	3.5382

Table 3. Comparison of PSNR and MAE on different noise level restoration for '*Monarch*' (Test image).

Algorithm	10%	PSNR(dB) 20%	30%	10%	MAE 20%	30%
SWM	30.8593	27.5224	24.9762	1.4597	2.5792	4.1635
CWSWM	31.0051	28.3536	24.6558	1.2774	2.3460	4.3291
ERID	30.7964	28.1359	25.5880	1.7460	2.6583	4.7727
TSM	32.1280	29.3735	26.7156	1.2081	1.8595	3.1545
MSWM	32.8700	29.5661	26.9273	1.6590	2.4229	3.7633
ENPSM	33.5378	30.5975	28.1224	0.9980	1.6652	2.9663

detection under the nonparametric concept and the criterion of choosing median value based on noise-free pixels. On the other hand, the SWM, CWSWM and ERID filters have completely failed to compete.

Processing time efficiency

We had also conducted a processing time analysis for each filter for the aim of performing its denoising task. All the algorithms were implemented in Matlab R2010a and the simulations were carried out using a personal computer with AMD Athlon II 2.1GHz processor, 2GB of RAM. The graph of average processing time in seconds for 100 standard grayscale test images after with the application of the proposed ENPSM filter and other conventional filters is shown in Figure 7.

Overall, the processing time of each filter remains almost constant at all levels of noise density. The MSWM filter consumes the highest processing time of all because it uses a more complex noise detection mechanism (that is, double detection stage) to complete its respective noise filtering processes as compared to the other filters. Generally, the filter with the multi-stage noise detection processes (for example, TSM and MSWM) suffers from slow processing time. Meanwhile, except for SWM, the proposed method consistently outperforms other filters across a wide range of noise levels with a relatively fast average processing time. This is because the proposed filter applies a simple noise detection algorithm in its implementation, which is based on single local threshold. Although the SWM is shown to have a better processing time compared to the ENPSM, the simulation results of their filtered images are perceptibly degraded. The ENPSM filter has met the objective in meeting the trade-off between good performance and efficient processing time. Thus, as far as the denoising performance is concerned, the proposed

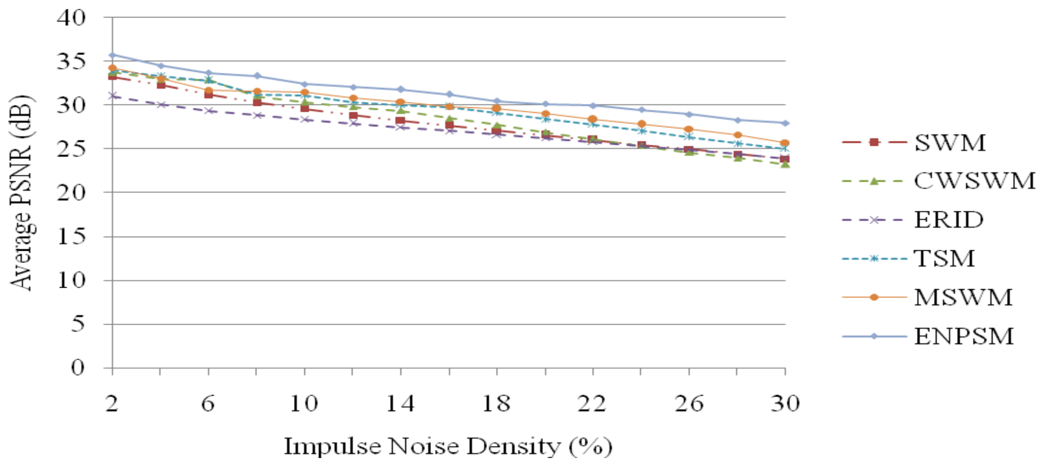


Figure 5. The graph of an average PSNR based on different noise level restorations for 100 standard grayscale test images.

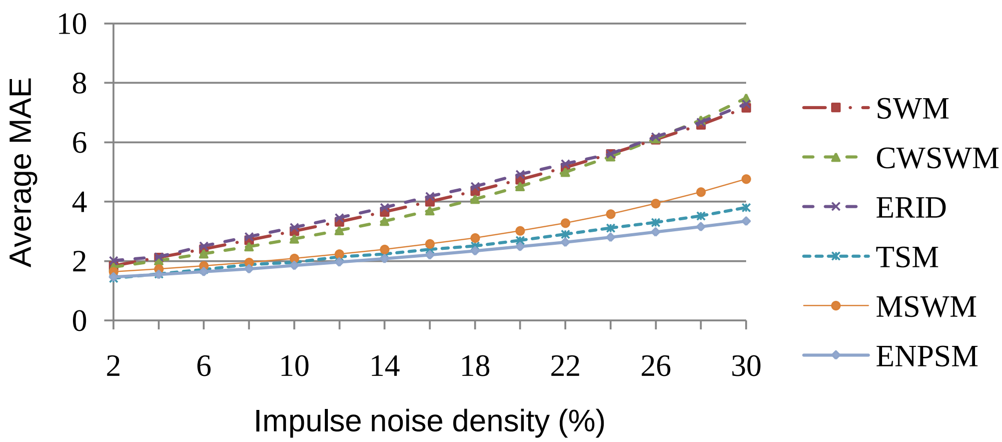


Figure 6. The graph of an average MAE based on different noise level restorations for 100 standard grayscale test images.

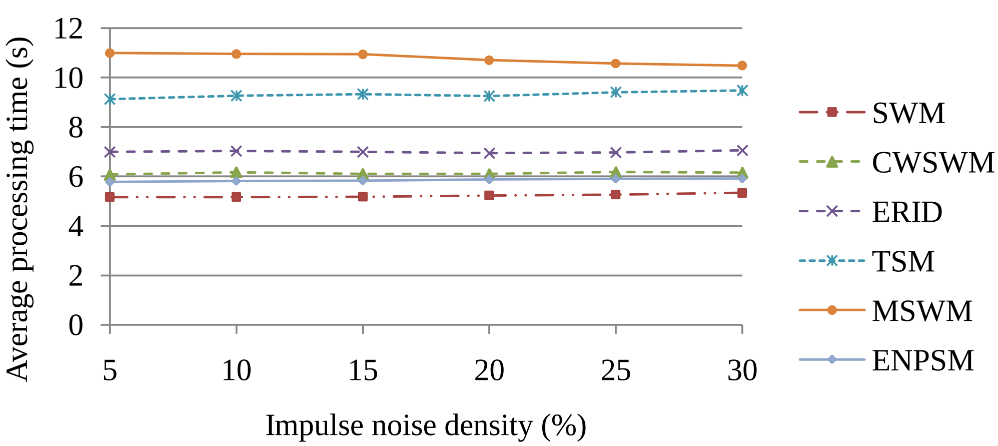


Figure 7. The graph of an average processing time (s) versus impulse noise density (%) computed from a total of 100 standard grayscale test images.

ENPSM can consequently be regarded as the best filter.

Conclusion

Throughout this study, we have developed an effective algorithm for the detection and suppression of random-valued impulse noise. By incorporating a robust local variance thresholding and recursive pixel restoration technique into the filtering mechanism, the proposed ENPSM filter is able to reduce the random-valued impulse noise effect, while at the same time preserving the details and edge of fine images. Additionally, no complicated tuning parameters or special training is required since this filter is based on a nonparametric framework. Experimentally, the proposed algorithm has been shown to significantly outperform a number of well-known techniques both visually and quantitatively.

REFERENCES

Aizenberg I, Butakoff C (2004). Effective impulse detector based on rank-order criteria. IEEE Signal Process. Lett., 3(11): 363-366.

Chen Y, Ma KK, Chen LH (1999). Tri-State Median Filter for Image Denoising. IEEE Trans. Image Process., 8(12): 1834-1838.

Chen T, Wu HR (2001). Space variant median filters for the restoration of impulse noise corrupted images. IEEE Trans. Circuits Syst., 2(48): 784-789.

Dong Y, Chan RH, Xu S (2007). A detection statistic for random-valued impulse noise. IEEE Trans. Image Process., 4(16): 1112-1120.

Gonzalez RC, Woods RE (1992). *Digital image processing*. New York: Addison-Wesley.

Hwang H, Haddad RA (1995). Adaptive Median Filters: New Algorithms and Results. IEEE Trans. Image Process., 4(4): 499-502.

Kang CC, Wang WJ (2009). Modified Switching Median Filter with One More Noise Detector for Impulse Noise Removal. AEU-Int. J. Electron. Commun., 63: 998-1004.

Sun T, Neuvo Y (1994). Detail-Preserving Median Based Filters in Image Processing. Pattern Recog. Lett., 15: 341-347.

Sung JK, Yong HL (1991). Center Weighted Median Filters and Their Applications to Image Enhancement. IEEE Trans. Circuits Syst., 38(9): 984-983.

Srinivasan KS, Ebenezer D (2007). A new fast and efficient decision-based algorithm for removal of high-density impulse noise. IEEE Signal Process. Lett., 14(3): 189-192.

Toh KKV, Ibrahim H, Mahyuddin MN (2008). Salt-and-Pepper Noise Detection and Reduction Using Fuzzy Switching Median Filter. IEEE Trans. Consum. Electron., 54(4): 1956-1961.

Toh KKV, Mat Isa NA (2010). Cluster-Based Adaptive Fuzzy Switching Median Filter for Universal Impulse Noise Reduction. IEEE Trans. Consum. Electron., 56(4): 1956-1961.

Toh KKV, Mat Isa NA (2010). Noise Adaptive Fuzzy Switching Median Filter for Salt-and-Pepper Noise Reduction. IEEE Signal Process. Lett., 17(3): 1956-1961.

Zhang S, Karim MA (2002). A New Impulse Detector for Switching Median Filters. IEEE Signal Process. Lett., 9(11): 360-363.