Removal of Low Level Random-Valued Impulse Noise Using Dual Sliding Statistics Switching Median Filter

Suid M. H.[a,*], Saealal M. S.[b], Mat Jusof M.F.[c], Mat Isa N. A.[d]

[a,b,c]**Faculty of Electrical & Electronic, Universiti Malaysia Pahang**, 26600, Pekan, Pahang, Malaysia

[a]E-mail address: m.helmi_77@yahoo.com

[b]E-mail address: salihin@ump.edu.my

[c]E-mail address: mfalfazli@ump.edu.my

[d]**Imaging and Intelligent System Research Team (ISRT)**
School of Electrical and Electronic Engineering , Universiti Sains Malaysia,
14300 Nibong Tebal, Penang, Malaysia
E-mail address: ashidi@eng.usn.my

Abstract

A new nonlinear filtering algorithm for effectively denoising images corrupted by the random-valued impulse noise, called dual sliding statistics switching median (DSSSM) filter is presented in this paper. The proposed DSSSM filter is made up of two subunits; i.e. impulse noise detection and noise filtering. Initially, the impulse noise detection stage of DSSSM algorithm begins by processing the statistics of a localized detection window in sorted order and non-sorted order, simultaneously. Next, the median of absolute difference (MAD) obtained from both sorted statistics and non-sorted statistics will be further processed in order to classify any possible noise pixels. Subsequently, the filtering stage will replace the detected noise pixels with the estimated median value of the surrounding pixels. In addition, fuzzy based local information is used in the filtering stage to help the filter preserves the edges and details. Extensive simulations results conducted on gray scale images indicate that the DSSSM filter performs significantly better than a number of well-known impulse noise filters existing in literature in terms of noise suppression and detail preservation; with as much as 30% impulse noise corruption rate. Finally, this DSSSM filter is algorithmically simple and suitable to be implemented for electronic imaging products.

Keyword: Image processing, random-valued impulse noise, digital image, nonlinear noise filtering.

1. Introduction

The use of digital image-based visual information have gained a lot attention due to its flexibility and this phenomenon is expected to continue growing. Unfortunately, digital images are frequently subjected to the contamination of impulse noise that typically due to the interferences generated during transmission/acquisition or storage through electronic medium, poor sensor configuration and timing errors in analog-to-digital conversion [1]. Therefore, it is imperative to remove the impulse noise effect before any subsequent image processing operations can be carried out as the occurrences of impulse noise can severely damage the information in the original image.

One of the most effective approaches to cater for the occurrence of impulse noise and for the improvement of the quality of the acquired image is by using denoising-based algorithm. Accordingly, a large number of nonlinear filters have been widely exploited to remove the impulse noise as they are generally more superior than linear filtering techniques. For instance, standard median (SM) filter [2] and adaptive median (AM) filter [3] are two of the most basic nonlinear filtering techniques for suppressing impulse noise. Ironically, this SM is implemented unconditionally across the image while its variants (e.g. see AM) inherited this clumsy smoothing property; thus they tend to modify both noise and noise-free pixels simultaneously. Consequently, the detailed regions such as object edges and fine textures in image are smeared and appear blurry or jittered.

To get rid of the problem, various filters under switching scheme have been studied and experimented by a number of recently published works; such as switching median filter I and II (SWM-I and SWM-II) [4], multi-state median (MSM) filter [5], Laplacian switching median (LSM) filter [6], enhanced rank impulse detector (ERID) [7] and directional weighted median (DWM) filter [8], etc. With this kind of filtering properties, these techniques are shown to be more effective to preserve most of the image details compared to the conventional non-switching techniques.

Of late, in accordance with the evolution in digital image acquisition technologies, the corruption rate of impulse noise in digital images has managed to be reduced to the level that may be regarded as low; i.e. less than 30% noise density [9]. Based on the aforementioned statements and observations; hence our aim in this paper is to develop an efficient filtering technique with a reasonable processing time, particularly for the range of low level impulse noise. Towards this, we introduce a new iterative and recursive filter known as dual sliding statistics switching median (DSSSM). This proposed filter is relatively fast and can remove the impulse noise dexterously without jeopardizing the details and textures inside the image.

2. Methodology

2.1 Impulse Noise Model

In this paper, the experiment picture use the Impulse Noise Model. Theoretically, impulse noise contaminates an image with a random amplitude which could either fall within the image dynamic range (i.e. random-valued impulse noise) or out of the range (i.e. salt-and-pepper noise), and usually only certain percentage of pixels are affected. In this work, we tend to focus on the random-valued impulse noise and the model of this impulse noise is described for clarity. 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 density 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 noise pixel value independent from $o(i, j)$. The image is said to be corrupted by the random-valued impulse noise when $n(i, j)$ uniformly distributed within the image dynamic range, i.e. $n(i, j)$ □ [*Nmin*, *Nmax*]. For example, in an 8-bit gray scale image with 256 gray levels, the $n(i, j)$ may range from 0 (*Nmin*) to 255 (*Nmax*).The form of random-valued impulse noise may be best described by Figure 1.

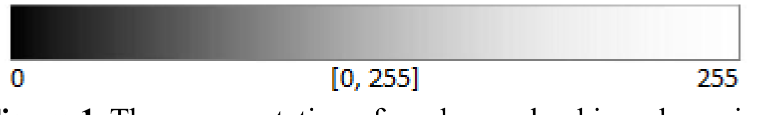

Figure 1. The representation of random-valued impulse noise

In practical, identifying this such noise is more challenging compared to the salt-and-pepper noise because the intensity of noisy pixel is very similar to its surrounding.

2.2 Dual Sliding Statistics Switching Median Filter

Dual sliding switching median (DSSSM) filter is an iterative nonlinear filter which consists of two processing stages. The first stage involves the detection of impulse noise and its location. A noise mask, acting as a classifier to separate the noise pixels from noise-free pixels is generated during this process. In the second stage, all noise-free pixels are left uncorrected while the other noise pixels will be subjected for further processing. At this level, the pixel restoration process is carried out recursively with the assistance of fuzzy based local information.

In digital image, the noisy pixel can be characterized by a pixel with the intensity that varies greatly from those of its neighboring pixels. Basically, the intensities of these pixels are represented by a numerical integer. Based on this fact, the impulse detection can be realized by analysing the local image statistics within a window patch. In the beginning of the detection process, the proposed DSSSM filter employs a square local window $W(i, j)$ with odd dimensions $(2N+1) \times (2N+1)$ and is centered at $x(i, j)$. It is given as:

$$W(i,j) = \{\mathrm{x(i+k, j+l)}\} \text{ ; where k,l } \in \text{ (-N,...,0,...,N)} \tag{2}$$

All the pixel's elements within $W(i, j)$ are then stored in two separate arrays which represent the sorted statistics and non-sorted statistics, respectively. The process is continued by finding the median pixel $P_{med}(i, j)$ and central pixel $P_{center}(i, j)$. Both $P_{med}(i, j)$ and $P_{center}(i, j)$ are defined by:

$$P_{med}(i,j) = med\{x(i+k, \mathrm{j+l})\} \tag{3}$$

$$P_{center}(i,j) = x(i,j) \tag{4}$$

Next, the median pixel $P_{med}(i, j)$ and central pixel $P_{center}(i, j)$ are subtracted from all the pixels in $W(i, j)$. This modus operandi will produce two sets of absolute differences arrays, namely $d_{med}(i+k, j+l)$ and $d_{center}(i+k, j+l)$. Mathematically, these absolute differences arrays are computed as follows:

$$d_{med}(i+k, j+l) = \left| x(i+k, j+l) - P_{med}(i,j) \right| \text{ ; with k, l } \neq 0 \tag{5}$$

$$d_{center}(i+k, j+l) = \left| x(i+k, j+l) - P_{med}(i,j) \right| \text{ ; with k, l } \neq 0 \tag{6}$$

At this point, all the values computed in $d_{med}(i+k, j+l)$ and $d_{center}(i+k, j+l)$ are rearranged in ascending order. After that, the median of absolute differences (i.e. MAD_{med} and MAD_{center}) will be identified based on:

$$MAD_{med} = med\{d_{med}(i+k, j+l)\} \tag{7}$$

$$MAD_{center} = med\{d_{med}(i+k, j+l)\} \tag{8}$$

In order to make a distinction whether current processing pixel is a noise or not, the difference between MAD_{med} and MAD_{center} will be first calculated. If the MAD difference is denoted as $diffMAD$, then alternatively $diffMAD$ can be written as follows:

$$diffMAD = \left| MAD_{med} - MAD_{center} \right| \tag{9}$$

This $diffMAD$ provides information about the likelihood of corruption for the current processing pixel. For example, if $diffMAD$ value is large then the current pixel is very likely being contaminated by impulse noise. On the other hand, in the case where $diffMAD$ is small, the current pixel may be considered as a noise-free.

After $diffMAD$ is counted, a binary noise mask $M(i, j)$ will be formed to mark the locations of noise pixels and noise-free pixels. Thus, the process of generating noise mask can be grasped as:

$$\mathrm{M}(i, j) = \begin{cases} 1, & diffMAD > T^{(t)}{}_{DSSSM} \\ 0, & diffMAD \leq T^{(t)}{}_{DSSSM} \end{cases} \tag{10}$$

where $M(i, j) = 1$ signifies the noise pixel, $M(i, j) = 0$ represents the noise-free pixel and $T^{(t)}{}_{DSSSM}$ actually is the threshold in the t-th iteration.

In step-by-step implementation, the proposed DSSSM algorithm is elucidated 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 [10]).

Step 2: Put all elements within $W(i, j)$ in two separate arrays, then identify the median pixel $P_{med}(i, j)$ and central pixel $P_{center}(i, j)$ using Eq. (3) and Eq. (4), respectively.

Step 3: Compute the absolute difference luminance $d_{med}(i+k, j+l)$ and $d_{center}(i+k, j+l)$ according to Eq. (5) and Eq. (6), respectively.

Step 4: Rearrange each value obtained in $d_{med}(i+k, j+l)$ and $d_{center}(i+k, j+l)$ in ascendingorder. Then, calculate the median of absolute differences MAD_{med} and MAD_{center} based on Eq. (7) and Eq. (8), respectively.

Step 5: Calculate the absolute MAD difference $diffMAD$ based on Eq. (9).

Step 6: Compare the absolute $diffMAD$ value found in Step 5 with the decision maker threshold $T^{(t)}{}_{DSSSM}$ and generate the binary mask $M(i, j)$ based on Eq. (10).

(Repeat Step 2 to Step 6 until the entire pixels in the image have been processed)

3. Simulation Result and Discussions

The performance of the proposed DSSSM filter will be compared to other related state-of-the-art impulse noise filters based on their simulation results. Test images of size 512×512, obtained from diverse online sources were used for the simulations of each implemented filters. Each of the test images was corrupted with the impulse noise model described in (1), ranging from 5% to 30% with an increment of 5%. This set of standard test images contains various characteristics which are suitable to assess the robustness of the implemented filters.

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:

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right)(dB) \tag{11}$$

For the above formulae, MSE stands for the mean-squared error and it is given as:

$$MSE = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\frac{\left[o_{i,j} - y_{i,j}\right]^2}{M \times N} \tag{12}$$

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:

$$MAE = \frac{1}{M \times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left|o_{i,j} - y_{i,j}\right| \tag{13}$$

As reported in Table 1, the proposed DSSSM filtering technique consistently yields the highest PSNR values compared to the other existing conventional filters. The higher PSNR value, the clearer filtered image produced.

Table 1. Comparison of PSNR on Different Noise Level Restoration for '*Starfish*', '*Boat*' and '*Goldhill*' (Test Image).

		PSNR(dB)		
Images	Algorithms	10%	20%	30%
Starfish	SWM-I	31.6219	27.8273	24.7745
	SWM-II	33.056	27.8818	23.8052
	TSM	35.0013	30.2872	26.1675
	DWM	32.6523	29.6524	27.9957
	LUO	35.1372	31.4958	28.0056
	ACWM	35.3272	30.6981	26.55
	DSSSM	**35.3753**	**32.7072**	**30.5841**

Meanwhile, the similar phenomenon is occurred in the analysis outlined in Table 2, where the proposed DSSSM filter without fail outclasses the other filters in comparison by producing the best MAE results for the cases of 20% and 30% impulse noise density. On the contrary, at 10% of impulse noise density, it can be observed that ACWM gives the better MAE results as compared to our proposed filter.

Table 2. Comparison of MAE on Different Noise Level Restoration for '*Starfish*', '*Boat*' and '*Goldhill*' (Test Image).

		MAE		
Images	Algorithms	10%	20%	30%
Starfish	SWM-I	1.37569	3.01962	5.21482
	SWM-II	1.16153	2.82004	5.49509
	TSM	0.925304	2.02381	3.84945
	DWM	1.17076	2.3494	3.52177
	LUO	0.983086	1.88244	3.21782
	ACWM	**0.759693**	1.78849	3.48141
	DSSSM	0.826065	**1.58328**	**2.49641**

Figure 3. Simulation results on a portion of *Starfish* using; (a) original image, (b) noisy image with 10% density of impulse noise, (c) SWM-I, (d) SWM-II, (e) TSM, (f) DWM, (g) LUO, (h) ACWM and (i) DSSSM.

4. Conclusion

Throughout this study, an effective algorithm for the detection and suppression of random-valued impulse noise have been introduced. The proposed DSSSM filter is constructed by incorporating a robust impulse noise detection based on adaptive thresholding and recursive pixel restoration technique. Additionally, fuzzy reasoning set is embedded as part of the filtering mechanism in order to handle any imprecise local information. Extensive simulation results reveal that the DSSSM filter is able to reduce the random-valued impulse noise effect, while at the same time preserving the details and structures of fine images. Furthermore, its filtering performance is tremendously consistent all the time as compared to the number of well-known conventional techniques; and all these good results are achieved with a fairly efficient processing time.

2.3 Acknowledgments and Legal Responsibility

This work was supported by Faculty of Electrical & Electronics Engineering, Universiti Malaysia Pahang under short term Research Grant Scheme RDU120344, and School of Electrical and Electronic Engineering, Universiti Sains Malaysia.

5. References

[1] W. Luo, Efficient removal of impulse noise from digital images, *IEEE Trans. Consumer Electronics*, *2006*, pp. 523-527.

[2] R. C. Gonzalez and R. E. Woods, Digital image processing, *New York: Addison-Wesley, 1992*.

[3] H. Hwang and R. A. Haddad, Adaptive Median Filters: New Algorithms and Results, *IEEE Transactions on Image Processing, 1995,* pp. 499-502.

[4] T. Sun and Y. Neuvo. Detail-Preserving Median Based Filters in Image Processing. Pattern Recognition Letters,15 (1994) 341–347.

[5] T. Chen and H. R. Wu, Space variant median filters for the restoration of impulse noise corrupted images, *IEEE Trans. on Circuits and Systems II, 2001,* pp. 784–789.

[6] S. Zhang and M. A. Karim, A new impulse detector for switching median filters, *IEEE Signal Processing Letters, 2002,* pp. 360-363.

[7] I. Aizenberg and C. Butakoff, Effective impulse detector based on rank-order criteria, *IEEE Signal Process. Letters, 2004,* pp. 363-366.

[8] Y. Dong and S. Xu, A new directional weighted median filter for removal of random-valued impulse noise, *IEEE Signal Processing Letters, 2007,* pp. 193-196.

[9] K. K. V. Toh and N. A. Mat Isa, Cluster-based adaptive fuzzy switching median filter for universal impulse noise reduction, *IEEE Trans. Consumer Electronics, 2010,* pp. 2560-2568.

[10] http://homepages.inf.ed.ac.uk/rbf/HIPR2/median.htm (accessed on April 2012).