A new approach of hybrid switching median filter for very low level impulse noise reduction in digital images

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Abstract — Most of the image processing applications are greatly affected by the quality of images. Unfortunately, noise often contaminates images; yielding degradation of the quality of images. In order to overcome this flaw, a new filtering technique called the adroit hybrid switching median (AHSM) filter is presented in this work. The proposed filter is the integration of rank-ordered filtering and directional correlation-dependent filtering concepts. At first, the proposed algorithm will use a rank order based on the impulse detector to classify any potential noise pixels. Subsequently, the detected noise pixels are replaced by the estimated median value in the filtering stage. As a complement, a directional correlation-dependent filtering concept is adopted in the last iteration to clear the remainder noise pixels which are not attained in the previous filtering stage. This method is able to minimise the effects of random-valued impulse noise without degrading the details of the images. Both quantitative and qualitative analyses favor the proposed AHSM method, which consistently outperforms the conventional filtering techniques. Furthermore, the relatively easy-to-implement algorithm suggests the AHSM filter's applicability in electronic imaging products.

Keywords: Image processing, random-valued impulse noise, noise filtering, hybrid switching median filter.

1. INTRODUCTION

With recent evolutions taking centre stage in the field of multimedia technology, the usage of digital images has gained a great deal of attention, where they are widely used in many modern daily life applications such as in the geographical analysis and image-based control system. Fundamentally speaking, most of these modern technologies are involved with a number of image processing operations such as object recognition and edge detection; both of which are very highly dependent on the images' qualities in order for them to work faultlessly. Nonetheless, digital images are frequently subjected to the contamination of impulse noise which is due typically to the transmission and/or acquisition error, faulty memory locations and timing errors in the analog-to-digital conversion [1]. 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 having low contamination rate. However, it is still imperative to eliminate impulse noise, as the occurrences of noise effect can rigorously damage the information contained in the original images [2].

Towards this, the image restoration algorithm is known to be the most effective approach to cater for the occurrence of impulse noise and recover the quality of original image since it is more economical. Recently, a large number of non-linear filtering techniques have been widely applied to remove the impulse noise as their performances are more impressive compared to those linear-filtering counterparts. For instance, the standard median (SM) filter [3] is one of the natural choices for removing impulse noise. However, the SM filter tends to destroy many desirable details since it is worked in the raster-scan which treats all the pixels equally without considering whether or not it is noise-free pixel. Consequently, the detailed regions such as object edges and fine textures are smeared and appear blurry. In order to improve the performance, the work in [4] has proposed the adaptive median (AM) filter. Once again, it fails to filter out impulse noise in the image satisfactorily, since this technique inherits the same clumsy smoothing property as the SM filter.

To get rid of the problem, various filters under the switching scheme have been explored and experimented by recently published works. Among the techniques which fall within this group are the switching median I and II (SWM I and SWWM II) filters [5], multi-state median (MSM) filter [6], Laplacian switching (LSM) filter [7], progressive switching median (PSM) filter [8] and directional weighted median (DWM) filter [9]. Generally , this class of filtering scheme works based on the impulse detection mechanism to differentiate between noise and noise-free pixels. With this impulse noise detector, those techniques are reported to be more effective to preserve most of the image details, compared to the conventional and uniformly applied median filters.

In the meantime, various filters based on the adaptive switching scheme have been proposed. For example, Chen and Wu have introduced their technique called the adaptive center-weighted median (ACWM) filter [10]. In addition, with a slight modification to the ACWM filter, Zhang and Wang have introduced the functional minimization effective median (FMEM) filter [11]. Briefly put, both of these filters are two stages of an iterative median filter with an adaptive center weight. These two filters do offer a good filtering performance, but their computational complexities are higher than most the previously mentioned filters.

In a different way, numerous high-end methods based on the hybrid switching scheme filter have been developed by many researchers, recently. They have embedded other order statistics (e.g. rank-order statistic, etc.) and image processing techniques (e.g. mathematical morphology, directional detection, etc.) into their proposed filters as part of the filtering mechanism. For example, the tri-state median (TSM) filter [12] is formed by a combination of the SM and center-weighted median (CWM) filters [13]. In brief, 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 (i.e. which retains the original pixel value), the noisy pixel (i.e. replaced by the output of SM) and the possibly noise-free pixel (i.e. replaced by the output of CWM). Apart from that, a more sophisticated filtering technique has been presented by Luo in [14]. This filter uses the rank order absolute difference (ROAD) statistics to classify and remove impulse noise from corrupted images. Noticeably, the restoration abilities of those aforementioned techniques have been improved but at the cost of loss of fine image details and an increase in complexity.

Based on the abovementioned observation, we introduce a new iterative and recursive switching-based filter called the adroit hybrid switching median (AHSM) filter, for detail-preserving restoration. This proposed filter is relatively fast and can remove the impulse noise dexterously without jeopardizing the details and textures inside the image. The organization of this paper is as follows. Section 2 discusses the impulse noise model. The design of the proposed filter is then described in Section 3. Simulations and experimental results are presented in Section 4, and finally, a brief conclusion is drawn in Section 5.

2. IMPULSE NOISE MODEL

Before we venture forth, the type of impulse noise model is defined in this section for clarity. Theoretically, impulse noise contaminates an image with a random amplitude which could either fall within the image's 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 altered. For more details, 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:

$$x(i,j) = \begin{cases} n(i,j) & \text{: with probability } r \\ o(i,j) & \text{: with probability } 1\text{-}r \end{cases} \tag{1}$$

where $n(i, j)$ is the noise pixel value. The image is said to be corrupted by the random-valued impulse noise when $n(i, j)$ is uniformly distributed within the image's dynamic range, i.e. $n(i, j) \in [Nmin, Nmax]$. For example, in an 8-bit gray scale image with 256 gray levels, the $n(i, j)$ may range from 0 ($Nmin$) to 255 ($Nmax$). Meanwhile, for the salt-and –pepper noise; $n(i, j)$ is assumed to take the maximal and minimal intensities, i.e. $n(i, j) \in (Nmin, Nmax)$.

Although many researchers have placed an emphasis on obtaining a good filter for removing salt-and-pepper noise (i.e. which is the simplest form of noise) such as the noise adaptive fuzzy switching median filter [15] and decision-based algorithm filter [16], this work takes one step further by focusing on the detection and suppression of random-valued impulse noise. In practice, identifying such noise is more challenging compared to the salt-and-pepper noise because the intensity of noisy pixel is very similar to its surrounding.

3. THE ADROIT HYBRID SWITCHING MEDIAN FILTER

A new version of the hybrid-based median filter, called the adroit hybrid switching median (AHSM) filter is discussed in this section. The proposed filter is particularly designed for images corrupted with a very low level of random-valued impulse noise (i.e. ranging from 1% to 15% noise level). Generally, the AHSM filter is a dual mode non-linear filter which is recursively implemented in an iterative manner;

1. The earlier iterations are based on the second order rank-ordered filtering concept.

2. The last iteration is based on the directional correlation-dependent filtering concept.

Each iteration consists of two processing phases. The first phase involves the impulse noise detection process. During this process, a noise mask which is acting as a classifier to unscramble the noise pixels from noise-free pixels is generated. In the meantime, the second phase will perform a recursive pixel restoration process and at this level, noise pixels will be subjected to be replaced by the estimated median value while the other noise-free pixels are left uncorrected.

For better understanding, the main parts of the AHSM filter (i.e. second order rank ordered filtering concept and directional correlation-dependent filtering concept) are elaborated in more specific in the following subsections.

3.1 Second Order Rank Ordered filtering concept (Mode 1)

In digital images, the intensity of pixels is represented by a numerical integer. Hence, the objective of impulse noise detection can be realized by analyzing the local image statistics within a window patch, based on the assumption that the noise pixel intensity is significantly different from that of other pixels in their surroundings.

To accomplish this objective, the proposed AHSM filter employs a square local detection window $W(i, j)$ with an odd dimension $(2N+1) \times (2N+1)$ and is centered at $x(i, j)$. It is defined as:

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

In this technique, the detection window size is set to be 3x3 (i.e. $N = 1$) due to the fact that larger window size will make the image blurry [16]. The impulse noise detection process begins by sorting all pixels within the local detection window in ascending order as to find the median pixel $m(i, j)$, which is given by:

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

Then, the median pixel $m(i, j)$ is subtracted from all pixels in $W(i, j)$ and mathematically, this first-order absolute differences $d_1(i+k, j+l)$ are computed by:

$$d_1(i+k,\ j+l) = |x(i+k,\ j+l) - m(i,j)|; \text{ with } k,l \neq 0 \tag{4}$$

Next, the first-order absolute differences $d_1(i+k, j+l)$ are rearranged as $\{d_1(1) \leq d_1(2) \leq \ldots \leq d_1((2N+1)^2-1)\}$ in ascending order. If the set of sorted $\{d_1(i+k, j+l)\}$ is denoted as $d_s(a)$, then $d_s(a)$ can be written as follows:

$$d_s(a) = d_1(a):\ 1 \leq a \leq (2N+1)^2 - 1 \tag{5}$$

It could be observed that $d_s(a)$ has a discontinuity in its variational series of the sorted first-order absolute differences. The lower ranks (i.e. a = 1, 2, 3,…) in $d_s(a)$ represent small differences between the median pixel and its neighboring pixels, while higher ranks (i.e. a = …, $(2N+1)^2-3$, $(2N+1)^2-2$, $(2N+1)^2-1$) indicate large differences that correspond to noise pixels. In order to locate this discontinuity, the second-order absolute differences $d_2(a')$ are computed as follows:

$$d_2(a') = |d_s(a'+1) - d_s(a')| : 1 \leq a' < (2N+1)^2 - 1 \tag{6}$$

Based on the values obtained in $d_2(a')$, the anomalous data are able to be determined and eliminated from $d_s(a)$. All indexed data in $d_s(a)$ will be featured in the set of S as long as the criterion $d_2(a') \leq T_d^{(t)}$ is satisfied. When $d_2(a') > T_d^{(t)}$, the highest rank data in $d_s(a)$ will be eliminated. Basically, $T_d^{(t)}$ is the threshold in the t-th iteration.

In order to distinguish between the noise pixel and the noise-free pixels, the optimum detection threshold firstly needs to be identified. Towards this, the predefined noise detection threshold T^1_{AHSM} is assigned as an addition to the max value from the S array set with a constant value of five. By doing this, the robustness of the proposed filter towards noise can be increased. The term T^1_{AHSM} is defined by:

$$T^1_{AHSM} = (\max\{S\}) + 5 \quad (7)$$

After T^1_{AHSM} is obtained, this process continues by calculating the absolute luminance differences between the median pixel $m(i, j)$ and the central pixel $x(i, j)$. Alternatively, the absolute luminance is named as *AbsDiff* and can be written as follows:

$$AbsDiff = |x(i,j) - m(i,j)| \quad (8)$$

After *AbsDiff* 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 the two-dimensional binary noise mask is formed based on:

$$M(i, j) = \begin{cases} 1, & AbsDiff > T^1_{AHSM} \\ 0, & \text{Otherwise} \end{cases} \quad (9)$$

where $M(i, j) = 1$ indicates the position of noise pixel and $M(i, j) = 0$ represents the noise-free pixels.

3.2 Directional Correlation-Dependent filtering concept (Mode 2)

The proposed filter also incorporates the behavior of the directional correlation-dependent operating concept in its implementation. This second filtering mode will act as a sweeper to clean up the remainder noise pixels which are not successfully detected by the previous rank order filtering concept.

Here, a 3x3 window operator as shown in Figure 3 is used to be paired with the input image; each of which is sensitive to edges in different orientations.

1_a	2_a	3a
4_a	$x(i, j)$	4_b
3_b	2_b	1_b

Figure 3. One-dimensional edge-sensitive operator.

The detection action begins by computing the four average directional differences around the center pixel $x(i, j)$. These processes are given by:

$$AvgD_1 = (|x(i,j) - 1_a| + |x(i,j) - 1_b|)/2 \quad (10)$$

$$AvgD_2 = (|x(i,j) - 2_a| + |x(i,j) - 2_b|)/2 \quad (11)$$

$$AvgD_3 = (|x(i,j) - 3_a| + |x(i,j) - 3_b|)/2 \quad (12)$$

$$AvgD_4 = (|x(i,j) - 4_a| + |x(i,j) - 4_b|)/2 \quad (13)$$

Next, each set of four average directional differences will be compared with a predefined threshold T^2_{AHSM} , in order to determine whether $x(i, j)$ is an impulse. If at least one of the sets is less than, or equal to T^2_{AHSM}, thus $x(i, j)$ will be treated as a noise-free pixel and impulse detection mask $M(i, j)$ is marked as 0. Otherwise, for the cases where all the four sets are larger than T^2_{AHSM}, $M(i, j)$ is marked as 1 to indicate that the current processing pixel is a noise. The impulse noise masking process is given as follows:

$$M(i,j)=\begin{cases}1: & \text{if } AvgD_1 \wedge AvgD_2 \wedge AvgD_3 \wedge AvgD_4 > T^2{}_{AHSM} \\ 0: & \text{Otherwise}\end{cases} \tag{14}$$

3.3 Parameters for Each Iterations

Generally, the selection of threshold set and number of iterations needed for every level of noise density is essential since the performance of the proposed AHSM filter is highly dependent on these two parameters. In this framework, the number of iterations have been fixed based on the impulse noise density. By considering the trade-off between good filtering performance and efficient processing time, the suggested number of iterations for the AHSM filter is listed in Table 1.

Table 1. The suggested number of iterations for different noise densities.

Number of Iterations	**Impulse Noise Density**
3 (First two iterations using Mode 1; last iteration using Mode 2)	$r \leq 5\%$
4 (First three iterations using Mode 1; last iteration using Mode 2)	$5\% < r \leq 15\%$

Table 2. The suggested threshold for different noise densities.

Impulse Noise Density	$T_d^{(1)}, T_d^{(2)}$	T^2_{AHSM}
$r \leq 5\%$	35, 30	35
Impulse Noise Density	$T_d^{(1)}, T_d^{(2)}, T_d^{(3)}$	T^2_{AHSM}
$5\% < r \leq 15\%$	35, 30, 25	35

In the meantime, based on the results observed In a series of simulations using several standard test images, the suggested threshold sets for each iteration are tabulated in Table 2. All these suggested threshold values are empirically determined for the sake of achieving optimal performance. Notably, the threshold $T_d^{(t)}$ is applied in a decreasing manner. The reason in lowering $T_d^{(t)}$ is to trace the remaining noise pixels which have been misclassified as noise-free at the preceding iteration.

4. SIMULATION RESULTS AND DISCUSSIONS

In this section, the good performance of the proposed AHSM filter is demonstrated using a total of eighty 8-bit standard grayscale images obtained from diverse online sources, with 512×512 in size. Each image is superimposed with the random-valued impulse noise for noise densities ranging from 1% to 15%. For comparison, several well-known impulse noise filters are also used to restore the contaminated test images. These state-of-the-art filtering techniques are the Tri-state Median (TSM) filter, Two-stage Efficient Algorithm (TEA) filter and Functional Minimization Effective Median (FMEM) filter. Some of the filters mentioned above work with a number of tuning parameters.

However, some of these values need to be slightly modified depending on the image contents to obtain the best restoration for fair comparison.

In order to test the filters' efficiencies and effectiveness, all the simulation results of the impulse noise filters implemented will be interpreted qualitatively and quantitatively.

4.1 Qualitative Analysis

Since image is subjective to the human eyes, visual inspection is carried out on the filtered images as to evaluate the effectiveness of the filters in removing impulse noise and producing good image qualities. Among the 80 test images, the simulation results for the enlarged portion of the filtered *Boat*, *Lena* and *Cameraman* images are previously contaminated with 5%, 10% and 15% random-valued impulse noise, which are respectively shown in Figure 5.

As can be seen in the image called *Boat*, obviously the filtered images for the DWM and PSM filters contain a lot of impulse noise grain. Poor restoration results of these two conventional filters are probably caused by their detection mechanisms which are not robust and less precise. Apart from these two filters, the other conventional filters such as the TSM, TEA and FMEM are found to be able to yield better filtered images with no visible grainy effect, but unfortunately there are noticeable undesirable effects on the details and edges of the images' objects (e.g. as referred to the ship's mast and rope that have been circled). On the contrary, the proposed AHSM filter has the most appealing visual results at this 5% noise level since it successfully suppresses the impulse noise, as well as significantly preserves the image structures. For example, the shape of the rope and mast straight line of the ship are seen less distorted and jagged in the image produced by the AHSM filter.

For *Lena*, which is contaminated with 10% of random-valued impulse noise, again the proposed filter consistently outperforms the conventional filtering techniques by providing a better image quality with less noise contamination. Conversely, the resultant images produced by the other conventional techniques can be visualized (i.e. TSM, TEA and FMEM) are still influenced with jagged effects; particularly at the cap edge portion that has been circled.

Similar observations are obtained for the image named *Cameraman* where the proposed AHSM filtering technique outperforms the conventional filters by exhibiting clearer and less noise-contaminated resultant image. The filtered images using the TSM, TEA, FMEM and ACWM techniques, although still comprehensible in image contents but are degraded by a significant amount of noticeable noise blotches. On the other hand, the DWM and PSM filters have completely failed to restore the noisy image properly. This observation indicates that the combination of the rank-ordered filtering concept and directional correlation-dependent filtering concept significantly helps the proposed AHSM filter to reduce the noise stains dexterously.

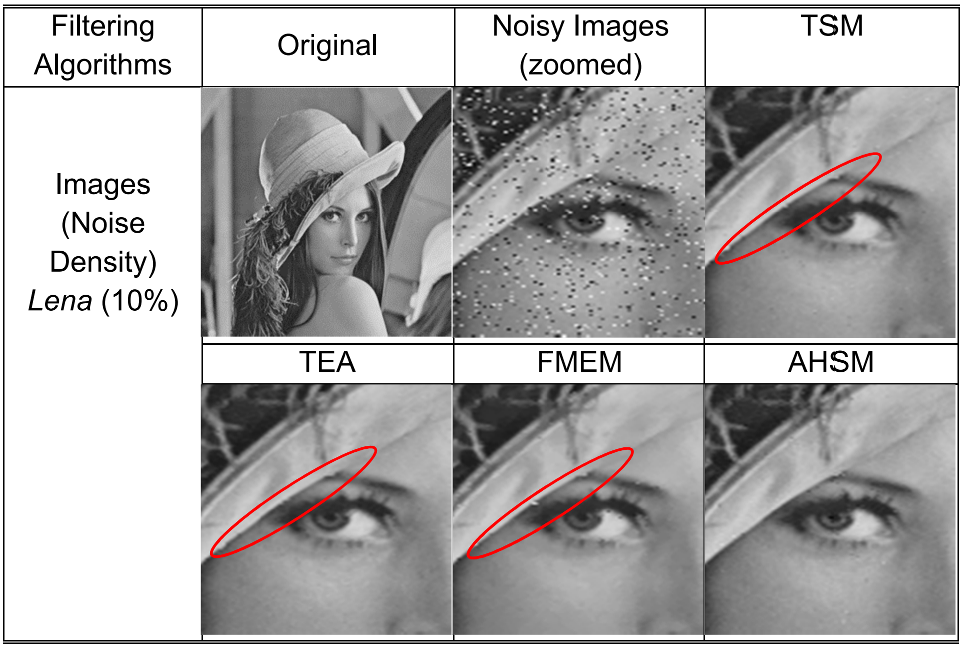

Figure 5. Simulation results of images named.

4.2 Quantitative Analysis

In addition to the visual inspection, the quantitative evaluations for images shown in Figure 5 are tabulated in Tables 3 and 4. The performance is evaluated quantitatively using the benchmark evaluation functions, namely the mean of absolute error (MAE) (i.e. to characterize the filter's detail preservation behavior) and peak signal-to-noise ratio (PSNR) (i.e. to quantify the glossy compression losses). Mathematically, these two functions are defined as:

$$\mathrm{MAE} = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} | o(i, j) - y(i, j) | \tag{15}$$

where $M \times N$ is the image size, $o(i, j)$ is the original noise-free image and $y(i, j)$ is the filtered image.

$$\mathrm{PSNR} = 10 \log_{10} \left(\frac{255^2}{\mathrm{MSE}} \right) (\mathrm{dB}) \tag{16}$$

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

$$\mathrm{MSE} = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \frac{[o(i, j) - y(i, j)]^2}{M \times N} \tag{17}$$

From the functions, the smaller MAE values indicate the better detail preservation result (i.e. the more similar the filtered image to the original image, the smaller the MAE). Conversely, larger PSNR values indicate the better restoration result.(i.e. a high signal-to-noise ratio results in a small mean-squared error; where the small mean-squared error signifies the greater similarity between the filtered and the original images). In all tables, the best results obtained are made bold. From Table 4, the proposed AHSM filtering technique consistently outperforms the other existing conventional filters by yielding the highest PSNR values at all levels of the impulse noise. These results strongly support the qualitative findings in Section 4.1.

Table 4. Comparison of PSNR on Different Noise Level Restorations for '*Lena*' (Images).

Images	Algorithms	PSNR(dB) 5%	10%	15%
Lena	TSM	39.4952	36.8717	34.5171
	TEA	40.3206	37.4897	35.5857
	DWM	36.7744	33.9623	32.0977
	PSM	35.2197	32.1545	30.3711
	FMEM	37.1826	35.7359	34.2954
	ACWM	40.8191	37.3599	34.8661
	AHSM	**41.4008**	**38.2212**	**36.0577**

Table 5. Comparison of MAE on Different Noise Level Restorations for '*Lena*' (Images).

Images	Algorithms	PSNR(dB) 5%	10%	15%
Lena	TSM	0.3942	0.7095	1.0882
	TEA	0.4353	0.7217	1.0562
	DWM	0.5038	0.9864	1.4998
	PSM	0.6224	1.2634	1.907
	FMEM	1.1543	1.3816	1.6299
	ACWM	0.2957	0.5891	0.9414
	AHSM	**0.2903**	**0.5776**	**0.8992**

In addition, similar findings could be observed in the analysis outlined in Table 5, where the proposed AHSM filter outclasses the other filters in comparison by yielding the best MAE results for almost every level of impulse noise, except for *Cameraman* with r = 5%. As a conclusion, in terms of overall performance, the AHSM filtering technique still emerges as the best filter.

5. CONCLUSION

Throughout this study, an effective and proficient impulse noise removal technique based on the switching median filter framework has been developed. The proposed AHSM filter is able to suppress very low density of random-valued impulse noise, at the same time preserving image details and structures. The AHSM filter is constructed by combining a powerful dual mode impulse noise detector with a simple median-based switching filtering technique. Extensive simulation results have been able to verify its excellent impulse noise suppression and detail preservation abilities by attaining the highest PSNR average and the lowest MAE average values across a series of very low impulse noise corruption rates. All these excellent results are achieved with a fairly efficient processing time.

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