Nonparametric Switching Median Filter for the Removal of Low Level Impulse Noise

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Abstract

Most image processing applications are greatly affected by the quality of the images. However, noise is ubiquitous and often contaminates images during acquisition. In order to overcome this drawback, a new switching-based median filter technique called nonparametric switching median filter (NPSWM) is proposed for impulse noise detection and suppression in digital images. The proposed algorithm is developed based on the nonparametric framework to determine noise and noise-free pixels. In the second stage, recursive restoration technique is used to replace the detected noise pixel by the median value of the surrounding pixels. The performance of the proposed algorithm is tested and compared with some state-of-the-art switching-based median filters existing in literature. Experimental results show that the proposed algorithm achieves superior outcomes, both in terms of subjective and objective evaluations, particularly for the cases where the images are corrupted by low level of impulse noise densities (up to 30% noise level).

Index terms *— image processing, nonparametric switching median filter, impulse noise.*

1. Introduction

Digital images in many consumer electronic products are inevitably contaminated by impulse noise during image acquisition or transmission through noisy communication channels [1]. Fortunately, digital images acquired from many electronic devices are lowly corrupted by impulse noise due to the advancement in digital imaging systems. However, even at low densities, the occurrence of impulse noise can severely damage the information or data in the original image; therefore the need to remove or reduce impulse noise is imperative before subsequent image processing tasks such as image segmentation, object identification and edge detection etc. are carried out. The most effective approach to cater the occurrence of impulse noise is by using denoising-based algorithm, which also applicable to be embedded in consumer electronic product's system. A large number of median-based filters have been proposed to remove the impulse noise. Among them, the standard median filter (MED) [1] and its modification are widely used. Clearly, the conventional median filter is implemented uniformly across the image while its variants (e.g. see [2]) 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 and/or jittered. To get rid of the problem, various filters of parametric scheme such as switching-based and hybrid switching- based have been studied and experimented.

The switching-based median filters are introduced by some published works [4], [5] in order to avoid the damage of noise-free pixels. In this framework, a fixed-size filtering window and predefined threshold are used to distinguish between noise and noise-free pixels. The switching median filter (SWM) [4] determines the difference between the current pixel and the median pixel in the corresponding filtering window and then uses a threshold to distinguish between noise and noise-free pixels. Similarly, based on weight adjustment to the centre pixel, the centre weighted switching median filter (CWSWM) is introduced in [4] for the removal of impulse noise without degrading the image details. In addition, Zhang and Karim in [5] proposed the Laplacian switching median filter (LSM) to preserve the edge including thin lines. It detects the details and preserves the details by using a set of four1-dimensional Laplacian kernels that is convolved with the input image. One of the main disadvantages of these filtering classes is that its fixed predefined threshold used in the impulse noise detection process in certain circumstances, prone in yielding pixel misclassification.

To address the aforementioned drawbacks, the hybrid switching-based median filters have been proposed in [6]-[7]. Many researchers have embedded other order statistics (e.g. rank- order statistic, median of absolute deviations, etc.) into the hybrid switching based methodologies as part of its filtering mechanism. Combination of the centre weighted median filter (CWM) [3] and SWM techniques formed the tri-state median filter (TSM) [6] has been developed on purpose to preserve the image details. Briefly, the TSM uses two predefined thresholds to determine whether the current pixel should be retained or replaced by the output of median or of centre weighted median.

In the filter proposed in [7], a second impulse detection process is added into SWM framework. The proposed impulse noise detector is established based on the rank order arrangement of the pixels in the filtering window. Unfortunately, the incorporation of different methods only increases the complexity of the filters, thus requires longer processing time to complete its task.

In general, the performances of these filtering methods discussed in [4]-[7] are very much dependent on the predefined parameters. Such "rigid" modelling under the parametric framework only limits the performance of the filter because the responses towards varying noise density are dependent on the fixed parametric framework. Based on the aforementioned observation, we introduce a more flexible switching-based algorithm called nonparametric switching median filter (NPSWM). This method is a combination of variance thresholding based on local measurements in the impulse noise detection module and recursive pixel restoration technique in the filtering module.

The remaining of the paper is organized as follows. Section 2 discusses the implementation of the conventional parametric filtering algorithms namely SWM, CWSWM, TSM and MSWM. Section 3 introduces and explains the proposed algorithm in detail. In Section 4, simulations and experimental results are presented to show the feasibility of the proposed algorithm by using both qualitative and quantitative analyses. Finally, Section 5 concludes the work in this paper.

2. Conventional Parametric Switching-based Median Filter

In this section, a total of four different types of impulse noise filter namely SWM, CWSWM, TSM and MSWM will be discussed in detail. These filters are selected since they have been receiving much attention in the field of impulse noise filtering. For explanation of all filters' implementation, consider $\{x_{i-k,\, j-l}, \ldots, x_{i,j}, \ldots, x_{i+k, j+l}\}$ which represents the input sample in the $(2N+1)\times(2N+1)$ filtering window where $x_{i,j}$ is the current pixel location at position (i, j) in the image.

2.1 Switching Median Filter (SWM)

Basically, the impulse detection in the SWM filter is based on the assumption that a noise- free image consists of locally smooth varying areas which are separated by edges while a noise pixel takes a gray value substantially larger or smaller than those of its neighbours. In order to determine whether the current pixel, $x_{i,\, j}$ is an impulse noise, the absolute difference value between $x_{i,\, j}$ and $m_{i,\, j}$ is calculated and compared with a predefined threshold T. The output of SWM is defined as:

$$y_{i,j} = \begin{cases} m_{i,j}, & |x_{i,j} - m_{i,j}| \geq T \\ x_{i,j}, & |x_{i,j} - m_{i,j}| < T \end{cases} \qquad (1)$$

$$m_{i,j} = \text{Median}\{x_{i-k,j-l}, \ldots, x_{i,\, j}, \ldots, x_{i+k,\, j+l}\} \qquad (2)$$

where $y_{i,j}$ is the filtered pixel locating at position (*i*, *j*) and *T* is a predefined threshold.

2.2 Centre Weighted Switching Median Filter (CWSWM)

For CWSWM, some modifications have been made to the impulse detection process. Theoretically, this filter gives more weight to the central value within the filtering window. The restoration term of CWSWM is given by:

$$y_{i,j} = \begin{cases} m^{w}_{i,j}, & |x_{i,j} - m^{w}_{i,j}| \geq T \\ x_{i,j}, & \text{otherwise} \end{cases} \qquad (3)$$

$$m_{i,j} = \text{Median}\{x_{i-k,\, j-l}, \ldots, w \lozenge x_{i,\, j}, \ldots, x_{i+k,\, j+l}\} \quad (4)$$

Where $w \lozenge x_{i,\, j}$ denotes that there are w copies of $x_{i,\, j}$ in the array. $y_{i,\, j}$ refers to the filtered pixel, while T indicates the predefined threshold value.

2.3 Tri-state Median Filter (TSM)

In TSM, its noise detection is realized by an impulse detector, which takes the outputs from the SWM and CWM filters and compares them with the centre pixel value in order to make a tri-state decision. For instance, consider a filtering window of size (2N+1) × (2N+1) cantered at $x_{i,\, j}$. The output of TSM is obtained by:

$$y_{i,j} = \begin{cases} x_{i,j}, & T \geq d_1 \\ m^{CWM}_{i,j}, & d_2 \leq T < d_1 \\ m^{SWM}_{i,j}, & T < d_2 \end{cases} \qquad (5)$$

where $m_{i,\, j}^{CWM}$ and $m_{i,\, j}^{SWM}$ are the median of CWM and SWM, respectively. Mathematically $d_1 = |x_{i,\, j} - m_{i,\, j}^{SWM}|$ and $d_2 = |x_{i,\, j} - m_{i,\, j}^{CWM}|$. Yet, T is a predefined parameter used to trace any presence of impulse noise in the filtering window.

2.4 Modified Switching Median Filter (MSWM)

MSWM filter represents a broad spectrum of impulse noise filter based on the parametric approach and can be considered as a dexterous filter. As an illustration, let $x_{i,\, j}$ and $y_{i,\, j}$ represent the pixel values at position (i, j) in the corrupted and restored image, respectively. The median pixel $m_{i,\, j}$ in the filtering window of size (2N+1) × (2N+1) centred at $x_{i,\, j}$ is given by (2). In order to determine whether $x_{i,\, j}$ is an impulse noise, the MSWM measures the absolute difference value between $x_{i,j}$ and $m_{i,j}$ and compares it with a predefined threshold T_1.

The argument is based on

$$y_{i,j} = \begin{cases} m_{i,j}, & |x_{i,j} - m_{i,j}| \geq T_1 \\ x_{i,j}, & |x_{i,j} - m_{i,j}| < T_1 \end{cases} \quad (6)$$

where $|x_{i,j} - m_{i,j}| \geq T_1$ denotes that the current pixel is much more different from its neighbours and can be treated as a noise. For the cases where $|x_{i,j} - m_{i,j}| < T_1$ the current pixel will undergo a second noise detection process that is given by:

$$y_{i,j} = \begin{cases} m_{i,j}, & |R(x_{i,j}) - R(m_{i,j})| \geq T_2 \\ x_{i,j}, & |R(x_{i,j}) - R(m_{i,j})| < T_2 \end{cases} \quad (7)$$

Where T_2 is another threshold. $R(x_{i,j})$ and $R(m_{i,j})$ refer to rank order value of current pixel and median pixel in the filtering window, respectively. The case $|R(x_{i,j}) - R(m_{i,j})| \geq T_2$ means that the rank order of the current pixel $x_{i,j}$ is larger than corresponding $m_{i,j}$ and it denotes that $x_{i,j}$ is a noise pixel and must be filtered. Otherwise, the $x_{i,j}$ remains unchanged.

3. The Proposed Nonparametric Switching Median Filter

The proposed NPSWM filter is a recursive double-stage filter where initially it will perform the impulse noise detection based on a nonparametric framework. Yet, the meaning of nonparametric refers to the technique which a function that has no dependency on a fixed predefined parameter (i.e. the parameter is flexible and not fixed in advance). When a 'noise pixel' is detected, it is subjected to the next filtering stage. Otherwise, when a pixel is classified as 'noise free', it will be retained and the filtering action is spared to avoid altering any fine details and textures. The combination of these features (i.e. nonparametric noise detection and recursive pixel restoration), allows the filter to be more versatile and stable.

3.1 Detection Stage

The proposed NPSWM filter uses a square filtering window $W_{i,j}$ with odd $(2N+1) \times (2N+1)$ dimensions (i.e. N = 1) and centred at $x_{i,j}$. It is given as:

$$m_{i,j}=\{x_{i-k,j-l},..,x_{i,j},.., x_{i+k,j+l}\}; \text{ for } -N\leq K, l\leq K, \quad (8)$$

The detection process begins by sorting all pixels within the filtering window in ascending order as to find the median pixel $m_{i,j}$, which is defined by (2).

After the median pixel is found, the absolute luminance difference $d_{i,j}$ between all pixels within the filtering window and the median pixel is computed by using:

$$d_{i\pm k,j\pm l} = x_{i\pm k,j\pm l} - m_{i,j} \text{ for } -N\leq K, l\leq K, (k,l)\neq(0,0) \quad (9)$$

Next, each value computed in $d_{i\pm k,j\pm l}$ will be sorted in ascending order once again. To increase the robustness of this filter towards noise, the predefined threshold T_{NPSWM} is assigned as the median value in the sorted array. The term T_{NPSWM} is defined by:

$$T_{NPSWM} = \text{Median}(d_{i\pm k,j\pm l}) \text{ for } -N\leq K, l\leq K, (k,l)\neq(0,0) \quad (10)$$

This is an attractive merit of the proposed NPSWM filtering scheme since it provides a variable T_{NPSWM} according to the local measurements of each filtering window. By employing this nonparametric concept, the possibility of pixel misclassification can be reduced in a proper manner. Then the impulse detector will measure the absolute difference value between $x_{i,j}$ and $m_{i,j}$ and compare the resultant value with T_{NPSWM}, in order to determine whether $x_{i,j}$ is an impulse noise. Thus, the impulse noise detection process can be realized by:

$$M_{i,j} = \begin{cases} 1, & |x_{i,j} - m_{i,j}| \geq T_{NPSWM}, \\ 0, & |x_{i,j} - m_{i,j}| < T_{NPSWM}, \end{cases} \quad (11)$$

where $M_{i,j}$ is a noise mask created to mark the location of impulse noise. $|x_{i,j} - m_{i,j}| \geq T_{NPSWM}$ (or $M_{i,j} = 1$) represents 'noise pixel' subjected to the next filtering stage, while $|x_{i,j} - m_{i,j}| < T_{NPSWM}$ (or $M_{i,j} = 0$) represents 'noise-free pixel' to be retained.

3.2 Filtering Stage

The correction term to restore a detected 'noise pixel' is a linear combination between the current processing pixel $x_{i,j}$ and median pixel $m_{i,j}$. The restoration term denoted as $y_{i,j}^{NPSWM}$ is defined by:

$$y_{i,j}^{NPSWM} = ([1 - M_{i,j}] * x_{i,j}) + m_{i,j} \quad (12)$$

As to enhance the filtering process, a recursive restoration concept is applied to the data (i.e. a processed pixel is immediately replaced by the filtered pixel, and the filtered pixel is used in further calculations).

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

(Step 1); 3×3 filtering window, $x_{i,\,j}$ = 165

↓

32	134	134	139	139	139	140	142	165

(Step 2); $m_{i,\,j}$ = 139

↓

107	5	5	0	0	1	3	26

(Step 3); $d_{i\pm k,\, j\pm l}$

↓

0	0	1	3	5	5	26	107

(Step 4); T_{NPSWM} = 4, i.e. (5+3)/2

↓

$|x_{i,\,j} - m_{i,\,j}| = |165 - 139|$
$= 26$

(Step 5); absolute luminance difference between the centre pixel and the median pixel

↓

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

↓

(Step 6); $y_{i,\,j}^{NPSWM} = 139$

* Since $|x_{i,\,j} - m_{i,\,j}| > T_{NPSWM}$, i.e. 26 > 4; therefore the current processing pixel is replaced by the median pixel of intensities 139.

Fig. 1 An illustrative example on NPSWM filter's impulse noise detection and filtering operation.

The justification of making the proposed NPSWM filter to behave recursively is to increase its ability in selecting a more accurate median pixel. The whole process of the proposed algorithm is illustrated in Fig. 1.

4. Experimental Results

In this section, the feasibility of the proposed NPSWM filter will be compared to the conventional switching-based median filters based on their simulation results. The following conventional methods with their suggested tuning parameter are used to compare with the proposed algorithm; SWM (T=50) [4], CWSWM (T=30, w=3) [4], TSM (T=20, w=3) [6] and MSWM (T_1=30, T_2=3) [7]. Several standard real images corrupted with the impulse noise have been used in this experiment as to test the effectiveness and efficiency of the filters. The implementation of all tested filtering algorithms has been verified accordingly with the corresponding reference papers.

4.1 Qualitative Analysis

Since quality of image is subjective to the human eyes, visual inspection is carried out on the filtered images as to judge the effectiveness of the filters in removing impulse noise. A total of three out of numerous tested standard real images obtained from public internet database are chosen in this analysis. The chosen set of Flower, Fruits and Yacht images contains various characteristics suitable to test the performance of the implemented filters. The simulation results for these images are presented in Figs. 2, 3 and 4 respectively. In all figures, a portion of each image is used. In each figure, image (b) represents the noise corrupted images. Flower, Fruits and Yacht images are corrupted with 10%, 20% and 30% density of impulse noise respectively.

As can be seen in Fig. 2, at 10% impulse noise density, the noise filtering performance of NPSWM filter is basically similar to those of the conventional noise filtering algorithms. All filters are found to be able of producing perceptible reconstructed image at this noise level.

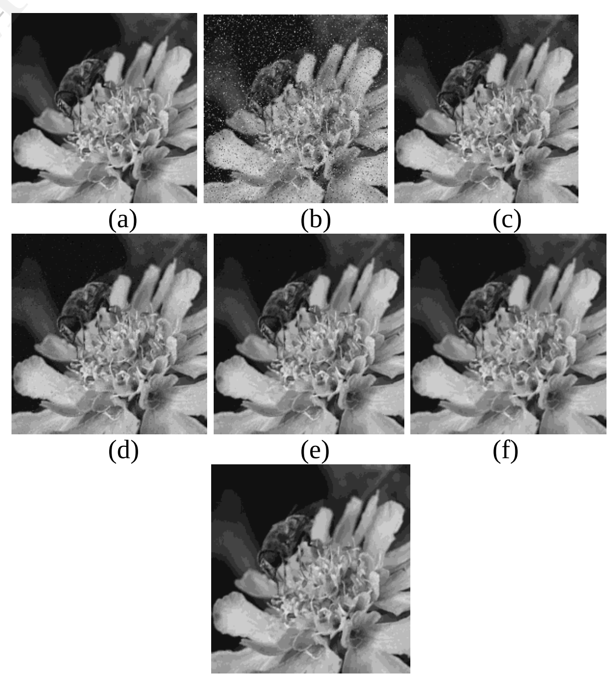

Fig. 2 Simulation results on a portion of *Flower* with 10% density of impulse noise using; (a) original image, (b) noisy image, (c) SWM, (d) CWSWM, (e) TSM, (f) MSWM and (g) NPSWM

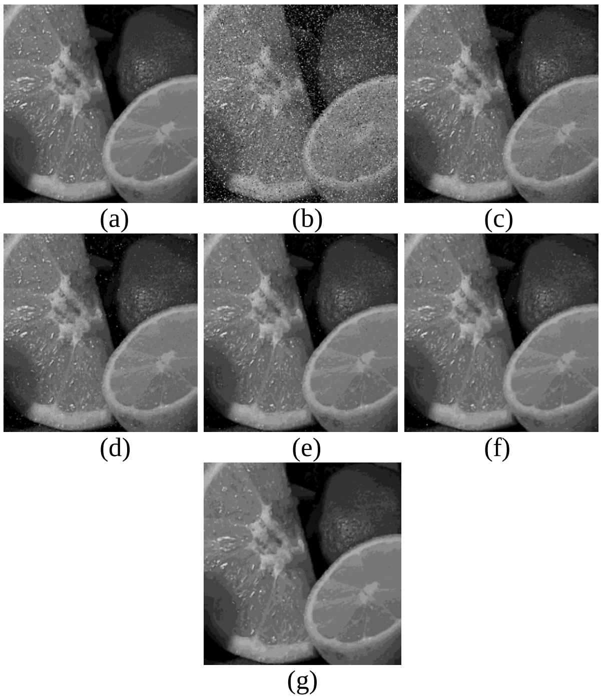

Fig. 3 Simulation results on a portion of *Fruits* with 20% density of impulse noise using; (a) original image, (b) noisy image, (c) SWM, (d) CWSWM, (e) TSM, (f) MSWM and (g) NPSWM

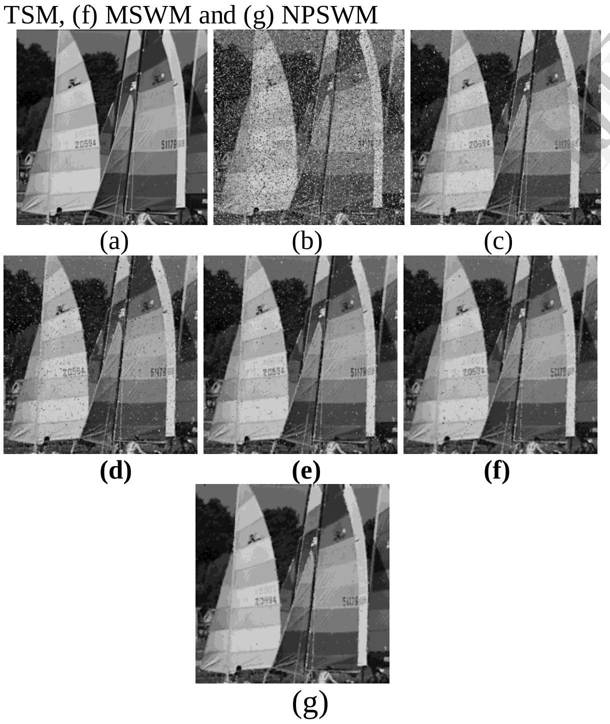

Fig. 4 Simulation results on a portion of *Yacht* with 30% density of impulse noise using; (a) original image, (b) noisy image, (c) SWM, (d) CWSWM, (e) TSM, (f) MSWM and (g) NPSWM

However, in the *Fruits* image which is contaminated with 20% of impulse noise (as shown in Fig. 3), we can visualize that the results produced by the conventional switching-based median filters are still influenced by the noise. We may be able to notice that some small noise patches are remained intact on the resultant images. On contrary, the proposed NPSWM filtering algorithm can significantly remove the effect of noise added to the images and at the same time preserve the object shapes.

The similar results are obtained for the Yacht image (shown in Fig. 4), where the proposed NPSWM filtering algorithm outperforms the conventional SWM, CWSWM, TSM and MSWM algorithms by giving clearer image; even the density of noise in this image is higher (i.e. 30% of impulse noise).

The proposed NPSWM filtering algorithm has successfully reduced the noise patches, created less corrupted image. This is due to the ability of the proposed algorithm to distinguish between the noise pixels and the noise-free pixels dexterously.

Although the conventional filtering algorithms can also suppress the noise but it is found that the image regions are still has minor distortion. The inability for the conventional switching-based median filters to effectively remove impulse noise can be attributed to several reasons. The main reason is the use of fixed parametric framework in the detection stage. This parametric framework is deemed unsuitable because it may lead to misclassification of 'noise' pixels as 'noise-free' pixels.

4.2 Quantitative Analysis

In this section, we tabulate a quantitative evaluation of the filtering results obtained in Figs. 2 to 4. Peak signal-to-noise ratio (PSNR) is used as a benchmark this analysis. The PSNR is defined by:

$$\text{PSNR}=10\log_{10}\left(\frac{255^2}{MSE}\right)=10\log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (13)$$

Where MAX is the maximum pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. Higher the PSNR better is the quality.

$$MSE=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(r_{ij}-x_{ij}\right)^2 \quad (14)$$

where r_{ij} is the original image, x_{ij} is the restored image The numerous results for images of Flower, Fruits and Yacht are tabulated in Table 1, 2, and 3, respectively. In all tables, the best results obtained are made bold.

Overall, it is shown that the proposed NPSWM consistently outperforms the other conventional algorithms except for the *Flower* image with 10% noise level. A further analysis of this study has been conducted against 50 standard real images. These images are contaminated with impulse noise ranging from 10% - 30%. Using the same aforementioned PSNR quality assessment, the average PSNR values obtained for all algorithms are tabulated in Table 4. As expected, it can be seen from the table that the proposed NPSWM algorithms provides the highest PSNR value among other filtering algorithms. It is evident that NPSWM's filtering performance is tremendously consistent.

Table 1 Comparison of PSNR on Different Noise Level Restoration for Image 'Flower'

Images	Algorithms	10%	20%	30%
Flower	SWM	32.7222	28.6679	25.2900
	CWSWM	35.2000	28.7135	23.8703
	TSM	**38.6550**	31.9417	26.6947
	MSWSM	37.7154	33.0015	27.2426
	NPSWM	38.1313	**35.2274**	**32.1274**

Table 2 Comparison of PSNR on Different Noise Level Restoration for Image 'Fruits'

Images	Algorithms	10%	20%	30%
Fruits	SWM	32.3881	28.7971	25.2900
	CWSWM	35.5065	28.8246	23.9414
	TSM	35.7822	31.9417	26.5623
	MSWSM	35.6073	32.1356	27.3501
	NPSWM	**36.1214**	**33.5335**	**31.3619**

Table 3 Comparison of PSNR on Different Noise Level Restoration for Image 'Yacht'

Images	Algorithms	10%	20%	30%
Yacht	SWM	30.3851	26.9915	24.2694
	CWSWM	31.2182	27.1082	23.3062
	TSM	31.4804	28.9658	25.4419
	MSWSM	31.3725	28.6268	25.3878
	NPSWM	**31.5160**	**29.1585**	**26.6862**

Table 4 Comparison of Average PSNR on Different Noise Level Restoration for 50 Standard Real Images

Algorithms	10%	20%	30%
SWM	29.4315	26.4265	23.7212
CWSWM	30.1703	26.6879	22.9766
TSM	30.0141	27.1672	24.3427
MSWSM	29.5292	27.6866	24.9529
NPSWM	**30.2504**	**29.3089**	**26.5629**

4.3 Processing Time Efficiency

We also carry out processing time analysis for each filter to perform its denoising task. Such measure is important especially for application in consumer electronic products as the processing time is one of the criteria often considered in the design of noise filter. The graph of average processing time in seconds (s) for 50 standard real images after applying with the proposed NPSWM filter and other conventional filters is shown in Fig. 5.

Overall, the processing time of each filter remains almost constant at all level noise density. The MSWM filter which uses more complex noise detection mechanism (i.e. double detection stage), takes longer time to complete its filtering task as compared to the rest of the others filters. Except for SWM, consistently, our proposed method outperforms other filters across a wide range of noise level with a relatively fast average processing time. Even though the SWM is shown to have a better processing time compared to the NPSWM (with a slightly lower value, of ≈ 0.2 s) but it is unable to produce a desirable filtering quality. Thus, as far as denoising performance is concerned, the proposed NPSWM can be regarded as the best filter.

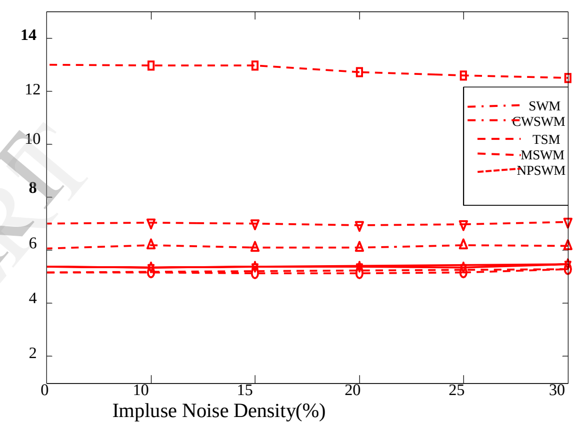

Fig. 5 The graph of average processing time (sec) versus impulse noise density (%) computed from a total 50 standard real images.

5. CONCLUSION

In this paper, a NPSWM filter for effective impulse noise detection and suppression is presented. The variance thresholding and recursive pixel restoration techniques that involved in the design of the filter make it able to suppress impulse noise effectively, at the same time preserving fine image edges and textures. Furthermore, this filter does not require any special tuning of parameter since its predefined threshold is established based on nonparametric framework. The simulation results indicate that a better noise filtering performance is achieved with fairly efficient processing time. It is a feasible approach for reducing the low noise effect in digital images.

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