FAST AND ROBUST RANDOM-VALUED IMAGE DENOISING ALGORITHM BASED ON ROAD STATISTICS

[1]SABAHALDIN A. HUSSAIN, [2]AHMED ABDULQADER HUSSEIN, [3]AHMED HAMEED REJA

[1]Computer Science Department, College of Science, Aljufra University, Libya
[2,3]Department of Electromechanical Engineering, University of Technology, Baghdad, Iraq
E-mail: sabahaldinalqaisi@yahoo.com, ahmedabdulqaderhussein@gmail.com,ahmad8171@yahoo.com.

Abstract - In this paper, an efficient, low computational complexity, and threshold free random-valued impulse noise removal is proposed. Based on a well-known Rank-Ordered Absolute Difference (ROAD), a four-state filter is proposed to detect and recover corrupted pixels. The minimum, maximum, sum and median ROAD are used as parameters for classifying impulse noise which eliminate the need for threshold value. The experimental results demonstrate the efficiency of the proposed algorithm in dealing with images corrupted by high random-valued and fixed-valued impulse noise as compared with two state-of-the-art denoising algorithms.

Index Terms - Image denoising, Random-valued impulse noise, Fixed-valued impulse noise, Impulse detector.

I. INTRODUCTION

Impulse noise is a typical noise which may be added to still images in digital cameras in various steps such as failure of sensor component during acquisition in poor imaging environments, faulty memory locations, timing errors, or bit errors during transmission through faulty radio channels. Generally, noise is one of the vital challenges in many image processing tasks such as face recognition[1], image segmentation[2], and image compression[3]. The presence of noise affects upon the performance of any subsequent processing algorithms and leads to incorrect results. Impulse noise can be classified into fixed-valued impulsive noise and random-valued impulsive noise. The gray scale of fixed-valued impulsive noise that is commonly known as "salt and pepper noise" is the maximum or the minimum of the possible image intensity levels. The detection of salt and pepper impulse noise is relatively easier than random-valued impulsive noise as there are only two intensity levels in the noisy pixels.

Due to the sever effect of impulse noise on image quality, noise removal algorithm is utilized as a necessary pre-processing step in many image processing fields to ensure the desired processing results. The rest of the paper is organized as follows. Section 2 introduces an overview of relative subject literature survey. Section 3 explains the proposed algorithm. The experimental results are discussed in section 4. Finally, the concluding remarks are given in section 5.

II. RELATED WORKS

In recent years, several algorithms have been proposed for removing impulsive noise. Among them, the standard median filter (MF)[4] was used widely because of its effectiveness in noise suppression capability for low to moderate impulsive noise density. However, MF applied uniformly across the entire image pixels and hence leads to modify both noisy and noise-free pixels. This will result recovered image of poor visual quality.

To overcome the MF limitations, switching strategy was introduced to decide whether a pixel is noisy and hence should be processed or noise free to keep it unchanged. Among the variety of switching based filtering techniques, weighted median filter(WMF)[5] which assigns different weights to the pixels inside the test window, adaptive length median filter(ALMF)[6], and center weight median filter(CWMF) which only weights the center pixel of the window was proposed[7]. In[8], an adaptive median filter (AMF) was proposed. The performance of AMF is good at lower noise density levels, due to the fact that there are only fewer corrupted pixels that are replaced by the median values. At higher noise densities, larger window size is frequently required to distinguish between noisy and noise free pixels. However, increasing the window size weakens the important property of correlation between the processed pixel and the median value. Consequently, the edges are blurred significantly. In[9], the authors suggest to use Signal-Dependent Rank Ordered Mean (SD-ROM) to discriminate and cancel noisy pixels. In this algorithm the noisy pixel is replaced by the rank ordered mean of the surrounding pixel values. In [10], a progressive switching median filter (PSM) containing impulse detector and noise filter for the removal of impulse noise was proposed. Both impulse detector and noise filter are applied progressively in iterative manners to detect and recover corrupted pixels using two steps. In the first step, a median value is determined for the pixels inside a fixed sized square test window (typically 3×3). In the second step, the centered pixel is considered as corrupted pixel if the difference between the median value and the center pixel is larger than a predefined threshold value. At such a case, the centered pixel is replaced by the median value. Otherwise, the centered pixel is considered as uncorrupted and kept unchanged. In[11], a tri-state

median filter(TSMF) was proposed. TSMF combines filter comprises of standard median filter, identity filter, center weighted median filter, and a switching logic. The impulse noise detector compares the central pixel value with the outputs received from the standard median filter and center weighted median filter to make a tri-state decision. The switching logic is controlled by a threshold value. Depending on this threshold value, the center pixel is replaced by the output of either MF or CWMF or identity filter (in case of noise free pixel). In[12], an adaptive centre weighted median filter that employs the switching scheme based on the impulse detection mechanism was proposed. The final output is switched between the median and the current pixel itself. While still using a simple thresholding operation, the ACWMF algorithm yields superior results to other switching schemes in suppressing impulse noise[13]. In[14], authors proposed a switching median filter based on the minimum absolute value of four convolutions obtained using one dimensional Laplacian operators. Pixel-Wise median of absolute deviation (PWMAD) from median is another technique based on modified median absolute deviation (MAD). MAD is used to estimate the presence of image details. In[15], an iterative pixel wise median of absolute deviation (PWMAD) is used which provides a reliable removal of impulses but with an amplified computational cost. In[16], an edge-preserving regularization variational approach has been proposed to remove impulse noise. Based on the same concept, a two-step method was proposed in[17]. In the first step, a noisy pixel candidate is identified using ACWMF filter [12]. In the second step, the noise candidates are restored by the edge-preserving regularization which allows edges and noise-free pixels to be preserved. The same procedure is adopted in [18] replacing ACWMF by AMF[8] in the noise detection phase. The main drawback of this method is that the processing time is very high because it uses a very large window size of 39×39 in both phases to ensure optimum denoising result. In[19], a new local image statistic called Rank-Ordered Absolute Difference (ROAD) is used as a criterion to identify the impulse noisy pixels. In[20], the authors proposed a hybrid filter consists of a median filter, an edge detector, and a neuro-fuzzy network. The internal parameters of the neuro-fuzzy network are optimized adaptively using artificially corrupted training images. The proposed hybrid filter offers the most important property of preserving image fine details while removing noisy pixels. In[21], an algorithm based on fuzzy impulse detection technique was proposed. In this algorithm a membership function for each pixel is calculated. The pixel value is replaced by a linear combination of its original value and the median value. In[22], an algorithm based on the concept of fuzzy gradient is proposed. To detect an impulse noise, a fuzzy set is constructed. This fuzzy set is represented by a membership function that will be used by the filtering phase, which is a fuzzy averaging of neighbouring pixels. In[23], a fuzzy random impulse noise reduction method (FRINRM) based on a two stage fuzzy detection and fuzzy filtering is proposed. FRINRM is capable of removing both fixed and random valued impulse noise. In[24], the authors proposed Directional Weighted Median filter (DWMF) with an iterative filtering approach. The impulse detector algorithm is based on absolute differences of pixels within test window. The noisy pixel is recovered using an adaptive weighted median filter. To ensure high detection accuracy, iterative filtering is applied which in turns increases computation complexity and removes important image features in each iteration. In[25], a modified progressive switching median filter (MPSMF) was proposed. MPSMF uses ACWMF for impulse detection phase, and uses PSMF for filtering phase. In[26], a one dimensional first order polynomial interpolation is applied where two non-noisy pixels are enough to find an interpolated value. The interpolated value is then used to replace the noisy pixel. In[27], the authors proposed a recursive filter called Cluster-based Adaptive Fuzzy Switching Median (CAFSM) for detail preserving restoration. In[28], the quaternion unit transform theory was applied for denoising colour images corrupted by impulse noise. Based on the difference between two colour pixels in the quaternion form, the output of the proposed filter is switched between vector median filter (in case of noisy pixel) and identity filter (in case of clean pixel). In[29], a triangular fuzzy membership function was used to identify the level of pixel corruption and accordingly assign adaptive threshold value for noise remover. In[30], an algorithm for denoising images corrupted by high impulse noise density rate was proposed. The algorithm can stand against burst of impulses using robust outlier exclusion with adaptive window size. In[31], a peer group concept along with the quaternion based distance measure was adopted for impulse noise detection in the first stage. The noisy pixels candidates are replaced by weighted vector median filter in the second stage.

Recently, several algorithms were proposed that proved good performance for highly corrupted images. These algorithms employ different optimizing parameters e.g. a threshold value, window size, set of fuzzy rules, member function, .. etc. Generally, most impulse type denoising algorithms are based on switching mechanism. The efficiency of any switching filter depends upon the accuracy of impulse detection phase. The switching decision is ,mostly, based on a predefined threshold value. Thus, the performance of such algorithms is very sensitive to the threshold value selection. Moreover, the performance of these algorithms gained at the expense of high computation complexity and implementation cost.

To overcome these problems, a robust random valued impulse noise suppression algorithm based on ROAD statistics with low computation cost is proposed in this

paper. The proposed filter is composed of two steps: noise detection followed by filtering. In noise detection, first order absolute difference between the center pixel and all of its neighbours is calculated and then sorted in ascending order. The minimum, maximum, sum and median ROAD are used as parameters for deciding the necessary action need to be taken for classifying impulse noise in noise detection phase which eliminate the need for threshold value. According to the state of the pixels inside a test window, a four-state filtering is achieved on each central pixel. The center pixel value is replaced by the output of the identity filter (IF), Most Occurrence Pixel Filter (MOPF), Minimum of Most Occurrence Pixel Filter (MMOPF), or by the median filter (MF). The performance of the proposed algorithm was compared with two low complexity state-of-the-art denoising algorithms namely PSMF[10], and ACWMF[12]. The experimental results demonstrate that the proposed algorithm delivers superior results for both fixed and random valued noise with low computation complexity and hence lends itself for real time applications.

III. PROPOSED ALGORITHM

As discussed previously, the main weakness of the MF is the replacement of every pixel in the image by the median value of pixels inside a pre-defined test window. Thus, better results are expected when detecting and processing only noisy pixels. Generally, the random valued noisy pixel may take an arbitrary value in the dynamic range [0,255] with uniform distribution. Accordingly, the impulse noise pixel of a corrupted image can be modelled mathematically as,

$$Crp(x,y) = \begin{cases} Org(x,y) \text{ with probability } 1-r \\ Imp(x,y) \text{ with pabability } r \end{cases} \quad (1)$$

Where, Org(x,y), Crp(x,y), and Imp(x,y) are the original, corrupted, and impulse pixel values at spatial location (x,y) respectively, and r is the percentage of impulse noise density level. Clearly, an important characteristic of the impulsive noise is that only part of the image pixels is corrupted and the rest are left unchanged. Thus, to get the benefit of this property, the proposed algorithm consists of detection and filtering phases. The detection phase is based on the ROAD statistics[19]. The noisy and noise free pixels can be decided by inferring $ROAD_{min}$, $ROAD_{max}$,, and $ROAD_{sum}$.

Let $\Omega_{x,y}$ be a square neighboring window size $N \times N$ of odd length centered at spatial location (x,y). For each pixel inside the test window, define D as the absolute difference between the center pixel and all of its neighbors.

$$\mathbf{D_{x,y}} = \left|\Omega_{i,j} - p(x,y)\right| \quad i,j = 1..N \quad (2)$$

Where $p(x,y)$ is the pixel under test. Now, let $\mathbf{d}$ be a vector of sorted elements of $\mathbf{D_{x,y}}$ in ascending order, define the following statistical parameters:

$$ROAD_{min} = \mathbf{d}(2) \quad (3)$$

$$ROAD_{max} = \mathbf{d}(N^2) \quad (4)$$

$$ROAD_{median} = \mathbf{d}((N^2+1)/2) \quad (5)$$

$$ROAD_{sum} = \sum_{k=2}^{N^2} \mathbf{d}(k) \quad (6)$$

According to the values of the derived ROAD, the proposed algorithm uses a rule based system consists of nested conditions to decide the suitable reaction need to be taken in order to recover the corrupted pixel. Firstly, if the median of the ROAD equals the extreme minimum or maximum ROAD then this will indicate that the test window contains enough noise free pixels which can be simply used to recover the corrupted center pixel. In this case the corrupted pixel can be accurately replaced by the most often repeated pixel value which is achieved through a proposed filter named Most Occurrence Pixel Filter (MOPF). Occasionally, the test window may contain different pixel intensities repeated equally. In this case the corrupted pixel is replaced by the minimum of most occurrence pixel value which is achieved through a proposed filter named Minimum of Most Occurrence Pixel Filter (MMOPF). Otherwise, if $ROAD_{sum} \leq p(x,y)$ and $p(x,y) \neq 0$ and $p(x,y) \neq 255$, then the center pixel is considered noise free and forwarded to the identity filter. Finally, if these conditions are not satisfied then the test window is considered highly corrupted and the center pixel is recovered by the conventional median filter. The above steps are repeated once using the next higher odd window size. Extensive simulation tests are carried out on a variety of degraded images to find the optimum window size. It has been observed that setting $N = 3$ enables the algorithm to deal with low to moderate noise levels, while for high noise level $N = 5$ gives more pleasant denoised image.

The proposed algorithm steps involved in detecting the presence of an impulse and restoring the corrupted pixel are described below.

Input: **A** An image corrupted by impulse noise.
Output: B is the denoised image.
Assign test window $\Omega_{x,y}$ of size $N \times N$ where N is an Odd number typically 3.
For each Non Border pixel $p(i,j) \in \boldsymbol{A}$, Define a slide window $\Omega_{x,y}$ centered at $p(x,y)$ over **A** and do the following:
Calculate Absolute Difference of the center pixel with all its neighbors inside the test window
Sort the result of step (a) in ascending order and calculate $Road_{Min}$, $Road_{Max}$, $Road_{Median}$, and $Road_{Sum}$.
Process the central pixel $p(x,y)$ using the following Rule Based System:

$$\boldsymbol{if}\ Road_{Min} = Road_{Median} \quad \boldsymbol{or} \quad Road_{Max} = Road_{Median} \quad \boldsymbol{then}$$

-Exclude the center pixel $p(x,y)$ and set,

$$\boldsymbol{B}(i,j) = MOPF(\Omega_{x,y}/p(x,y)) \quad \textbf{or}$$

$$\boldsymbol{B}(i,j) = MMOPF(\Omega_{x,y}/p(x,y))$$

$$\textbf{elseif } p(x,y) \neq 0 \; and \; p(x,y) \neq 255 \; and \; Road_{sum} \leq p(x,y) \; \textbf{then}$$

-Forward the center pixel to the identity filter (IF),

$$\boldsymbol{B}(i,j) = p(x,y)$$

$$\textbf{else} \quad \boldsymbol{B}(i,j) = Median(\Omega_{x,y})$$

$$\textbf{endif}$$

$$\textbf{end for}$$

Repeat the above steps with window $\bar{\Omega}_{x,y}$ of size $N+2 \times N+2$.

Output the denoised image **B**.

IV. EXPERIMENTAL RESULTS

In this paper, results are presented to illustrate the performance of the proposed algorithm. Extensive experiments are carried out on a set of 512×512 sized benchmark images for evaluating the performance of the proposed algorithm. Images artificially corrupted with random valued impulse noise based on uniformly distributed model over the dynamic range [0-255] are used in the test. In the experiments, the effectiveness of the proposed algorithm (we shall call it FRRVIDA) is demonstrated by comparing its performance with two state-of-the-art denoising algorithms namely PSMF[10], and ACWMF[12]. For unbiased comparison, the parameters of both algorithms are set according to [10] and [12] to acquire their best performance. Objectively, the relative denoising algorithms performance is measured using Peak Signal to Noise Ratio (PSNR) and Structural Similarity index(SSIM)[32]. The SSIM Index is one of the most commonly used measures for image quality assessment due to its robustness in reflecting the structural similarity between the denoised image and the referenced one. The denoising relative performance, in terms of PSNR and SSIM for an average of ten runs, is recorded in Table1 (where the value in parenthesis is the SSIM). The best denoising algorithm is highlighted in bold font for each test image.

As can be seen from Table1, the average output PSNR and SSIM of ACWMF and FRRVIDA are close to each other for almost all images under test although FRRVIDA outperforms other algorithms in terms of average SSIM values over the whole scope of impulse noise density rates. This result is coincided with denoised image visual quality as will be seen in subjective image analysis. While, PSMF is not robust in terms of both average PSNR and SSIM values. Its results become worse especially when noise density rate is increased. For illustration purpose, figure 1, and figure 2 show graphically the relative average PSNR and SSIM measures for different algorithms.

In terms of individual PSNR and SSIM values, both ACWMF and FRRVIDA outperform PSMF over the entire scope of impulse noise density rates. For r>0.4, FRRVIDA outperforms ACWMF all the time. While, for r <=0.4, ACWMF slightly outperforms FRRVIDA most of the time. However, the ACWMF suffers from its high computational complexity. As an example, we compare the computational complexity of PSMF, ACWMF, and FRRVIDA using CPU run time. Although CPU time is not an exact measure, it gives a rough estimation of complexity. All the experiments are done with an Intel Core-i7 processor at 1.8/2.4GHz with 12GB of RAM, using MATLAB R2015a environment under Microsoft Windows 10 64-bit operating system. The average execution time of ten runs for each denoising algorithm is recorded for a variety of image degradations of size 512×512. Results show that, the average execution time of ACWMF is about 4.544 seconds while FRRVIDA requires just 0.925 seconds. On the other hand, PSMF, requires about 0.543 seconds. Thus, by taking the computational complexity into our considerations, the proposed FRRVIDA exhibits good performance with low computational complexity as compared with PSMF and ACWMF.

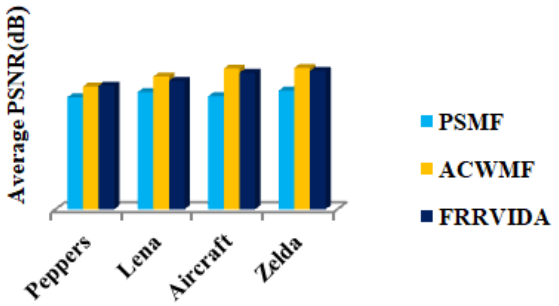


Figure 1. Average PSNR of denoising algorithms.

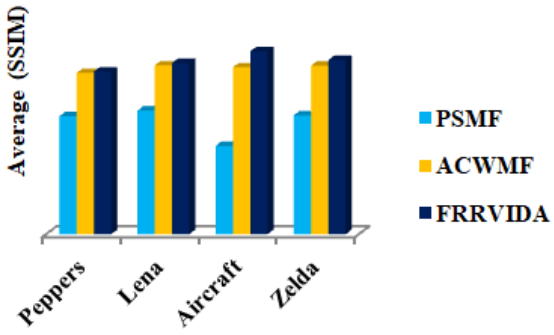
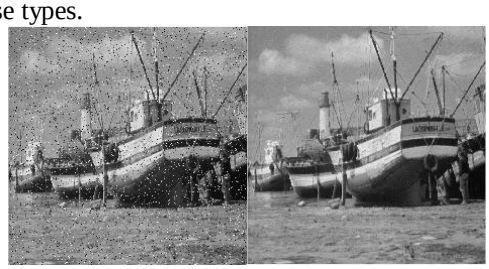


Figure 2. Average SSIM of denoising Algorithms

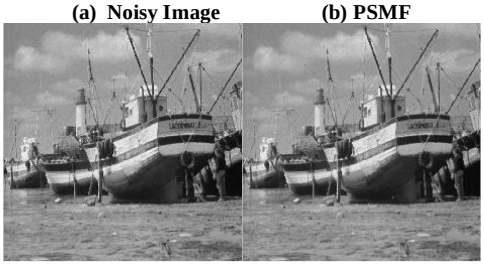
Subjectively, the performance of the proposed algorithm at different impulse noise density rates is compared with other denoising algorithms through the results shown in figure 3 to figure 8. Figure 3, shows that for low impulse noise density rate ($r \leq 0.2$), almost all denoising algorithms achieve nearly equivalent visual performance although PSMF exhibits lower PSNR and SSIM values. Figure 4, shows the effect of denoising for moderate noise density rate. Clearly, ACWMF and FRRVIDA show better performance compared with PSMF.

As an illustration, referring to figure 4b, we can notice residual impulses left untouched in the uniform sky

area of the image. For (r=0.4), refer to figure 5, PSMF left noticeable residual impulses and results in lower recovered image quality. This means that PSMF fails in classifying noisy from noise free pixels at such impulse noise density rate. While, ACWMF and FRRVIDA achieve nearly equivalent performance. For highly corrupted images, figure 6 and figure 7 show the denoising performance for r=0.5 and r=0.6 respectively. Clearly, it can be seen that FRRVIDA demonstrates better capability of distinguishing and cancelling noisy pixels and hence recovering image more accurately as compared with both PSMF and ACWMF. Finally, figure 8 shows the denoising performance against salt and pepper fixed-valued impulse noise type. Clearly, both PSMF and ACWMF produce poor image quality and hence failed in dealing with such high impulse noise type (refer to figure 8b&c). While the proposed algorithm succeeded in achieving superior recovered image quality. Hence, this result verifies the effectiveness of the proposed algorithm for both fixed and random valued impulse noise types.

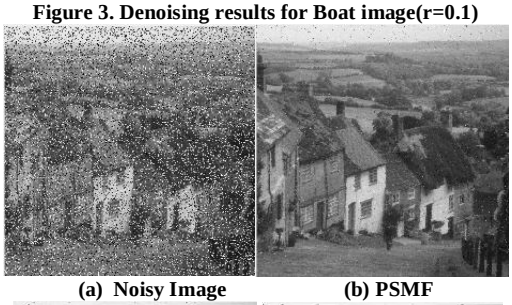


(a) Noisy Image **(b) PSMF**

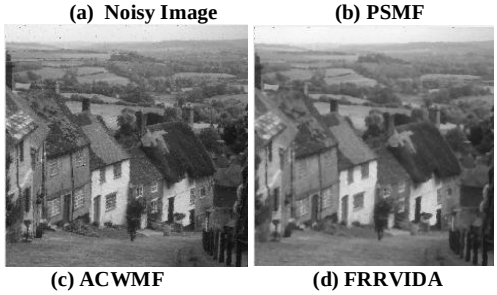


(c) ACWMF **(d) FRRVIDA**

Figure 3. Denoising results for Boat image(r=0.1)

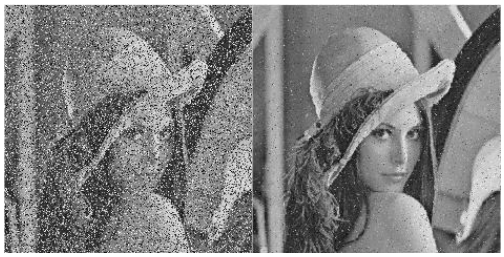


(a) Noisy Image **(b) PSMF**

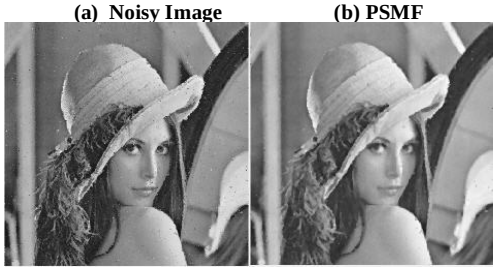


(c) ACWMF **(d) FRRVIDA**

Figure 4. Denoising results for Hill image(r=0.3)



(a) Noisy Image **(b) PSMF**



(c) ACWMF **(d) FRRVIDA**

Figure 5. Denoising results for Lena image(r=0.4)

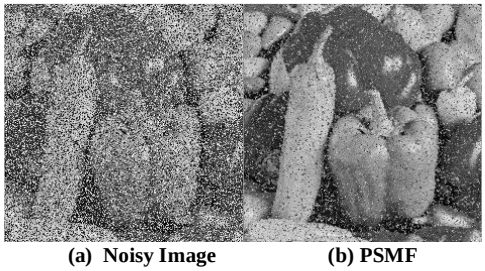


(a) Noisy Image **(b) PSMF**

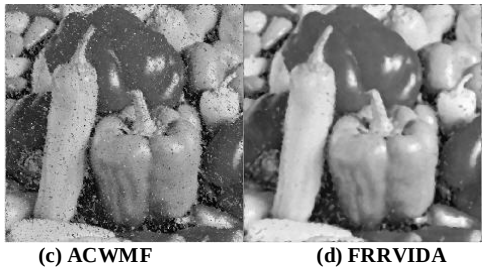


(c) ACWMF **(d) FRRVIDA**

Figure 6. Denoising results for Zelda image(r=0.5)

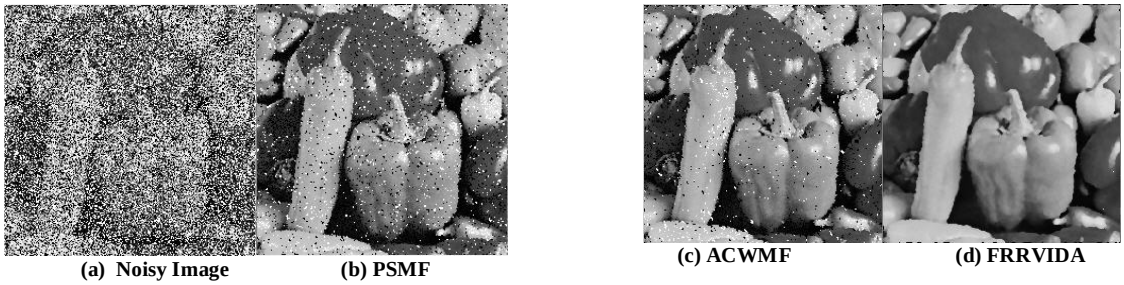


(a) Noisy Image **(b) PSMF**



(c) ACWMF **(d) FRRVIDA**

Figure 7. Denoising results for Peppers image(r=0.6)



(a) Noisy Image (b) PSMF (c) ACWMF (d) FRRVIDA

Figure 8. Denoising results for Peppers image(r=0.6)

Algorithm		PSMF	ACWMF	FRRVIDA
Peppers Image				
r	0.2	30.31(0.821)	**31.38(0.934)**	30.49(0.855)
	0.3	27.33(0.729)	**29.21(0.886)**	29.10(0.833)
	0.4	23.92(0.569)	26.82(**0.806**)	**27.18**(0.797)
	0.5	20.91(0.415)	23.87(0.682)	**24.64(0.739)**
	0.6	18.02(0.280)	20.64(0.520)	**21.71(0.663)**
Average		24.10(0.563)	26.38(0.766)	**26.62(0.777)**
Lena Image				
r	0.2	31.26(0.841)	**34.05(0.949)**	31.32(0.901)
	0.3	28.23(0.736)	**31.54(0.906)**	29.47(0.853)
	0.4	25.05(0.599)	**28.58(0.837)**	27.89(0.826)
	0.5	22.17(0.445)	25.8(0.731)	**26.03(0.774)**
	0.6	19.54(0.314)	22.83(0.585)	**23.51(0.716)**
Average		25.25(0.587)	**28.56**(0.802)	27.64(**0.814**)
Aircraft Image				
r	0.2	29.56(0.664)	**35.72(0.950)**	33.18(0.918)
	0.3	26.78(0.532)	**33.35(0.911)**	31.57(0.906)
	0.4	24.23(0.407)	**30.43**(0.837)	30.10(**0.888**)
	0.5	21.77(0.293)	27.53(0.718)	**27.62(0.862)**
	0.6	19.28(0.193)	24.26(0.547)	**24.98(0.809)**
Average		24.32(0.419)	**30.26**(0.793)	29.49(**0.877**)
Zelda Image				
r	0.2	32.64(0.842)	**37.70(0.957)**	33.81(0.902)
	0.3	29.15(0.724)	**34.39(0.915)**	32.83(0.883)
	0.4	25.27(0.571)	30.88(0.842)	**30.97(0.851)**
	0.5	21.86(0.411)	26.74(0.727)	**28.14(0.804)**
	0.6	18.83(0.277)	22.46(0.563)	**24.10(0.726)**
Average		25.55(0.565)	**30.43**(0.800)	29.97(**0.833**)

Table I. PSNR (SSIM) Results for Denoising Standard Images.

CONCLUSION

In this paper, an efficient impulse noise removal algorithm is presented. Experimental results indicate that the proposed FRRVIDA and ACWMF outperform PSMF over all impulse noise density rates. Even where FRRVIDA has not achieved highest PSNR or SSIM values (for $r \leq 0.4$), ACWMF and FRRVIDA achieve comparable denoising performance in terms of visual quality. For highly corrupted images ($r \geq 0.5$), results showed that the proposed algorithm outperforms ACWMF on the aspects of both PSNR/SSIM values and perceptual image quality. The main drawback of the PSMF is its incapability of dealing with highly corrupted images especially when $r \geq 0.3$. While, the major weakness of ACWMF is its high computation demands compared with both PSMF and FRRVIDA. The proposed algorithm has only window size parameter which can be easily assigned according to the image degradation level. Thus, the proposed algorithm performance, threshold free, and low computational complexity paved the way for possible implementation of the algorithm to meet real-time applications. The proposed algorithm can be extended to deal with mixed noise type such as Gaussian plus impulse noise of both types. This issue is left as future work.

REFERENCES

[1] Wang J., Lu C., Wang M., Li P., Yan S., and Hu X., "Robust Face Recognition via Adaptive Sparse Representation", IEEE Transactions on Cybernetics, Vol.44, No.12, pp.2368-2378, 2014.

[2] Hu Y., Chen J., Pan D., and Hao Z., "Edge-Guided Image Object Detection in Multiscale Segmentation for High-Resolution Remotely Sensed Imagery", IEEE

Transactions on Geoscience and Remote Sensing, Vol.54, No.8, pp.4702-4711, 2016.
[3] Hernández-Cabronero M., Blanes I., Pinho A. J., Marcellin M. W., and Serra-Sagristà J., "Progressive Lossy-to-Lossless Compression of DNA Microarray Images", IEEE Signal Processing Letters, Vol.23, No.5, pp.698-702, 2016.
[4] Gonzalez R. C., Woods R. E., and Eddins S. L., "Digital Image Processing Using MTLAB", Prentice Hall, 2010.
[5] Brownrigg D. R. K.," The Weighted Median Filter", Communications of the Association of Computing Machinery, Vol.27, No. 8, pp.807-818, 1984.
[6] Lin H. M., and Wilson A. N., "Median Filters with Adaptive Length", IEEE Transactions on Circuits and Systems, Vol.35, No.6, pp.675-690, 1988.
[7] Ko S. J., and Lee Y. H., "Center Weighted Median Filters and Their Application to Image Enhancement", IEEE Transactions on Circuits and Systems, Vol.38, No.9, pp.984-993, 1991.
[8] Hwang H., and Haddad R. A., "Adaptive Median Filters: New Algorithms and Results", IEEE Transactions on image processing, Vol.4, No.4, pp.499-502, 1995.
[9] Abreu E. and Mitra S. K., "A Signal-Dependent Rank Ordered Mean (SD-ROM) Filter-a New Approach for Removal of Impulses From Highly Corrupted Images", in Proceedings of International Conference on Acoustics, Speech, and Signal Processing (ICASSP-95), Vol. 4, pp. 2371 – 2374, 1995.
[10] Wang Z., and Zhang D., "Progressive Switching Median Filter for the Removal of Impulse Noise from Highly Corrupted Images", IEEE Transactions on Circuits and Systems, Vol. 46, No. 1, pp.78-80, 1999.
[11] Chen T., Ma K. and Chen L., "Tri-state Median Filter for Image Denoising", IEEE Transactions on Image Processing, Vol.8, No.12, pp.1834-1838, 1999.
[12] Chen T., and Wu H. R., "Adaptive Impulse Detection Using Center-Weighted Median Filters", IEEE Signal Processing Letters, Vol.8, No.1, pp.1–3, 2001.
[13] Chen T. and Wu H. R., "Space Variant Median Filters for the Restoration of Impulse Noise Corrupted Images", IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing, Vol. 48, No. 8, pp.784-789, 2001.
[14] Zhang S., and Karim M. A., "A New Impulse Detector for Switching Median Filters", IEEE Signal Processing Letters, Vol.9, No.11, pp.360–363, 2002.
[15] Crnojevic V., Senk V., and Trpovski Z., "Advanced Impulse Detection Based on Pixel-Wise MAD", IEEE Signal Processing Letters, Vol.11, No.7, pp.589 - 592, 2004.
[16] Nikolova M., "A Variational Approach to Remove Outliers and Impulse Noise", Journal of Mathematical Imaging and Vision, Vol. 20, No.1, pp. 99–120, 2004.
[17] Chan R. H., Hu C., and Nikolova M., "An Iterative Procedure for Removing Random-Valued Impulse Noise", IEEE Signal Processing Letters, Vol.11, No.12, pp.921–924, 2004.
[18] Chan R. H., Ho C.W., and Nikolova M., "Salt-and-pepper Noise Removal by Median-type Noise Detectors and Detail Preserving Regularization", IEEE Transactions on Image Processing, Vol. 14, No. 10, pp.1479–1485, 2005.
[19] Garnett R., Huegerich T., Chui C., and He W., "A Universal Noise Removal Algorithm With an Impulse Detector", IEEE Transactions on Image Processing, Vol.14, No.11, pp.1747-1754, 2005.
[20] Yuksel M. E., "A Hybrid Neuro-Fuzzy Filter for Edge Preserving Restoration of Images Corrupted by Impulse Noise", IEEE Transactions on Image Processing, Vol.15, No.4, pp. 928-936, 2006.
[21] Luo W., "Efficient Removal of Impulse Noise from Digital Images", IEEE Transactions on Consumer Electronics, Vol.52, No.2, 2006.
[22] Schulte S., Nachtegael M., De Witte V., Van der Weken D., and Kerre E.E., "A Fuzzy Impulse Noise Detection and Reduction Method", IEEE Transactions on image Processing, Vol.14, No.5, pp.1153–1162, 2006.
[23] Schulte S., De Witte V., Nachtegael M., Van Der Weken D., and Kerre E.E., "Fuzzy Random Impulse Noise Reduction Method", Fuzzy Sets and Systems, Vol.158, pp.270-283, 2007.
[24] Dong Y., and Xu S., "A New Directional Weighted Median Filter for Removal of Random Valued Impulse Noise", IEEE Transactions on Signal Processing Letters, Vol.14, No.3, pp.193-196, 2007.
[25] Kuykin D., Khryashchev V., and Apalkov I., "Modified Progressive Switched Median Filter for Image Enhancement", Proceedings of the International Conference on Computer Graphics and Vision, pp.303-304, 2009.
[26] Hsieh C. H., Hung S. Y., Lan C. W., and Huang P. C., "Impulse Noise Removal Based on Grey Polynomial Interpolation", Seventh Interpolation Conference on Information Technology, IEEE Proceedings, 2010.
[27] Toh K. K. V., and Isa N. A. M., "Cluster-Based Adaptive Fuzzy Switching Median Filter for Universal Impulse Noise Reduction", IEEE Transactions on Consumer Electronics, Vol.56, No.4, pp.2560-2568, 2010.
[28] Geng X., Hu X., and Xiao J., "Quaternion Switching Filter for Impulse Noise Reduction in Color Image", Signal Processing, Vol.92, pp.150–162, 2012.
[29] Sultana M., Uddin M. S., and Sabrina F., "High Density Impulse Denoising by a Novel Adaptive Fuzzy Filter", International Conference on Informatics, Electronics and Vision (ICIEV), pp.1-5, 2013.
[30] Hussain S. A., and Gorashi S. M., "Robust Outliers Exclusion for High Density Impulse Noise Suppression Algorithm", IEEE International Conference on Signal and Image Processing Applications, Melaka, pp.43-48, 2013.
[31] Jin L., Zhu Z., Xu X., and Li X., "Two-Stage Quaternion Switching Vector Filter for Color Impulse Noise Removal", Signal Processing, Vol. 128, pp.171-185, 2016.
[32] Wang Z., Bovik A. C., Sheikh H. R., and Simoncelli E. P., "Image Quality Assessment: From Error Visibility to Structural Similarity", IEEE Transactions on Image Processing, Vol. 13, No. 4, pp. 600-611, 2004.

★★★