Modified Pixels based Fast Median Filter in Impulse Noise Environments

Man Hee Lee and Soo Young Shin
Department of IT Convergence Engineering Wireless and Emerging Network System (WENS) Lab. Kumoh National Institute of Technology, Gumi, South Korea, 39711

Article Info

Article history:

Received Jun 9, 2017
Revised Nov 20, 2017
Accepted Dec 21, 2017

Keywords:

Pixel Modification
Cyclic Redundancy Check (CRC)
Impulse Noise
Median Filter (MF)
Noise Mitigation

ABSTRACT

This paper proposes a modified pixel-based fast median filter (MP-FMF) for impulse noise environ- ments. The key idea behind MP-FMF is the reduction in the processing time by using modified pixels. It consists of three steps, namely, error detection, threshold decision, and noise mitigation. The presence of noise is detected by using modified pixels that include a cyclic redundancy check (CRC) function. Subse- quently, the threshold values are decided by estimating the noise density. For noise mitigation, corrupted pixels are corrected with the neighboring pixels based on the principle of the median filter. The MP-FMF has a fast processing time and provides image quality correction and introduces features when the noise density is high. In addition, we introduce a new evaluation metric and investigate the performance of the proposed algorithm in terms of the quality, features, and computation time.

.

Corresponding Author:

Soo Young Shin,
Department of IT Convergence Engineering Wireless and Emerging Network System (WENS),
Lab. Kumoh National Institute of Technology,
Gumi, South Koread, 39711.
Email: wdragon@kumoh.ac.kr

1. INTRODUCTION

The dramatic development in both Internet and wireless communications has resulted in images and videos being transmitted wirelessly. Numerous multimedia applications such as enter- tainment, video surveillance, and medical imaging, that are primarily based on images and videos are thriving in proportion to the increasing number of hand-held Internet devices such as smart phones and tablets. Among these applications, visual signal processing is gaining increased at- tention for handling visual information transmissions over error-prone wireless communications. Owing to the nature of wireless technologies, noise handling is one of the primary issues for visual information, particularly in image processing areas, such as acquisition and transmission.

Noise is a known phenomenon in image processing that frequently causes data corrup- tion. Among common noise contributors, impulse noise is also known for its vital role in pre- processing steps. It results in dead pixels, error in data transmission, malfunction of pixel ele- ments in camera sensors, and timing errors during the process. [1-3] Various methods have been developed to remove the unwanted component, i.e., impulse noise for a device or process. Various image processing methods such as compression, filtering, rotating, scaling, and aver- aging have been proposed to recover the original images. In particular, filtering provides better quality visuals and overcomes the noise problem. The details of this are mentioned in [4].

Algorithms for filtering for achieving better results have already been suggested in digital image processing. Some of the algorithms are: standard median filter (SMF) [5], weighted me- dian filter (WMF) [6], center weighted median filter (CWMF) [7], switching weighted median filter (SWMF) [8], recursive median filter (RMF) [9], and iterative median filter (IMF) [10]. Most of the algorithms use a nonlinear approach to avoid cases in which noise is not additive and a linear filter failure occurs.

This is the same for conventional approaches in which the processing time increases with the size or resolution of the image. This is because high-quality images increase the processing time. The proposed algorithm attempts to solve this problem by exploiting modified pixels for detecting corrupted pixels. The SMF has to be modified and reconfigured to formulate a new methodology for correcting the image quality. The combination of detection and correction pro- duces image features. We introduce a new evaluation metric and investigate the performance of the proposed algorithm on the basis of quality, featuring, and computation time.

The significant contributions of this paper are as follows:

a. The quality of the proposed algorithm is ensured by image quality assessment (IQA). This is shown in detail for two categories: pixel based and human visual system (HVS) based IQA.
b. A fast processing time is achieved compared to other algorithms: MF and AMF.
c. A new evaluation technique is introduced for examining the effect of varying the window size with static image resolution.

The rest of this paper is organized as follows: Section 2. briefly introduces two types of filters and evaluation techniques for the background ti compare with conventional algorithms. In Section 3, the different steps of the proposed algorithm are described: error detection, threshold decision, and noise mitigation. Furthermore, a new evaluation technique is explained. Computa- tion time and featuring are considered for performance evaluation. The results considering these parameters are discussed in Section 4. Finally, the conclusions of the study are presented.

2. RELATED WORKS

2.1. Filtering algorithm

As previously mentioned, various filtering algorithms have been investigated to recover images from impulse noise. In this section, we discuss two filter algorithms, focusing on their advantages and disadvantages in detail.

The mean filter (MF) is a simple linear filter that is an easy and intuitive to implement algorithm for smoothing images. The concept of the MF is to replace each pixel intensity value in an image with the mean of its neighboring pixels. This reduces the amount of variation in the intensity between the pixels; however, a single pixel with a very untypical value can affect the mean significantly.

The median filter is a nonlinear filter that is also called the standard median filter (SMF). It is a consistent algorithm to remove impulse noise. The value of the center pixel is replaced by the median of the neighboring pixels based on the size of the window. The SMF is effective at low noises, but it cannot differentiate between corrupted and non-corrupted pixels.

The adaptive median filter (AMF) is designed to solve the issue that SMF faces. The difference between both the filters is that AMF has a variable window size surrounding each center pixel and it leverages the center pixel based on the threshold. Therefore, AMF has been applied broadly as an advanced algorithm of MF because it can reduce distortions such as excessive thinning or thickening of object edges.

2.2. Evaluation techniques

To measure the quality of the images, IQA is exploited, and it is broadly classified into two categories: pixel based and HVS based. For pixel based IQA, the peak signal-to-noise ratio (PSNR) and weighted PSNR are two representative IQA models that are expressed in dB. For HSV based IQA, multi-scale structural similarity (MS-SSIM), universal quality index (UQI), and feature similarity (FSIM) have provided image quality according to human perception. It must have a maximum unit value while making different contributions in the view of IQA.

The PSNR is the ratio between the maximum original power and corrupting noise power, and it operates directly on the intensity of the image. The well-known PSNR is usually applied to a single channel. WPSNR is an extended version of PSNR to cope with the limitation of having multiple weighting factors. These weight coefficients are provided for three different color channels [11].

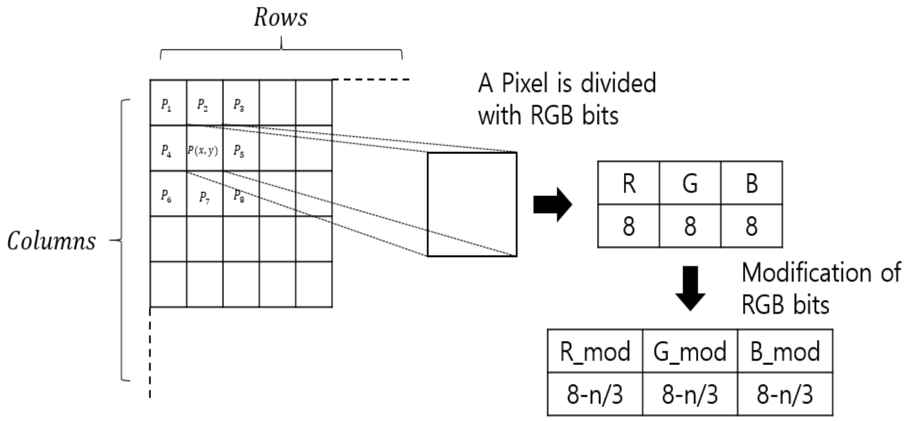


Figure 1. System model of the modified pixels

To measure the quality of the images, IQA is exploited, and it is broadly classified into two categories: pixel based and HVS based. For pixel based IQA, the peak signal-to-noise ratio (PSNR) and weighted PSNR are two representative IQA models that are expressed in dB. For HSV based IQA, multi-scale structural similarity (MS-SSIM), universal quality index (UQI), and feature similarity (FSIM) have provided image quality according to human perception. It must have a maximum unit value while making different contributions in the view of IQA.

The PSNR is the ratio between the maximum original power and corrupting noise power, and it operates directly on the intensity of the image. The well-known PSNR is usually applied to a single channel. WPSNR is an extended version of PSNR to cope with the limitation of having multiple weighting factors. These weight coefficients are provided for three different color channels [11]

MS-SSIM is an extension of SSIM, having more flexibility for varying the viewing condi- tions. Furthermore, UQI is expressed as a combination of three factors, namely, loss of corre- lation, luminance distortion, and contrast distortion. It exhibits a better performance than mean square error (MSE). Lastly, FSIM is based on low-level features. In particular, phase congruency is used as the primary feature, and it is a dimensionless measure of significant local structure [12, 13]

3. MODIFIED PIXEL-BASED FAST MEDIAN FILTER (MP-FMF)

3.1. Modified Pixel

In this section, we have proposed a modified pixel for modifying the original pixel format before transmission. This is a mandatory step for applying the proposed algorithm. The system model of the modified pixels is shown in Figure 1. Let us assume that $\boldsymbol{i} \times \boldsymbol{j}$ size of image has $\boldsymbol{i} \times \boldsymbol{j}$ number of pixels. It is defined that the center pixel is expressed as $P(x, y)$ and the neighboring pixels are represented by P_1 to P_8. A pixel is expressed as 8 bits in the binary system. We consider the least significant bit (LSB) to generate the cyclic redundancy check (CRC) code in a pixel with n polynomials. The length of the polynomial affects the length of LSB that is expressed in $8 - \boldsymbol{n}/3$ bits. The code rate is the same as with normal pixels because binary bits are encoded in the range of LSB with polynomial n.

When the proposed pixel is applied to the edge pixels, extra pixel information is required. In the SMF, the edge pixels are not allowed to perform filtering owing to the lack of neighboring pixels. However, an extended mask for the image for every edge pixel is suggested in this paper to cope with this limitation. This concept of an extended mask is mentioned in [14]. The image is surrounded with zero value of pixels as an extended mask, as shown in Figure 2. The size of the extended mask is denoted as $(\boldsymbol{i} + 2) \times (\boldsymbol{j} + 2)$.

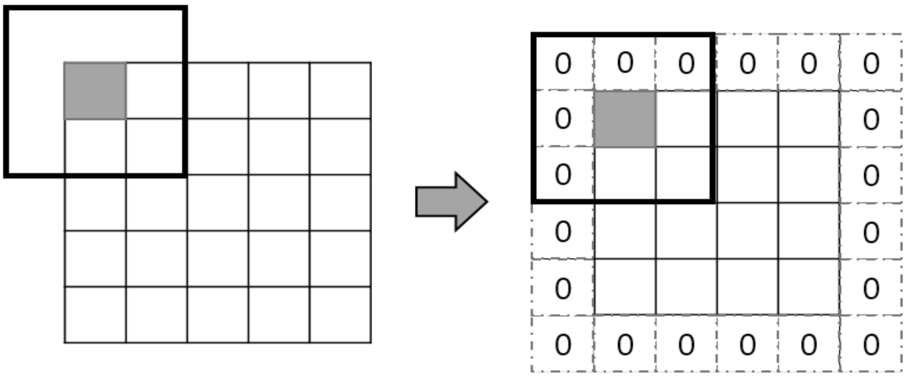


Figure 2. Extended mask for an image

3.2. Proposed Algorithm

MP-FMF uses an extended mask of $(i + 2) \times (j + 2)$ size and applies the CRC code for detecting the error pixels. Center pixel $P(x, y)$ is replaced with the median value of the neighboring pixels when an error pixel is detected by the CRC code. The following are the steps of the MP-FMF algorithm as represented from the receiver side:

1. The algorithm implements two iterations. In the first iteration, the original pixels are reshaped for the modified pixels, and each pixel is isolated with information bits. Among these bits, LSB 2 bits of each pixel are subtracted and exploited to encode the original bits using n polynomial.
2. If a pixel has an error, then the value of the corresponding pixel is processed from the received image with median filtering having error detected marks. The replaced pixel can be represented as:

$$P(x, y) = med(W_1P_1, \cdots, W_8P_8) \tag{1}$$

$$W_k = \begin{cases} 0, & \text{if the pixel has an error} \\ 1, & \text{otherwise} \end{cases} \tag{2}$$

where W_k is the k_{th} error detected mark and $med(\cdot)$ is the median function. The error detected mark is used for introducing an expression on the corrupted pixels.

3. T he second iteration process is applied to grab the fickle values on the pixels that are error pixels. MP-FMF works by the same process as the first iteration as follows:

$$P_(x, y) = med(W_1P_1, \cdots, W_8P_8) \quad \text{if } P(x, y) < P_{th} \tag{3}$$

where P_{th} denotes the threshold value for suppressing the impulse noise.

Overall, MP-FMF has three steps: error detection, threshold decision and noise mitigation. In the first iteration, the proposed algorithm has a functionality for detecting the corrupted pixels. In the second iteration, it suppresses the fickle noise for the decision. The combination of the two iterations achieves mitigation of the impulse noise from the image.

3.3. New evaluation technique: proportional check

We named the new evaluation technique as proportional check in accordance with its characteristic. This technique is described in a different way compared with conventional evalu- ations that are focused on window size for performance. Usually different window sizes can be adjusted to increase the performance of filtering. In this paper, we suggest that the proposed evaluation technique has a similar effect on the performance by varying the window size. The simple proportion mathematics shown in Figure 3 can be represented as (4).

$$\begin{aligned} Vi &: Xi = Wi : Yi \\ Vj &: Xj = Wj : Yj \end{aligned} \tag{4}$$

For example, let us assume that there are two different resolutions of images. The image resolution of 512 × 512 is for $X_{i,j}$ and 256 × 256 is for $Y_{i,j}$, respectively. When window size $V_{i,j}$ is supposed to be 9, the other $W_{i,j}$ can be calculated as 3 with the ceiling. This implies that the effect of varying the window size can be noticed if the window size of the image is static and varies with the image resolution.

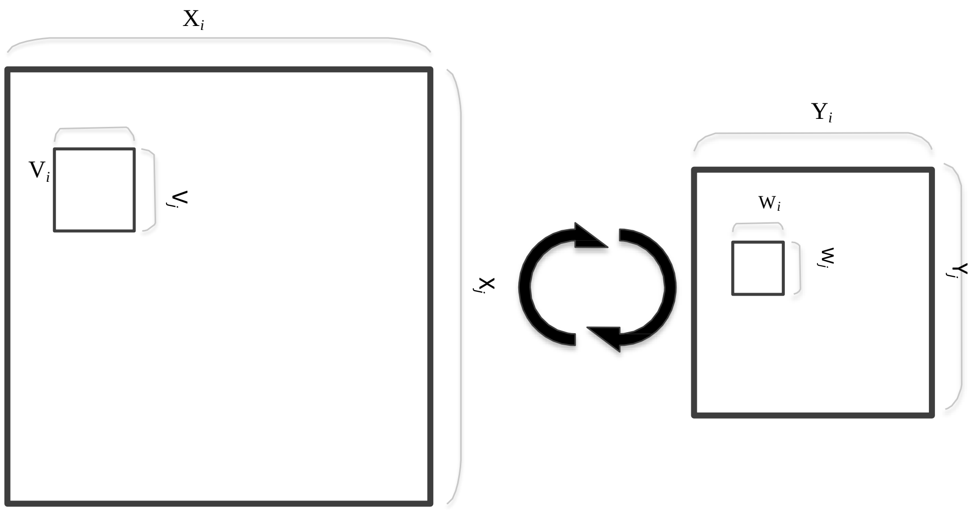


Figure 3. Proporton technique for evaluation of the window size

4. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we demonstrate the performances of the proposed, MF, and AMF method- ologies, i.e., we verify the effectiveness in terms of quality, computational time, and featuring. In addition, we introduce a new performance technique for examining the effect of the window size on the filtering algorithm.

In Figure 4, we have used four standard images, namely, lena, aerial, airplane, and peppers to compare their quality perceptually. The first iteration shows various pixels containing the salt and pepper noise, but the second iteration of the proposed algorithm produces a view that is similar to MF and AMF. The results have been derived from image sizes 256 × 256 with 10% noise density.

In Figure 5, we have presented each filtering method under three conditions of noise density ranging from 10% to 30%. To be specific, a canny edge detector that was developed by John F.

Canny in [15] is used to clearly show the featuring performance. When the noise density is 30%, the second iteration of the proposed method shows a superior performance than the other algorithms in terms of the featuring quality.

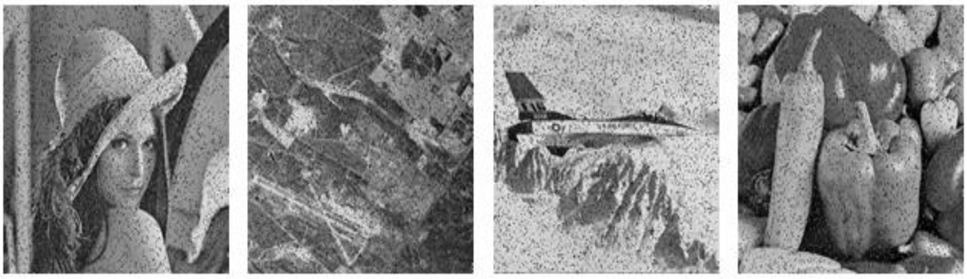
In Figure 6, a new evaluation metric is presented to compare the effect of varying the window size. The image resolution is increased by three steps from 128 × 128 to 512 × 512, and the noise density is the same as in Figure 4. It can be seen that decreasing the resolution of the images leads to a perpetual high-quality performance according to the principle of the effect of increasing window size.

To evaluate the proposed algorithm, we categorized two IQAs: pixel based and HVS based that are shown in Table 1. The proposed method has 8 dB less PSNR and WPSNR (pixel based) under same test environments as shown in Figure 4. For MS-SSIM and FSIM (HVS based), the proposed method has less 0.06 except for the peppers image. For UQI, only the aerial image of the proposed method has a higher value than MF. Generally, the highest quality is shown with the MF and least quality with the AMF because the MF averages each pixel value and the AMF reduces the size of the image as a buffer size.

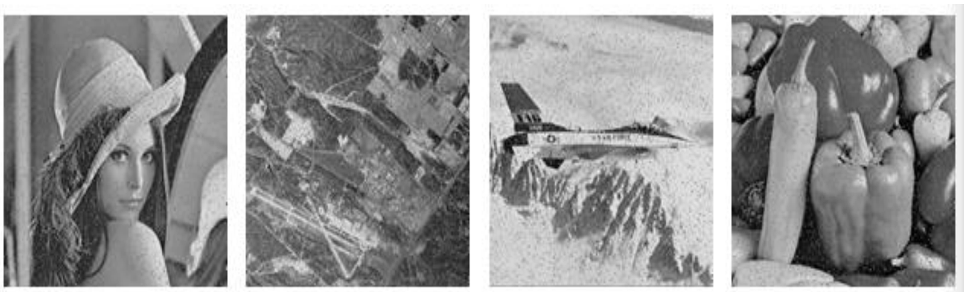
Finally, the computation time is obtained through the analysis of the total simulation time, as shown in Figure 7. The proposed algorithm includes the steps of detecting corrupted pixels and operating the SMF principle. The blue bar represents the processing time of conventional algorithms and the red bar shows the proposed varying image size from 128 × 128 to 512 × 512. Conventional algorithms show an exponential increase, while the second iteration of the proposed algorithm requires 10 % less time on image size 512 × 512.

(a) MF

(b) AMF

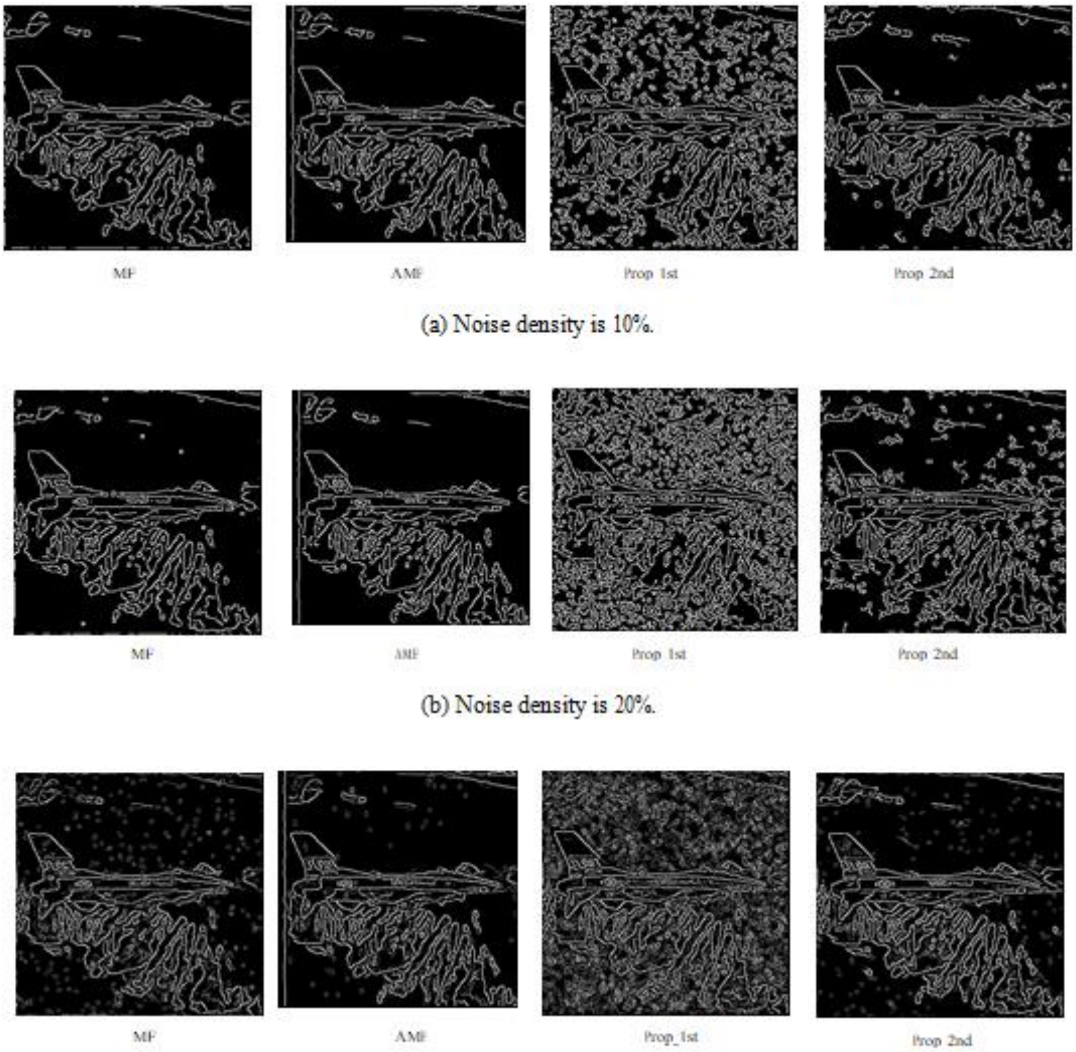


(c) First iteration of proposed algorithm



(d) Second iteration of proposed algorithm

Figure 4. Comparison of MF, AMF, and the proposed algorithm

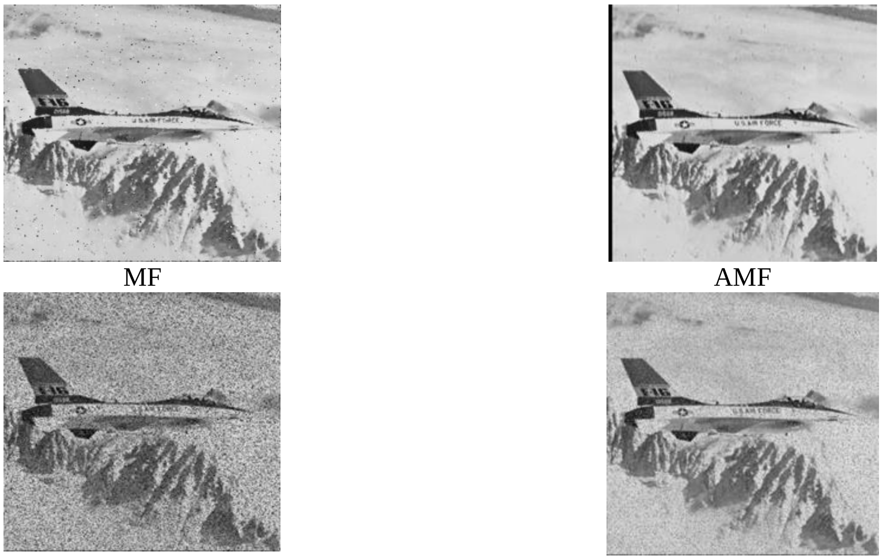


(a) Noise density is 10%.

(b) Noise density is 20%.

(c) Noise density is 30%.

Figure 5. Noise variance comparison of MF, AMF, and the proposed algorithm



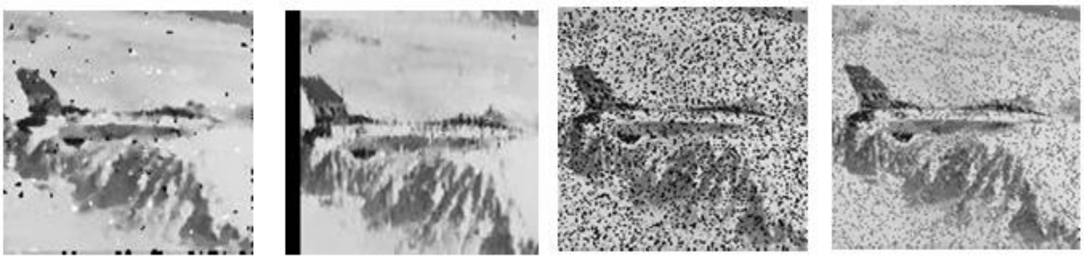
MF AMF

Prop 1st Prop2nd

(a) Resolution 512 × 512

MF AMF Prop 1st Prop 2nd

(b) Resolution 256 × 256.



MF AMF Prop_1st Prop 2nd

(c) Resolution 128 × 128.

Figure 6. Results for various resolutions using MF, AMF, and the proposed algorithm

Table 1. Comparison of the evaluation techniques

Cover image		MF	AMF	Prop 1st	Prop 2nd
Lena	PSNR [dB]	29.5428	15.2148	17.6437	25.2551
	WPSNR [dB]	30.8820	21.1815	27.7601	30.1986
	MS-SSIM				
	UQI	0.9855	0.9426	0.8148	0.9507
	FSIM				
		0.8527	0.6994	0.3581	0.6527
Aerial	PSNR [dB]	25.2960	15.1956	18.2225	26.0988
	WPSNR [dB]	31.3956	21.8791	29.6754	32.0955
	MS-SSIM				
	UQI	0.9545	0.8686	0.8629	0.9727
	FSIM				
		0.7020	0.4981	0.5347	0.8504
Airplane	PSNR [dB]	27.8772	11.9704	15.5135	24.5831
	WPSNR [dB]	30.6367	17.4631	26.3200	31.2960
	MS-SSIM				
	UQI	0.9835	0.9085	0.6911	0.9314
	FSIM				
		0.7479	0.5650	0.2700	0.5791
Peppers	PSNR [dB]	30.3171	14.7480	18.0435	23.8062
	WPSNR [dB]	35.8700	20.6382	28.0805	31.4062
	MS-SSIM				
	UQI	0.9907	0.9482	0.8314	0.9353
	FSIM				
		[illegible]	[illegible]	[illegible]	[illegible]

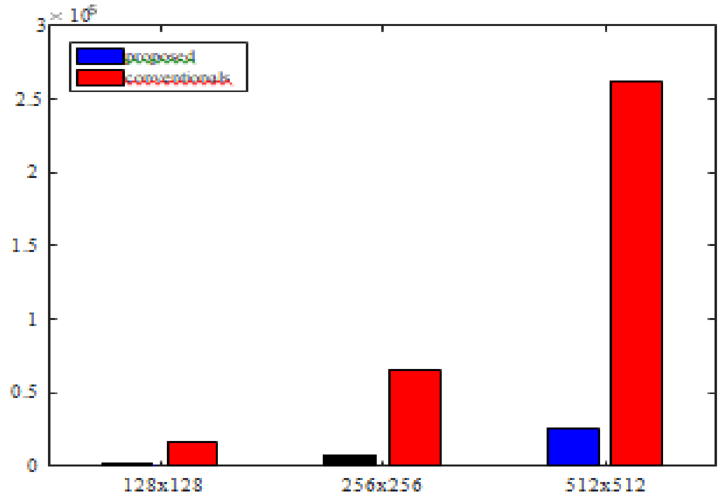


Figure 7. Computation time varying image resolution

5. CONCLUSIONS

In this study, we have demonstrated the use of modified pixel-based fast median filter (MP-FMF) for impulse noise environments. MP-FMF is divided into two parts, where the first is for detecting corrupted pixels with modified pixels, and the second is for overcoming the fickle noise with defined threshold values. Therefore, it exhibits less difference of approximately 8 dB in PSNR and WPSNR (pixel based) and of 0.06 in MS-SSIM and FSIM (HVS based) compared with two algorithms. MF and AMF are processed on the entire pixels, e.g., on the complete size of the image, thereby increasing the processing time exponentially. MP-FMF works on corrupted pixels and suppresses unstable noises. Therefore, it shows a linear increase in computation time. In the future, a shifting window size will be applied to increase the image quality similar to AMF. In another approach, a conditional switching filter between contemporary algorithms and the proposed algorithm based on various noise environments will be utilized.

ACKNOWLEDGEMENT

This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(2015R1D1A1A01061075).

REFERENCES

[1] R. Laskar, B. Bhowmick, R. Biswas, and S. Kar, “Removal of impulse noise from color image,” in *TENCON* 2009-2009 IEEE Region 10 Conference. IEEE, 2009, pp. 1–5.

[2] J. Harikiran, B. Saichandana, and B. Divakar, “Impulse noise removal in digital images,” International Journal of Computer Applications (0975–8887) Volume, 2010.

[3] D. Henderson and R. Hamernik, “Impulse noise: critical review,” The Journal of the Acoustical Society of America, vol. 80, no. 2, pp. 569–584, 1986.

[4] J. Pang, S. Zhang, and S. Zhang, “A median filter based on the proportion of the image variance,” in Information Technology, Networking, Electronic and Automation Control Confer- ence, IEEE. IEEE, 2016, pp. 123–127.

[5] T. Huang, G. Yang, and G. Tang, “A fast two-dimensional median filtering algorithm,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 27, no. 1, pp. 13–18, 1979.

[6] A. R. Lokhande, M. Das, and D. Salunke, “Efficient removal of impulse noise and analyze performance of median filter and center weighted median filter,” International Journal of En- gineering Science, vol. 2883, 2016.

[7] S. J. Ko and Y. H. Lee, “Center weighted median filters and their applications to image en- hancement,” *IEEE Transactions on Circuits and Systems*, vol. 38, no. 9, pp. 984–993, Sep. 1991.

[8] O. S. Faragallah and H. M. Ibrahem, “Adaptive switching weighted median filter framework for suppressing salt-and-pepper noise,” *AEU-International Journal of Electronics and Com- munications*, vol. 70, no. 8, pp. 1034–1040, 2016.

[9] A. Burian and P. Kuosmanen, “Tuning the smoothness of the recursive median filter,” *IEEE Transactions on Signal Processing*, vol. 50, no. 7, pp. 1631–1639, Jul 2002.

[10] S. Hoyos, J. Bacca, and G. R. Arce, “Spectral design of weighted median filters:a general iterative approach,” *IEEE Transactions on Signal Processing*, vol. 53, no. 3, pp. 1045–1056, March 2005.

[11] F. De Simone, D. Ticca, F. Dufaux, M. Ansorge, and T. Ebrahimi, “A comparative study of color image compression standards using perceptually driven quality metrics,” in *SPIE Optics and Photonics, Applications of Digital Image Processing XXXI*, vol. 70730, no. MMSPL-CONF-

[12] 2008-007. SPIE, 2008.

[13] Z. Wang, E. P. Simoncelli, and A. C. Bovik, “Multiscale structural similarity for image quality assessment,” in *Signals, Systems and Computers, 2004. Conference Record of the Thirty- Seventh Asilomar Conference on*, vol. 2. IEEE, 2003, pp. 1398–1402.

[14] L. Zhang, L. Zhang, X. Mou, and D. Zhang, “Fsim: A feature similarity index for image quality assessment,” *IEEE transactions on Image Processing*, vol. 20, no. 8, pp. 2378–2386, 2011.

[15] C. H. Seong and S. Y. Shin, “Adjacent pixels based noise mitigation filter in salt & pepper noise environment,” *Journal of the Institute of Electronics and Information Engineers*, vol. 54, no. 6, pp. 65–71, 2017.

[16] J. Canny, “A computational approach to edge detection,” *IEEE Transactions on pattern anal- ysis and machine intelligence*, no. 6, pp. 679–698, 1986.