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A random exploration based fast adaptive and selective mean filter for salt and pepper noise removal in satellite digital images

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ABSTRACT

The digital image is one of the discoveries that play an important role in various aspects of modern human life. These findings are useful in various fields, including defense (military and non-military), security, health, education, and others. In practice, the image acquisition process often suffers from problems, both in the process of capturing and transmitting images. Among the problems is the appearance of noise which results in the degradation of information in the image and thus disrupts further processes of image processing. One type of noise that damages digital images is salt and pepper noise which randomly changes the pixel values to 0 (black) or 255 (white). Researchers have proposed several methods to deal with this type of noise, including median filter, adaptive mean filter, switching median filter, modified decision based unsymmetric trimmed median filter, and different applied median filter. However, this method suffers from a decrease in performance when applied to images with high-intensity noise. Therefore, in this research, a new filtering method is proposed that can improve the image by randomly exploring pixels, then collecting the surrounding pixel data from the processed pixels (kernel). The kernel will be enlarged if there are no free-noise pixels in the kernel. Furthermore, the damaged pixels will be replaced using the mean data centering statistic. Images enhanced using the proposed method have better quality than the previous methods, both quantitatively (SSIM and PSNR) and qualitatively.

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INTRODUCTION

The digital image is one of the discoveries that play an important role in various aspects of modern human life. These findings are useful in various fields, including defense (military and non-military), security, health, education, and others. The digital image is acquired from a light-sensing device namely camera, then translated into numerical code according to the level of captured light intensity. One technology that utilizes the concept of digital imagery is satellite. This technology is capable of capturing and transmitting images of the earth surface from space which are then used for geographic, defense, security and intelligence. However, in practice, the process of acquiring images from satellites (or other light-sensing devices) often encounters problems, both during the process of capturing and transmitting images (Abdurrazzaq, Junoh, et al., 2020; Wenbin Luo, 2006). A common problem is the emergence of noise that results in degraded information contained in the image and interferes with further process in image processing (Fan et al., 2018).

Type of noise that often damage digital images is salt and pepper (SnP) noise. This noise randomly changes the pixel value in digital images to 0 (deep black) or 255 (bright white) (Singh et al., 2018). Such defects can be corrected by filtering method on the digital images. Median and Mean Filter are basic filtering techniques based on a statistical approach. This technique utilizes the pixel values around the processed pixel (neighborhood pixel/kernel) as a reference to restore image information on damaged pixels. However, these methods have drawbacks, that the restored image suffers a decrease in quality if the noise existence on the image are more than 20% of the total pixels. This means that the method cannot work effectively when dealing with high-intensity noise (Chan et al., 2005). In addition, if the kernel size is large, the restored image is blurred, making further image processing difficult.

Banyak metode telah diusulkan untuk menghilangkan SnP noise dengan menggunakan pendekatan statistika seperti Median Filter dan Mean Filter (Chan et al., 2005; Charmouti et al., 2022; Chen & Hong Ren Wu, 2001; Sheik Fareed & Khader, 2018) and pendekatan lain seperti Fuzzy and Algebra (Abdurrazzaq et al., 2019; Abdurrazzaq, Mohd, et al., 2020; Ojha & Tiwari, 2015; Singh et al., 2018).

Fareed and Khader (2018) have proposed the Fast Adaptive and Selective Mean Filter (FASMF) method to overcome salt and pepper noise (Sheik Fareed & Khader, 2018). FASMF method is able to overcome the drawbacks of the previous methods, such as Standard Median Filter (MF) (Chan et al., 2005), Switching Median Filter (SMF) (Sun & Neuvo, 1994; Zhou Wang & Zhang, 1999), Adaptive Median Filter (AMF) (Zhou Wang & Zhang, 1999), or Adaptive Center Weighted Median Filter. (ACWMF) (Chen & Hong Ren Wu, 2001). FASMF method is also able to work well for images with high intensity noise. However, FASMF method is still not optimal in performing images restoration. This method does not use the repaired pixels as a reference to replace other damaged pixels. As a result, in the process of substituting damaged pixels for images with high intensity noise, the FASMF method will increase the kernel size excessively. This will result in the FASMF algorithm being less efficient and the image texture being damaged. Therefore, this article proposes a new filtering method to overcome salt and pepper noise. This method is a modification of FASMF, but accommodates the repaired pixels as a reference for substitution of damaged pixels in other indexes. The proposed method also performs random pixel exploration so as to minimize the accumulation of errors in pixel references for improvement.

METHOD

1. Experimental Data

The objects studied in this paper are standard digital images used in image processing research, such as "Lena", "Cameraman", "Mandrill", "Plane", "Pepper", "Woman Blonde", "Lake", "Castle", "Living Room", "Pirates", "Bridge", and "Woman Dark Hair". This study also uses satellite image as experimental data. These images are available online in the "Image Database" in ([Online], n.d.). These images are grayscale images with a resolution of 512×512 pixels and 1024×1024 pixels.

2. Proposed Method

The proposed method to restore damage image caused by SnP noise works in two stages, namely noise detection stage, and pixel restoration stage.

1) Noise detection stage

Similar to the procedure performed by several existing methods, noise detection is performed by transforming the image matrix into a binary matrix with the transformation defined as follows:

$$\boldsymbol{T(x,y)} = \begin{cases} \mathbf{1}, \textbf{if } \boldsymbol{N(x,y)} = \mathbf{255} \textbf{ or } \mathbf{0} \\ \mathbf{0}, \quad \textbf{other} \end{cases} \quad \textbf{(1)}$$

T is a transformation that converts a matrix of noisy image N size $m \times n$ in pixels (x, y) into a binary matrix A with $\boldsymbol{A(x,y) = T(x,y)}$, $(\boldsymbol{x},\boldsymbol{y}) \in (\mathbb{Z}_{\boldsymbol{m}} + \mathbf{1}) \times (\mathbb{Z}_{\boldsymbol{n}} + \mathbf{1})$. Matrix A contains of the noisy pixel index on matrix $\boldsymbol{N}$. $\boldsymbol{A(x,y)}$ will have the value 1 if $\boldsymbol{N(x,y)}$ is a noisy pixel and the value 0 otherwise. Matrix A will be the reference in performing restoration of damaged images by salt and pepper noise.

2) Pixel restoration stage

a) Pre-restoration

In the repair stage, the pixels that are processed are only the $(\boldsymbol{p},\boldsymbol{q}) \,\boldsymbol{\epsilon}\, (\mathbb{Z}_{\boldsymbol{m}} + \mathbf{1})\, \boldsymbol{x}\, (\mathbb{Z}_{\boldsymbol{n}} + \mathbf{1})$ pixels in N which correspond to index A, where $\boldsymbol{A(p,q) = 1}$. An then, set $\boldsymbol{B} = \{\, (\boldsymbol{p},\boldsymbol{q}) \,\boldsymbol{\epsilon}\, (\mathbb{Z}_{\boldsymbol{m}} + \mathbf{1})\, \boldsymbol{x}\, (\mathbb{Z}_{\boldsymbol{n}} + \mathbf{1}),\ \boldsymbol{A(p,q)} = \mathbf{1} \,\}$. Member B must be unique and the members are pixels in N that are damaged by noise/noise. The next step is to take one member of B at random and do the restoration.

b) Restoration

Suppose cardinal B, $\boldsymbol{kard(B) = k}$, $\boldsymbol{k} \,\boldsymbol{\epsilon}\, \mathbb{Z}$. The first member is randomly selected in the set B, suppose $(\boldsymbol{p_1},\boldsymbol{q_1}) \,\boldsymbol{\epsilon}\, \boldsymbol{B}$ and it will be Index in matrix N which has restored in the first place. The restoration process begins with the creation of the kernel $\boldsymbol{W(p_1,q_1)}$ for data restoring reference as pixel replacement $\boldsymbol{N(p_1,q_1)}$, with the definition $\boldsymbol{W(p_1,q_1)}$ as follows:

$$\boldsymbol{W(p_1,q_1) = N(L\ x\ M)} \qquad \textbf{(2)}$$

$$\boldsymbol{L} = \{\, \boldsymbol{p_1 - l},\ \boldsymbol{p_1 - l + 1}, \dots, \boldsymbol{p_1}, \dots, \boldsymbol{p_1 + l - 1},\ \boldsymbol{p_1 + l} \,\} \cap [\, \mathbf{1}, \boldsymbol{n} \,] \cap \mathbb{Z}, \text{ dan } \boldsymbol{M} = \{\, \boldsymbol{q_1 - l},\ \boldsymbol{q_1 - l + 1}, \dots, \boldsymbol{q_1}, \dots, \boldsymbol{q_1 + l - 1}, \boldsymbol{q_1 + l} \,\} \cap [\, \mathbf{1}, \boldsymbol{m} \,] \cap \mathbb{Z}$$

At the initial stage, set kernel $\boldsymbol{l}$ with width 1. $\boldsymbol{l}$ will enlarge if W does not contain at least two members with entries not 0 or 255. This is meant so that data substitution pixel reference $\boldsymbol{N(p_1,q_1)}$ is not bias and to avoid damage to the texture of the repaired image. After obtaining the eligible kernel (when l stops growing), substitute $\boldsymbol{N(p_1,q_1)}$ with average statistical data center formulation for all entries that are neither 0 nor 255, as follows:

$$\boldsymbol{N(p_1,q_1) = mean(W_{W \neq 0 \,\cap\, W \neq 255})} \qquad \textbf{(3)}$$

This procedure continues until the k^{th} iteration so that all noisy pixels in N have been fixed.

To make it easier to understand how the proposed method works in the digital image restoration process, consider the following pseudocode and flowchart:

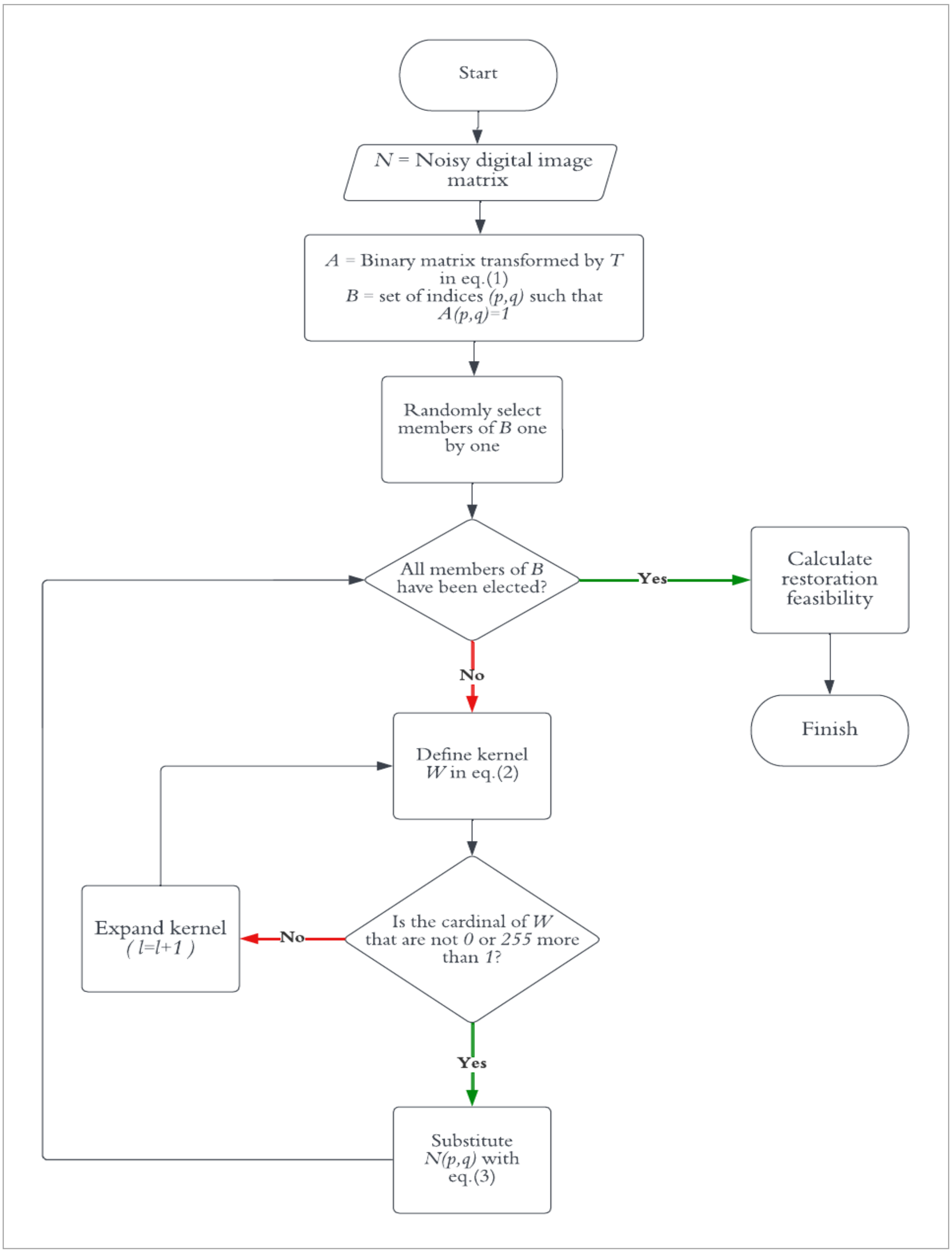


Figure 1. Flowchart

3) Image quality assessment

After the noisy image N was corrected using the proposed method, a feasibility test of the method was carried out by comparing the Peak Signal-to-Noise Ratio (PSNR) value and computational time between this method and other existing methods.

PSNR is the ratio between the maximum value of the signal/pixel measured by the amount of interference that affects the signal/pixel. PSNR is usually measured in decibels (dB). PSNR is used to compare the quality of the original image with the improved image. To determine the PSNR, the MSE (Mean Square Error) value must first be determined. MSE is the average squared error value between the original image and the repaired image. PSNR and MSE can be calculated by the following formula

$$PSNR = 20 \log_{10} \frac{255}{\sqrt{MSE}} \quad (4)$$

$$MSE = \frac{1}{m\,x\,n} \sum_{x=1}^{m} \sum_{y=1}^{n} \left(S_{xy} - C_{xy}\right)^2 \quad (5)$$

where (x, y) is pixel coordinate, $m \times n$ is the image size, S_{xy} represents the repaired image, and C_{xy} represents the original image. The greater the PSNR value of the improved image,the better the quality of the method used.

SSIM is a perception-based model. SSIM calculates how good digital images look to people. It compares between the original image and the restored image to determine the similarity of the images. The SSIM formula is calculated as follows.

$$SSIM = \frac{(2\mu_x\mu_y + C_1) + (2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1) + (\sigma_x^2 + \sigma_y^2 + C_2)} \quad (6)$$

where μ_x (σ_x) is the average intensities (standard deviation) value in x direction and μ_y (σ_y) is the average intensities (standard deviation) value in y direction. Additionally, C_1 and C_2 are constants that keep the SSIM value at one.

Meanwhile, computational time is the length (in seconds) of time required to run the algorithm in one image restoration process. Computational time can be an indicator in guessing the computational complexity of an algorithm.

RESULTS AND DISCUSSION

The performance feasibility of the proposed method has been tested by comparing PSNR and computational time to several methods, such as MF, SMF (Zhou Wang & Zhang, 1999), NAFSM (Ojha & Tiwari, 2015), DAMF (Erkan et al., 2018), TMF (Abdurrazzaq et al., 2019), ACWMF, AMF, PSMF, DBA, UTMF, AMF_Haidi, AWMF, MDBUTMF, FASMF (Sheik Fareed & Khader, 2018) and ATF (Abdurrazzaq, Mohd, et al., 2020). Table 1 shows the feasibility of the proposed method in overcoming high-intensity salt and pepper interference (90%) in digital images based on the PSNR indicator.

Tabel 1. PSNR comparison of the existing methods with 90% SnP noise

Met \ Citra	Lena	Bridge	Camera-man	Living-Room	Mand rill	Lake	Pirate	Woman-Blonde	Woman-DarkH	Plane
MF	8.88	8.58	11.39	8.97	8.96	8.22	8.93	9.06	6.19	6.03
SMF	19.82	16.73	18.41	18.61	17.00	16.71	18.74	19.40	21.27	17.88
MDBUTMF	23.57	19.89	22.75	21.76	18.77	20.79	22.80	22.25	26.19	23.56
NAFSM	23.39	19.49	22.35	21.59	18.79	20.96	22.72	22.25	25.96	21.76
T2FF	18,16	18,43	18,42	19,61	18,34	17,02	18,81	18,71	19.77	19.36
BPDF	10,72	10,39	11,62	10,71	8,84	7,08	10,89	9,12	10.83	8.02
DAMF	26.03	20.36	24.79	23.17	19.04	22.43	24.18	23.69	30.91	23.77
TSVD	19,91	17,09	19,48	18,51	17,75	16,99	19,41	19,67	17.64	17.61
TMF	21.25	18.24	20.40	20.02	18.36	18.59	20.39	20.72	22.637	19.95
ATF	25.47	20.58	24.11	23.01	19.92	21.67	24.00	23.69	28.39	22.81
TVF	22.99	18.92	13,97	21.63	19.12	19.45	21.68	22.08	25.17	20.52
FASMF	26.42	21.6	25.08	23.58	22.09	23.32	24.85	24.37	32.14	24.75
Proposed	26.68	22.02	25.31	23.94	22.51	23.51	25.1	24.68	32.58	25.13

Tabel 2. SSIM comparison of the existing methods with 90% SnP noise

Met \ Citra	Lena	Bridge	Camera-man	Living-Room	Mand rill	Lake	Pirate	Woman-Blonde	Woman-DarkH	Plane
MF	0.0623	0.0501	0.0818	0.0542	0.0468	0.0629	0.0577	0.0579	0.0081	0.0133
SMF	0.5788	0.2914	0.6617	0.4261	0.2987	0.454	0.4603	0.509	0.6881	0.5937
MDBUTMF	0.7032	0.4335	0.7477	0.5505	0.3768	0.5975	0.6162	0.6266	0.8066	0.7057
NAFSM	0.6786	0.4281	0.7135	0.5296	0.3702	0.5869	0.6047	0.6088	0.7802	0.6905
T2FF	0,4979	0,3542	0,6482	0,4512	0,3265	0,4532	0,4605	0,4927	0.6537	0.6264
BPDF	0,2876	0,1449	0,4950	0,1977	0,0975	0,1007	0,2402	0,1938	0.4311	0.1368
DAMF	0.4979	0.3542	0.6482	0.4512	0.3265	0.4532	0.4605	0.4927	0.6578	0.6266
TSVD	0,4404	0,2983	0,4992	0,3665	0,3105	0,3568	0,3951	0,4186	0.3548	0.3689
TMF	0.2876	0.1449	0.495	0.1977	0.0975	0.1007	0.2402	0.1938	0.4262	0.1414
ATF	0.766	0.5117	0.8337	0.6268	0.4416	0.6587	0.6823	0.6702	0.8653	0.7876
TVF	0.6921	0.3923	0,1366	0.7307	0.3877	0.5521	0.5758	0.6153	0.7843	0.6778
FASMF	0.4404	0.2983	0.4992	0.3665	0.3105	0.3568	0.3951	0.4186	0.3509	0.3638
Proposed	0.5832	0.3513	0.5993	0.4637	0.3481	0.4847	0.4887	0.5301	0.6524	0.6195

Table 1 shows that the proposed method produces very good performance in restoring digital images from high-intensity salt and pepper interference (90%). This shows that the proposed method is able to work much better than the previously proposed FASMF method. The proposed method is able to produce better performance than the FASMF method (and other methods above) both for images with medium texture accuracy (Lena) and for images with high texture accuracy (Mandrill).

Based on Table 2, it is clear that the proposed method has a better level of similarity compared to the FASMF. However, there are some methods that have slightly better SSIM value. But in terms of PSNR, the proposed method is much better than the existing methods. This means that the proposed method has a better ability to remove noise from corrupted images.

Tabel 3. PSNR comparison of the existing methods for Lena image with 10% - 90% SnP noise

Met \ Noise	10%	20%	30%	40%	50%	60%	70%	80%	90%
MF	32.58	30.95	29.19	26.93	23.85	20.55	16.60	13.02	8.88
ACWMF	39.97	34.99	31.66	28.29	24.03	20.42	16.57	12.59	9.05
AMF	38.15	35.73	33.85	31.93	30.25	28.56	26.88	24.87	22.14
PSMF	32.97	30.79	30.23	27.93	25.12	21.55	18.9	15.59	12.83
DBA	35.14	31.43	29.14	27.01	25.09	23.35	21.34	19.1	16.03
UTMF	43.1	39.22	36.71	34.33	32.26	30.01	27.9	24.88	20.08
AMF_Haidi	37.59	37.12	35.21	33.63	32.11	30.68	29.36	27.43	25.26
AWMF	39.09	37.28	36.03	34.84	33.51	32.12	30.7	28.64	26.19
SMF	37.23	35.44	33.46	31.48	29.33	27.49	25.08	22.95	19.82
MDBUTMF	38.48	34.71	33.56	32.36	30.95	29.95	28.80	27.50	23.57
NAFSM	38.73	35.64	33.81	32.28	30.90	29.84	28.61	27.077	23.39
DAMF	43.24	39.26	36.80	34.88	33.24	31.82	30.22	28.59	26.03
TMF	42.48	38.24	35.15	32.73	30.99	28.83	26.67	24.38	21.25
ATF	43.05	39.14	36.57	34.72	33.15	31.77	30.21	28.46	25.47
FASMF	42.51	39.16	37.09	35.40	33.84	32.31	30.93	28.81	26.42
Proposed	42.39	39.109	36.94	35.26	33.82	32.47	30.93	29.19	26.68

Table 3 in more detail describes the advantages of the proposed method compared to other methods. It is clear that this method works better for the distorted image of Lena with an intensity of 60%, 70%, 80%, and 90%. This can be evidence that the proposed method is very suitable for images with high noise density, compared to using the other methods above. However, on images with low and medium noise, the DAMF and FASMF methods have better performance than proposed.

Tabel 4. Comparison of computational time (seconds) of the existing methods for Lena image with 10% - 90% SnP noise

Met \ Noise	10%	20%	30%	40%	50%	60%	70%	80%	90%
MF	11.02	11	10.76	10.85	10.84	10.8	10.74	10.79	10.79
ACWMF	42.95	42.99	43.18	42.37	41.65	41.64	41.67	41.58	41.57
AMF	14.4	16.97	14.77	14.5	15.77	20.36	21.84	31.51	65.89
PSMF	42.07	43.21	50.62	51.96	53.09	54.55	55.89	58.65	59.45
DBA	4.92	5.07	5.35	6.08	6.12	6.59	6.95	7.46	7.51
UTMF	5.74	6.44	7.6	8.61	9.78	10.74	11.77	12.98	14.56
AMF_Haidi	3.2	4.28	6.34	8.29	13.54	17.31	23.63	32.92	59.09
AWMF	71.21	51.78	42.19	37.67	32.02	32.2	31.25	33.34	42.2
T2FF	0.543	0.922	1.49	2.32	3.202	4.422	5.691	12.5	10.04
BPDF	0.414	0.535	0.769	1.009	1.302	1.512	1.688	1.978	2.271
TSVD	4.389	4.477	4.849	5.177	5.230	5.674	17.94	5.568	6.122
TMF	4.722	4.368	4.680	4.563	4.777	5.217	4.998	5.194	5.809
ATF	0.987	0.975	1.051	1.093	1.089	1.091	1.115	1.191	1.175
TVF	32.44	57.01	69.83	58.61	34.12	48.14	71.63	22.32	21.26
FASMF	1.89	3.47	5.06	6.69	8.38	10.24	12.92	16.83	24.61
Proposed	0.335	0.601	0.797	1.085	1.315	1.571	1.852	2.109	2.422

Table 3 summarizes the time required for each method's algorithm to restore the distorted Lena image with an intensity of 10% - 90%. It is clear that the proposed method is able to perform computations very efficiently. This modified FASMF method is able to complete the restoration of the Lena image with a disturbance intensity of 90% for 2,422 seconds, or ten times faster than the FASMF method. This method is also able to work better for fixed kernel 3 x 3 (fixed windows) methods such as MF and UTMF as well as adaptive kernels such as AMF, AWMF, AMF_Haidi, ATF, and FASMF.

Next will be attached a visual view of the image improvement using several methods and with variations in the intensity of the disturbance. The image used is a picture of Lena. Comparison of the visual appearance of the results of image restoration using several filtration methods and the intensity of interference can be seen in Figure 2.

The comparison in Figure 2 shows that the proposed method is able to produce a much better visual appearance than the MF, ACWMF, DBA, PSMF, and UTMF methods. The proposed method also looks sharper when compared to the AMF and AMF_Haidi methods. This means that on an image with a disturbance intensity of 90%, the proposed method is able to restore image information very well.

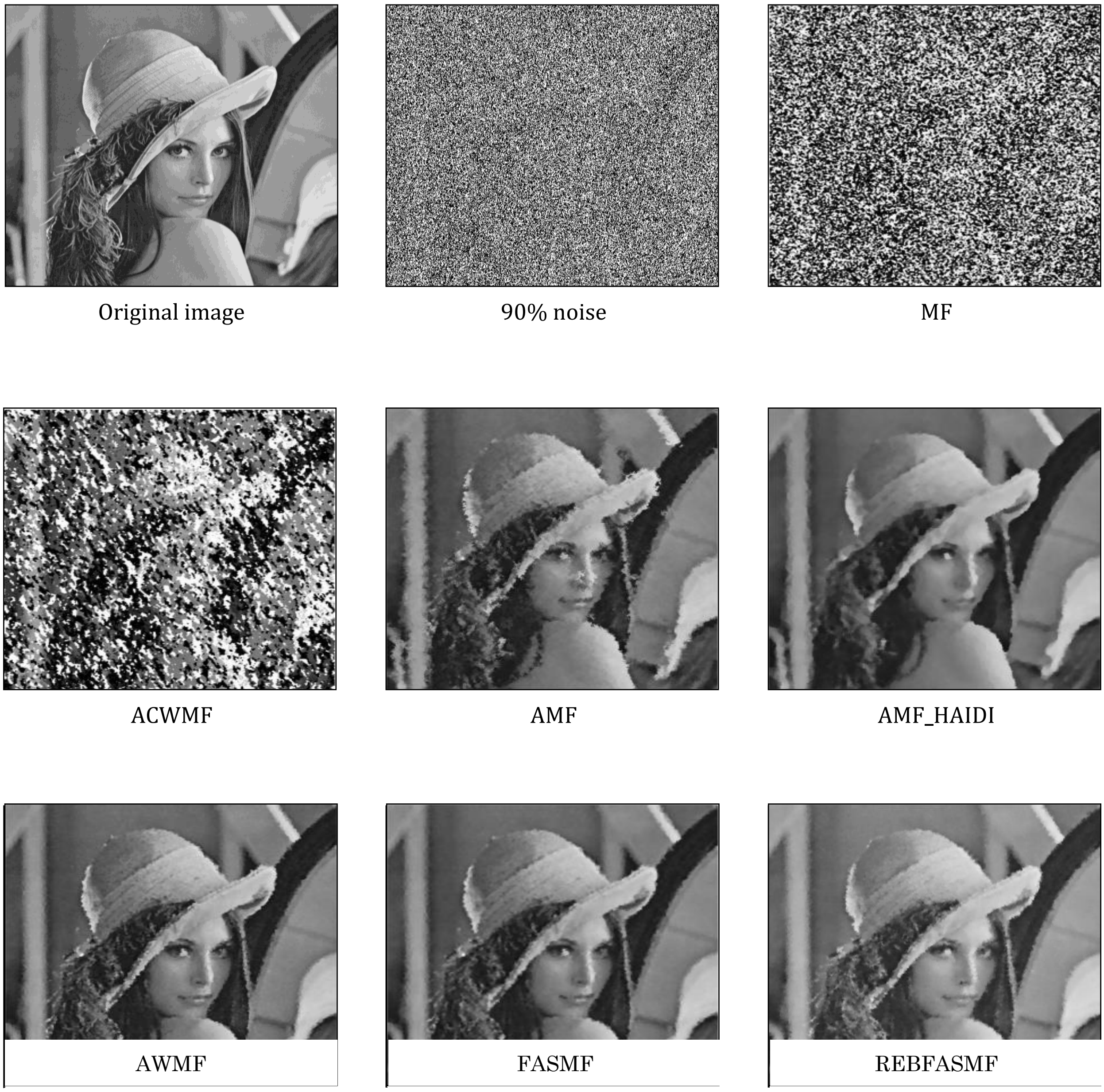


Figure 2. Comparison of the visual appearance of the restoration of several image filtration methods [Lena, SnP Noise 90%]

Meanwhile, the comparison in Figure 4 shows that the proposed method is able to work well to restore damaged information in satellite images (Figure 3). This method is successful in restoring satellite images, both for small disturbances (10% - 50%) and for high disturbances (60% - 90%).

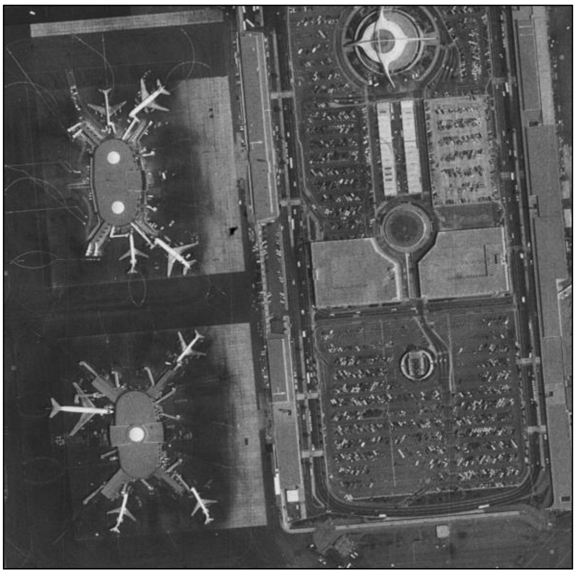


Figure 3. Free-noise satellite image

CONCLUSIONS AND SUGGESTIONS

The proposed is a modification of the FASMF method that can solve the problem of digital image filtration from high-intensity salt and pepper interference. Modification of FASMF to the proposed method can improve the quality of the improved image and reduce the complexity of the algorithm. In digital images with 90% SnP interference, the proposed method is able to exceed the performance of the FASMF method and several other methods for all tested images. Meanwhile, on digital Lena images with 10% - 90% SnP interference, the proposed method is able to exceed the performance of the FASMF method and several other methods for images with a disturbance intensity of 60%, 70%, 80%, and 90%.

Meanwhile, in terms of computational time, the Proposed algorithm is very efficient. The proposed method is able to complete the image restoration process with high-intensity disturbances ten times faster than the FASMF method. This method is also able to work better for fixed kernel $\mathbf{3 \times 3}$ (fixed windows) methods such as MF and UTMF as well as adaptive kernels such as AMF, AWMF, AMF_Haidi, and FASMF. Based on the experimental results that have been carried out, the proposed method can work well and quickly to remove SnP noise. For further research, it is necessary to modify and adjust the detection process so that it can be used to eliminate impulse noise in general.

REFERENCES

Abdurrazzaq, A., Junoh, A. K., Wan Muhamad, W. Z. A., Yahya, Z., & Mohd, I. (2020). An overview of multi-filters for eliminating impulse noise for digital images. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *18*(1), 385. https://doi.org/10.12928/telkomnika.v18i1.12888

ABDURRAZZAQ, A., MOHD, I., JUNOH, A. K., & YAHYA, Z. (2019). A hybrid of tropical-singular value decomposition method for salt and peppernoise removal. *TURKISH JOURNAL OF ELECTRICAL ENGINEERING & COMPUTER SCIENCES*, *27*(3), 1667–1679. https://doi.org/10.3906/elk-1807-93

Abdurrazzaq, A., Mohd, I., Junoh, A. K., & Yahya, Z. (2019). Modified tropical algebra based median filter for removing salt and pepper noise in digital image. *IET Image Processing*, *13*(14), 2790–2795. https://doi.org/10.1049/iet-ipr.2018.6201

Abdurrazzaq, A., Mohd, I., Junoh, A. K., & Yahya, Z. (2020). Tropical algebra based adaptive filter for noise removal in digital image. *Multimedia*

Tools and Applications, *79*(27–28), 19659–19668. https://doi.org/10.1007/s11042-020-08847-0

Chan, R. H., Chung-Wa, & Nikolova, M. (2005). Salt-and-pepper noise removal by median-type noise detectors and detail-preserving regularization. *IEEE Transactions on Image Processing*, *14*(10), 1479–1485. https://doi.org/10.1109/TIP.2005.852196

Charmouti, B., Junoh, A. K., Abdurrazzaq, A., & Mashor, M. Y. (2022). A new denoising method for removing salt & pepper noise from image. *Multimedia Tools and Applications*, *81*(3), 3981–3993. https://doi.org/10.1007/s11042-021-11615-3

Chen, T., & Hong Ren Wu. (2001). Adaptive impulse detection using center-weighted median filters. *IEEE Signal Processing Letters*, *8*(1), 1–3. https://doi.org/10.1109/97.889633

Erkan, U., Gökrem, L., & Enginoğlu, S. (2018). Different applied median filter in salt and pepper noise. *Computers & Electrical Engineering*, *70*, 789–798. https://doi.org/10.1016/j.compeleceng.2018.01.019

Fan, H., Li, C., Guo, Y., Kuang, G., & Ma, J. (2018). Spatial–spectral total variation regularized low-rank tensor decomposition for hyperspectral image denoising. *IEEE Transactions on Geoscience and Remote Sensing*, *56*(10), 6196–6213. https://doi.org/10.1109/TGRS.2018.2833473

Ojha, A., & Tiwari, N. (2015). An image denoising technique using NAFSM with evolutionary algorithm. *2015 International Conference on Computational Intelligence and Communication Networks (CICN)*, 272–277. https://doi.org/10.1109/CICN.2015.61

[Online]. (n.d.). *http://imageprocessingplace.com/rootles%20V3/image%20databases.TMF*.

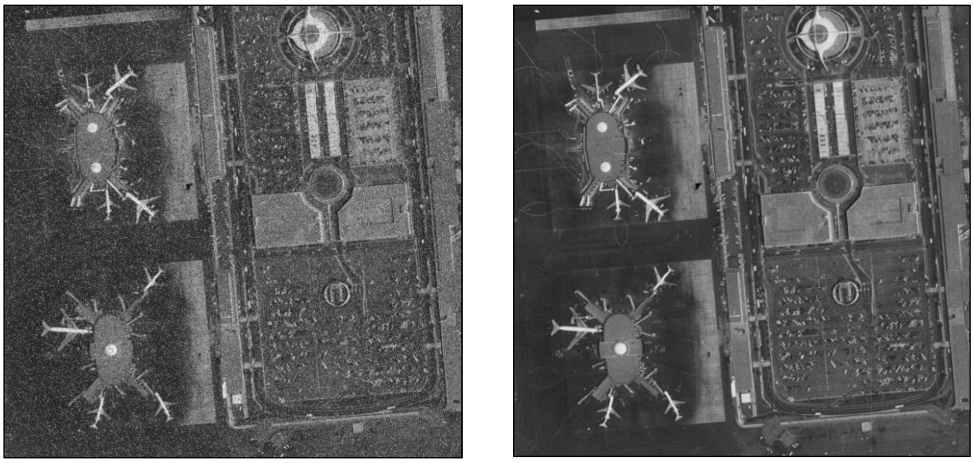
Sheik Fareed, S. B., & Khader, S. S. (2018). Fast adaptive and selective mean filter for the removal of high-density salt and pepper noise. *IET Image Processing*, *12*(8), 1378–1387. https://doi.org/10.1049/iet-ipr.2017.0199

Singh, V., Dev, R., Dhar, N. K., Agrawal, P., & Verma, N. K. (2018). Adaptive type-2 fuzzy approach for filtering salt and pepper noise in grayscale images. *IEEE Transactions on Fuzzy Systems*, *26*(5), 3170–3176. https://doi.org/10.1109/TFUZZ.2018.2805289

Sun, T., & Neuvo, Y. (1994). Detail-preserving median based filters in image processing. *Pattern Recognition Letters*, *15*(4), 341–347. https://doi.org/10.1016/0167-8655(94)90082-5

Wenbin Luo. (2006). Efficient removal of impulse noise from digital images. *IEEE Transactions on Consumer Electronics*, *52*(2), 523–527. https://doi.org/10.1109/TCE.2006.1649674

Zhou Wang, & Zhang, D. (1999). Progressive switching median filter for the removal of impulse noise from highly corrupted images. *IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing*, *46*(1), 78–80. https://doi.org/10.1109/82.749102



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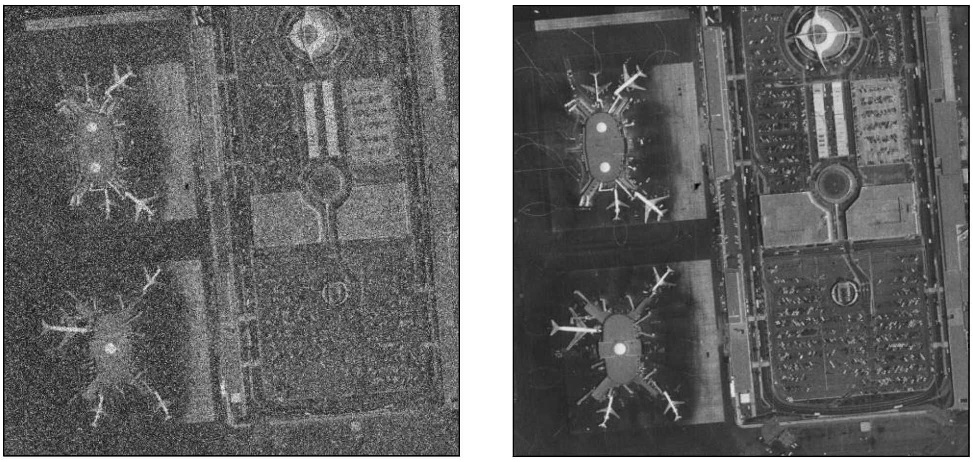

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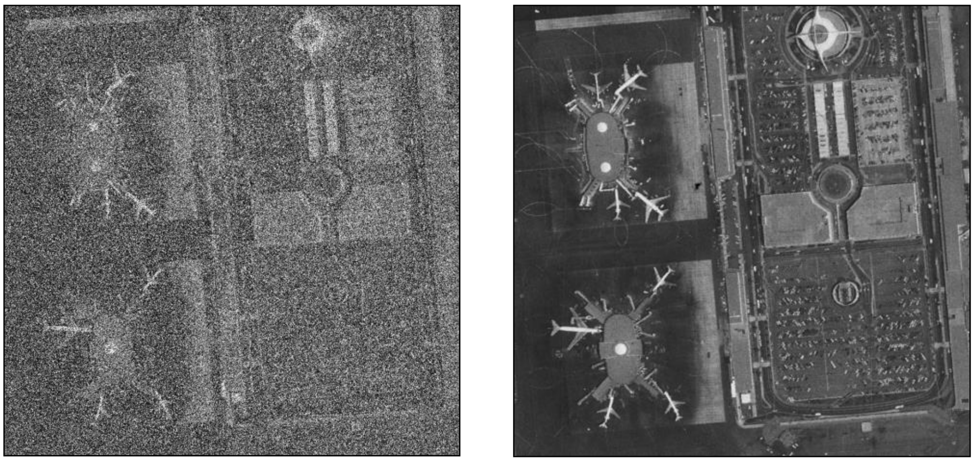

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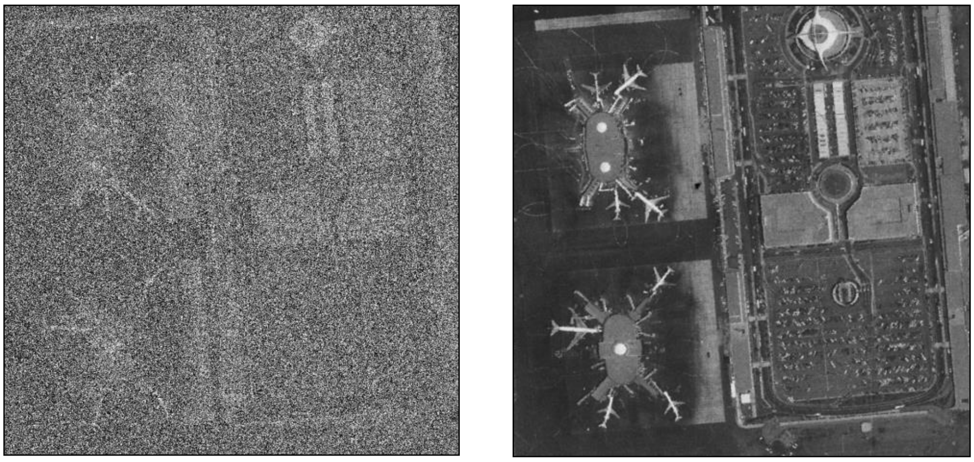

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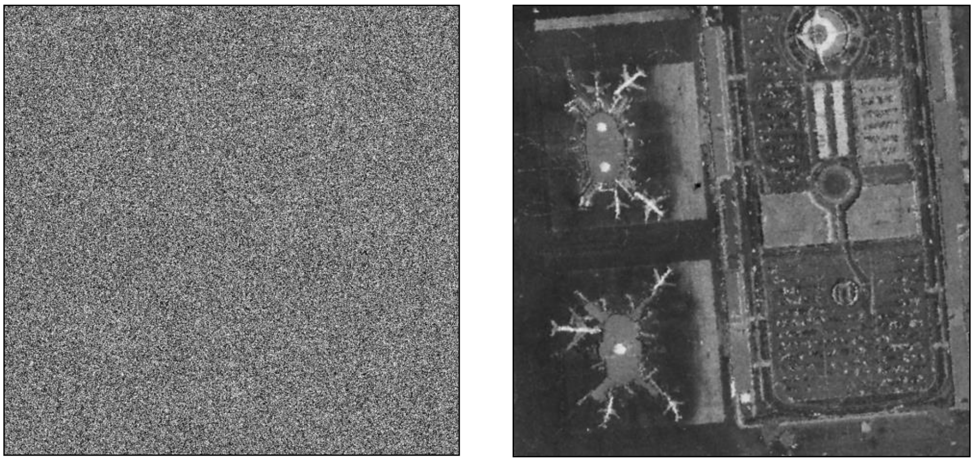

Noise 90%

Figure 4. Comparison of the visual appearance of the restoration of SnP disturbances in Satellite Imagery [Aircraft Ground – Satellite]