Three-stage Unstructured Filter for Removing Mixed Gaussian plus Random Impulse Noise

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Abstract: Digital image processing is often contaminated by more than one type of noise, such as mixed noise. In this paper, we propose a three-stage process to develop K-SVD method not only for reducing Gaussian noise but also for mixed Gaussian and impulse noise with optimizing input system and preserving edge structure. A three-stage process is combining of impulse noise removal, edge reconstruction and image smoothing. Pressing of an impulse noise in the early stages by Decision Based Algorithm (DBA) and repairing edge structure by an edge-map are able to optimize the performance of the K-SVD method for smoothing an image. The performance of the filter is analysed in terms of Peak Signal to Noise Ratio (PSNR), Mean Structural Similarity (MSSIM) index and Blind Image Quality Index (BIQI). The simulation result is obtained a significant improvement over the previous research.

1 INTRODUCTION

The quality of an image may decrease due to disturbance or unwanted signals, which is called with noise. The corrupted image with noise is one of the main problems in the image processing and computer vision. Two common type of image noise are Gaussian noise and Impulse noise. Contamination image with noise makes a user difficult to recognize the original image data. In such adverse conditions, it is needed an implementation to restore the noisy image to become an image that has a better quality. Noise removal is necessary in image processing to acquire useful important information that we want (Fitri et al., 2012b).

Gaussian and impulse noises are caused by imperfection of camera sensors and communication channel, error in the data-acquisition system, interference from the outside instrumentation and error in the transmission channel, etc (Bogdan, 2010; Fitri et al., 2012a). Several previous papers have been proposed to suppress both of noises. Denoising method that only used for reducing one type of noise is much easier than the mixed noise removal.

There are two cases of noise distributions for impulse noise: fixed-valued impulse noise (salt-and-pepper) and random-valued impulse noise (Wenbin, 2007). A large number of algorithms have been proposed to reduce impulse noise from corrupted images. One of the most popular method to reduce impulse noise is median filter (Astola and Kuosmanen., 1997). These algorithms remove the impulsive noise but they were unable to preserve the sharpness of the edges. Median filter performs well at low noise density, but it fails at medium and high densities (Veerakumar et al., 2013). Moreover, various modified median filters are also proposed, e.g. the Vector Median Filter (VMF) (Laskar et al., 2009) and the Spatial Median Filter (SMF) (Church et al., 2008). Although these filters obtain a better performance in lesser execution time, VMF approaches still have the drawbacks like blurring and low performances when the noise ratio is high (Lezoray et al., 2008), while SMF cannot preserve the original local features and maintain the edge area. The other one is Gaussian noise removal. Additive Gaussian noise is characterized by adding a value to each image pixel and the values obey a zero-mean Gaussian distribution with noise variance σ (Yingyue et al., 2013). Some researchers are often used total-

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variation methods to develop their research (Tony and Ke, 2006; Chan et al., 2005). The main drawback of the total variation methods is the texture information over-smooth in the image (Buades et al., 2005). Sparse land model and K-Singular Value Decomposition (K-SVD) algorithms (Michal and Michael, 2006) are also used to reduce Gaussian noise (Michael and Michal, 2006). K-SVD is an iterative method that alternates between sparse coding of examples based on the current dictionary and a process of updating the dictionary atoms to better fit the data. This algorithm is flexible and works in conjunction with any pursuit algorithm.

Rarely, an image is only contaminated by one type of noise (Gaussian or random impulse noise). Digital image processing is often contaminated by more than one type of noise, such as mixed noise. Some representative mixed noise removals are Two-phase method (TP) (Jian et al., 2008) and Fast two-phase image deblurring (FTPID) (Jian et al., 2010) which can work well in the reducing Gaussian and impulse of noise. The two-phase method uses variational methods involving an L1 shaped data-fidelity term. These methods can handle salt-and-pepper noise, but not optimal for random impulse noise.

To overcome the problem of the previous methods, we propose a three-stage process to develop K-SVD method not only for reducing Gaussian noise but also for mixed Gaussian and impulse noise with optimizing input system and preserving edge structure. A three-stage process develops the connection between an impulse noise removal, an edge reconstruction and the smoothing image methods. Pressing of an impulse noise in the early stages by Decision Based Algorithm (DBA) and repairing edge structure by an edge-map are able to optimize the input of the K-SVD method for smoothing an image.

The rest of the paper is organized as follows: Section II describes about the detailed explanation of the proposed method, Section III shows the experimental result of our simulation program, and Section IV is a conclusion.

2 PROPOSED METHOD

We propose a three-stage process to remove mixed Gaussian and impulse in the image F. The first stage is impulse noise removal. The second stage is the repairing edges region on the image. The third stage is the smoothing image.

2.1 Impulse Noise Removal

Impulse noise removal is only applied to the pixels that are detected as the impulse noise. The filtering process just conducted on the noisy pixel known as a Decision Based Algorithm (DBA).

We make an impulse noise detector which is capable for detecting both types of impulse noise. There are salt-and-pepper and random-valued impulse noises. The impulse noise filtered image ($\hat{\mathbf{X}}$) is obtained by placing the free impulse noise pixel and new pixel from $\hat{\mathbf{F}}$ at (i, j) position. $\hat{\mathbf{F}}$ is the average value of two free-noisy pixels that are located around (i, j). Detection of salt-and-pepper and random-valued impulse noise at each position (i, j) in the corrupted image ($\mathbf{F}$) is presented in Eq.(1).

$$\hat{X}_{ij} = \begin{cases} \hat{F}_{ij} & \text{if } F_{ij} = 0 \text{ or } F_{ij} = 255 \text{ or } F_{ij} \leq \tau_L \text{ or } F_{ij} \geq \tau_H \\ F_{ij} & \text{other} \end{cases} \tag{1}$$

τ_L and τ_H are the minimum and maximum limits of threshold value respectively, which is calculated by Eqs.(2) and (3).

$$\tau_L = MIN(\mathbf{W}) + \frac{MED(\mathbf{W}) - MIN(\mathbf{W})}{2} \tag{2}$$

$$\tau_H = MED(\mathbf{W}) + \frac{MAX(\mathbf{W}) - MED(\mathbf{W})}{2} \tag{3}$$

where *MIN, MED* and *MAX* are operators to obtain minimum, median and maximum value respectively. $\mathbf{W}$ is the 3×3 sample pixel window.

Observations of two pixels are performed in the horizontal, vertical, left and right-diagonal directions. If the observations are not found free-noisy pixels, we average values of two pixels $\hat{X}_{i,j-1}$ and $\hat{X}_{i-1,j}$

2.2 Edge Reconstruction

The edge reconstruction process is guided by an edge-map that is obtained from the threshold results of the edge image detection. We use two Sobel kernels to detect the edge area from an image there are horizontal ($\mathbf{H_h}$) and vertical ($\mathbf{H_v}$) derivative kernel.

The horizontal and vertical gradients of the image intensity function can be written in Eq.(4).

$$G = \frac{1}{2}\left(\hat{\mathbf{X}} * \mathbf{H_h} + \hat{\mathbf{X}} * \mathbf{H_v}\right) \tag{4}$$

$\hat{\mathbf{X}}$ is an image that contains no impulse noise. $*$ denotes the 2-dimensional convolution operation.

Meanwhile, the edge-map is resulted from the threshold that has two intensity conditions there are bright (1) and dark (0). The threshold image result is a binary image ($\hat{\mathbf{G}}$). The bright intensity (1) is given, when the pixel values of G_{ij} is greater than the threshold (τ) and vice versa. We only repair the area that are detected as edges and ignores the non-edge regions. We scan $\hat{\mathbf{G}}$ by using 5×5 window ($\mathbf{W}_{\hat{\mathbf{G}}}$). If in the scanning process, elements of the window contain an edge, then check the direction of an edge in the window as follows:

1 If an edge position in the $\mathbf{W}_{\hat{\mathbf{G}}}$ window is at the horizontal direction, then the $\hat{\mathbf{X}}$ image at the three coordinates in the horizontal direction $\hat{X}(i, j+k)$ is updated with an average of three pixels from these direction as illustrated in Eq.(5). k=[-1,0,1].

$$\hat{X}(i, j+k) = \frac{1}{3}\sum_{k=-1}^{1}\hat{X}(i, j+k) \tag{5}$$

2 If an edge position in the $\mathbf{W}_{\hat{\mathbf{G}}}$ window is at the vertical direction, then we use Eq.(6) to repair the edge image.

$$\hat{X}(i+k, j) = \frac{1}{3}\sum_{k=-1}^{1}\hat{X}(i+k, j) \tag{6}$$

3 If an edge position in the $\mathbf{W}_{\hat{\mathbf{G}}}$ window is at the left-diagonal direction, then the $\hat{X}(i-1, j+1), \hat{X}(i, j)$ and $\hat{X}(i+1, j-1)$ are updated by using Eq.(7).

$$\hat{X}(i+k, j-k) = \frac{1}{3}\sum_{k=-1}^{1}\hat{X}(i+k, j-k) \tag{7}$$

4 If an edge position in the $\mathbf{W}_{\hat{\mathbf{G}}}$ window is at the right-diagonal direction, then the $\hat{X}(i-1, j-2), \hat{X}(i, j)$ end $\hat{X}(i+1, j+1)$ are updated by using Eq.(8).

$$\hat{X}(i-k, j+k) = \frac{1}{3}\sum_{k=-1}^{1}\hat{X}(i-k, j+k) \tag{8}$$

Finally, the $\hat{\mathbf{X}}$ image that has been reconstructed based on four rules symbolized by $\mathbf{X}$.

2.3 Image Smoothing Based on K-SVD

K-SVD method is a combination of K-mean clustering process and Singular Value Decomposition (SVD). K-SVD is denoising method based on a sparse representation with learning dictionary which contains a prototype signal-atom (Michal and Michael, 2006). It is limited in handling small patches. In order to maximize performance for K-SVD method, we minimize an impulse noise and reconstruct the edge area on the input part, firstly. The $\mathbf{X}$ is an image that has undergone reconstruction in the early stage with eliminating impulse noise and improving edge area.

Denoising procedure using Eq.(9) is based on dictionary learned patches from the corrupted image, that are described as follows. Input image is symbolized by X_{ij} and output image is reconstruction image (Y_{ij}).

$$\begin{aligned} \underset{\mathbf{Y},\mathbf{D},\alpha}{min}\{ \quad & \lambda \parallel X_{ij} - Y_{ij} \parallel + \textstyle\sum_{ij}\mu_{ij} \parallel \alpha_{ij} \parallel_0 \\ & + \textstyle\sum_{ij} \parallel \mathbf{D}\alpha_{ij} - R_{ij}Y_{ij} \parallel_2^2 \} \end{aligned} \tag{9}$$

λ is regulation parameter, μ_{ij} is a patch-specific weight that are determined by the optimization procedure, α_{ij} is a size k column vector, $\mathbf{D}$ is the learn dictionary with matrix size $n \times k$ and R_{ij} is a size n column vector.

There are several parameters that are used in K-SVD methods. These parameters are n (the block size of image patches), k (size of dictionary), J (number of iterations), λ (weight of the noisy image), σ (standard deviation of Gaussian noise) and C (multiplier coefficient). We use the default parameters for denoising procedure that will be a good starting point by using the original K-SVD are as follows: n=8, J=4, $k = J \times n^2$, λ=$\frac{30}{\sigma}$ and C=1.15.

Description of K-SVD method uses the setting parameters which are defined in Eq.(9). The detail information about denoising procedure of K-SVD is explained in the several steps.

1. Initialization: set $Y_{ij} = X_{ij}$ and $\mathbf{D}$ are some initial dictionary.
2. Repeat J times
   (a) Sparse Coding Stage: Use any pursuit algorithm to compute the representation vectors α_{ij} for each patch $R_{ij}\ \hat{Y}_{ij}$. The mathematical aproach can be formulated as follows:
   $\forall_{ij} \min_{\alpha_{ij}} ||\alpha_{ij}||_0$ subject to $||\mathbf{D}\alpha_{ij} - R_{ij}\hat{Y}||_2^2 \leq n(C\sigma)^2$
   (b) Dictionary Update Stage: for each column l=1,2,...,k in $\mathbf{D}$.
   - Find the patches ω_l that use in this atom $d_l, \omega_l = \{(ij)|\alpha_{ij}(l) \neq 0\}$
   - For each patch $(i, j) \in \omega_l$ compute its representation error
   $$e_{ij}^l = R_{ij}Y_{ij} - \sum_{m \neq l} d_m \alpha_{ij}(m)$$
   - Set $E_l = (e_{ij}^l)_{ij \in \omega_l}$
   - Apply SVD decomposition and update d_l and $\alpha_{ij}(l)_{(i,j)\in\omega_1}$
   (c) Compute the image reconstructed: T is transpose matrix and I is an identity square matrix.
   $$Y_{ij} = \frac{\lambda X_{ij} + \sum_{ij} R_{ij}^T \mathbf{D}\alpha_{ij}}{\lambda I + \sum_{ij} R_{ij}^T R_{ij}}$$

Figure 1: Denoising results of different algorithms on Lena image corrupted by noise variance (σ=15) and impulse noise density (p = 50%). (a) Original image, (b) Corrupted image, (c) TP (Jian et al., 2008), (d) FTPID (Jian et al., 2010), (e) AF, (f) Proposed Method.

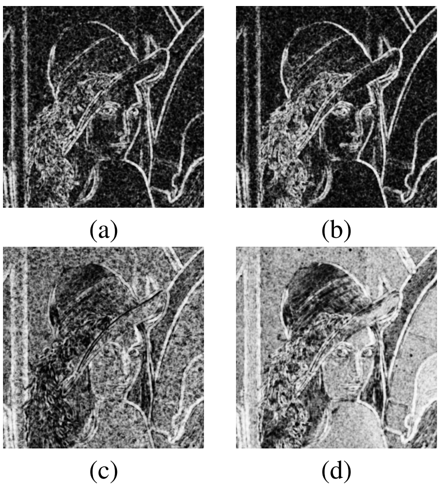

Figure 2: SSIM-map of Fig.1. (a) TP (Jian et al., 2008), (b) FTPID (Jian et al., 2010),(c) AF, (d) Proposed Method.

3 EXPERIMENTAL RESULT

We have tested the performance of our proposed method on a different image sample, some of which are Cameraman, Lena, Man and Pepper. Different density of Gaussian noise plus random-valued impulse noise has been tested in our research. We denote the random-valued impulse noise by p as density level (30%, 50% and 70%) and Gaussian noise by σ as standard deviation (5, 10 and 15). It means that $p+\sigma$ is the corrupted image by the mixed Gaussian and impulse noise.

Simulation result is obtained from MATLAB 7.5.0 release 2007b. We use a Personal Computer (PC) that has specification of CPU 3.3 GHz and 4GB RAM. The performance of our proposed method is evaluated by Qualitative and Quantitative parameters. Both parameters were used since they complement each other for more complete analysis.

3.1 Qualitative Parameter

Qualitative parameter by visual observation is more subjective than the quantitative parameter, where it can be observed but not measured. We compare our proposed method with many other well-known algorithms published in the (Jian et al., 2008; Jian et al., 2010) literatures and Adaptive Fuzzy (AF).

3.1.1 Visual Observation

The test image used for this comparison is Lena original image (512×512) as shown in Fig.1(a), which is corrupted by mixed Gaussian and impulse noise (p=50% plus σ=15) as shown in Fig.1(b). Furthermore, Fig.1(c) and (d) are the filtering results of TP and FTPID methods, respectively. The filtering result of TP is almost similar to FTPID method. However, FTPID method is a little smoother than TP method. Meanwhile, the filtering result of AF method is presented in Fig.1(e). In this paper, the visual quality filters of AF method is better than both methods. The filtering result of the proposed method is visualized in Fig.1(f). The proposed method is highly effective for removing impulse noise plus Gaussian noise from the corrupted image. By comparing TP and FTPID, we can see clearly that the proposed method successfully suppresses the noise and preserves the edge details and texture very accurately.

3.1.2 The Structural Similarity-map (SSIM-map)

In addition, we also use SSIM-map in the qualitative evaluation. SSIM-map is a local perceptual quality indicator that is used to measure the similarity between original image and the filtering image result. If the pixels have the similarities, it will produce high intensity and vice versa. SSIM-map results from Lena image are presented in Fig.2.

Figures.2(a), (b), (c) and (d) are the SSIM-map of TP, FTPID, AF and our proposed method respectively. Regarding to Fig.2, the level contrasts of SSIM-map image results from lowest to highest are TP, FTPID, AF and our proposed method respectively.

Generally, our method has more contrast than all comparison methods that has been used in this paper (TP, FTPID and AF). In this case, our proposed method produces the highest intensity, that is related to the condition of pixel between proposed method, and original image that has the similarity value in every coordinates.

3.2 Quantitative Parameter

Quantitative measurement is an important because qualitative measurement by visual assessment of the image is subjective. Quantitative assessment in the numerical variable is used for measurement, comparison or to track performance. They represent a measurable quantity that make it easy to analysis.

Qualitative measurement involves gathering data that is absolute, such as numerical data. In order to provide quantitative measures on the performance of the filtering result, we used Peak Signal-to-Noise Ratio (PSNR), Mean Structural Similarity (MSSIM) index and Blind Image Quality Index (BIQI).

3.2.1 Peak Signal-to-Noise Ratio (PSNR)

The quality of the restored images is measured by Peak Signal-to-Noise Ratio (PSNR). It uses a standard mathematical model to measure the quality image. The higher PSNR value, the better quality image and vice versa.

PSNR is usually expressed in terms of a logarithmic decibel (dB) scale as illustrated in Eq.(10). M is represented as row of an image; N is a column of an image; x_{ij} is an original image and y_{ij} is the filtering result.

$$PSNR = 20\log\frac{255.M.N}{\sum_{j=1}^{M}\sum_{i=1}^{N}(x_{ij}-y_{ij})^2} \tag{10}$$

Table 1 presents the PSNR results of the three comparative denoising algorithms on all test images. PSNR values of the proposed method demonstrate much better performance than TP, FTPID and AF, when the level noise ($30\% \leq p \leq 70\%$) and ($5 \leq \sigma \leq 15$)

3.2.2 Mean Structural Similarity (MSSIM) Index

The structural similarity (SSIM) index is a method for measuring the similarity between two images (original image as reference image and the filtering image results as the reconstructed image) (Zhou et al., 2004).

An image quality MSSIM index is calculated by computing the average of SSIM value over all windows as defined in Eq.(11)

$$MSSIM(I,F) = \frac{1}{M}\sum_{j=1}^{M} SSIM(i_j, f_j) \tag{11}$$

I and F are reference and the filtered images, respectively. The i_j and f_j are the image contents at the jth local window. M is the number of local windows of the image. We use Eq.(12) to obtain $SSIM$ value.

$$SSIM(i,f) = \frac{(2\mu_i\mu_f + C_1)(2\sigma_{if} + C_2)}{(\mu_i^2 + \mu_f^2 + C_1)(\sigma_i^2 + \sigma_f^2 + C_2)} \tag{12}$$

μ_i and μ_f are the mean intensity of image i and f respectively. σ_i and σ_f are standard deviation of image i and f respectively. σ_{if} is covariance.

The response of MSSIM value is similar with PSNR. MSSIM value is ranging between 0 and 1. The higher MSSIM index value, the better quality of the filtering image result. In this case, if the results of MSSIM index value close to 1 indicates that the filtering image result almost similar with original image.

The MSSIM index result in the several methods are presented in Table 2. Referring to Table 2, the proposed method has a highest value than TP, FTPID and AF methods. The MSSIM index value of the proposed method is close to one. It means, the quality filter of the proposed method is better than all comparison methods.

3.2.3 Blind Image Quality Index (BIQI)

In another hand, we also use BIQI (Blind Image Quality Index) to evaluate on the quality image assessment by using distortion-specific image quality measure as well as a distortion-type classifier. It is obvious that BIQI performs well in terms of correlation with human perception, and it is competitive with that of full-reference PSNR across distortion types and the database. (Anush and Alan, 2010).

Blind image quality index is calculated by using Eq.(13)

$$(BIQI) = \Sigma_{i=n}^{m} p_i q_i \tag{13}$$

p_i is the probability of each distortions in the image and q_i the quality score corresponding to the distortions (Anna et al.,).

Table 1: Comparison result of PSNR value.

Images	p (%)	σ = 5				σ = 10				σ = 15			
		Methods				Methods				Methods			
		TP	FTPID	AF	Proposed	TP	FTPID	AF	Proposed	TP	FTPID	AF	Proposed
Cameraman	30	29.31	29.90	29.93	31.49	26.70	27.71	29.49	30.58	25.65	26.10	28.88	29.58
Lena		33.08	34.15	31.09	34.19	30.66	31.33	30.55	32.49	29.12	29.67	29.88	31.39
Man		31.98	33.06	34.24	34.82	29.80	30.35	32.55	32.73	28.57	28.29	30.66	31.28
Pepper		32.68	33.87	35.28	37.15	30.64	31.66	33.44	35.19	29.63	30.25	31.19	33.42
Cameraman	50	26.92	27.40	29.04	30.10	25.45	25.99	28.61	29.37	24.10	24.69	27.99	28.69
Lena		31.40	32.30	30.46	32.54	29.23	29.88	29.91	31.29	27.93	28.42	29.19	30.32
Man		30.91	31.08	32.78	33.15	28.74	29.21	31.32	31.49	27.64	28.01	29.58	30.16
Pepper		30.96	31.83	33.72	35.48	29.37	30.24	32.15	34.09	28.22	28.85	30.12	32.49
Cameraman	70	24.69	24.67	27.37	27.57	23.35	23.45	26.98	27.24	22.41	22.67	26.39	26.79
Lena		29.56	29.73	29.09	30.07	27.75	28.11	28.59	29.46	25.87	26.48	27.89	28.87
Man		29.56	29.73	30.32	30.50	27.38	27.64	29.29	29.50	26.27	26.57	27.95	28.58
Pepper		29.35	29.58	31.18	32.67	27.83	28.43	30.03	31.70	26.82	27.07	28.45	30.53

Table 2: Comparison result of MSSIM index value.

Images	p (%)	σ = 5				σ = 10				σ = 15			
		Methods				Methods				Methods			
		TP	FTPID	AF	Proposed	TP	FTPID	AF	Proposed	TP	FTPID	AF	Proposed
Cameraman	30	0.81	0.83	0.95	0.97	0.58	0.60	0.87	0.93	0.42	0.44	0.87	0.90
Lena		0.82	0.85	0.87	0.92	0.62	0.65	0.84	0.88	0.46	0.49	0.81	0.85
Man		0.84	0.86	0.94	0.96	0.63	0.66	0.88	0.92	0.47	0.50	0.80	0.88
Pepper		0.81	0.83	0.95	0.97	0.56	0.58	0.87	0.95	0.38	0.41	0.78	0.94
Cameraman	50	0.79	0.85	0.94	0.96	0.56	0.64	0.85	0.92	0.42	0.49	0.84	0.88
Lena		0.78	0.84	0.85	0.90	0.59	0.67	0.83	0.86	0.44	0.53	0.79	0.83
Man		0.80	0.87	0.92	0.94	0.61	0.69	0.86	0.90	0.46	0.54	0.77	0.86
Pepper		0.80	0.86	0.94	0.96	0.55	0.64	0.86	0.95	0.38	0.47	0.75	0.93
Cameraman	70	0.74	0.87	0.91	0.93	0.52	0.69	0.83	0.90	0.38	0.55	0.81	0.86
Lena		0.70	0.83	0.83	0.86	0.53	0.70	0.80	0.83	0.40	0.58	0.75	0.80
Man		0.73	0.86	0.89	0.90	0.55	0.73	0.82	0.86	0.41	0.60	0.73	0.83
Pepper		0.76	0.89	0.93	0.95	0.53	0.72	0.84	0.93	0.37	0.56	0.73	0.91

Table 3: The quality score of the filtering image result.

Images	*p* (%)	σ = 5				σ = 10				σ = 15			
		Methods				Methods				Methods			
		TP	FTPID	AF	Proposed	TP	FTPID	AF	Proposed	TP	FTPID	AF	Proposed
Cameraman	30	38.92	41.65	36.64	35.79	53.60	55.94	52.52	40.38	56.22	56.74	53.08	42.67
Lena		34.56	35.95	38.86	31.05	49.02	49.44	47.91	35.33	54.13	54.53	54.43	34.89
Man		41.05	37.40	40.72	40.45	52.22	54.65	53.14	38.72	55.16	56.40	54.47	39.83
Pepper		57.86	59.13	55.78	40.41	64.49	67.66	65.43	44.79	65.32	66.91	66.40	45.67
Cameraman	50	34.57	35.89	43.43	35.36	47.30	53.64	47.21	41.87	52.92	56.34	51.43	44.47
Lena		30.20	31.96	31.23	31.92	45.32	46.77	45.38	36.53	51.58	52.82	52.75	35.53
Man		40.07	47.17	44.07	39.75	52.46	61.36	57.04	39.01	54.01	60.75	60.69	40.98
Pepper		64.27	66.18	59.36	40.56	65.27	67.24	66.61	44.82	67.90	67.79	66.92	45.90
Cameraman	70	27.34	40.25	42.83	34.49	46.79	50.71	46.67	42.87	44.74	55.60	52.92	44.74
Lena		31.50	37.33	40.44	35.56	40.41	45.53	47.72	38.82	46.65	55.59	55.91	37.34
Man		34.82	43.63	44.81	40.36	46.63	54.69	55.53	40.20	56.15	58.21	57.21	43.09
Pepper		44.39	50.94	46.44	38.82	66.68	68.33	65.72	44.72	67.94	69.28	67.07	46.70

A quality score of the filtering image result is presented in Table 3. The score typically has a value between 0 and 100. In this case, 0 represents the best quality and, 100 as the worst.

Referring to Table 3, the quality of the proposed method in some experiments data has a lowest value than TP, FTPID and AF as the comparison methods. However, in the small variance noise, the proposed method is not always obtained the lowest BIQI value. In this case, the smallest BIQI value was obtained in the FTPID or TP methods in condition (σ=5 and p=30%, 50% and 70%).

The lowest value indicates the better quality of the filtering result. Even though the final BIQI value of the proposed method was not close to zero, that result is enough to consider that noise was reduced.

4 CONCLUSION

A three-stage process method that develops the connection between an impulse noise removal, an edge reconstruction and the smoothing image methods for reducing the mixed Gaussian plus random impulse noise in the corrupted image is proposed. Pressing of an impulse noise in the early stages by Decision Based Algorithms (DBA) and repairing edge structure by an edge-map are able to optimize the performance of the K-SVD method for smoothing an image.

The qualitative parameters show that our proposed method cannot only remove most of the mixed noise, but also preserve the edge details, smooth quality and maintain textures of an image. Our simulation result is obtained a significant improvement over the previous research. The proposed method is capable of overcoming the drawback of previous studies and provides a satisfactory result.

For future work, we will give an attention on the computing time process. Hence, the next method not only optimal to reduce the mixed Gaussian plus impulse noise in many variation density, but also produces a faster computational time process in several noise densities.

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