An Empirical Evaluation of the Parameters of Trilateral Filter for Noise Removal Implementation on Gaussian and Impulsive Noise

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ABSTRACT

Since 1998, the Bilateral filter (BF) is worldwide accepted for its performance in practical point of view under Gaussian noise however the Bilateral filter has a poor performance for impulsive noise. Based on the combining of the Rank-Ordered Absolute Differences (ROAD) detection technique and the Bilateral filter for automatically reducing or persecuting of impulsive and Gaussian noise, this Trilateral filter (TF) has been proposed by Roman Garnett et al. since 2005 but the Trilateral filter efficiency is rest absolutely on spatial, radiometric, ROAD and joint impulsivity variance. Hence, this paper computationally determines the optimized values of the spatial, radiometric, ROAD and joint impulsivity variance of the Trilateral filter (TF) for maximum performance. In the experiment, nine noisy standard images (Girl-Tiffany, Pepper, Baboon, House, Resolution, Lena, Airplain, Mobile and Pentagon) under both five power-level Gaussian noise setting and five density impulsive noise setting, are used for estimating optimized parameters of Trilateral filter and for demonstrating the its overall performance, which is compared with classical noise removal techniques such as median filter, linear smoothing filter and Bilateral filter (BF). From the noise removal results of empirically experiments with the highest PSNR criterion, the trilateral filter with the optimized parameters has the superior performance because the ROAD variance and joint impulsivity variance can be statistically analyzed and estimated for each experimental case.

Keywords: Trilateral Filter (TF), Rank-Ordered Absolute Differences (ROAD), Bilateral Filter (BF), Denoising Algorithm, Digital Image Processing (DIP)

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1. TRIALTERAL FILTER THEORY REVIWING IN APPLING FOR NOISE REMOVAL

Because of communication channel errors, A/D convertor errors and pixel element malfunctioning in the photo sensors, observed images are usually contaminated by impulse noise and because of thermal noise in electronic device, the observed images are also contaminated by Gaussian noise hence image noise removal has become to be one of elementary to other advanced image processing techniques, for example remote sensing, image enlargement, face classification, etc.,

The objective of noise removal technique is to persecute the noise from an image while maintaining its details. In practical point of view under Gaussian noise, the Bilateral filter (BF), which is presented by Tomasi and Manduchi [1] in 1998, has been broadly accepted for its performance [12] in Digital Image Processing (DIP) and Computer Vision (CV) because Gaussian noise can be well persecuted and the image edge/detail can be well maintained nevertheless, under impulsive noise, the Bilateral filter (BF) dramatically gives a poor performance in both objective and subjective point of view. In order to handle for Gaussian noise and impulsive noise, the Trilateral filter (TF), which is presented by Roman Garnett et al. [7] in 2005, is developed to be a unified filtering framework for removing Gaussian and impulsive noise because of merging of the impulse detection technique (which is based on Rank-Ordered Absolute Differences (ROAD)) and the BF.

Subsequently, for suppressing random-magnitude impulse noise, a novel two-state filter based on Rank-Ordered Relative Differences (RORD) statistic that

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is another improved ROAD statistic and a weighted mean filter is proposed by Hancheng Yu et al. [3] in 2008. Later, for detecting impulsive noise, Gaussian noise and Gaussian-impulse combination noise, exclusively random-valued impulse noise for the reason that the ROAD statistics cannot well distinguish the noisy pixel (corrupted by random-valued impulse noise) from the noise-free pixel, an adaptive Trilateral filter with two phases is proposed by Neha Jain [6] in 2009, which is another improved Trilateral filter, employing by ROAD and ROLD (Rank-Ordered Logarithmic Differences) [15]. Next, for suppressing streaks, scratches, stripes and impulse noise, a two stage hybrid filter, employing by adaptive window-size median filter and ROAD for the reason that large processing complexity of ROLD statistics is proposed by V.R. Vijaykumar et al. [10] in 2010. Succeeding, for optimizing each weight contributions, an improved Trilateral filter, so called an entropy-based trilateral (EnTri) filter, employing by a median metric weighting function and entropy function is proposed by Herng-Hua Chang [4] in 2010. For classifying image pixels as either an impulse or a non-impulse pixel, another improved Trilateral filter, employing by EC-ROAD (Rank-ordered Absolute Differences statistics with Extremum Compression) is proposed by Guangyu Xu et al. [2] in 2011 for the reason that the EC-ROAD statistics can successfully classifying image pixels. Subsequently, for persecuting the effect of the pixels that have dramatically different magnitudes from those of its neighborhood in each windowed area and for mathematically proving in the Robust Self-Cross Bilateral Filter (RSCBF) framework, the Trilateral filter is presented by Tadahiro Azetsu et al. [8] in 2013. Later, for removing noise in the retinal image during the Retinal analysis preprocessing in the automatic Feature extraction of Cataract, the Trilateral filter is implemented by Meimei Yang et al. [5] in 2013. Next, for real time performing by reducing the cycle time of system clock, a fast computational technique of Trilateral filter, employing by a hardware accelerator with a new designed pipelined architecture is proposed by Wen-Chung Kao et al. [13] in 2007 for the reason that the Trilateral filter has an exhaustively high complexity in calculation. Succeeding, for 100-1000 times accelerated computational performance compared with than its original Trilateral filter, the fast Trilateral filter is proposed Tobi Vaudrey et al. [9] in 2009 for the reason that the fast Trilateral filter, employing by the LUT (look-up-table) kernel truncation depended on data accuracy and does not apply parallel processing technique. For another accelerated computational performance, Trilateral filter, employing by a parallel hardware accelerator (such as GPU, Cell Processors or OpenMP) is proposed by Xujie Li [14] in 2011 for the reason that the computation of Trilateral filter is decomposed into two bilateral filters that are computed separately.

From the previous research literature review of the Bilateral filter and Trilateral filter, which are an important research fractions, during this decade, it obviously shows that the research on the Trilateral filter is most vigorous and most profitable filter however the Trilateral filter efficiency is absolutely rest on four unknown parameters: spatial, radiometric, ROAD and joint impulsivity variance. Thereby, this research paper empirically explores the efficient influence impact of these four parameters of the Trilateral filter (TF) when this Trilateral filter (TF) is used for noise removal prospective attitude.

2. PHILOSOPHY REVIEW OF TRILATERAL FILTER

For applying on the noise situation, which is Gaussian distribution, the inspected image $\underline{Y}$, which is consistently defiled by this noise and is called as the noisy image, is construed as the authentic image by the succeeding algebraic explanation.

$$\underline{Y} = \underline{X} + \underline{N} \tag{1}$$

For maintaining the high component spectrum (if a digital signal is a 1D signal) or the edge basis (if a digital signal is a 2D signal or image) and for persecuting this noise $\underline{N}$ from the inspected signal $\underline{Y}$, Bilateral filter, which is consistently appointed as the nonlinear filter, is first introduced by Tomasi et al. [1] in 1998.

Initially, the weighting function, which is devoted for flatting in windowed smooth area of identical magnitude (where the $2N+1$ numbers of pixels are a neighborhood of $\mathbf{i}$) but for maintaining its details or edges, for 1D digital signals are construed as the $w_{BF}(\mathbf{i})$ or 2D signals or images are construed as $w_{BF}(\mathbf{i}, \mathbf{j})$.

In this article, the position of the pixel element under interesting is construed as i and its $2N+1$ neighborhood of interesting pixel elements is construed as $\Omega = \Omega_i(N)$. For bilateral filter, the restored image pixels or signals are construed by the succeeding algebraic explanation.

$$\hat{x}(\mathbf{i}) = \frac{\sum_{m=i-N}^{i+N} \sum_{n=j-N}^{j+N} w_{BF}(\mathbf{i}, \mathbf{j}) y(\mathbf{i}, \mathbf{j})}{\sum_{m=i-N}^{i+N} \sum_{n=j-N}^{j+N} w_{BF}(\mathbf{i}, \mathbf{j})} \tag{2}$$

or

$$\hat{x}(\mathbf{i}) = \frac{\sum_{m=i-N}^{i+N} \sum_{n=j-N}^{j+N} w_S(\mathbf{i}, \mathbf{j}) w_R(\mathbf{i}, \mathbf{j}) y(\mathbf{i}, \mathbf{j})}{\sum_{m=i-N}^{i+N} \sum_{n=j-N}^{j+N} w_S(\mathbf{i}, \mathbf{j}) w_R(\mathbf{i}, \mathbf{j})} \tag{3}$$

The spatial weighting function $w_S(\mathbf{i},\mathbf{j})$ and radiometric weighting function $w_R(\mathbf{i},\mathbf{j})$, is construed by the succeeding algebraic explanation, is combined to be the Bilateral filter weighting function $w_{BF}(\mathbf{i},\mathbf{j})$, employing by both the position and the magnitude in a neighborhood, which is generally normalized, is construed by the succeeding algebraic explanation, by multiplication operator.

$$w_{BF}(\mathbf{i},\mathbf{j}) = w_S(\mathbf{i},\mathbf{j})w_R(\mathbf{i},\mathbf{j}) \tag{4}$$

$$w_S(\mathbf{i},\mathbf{j}) = \exp\left(-|\mathbf{i}-\mathbf{j}|^2/2\sigma_S^2\right) \tag{5}$$

$$w_R(\mathbf{i},\mathbf{j}) = \exp\left(-|Y\mathbf{i}-Y\mathbf{j}|^2/2\sigma_R^2\right) \tag{6}$$

where

- $\mathbf{i}$ is construed as the position of the pixel element under interesting.
- $\mathbf{j}$ is construed as the position of the neighborhood of that pixel element under interesting. $(\mathbf{j} \in \Omega_i(N))$
- $Y(\mathbf{i})$ is construed as the intensity magnitude of the pixel element at position i_0 under interesting
- $Y(\mathbf{j})$ is construed as the intensity magnitude of the neighborhood of that pixel element under interesting

For removing Gaussian and impulsive noise, the Trilateral filter (TF), which is presented by Roman Garnett et al. [7] in 2005, is developed to be a unified filtering framework because of merging of the impulse detection technique (which is based on Rank-Ordered Absolute Differences (ROAD)) and the BF.

For a Trilateral filter, the restored image pixels or signals are construed by the succeeding algebraic explanation.

$$\hat{x}(\mathbf{i}) = \frac{\sum_{m=i-N}^{i+N}\sum_{n=j-N}^{j+N} w_{TF}(\mathbf{i},\mathbf{j})y(\mathbf{i},\mathbf{j})}{\sum_{m=i-N}^{i+N}\sum_{n=j-N}^{j+N} w_S(\mathbf{i},\mathbf{j})w_R(\mathbf{i},\mathbf{j})} \tag{7}$$

For a Trilateral filter, the overall weighting function $w_{TF}(\mathbf{i},\mathbf{j})$ is construed by the succeeding algebraic explanation.

$$w_{TF} = w_S(\mathbf{i},\mathbf{j})w_R(\mathbf{i},\mathbf{j})^{1-j(\mathbf{i},\mathbf{j})}w_I(\mathbf{j})^{j(\mathbf{i},\mathbf{j})} \tag{8}$$

where $w_I(\mathbf{j})$ is the impulsive weighting function, which is construed by the succeeding algebraic explanation.

$$w_I(\mathbf{j}) = \exp(-\mathrm{ROAD}(\mathbf{j})/2\sigma_I^2) \tag{9}$$

where σ_I is the ROAD variance [15] of the signal element at position $\mathbf{i}$ under consideration and ROAD$\mathbf{i}$ is theoretical formulated in the following expression.

$$\mathrm{ROAD}(\mathbf{i}) = \mathrm{ROAD}_4(\mathbf{i}) = \sum_{i=1}^{4} r_i(\mathbf{i}) \tag{10}$$

where $r_i(\mathbf{i}) = i^{th}$ smallest $d_{\mathbf{i},\mathbf{j}}$ for $\mathbf{j} \in \Omega_i(N)$ and $d_{(\mathbf{i},\mathbf{j})} = |Y(\mathbf{i}) - Y(\mathbf{j})|$.

The joint impulsivity function is construed by the succeeding algebraic explanation.

$$J(\mathbf{i},\mathbf{j}) = 1-\exp(-(\mathrm{ROAD}(\mathbf{i})-\mathrm{ROAD}(\mathbf{j}))/2\sigma_j^2) \tag{11}$$

where σ_J is the joint impulsivity variance of the signal element at position $\mathbf{i}$ under consideration.

By using the magnitude of noisy pixel and its neighborhood magnitude and neighborhood displacement (for calculating the weighting function $w_{TF}(\mathbf{i},\mathbf{j})$ of the Trilateral filter), the calculated noise removal result is construed by the succeeding algebraic explanation in Eq. (7).

For the property concept of the spatial weighting function, $w_S(\mathbf{i},\mathbf{j})$ is construed for the reason that two pixel magnitudes are extremely interdependence if both pixels are adjacent but two pixel magnitudes are independent if both pixels are far away hence $w_S(\mathbf{i},\mathbf{j})$ will inflate whereas the signal element at $\mathbf{i}$ and signal element at $\mathbf{j}$ are adjacent (as shown in Eq. (5)).

For the property concept of the radiometric weighting function, $w_R(\mathbf{i},\mathbf{j})$ is construed for the reason that two pixel magnitudes are extremely interdependence if both magnitudes are closely the same value but two pixel magnitudes are independent if both magnitudes are so difference for maintaining the detail and edges between two different area intensity hence $w_R(\mathbf{i},\mathbf{j})$ will inflate whereas two pixel magnitudes (at position $\mathbf{i}$ and position $\mathbf{j}$) are closely the same value (as shown in Eq. (6)).

For the property concept of the joint impulsivity, $J(\mathbf{i},\mathbf{j})$, which is range from 0 to 1, is construed for the reason that there is decline to zero if two pixel magnitudes (at position $\mathbf{i}$ and position $\mathbf{j}$) are not an impulse-like pixel or a smooth-like pixel therefore the overall weighting function of a Trilateral filter $w_{TF}(\mathbf{i},\mathbf{j})$ in Eq. (8) can be algebraic simplified to be $w_{TF}(\mathbf{i},\mathbf{j}) = w_S(\mathbf{i},\mathbf{j})w_R(\mathbf{i},\mathbf{j})$ (the original Bilateral filter) for non-impulsive noise. However, $J(\mathbf{i},\mathbf{j})$ inflates to one if either pixel magnitude (at position $\mathbf{i}$ and position $\mathbf{j}$) are an impulse-like pixel therefore the weighting function of a Trilateral filter $w_{TF}(\mathbf{i},\mathbf{j})$ in Eq. (8) algebraic simplified to be $w_{TF}(\mathbf{i},\mathbf{j}) = w_S(\mathbf{i},\mathbf{j})w_I(\mathbf{j})$ for impulsive noise.

3. SIMULATION PERFORMANCE SCRUTINY OF TRILATERAL FILTER

From the fact that the its performance of Trilateral filter in theoretical point of view builds upon five unknown parameters (window size, spatial variance σ_S, radiometric variance σ_R, the ROAD variance σ_I

and joint impulsivity variance σ_J), the first three parameters (parameters (window size, spatial variance σ_S and radiometric variance σ_R) is identical to the Bilateral filter parameters, which is comprehensively examined and estimated by computational simulation [11] for the best performance point of view thus these three parameters can be appointed for highest PSNR point of view in every noise setting by using the previous simulation outcome. Thereby, the later two unknown parameter of Trilateral filter (ROAD variance σ_I and joint impulsivity variance σ_J) are comprehensively examined and estimated by computational simulation for the best performance point of view in noise removal implementation.

Simulated by Matlab program, this experiment uses up to nine standard images, which are comprised of Girl-Tiffany (256×256), Pepper (256×256), Baboon (256×256), House (128×128), Resolution (128×128), Lena (256×256), Airplane (256×256), Mobile (Frame 10) (352×240) and Pentagon (512×512), for performance scrutiny in noisy setting such as Salt&Pepper noise (10%, 20%, 30%, 40% and 50%) and Additive Gaussian noise (SNR=15dB, SNR=20dB, SNR=25dB, SNR=30dB and SNR=35dB).

First, all nine original standard images are contaminated by each noise at different power (up to ten cases) for setting up the testing noisy image. Next, the noisy images are processed by noise removal algorithm using Trilateral filter for automatically reducing or persecuting of impulsive and Gaussian noise and, later, the noise removal results are analyzed with the state-of-art algorithm (bilateral filter, linear smoothing filter and median filter)

3.1 SIMULATION PERFORMANCE SCRUTINY OF THE ROAD VARIANCE (σ_I) OF TRILATERAL FILTER

Initially, by fix appointed 7×7 window size (for highest PSNR point of view [11]), and by fix appointed both Radiometric variance and Spatial variance for each noise power (for highest PSNR point of view [11]) and adaptively appointed joint impulsivity variance (σ_J) in range from 0 to 1200 with 10 for each adaptively appointed in Gaussian noise setting and from 0 to 120 with 1 for each adjusted tailoring in impulsive noise setting, this experiment empirically scrutinizes the value of the ROAD variance (σ_I) (in range from 0 to 1000 with 10 for each adaptive appointing in Gaussian noise setting and from 0 to 100 with 1 for each adaptive appointing in Impulsive noise setting), for highest PSNR point of view under both Gaussian and impulsive noise setting.

At first case, for highest PSNR point of view [11] in five Gaussian noise setting at SNR=15dB, SNR=20dB, SNR=25dB, SNR=30dB and SNR=35dB, the ROAD variance (σ_I) is estimated in the simulation performance experiment for

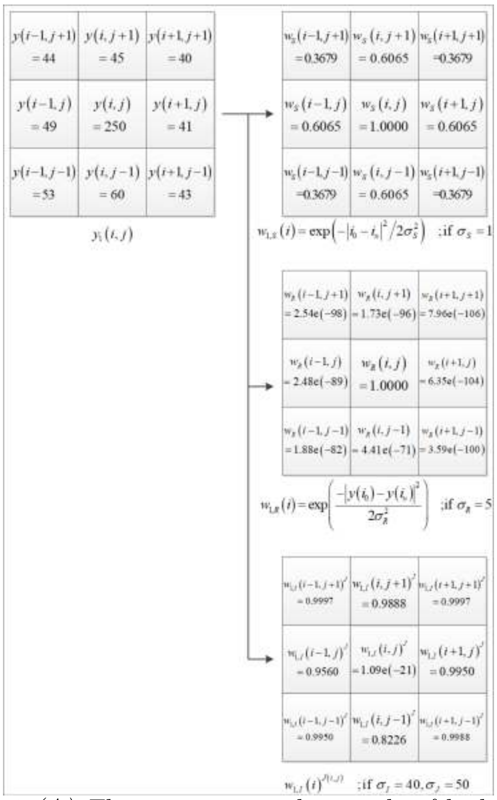

Fig.1:(A) The computational example of both $w_S(i)$ (spatial weighting function), the $w_R(i)$ (radiometric weighting function) and $w_I(i)$ (impulsive weighting) for a smooth region with impulse noise.

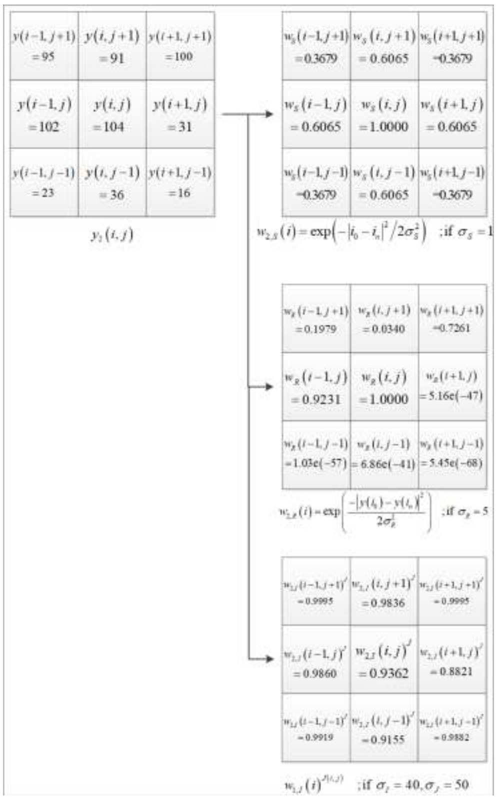

Fig.1: (B) The computational example of both $w_S(i)$ (spatial weighting function), the $w_R(i)$ (radiometric weighting function) and $w_I(i)$ (impulsive weighting) for a smooth region with impulse noise.

applying on Girl-Tiffany, Pepper, Baboon, House, Resolution, Lena, Airplane, Mobile (Frame 10) and Pentagon are presented in Table 1. Because the pixel of noise removal image is unlike an impulse pixel, joint impulsivity $J(\mathbf{i},\mathbf{j}) \approx 0$ (or $w_I(\mathbf{j})^{j(\mathbf{i},\mathbf{j})}$ is less impact to the overall weighting function) and a Trilateral filter weight w_{TF} can be theoretical simplified to be $w_{TF} = w_S(\mathbf{i},\mathbf{j})w_R(\mathbf{i},\mathbf{j})$. From these results, we can conclude that the ROAD variance (σ_I) has no impact to the overall Trilateral filter performance under the Gaussian noise.

Table 1: *The result of performance analysis of road variance (σ_I) impact.*

Gaussian Noise	SNR (dB)				
Analyzed Images	15	20	25	30	35
Girl-Tiffany (256×256)	40	10	10	420	310
Pepper (256×256)	430	930	1000	260	410
Baboon (256×256)	960	940	590	460	160
House (128×128)	340	440	500	580	160
Resolution (128×128)	150	270	1000	940	300
Lena (256×256)	790	690	910	800	170
Airplane (256×256)	250	770	1000	990	160
Mobile (Frame 10) (352×240)	1000	1000	940	970	70
Pentagon (512×512)	1000	890	790	660	240
Mean of ROAD variance	**551**	**660**	**749**	**676**	**220**
Variance of ROAD variance	**387**	**346**	**333**	**266**	**104**

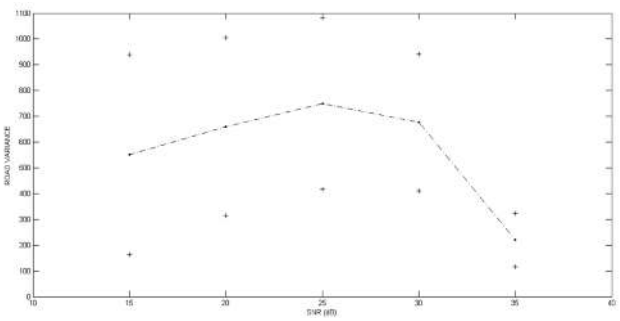

Fig.2: *The mean and SD of road variance for maximum PSNR (window size 7×7) under five gaussian ambiance.*

At second case, for highest PSNR point of view [11] in five Salt&Pepper noise setting at 10%, 20%, 30%, 40% and 50%, the ROAD variance (σ_I) is estimated in the simulation performance experiment for applying on Girl-Tiffany, Pepper, Baboon, House, Resolution, Lena, Airplane, Mobile (Frame 10) and Pentagon are presented in Table 2. Because the pixel of noise removal image is likely an impulse pixel, joint impulsivity $j(\mathbf{i},\mathbf{j}) \approx 1$ (or $w_R(\mathbf{i},\mathbf{j})^{1-j(\mathbf{i},\mathbf{j})}$ is less impact to the overall weighting function) and a Trilateral filter weight w_{TF} can be theoretical simplified to be $w_{TF} = w_S(\mathbf{i},\mathbf{j})w_I(\mathbf{j})^{j(\mathbf{i},\mathbf{j})}$ or $w_{TF} = w_S(\mathbf{i},\mathbf{j})w_I(\mathbf{j})$. Hence the value to the ROAD variance (σ_I) is great impact to the overall Trilateral filter performance. From Table 2, we can conclude that the optimized values of ROAD variance makes the highest PSNR is 81±14, 66±21, 61±23, 68±22, 94±9 for Salt and Pepper noise density at 10%, 20%, 30%, 40% and 50% respectively. Moreover, these means and variances of the ROAD variance values for highest PSNR point of view are presented in Figure 3.

Table 2: *The result of performance analysis of road variance (σ_I) impact.*

Impulsive Noise	The Noise Density)				
Analyzed Images	D=0.1	D=0.2	D=0.3	D=0.4	D=0.5
Girl-Tiffany (256×256)	71	63	63	70	76
Pepper (256×256)	65	47	43	56	91
Baboon (256×256)	94	78	66	81	100
House (128×128)	74	58	50	54	100
Resolution (128×128)	100	100	100	100	100
Lena (256×256)	74	50	40	49	100
Airplane (256×256)	67	49	53	67	82
Mobile (Frame 10) (352×240)	100	100	94	98	100
Pentagon (512×512)	81	50	39	35	100
Mean of ROAD variance	**81**	**66**	**61**	**68**	**94**
Variance of ROAD variance	**14**	**21**	**23**	**22**	**9**

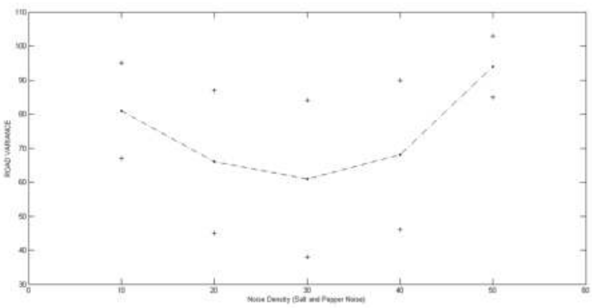

Fig.3: *The mean and SD of road variance for maximum PSNR (window size 7×7) under five impulsive ambiance.*

3.2 SIMULATION PERFORMANCE SCRUTINY OF THE JOINT IMPULSIVITY VARIANCE (σ_J) OF TRILATERAL FILTER

Initially, by setting window size at 7×7 (for maximum PSNR perspective [11]), and by setting both Radiometric variance and Spatial variance for each noise power for maximum PSNR perspective [11]) and by varying the ROAD variance (σ_I) from 0 to 1000 with 10 for each setting in Gaussian noise setting and from 0 to 100 with 1 for each setting in Impulsive noise setting, this experiment empirically determines the value of joint impulsivity variance (σ_J) from 0 to 1200 with 10 for each setting in Gaussian noise setting and from 0 to 120 with 1 for each setting in Impulsive noise setting, for maximum PSNR perspective under both Gaussian and impulsive noise setting.

At first case, for maximum PSNR perspective [11], joint impulsivity variance (σ_J) at

SNR=15dB, SNR=20dB, SNR=25dB, SNR=30dB and SNR=35dB is determined in the simulation performance experiment for applying on the nine tested standard images are presented in Table 3. Because the pixel of noise removal image is unlike an impulse pixel, joint impulsivity $J(\mathbf{i},\mathbf{j}) \approx 0$ (or $w_I(\mathbf{j})^{j(\mathbf{i},\mathbf{j})}$ is less impact to the overall weighting function) and a Trilateral filter weight w_{TF} can be theoretical simplified to be $w_{TF} = w_S(\mathbf{i},\mathbf{j})w_R(\mathbf{i},\mathbf{j})$. From these results, we can conclude that the joint impulsivity variance (σ_J) has no impact to the overall Trilateral filter performance under the Gaussian noise.

At second case, for maximum PSNR perspective [11], joint impulsivity variance (σ_J) at 10%, 20%, 30%, 40% and 50% of Salt&Pepper noise is estimated in the simulation performance experiment for applying on the nine tested standard images are presented in Table 4. Because the pixel of noise removal image is likely an impulse pixel, joint impulsivity $J(\mathbf{i},\mathbf{j}) \approx 1$ (or $w_R(\mathbf{i},\mathbf{j})^{1-j(\mathbf{i},\mathbf{j})}$ is less impact to the overall weighting function) and a Trilateral filter weight w_{TF} can be theoretical simplified to be $w_{TF} = w_S(\mathbf{i},\mathbf{j})w_I(\mathbf{j})^{j(\mathbf{i},\mathbf{j})}$ or $w_{TF} = w_S(\mathbf{i},\mathbf{j})w_I(\mathbf{j})$. Hence the value to joint impulsivity variance (σ_J) is great impact to the overall Trilateral filter performance. From Table 4, we can conclude that the optimized values of the joint impulsivity variance makes the highest PSNR is 81±14, 66±21, 61±23, 68±22, 94±9 for Salt and Pepper noise density at 10%, 20%, 30%, 40% and 50% respectively. The means and variances of joint impulsivity variance (σ_j) values for highest PSNR point of view are presented in Figure 5.

Table 3: *The result of performance analysis of joint impulsivily* (σ_J) *impact.*

Gaussian Noise	**SNR (dB))**				
Analyzed Images	15	20	25	30	35
Girl-Tiffany (256×256)	120	250	210	90	70
Pepper (256×256)	150	140	130	1200	160
Baboon (256×256)	1200	1200	1200	1200	1170
House (128×128)	220	470	630	860	180
Resolution (128×128)	1170	1200	450	460	270
Lena (256×256)	1190	1200	1200	1150	1200
Airplane (256×256)	120	100	110	120	180
Mobile (Frame 10) (352×240)	1200	1200	1200	1200	1200
Pentagon (512×512)	310	1200	1200	1130	920
Mean of ROAD variance	**631**	**773**	**703**	**823**	**594**
Variance of ROAD variance	**533**	**516**	**498**	**473**	**510**

3.3 SIMULATION PERFORMANCE SCRUTINY OF THE TRILATERAL FILTER

From the simulation performance scrutiny result from the previous section by appointing all five parameters (7×7 window size, Radiometric variance (σ_R), Spatial variance (σ_S), Joint impulsivity variance (σ_J) and ROAD variance (σ_I)) for highest PSNR point of view in each noise setting, this experiment presents the performance scrutiny result in PSNR, from applying on Girl-Tiffany, Pepper, Baboon, House, Resolution, Lena, Airplane, Mobile (Frame 10) and Pentagon for five Gaussian noise: SNR=15dB, SNR=20dB, SNR=25dB, SNR=30dB and SNR=35dB and for five Salt&Pepper noise: 10%, 20%, 30%, 40% and 50% in Table 5 and Table 6, respectively.

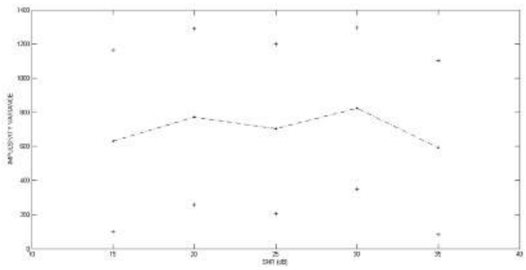

Fig.4: *The mean and SD of impulsivity variance for maximum PSNR (window size 7×7) under five gaussian ambiance.*

Table 4: *The result of performance analysis of joint impulsivily variance* (σ_J) *impact.*

Impulsive Noise	**The Noise Density)**				
Analyzed Images	D=0.1	D=0.2	D=0.3	D=0.4	D=0.5
Girl-Tiffany (256×256)	32	1	1	1	1
Pepper (256×256)	26	1	1	1	1
Baboon (256×256)	56	1	1	1	1
House (128×128)	34	1	1	1	1
Resolution (128×128)	120	1	1	1	1
Lena (256×256)	30	1	1	1	1
Airplane (256×256)	25	1	1	1	1
Mobile (Frame 10) (352×240)	61	1	1	1	1
Pentagon (512×512)	31	1	1	1	1
Mean of ROAD variance	**46**	**1**	**1**	**1**	**1**
Variance of ROAD variance	**31**	**1**	**1**	**1**	**1**

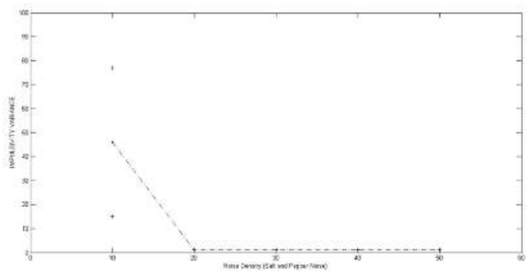

Fig.5: *The mean and SD of impulsivity variance for maximum PSNR (window size 7×7) under five impulsive ambiance.*

For Gaussian noise setting, the Bilateral filter or Trilateral filter, in which the Joint impulsivity variance (σ_J) is appointed to be infinity, has the highest PSNR in almost all cases therefore the trilateral filter works well for noise removal propose. For Salt&Pepper noise setting, the Trilateral filter has the highest PSNR in almost all cases for 10%, 20% and 30% but the median filter is slightly higher PSNR for 40% and 50%. From this result point of view, the trilateral filter can be employed on either Gaussian or Impulsive noise for using in noise removal proposes. From the mathematical formulation of trilateral filter and these simulation performance scrutinizes, there are no correlation between these four parameters but the setting range of the optimized values of each parameters for each noise ambiance can be summarized from each experiments.

Finally, by ceiling of a number of page obstructions, there are only three graphic results (Pepper, Baboon and Lena) of the simulation performance result for presenting in Figure 6, Figure 7 and Figure 8, respectively.

4. CONCLUSIONS

In this research paper, we scrutinize the simulation performance impact of these four parameters (spatial, radiometric, ROAD and joint impulsivity variance) of the Trilateral filter (TF) when the Trilateral filter is employed for noise removal in digital image processing. For producing the highest PSNR result of trilateral filter, a best setting value of new two unknown parameters: Joint impulsivity variance (σ_J) and ROAD variance (σ_I) are scrutinized and estimated for nine tested standard images under five Gaussian noise setting and five Salt&Pepper noise setting.

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References

[1] C. Tomasi and R. Manduchi, “Bilateral filtering for gray and color images,” *Proceedings of the 1998 IEEE International Conference on Computer Vision*, Bombay, India, pp.839-846, 1998.

[2] G. Xu, J. Tan and J. Zhong, “An Improved Trilateral Filter for Image Denoising using an Effective Impulse Detector,” *2011 4th International Congress on Image and Signal Processing*, Shanghai, pp.90-94, 2011.

[3] H. Yu, L. Zhao and H. Wang, “An Efficient Procedure for Removing Random-Valued Impulse Noise in Images,” in*IEEE Signal Processing Letters*, vol. 15, pp.922-925, 2008.

[4] H. H. Chang, “Entropy-based Trilateral Filtering for Noise Removal in Digital Images,” *2010 3rd International Congress on Image and Signal Processing (CISP2010)*, Yantai, pp.673-677, 2010.

[5] M. Yang, J.J. YANG, Q. Zhang, Y. Niu and J. Li, “Classification of Retinal Image for Automatic Cataract Detection,” *2013 IEEE 15th International Conference on e-Health Networking, Applications and Services (Healthcom 2013)*, Lisbon, pp.674-679, 2013.

[6] N. Jain, “Noise Cancellation Using Adaptive Trilateral Filter,” *Int. Journal of Recent Trends in Engineering and Technology*, vol. 1, no. 1, pp.329-333, Nov. 2009.

[7] R. Garnett, T. Huegerich, C. Chui and W. He, “A Universal Noise Removal Algorithm with an Impulse Detector,” in*IEEE Transactions on Image Processing*, vol. 14, no. 11, pp.1747-1754, Nov. 2005.

[8] T. Azetsu, N. Suetake and E. Uchino, “Trilateral Filter Using Rank Order Information of Pixel Value for Mixed Gaussian and Impulsive Noise Removal,” *2013 International Symposium on Intelligent Signal Processing and Communication Systems*, Naha, pp. 303-306, 2013.

[9] T. Vaudrey and R. Klette, “Fast Trilateral Filtering,” *International Conference on Computer Analysis of Images and Patterns CAIP 2009: Lecture Notes in Computer Science*, vol. 5702. Springer, Berlin, Heidelberg, pp.541-548, 2009.

[10] V. R. Vijaykumar and P. Jothibasu, “Decision Based Adaptive Median Filter to Remove Blotches, Scratches, Streaks, Stripes and Impulse Noise in Images,” *2010 IEEE International Conference on Image Processing*, Hong Kong, pp.117-120, 2010.

[11] V. Patanavijit, “The Bilateral Denoising Performance Influence of Window, Spatial and Radiometric Variance,” *2015 2nd International Conference on Advanced Informatics: Concepts, Theory and Applications (ICAICTA)*, Chonburi, pp.1-6, 2015.

[12] V. Patanavijit and K. Thakulsukanant, “Empirical Exploration Achievement of Noise Removal Algorithm Based on Trilateral Filter for Both Gaussian and Impulsive Noise Ambiance,” *2016 13th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, Chiang Mai, pp.1-6, Jun. 2016.

[13] W. C. Kao, H. S. Tai, C. P. Shen, J. A. Ye and H. F. Ho, “A Pipelined Architecture Design for Trilateral Noise Filtering,” *2007 IEEE International Symposium on Circuits and Systems*, New Orleans, LA, pp.3415-3418, 2007.

[14] X. Li, “The Research on Parallelized Fast Trilateral Filter on GPU Acceleration,” *2011 International Conference on Electronics, Communications and Control (ICECC)*, Ningbo, pp.1158-1161, 2011.

[15] Y. Dong, R. H. Chan and S. Xu, “A Detection Statistic for Random-Valued Impulse Noise,” in*IEEE Transactions on Image Processing*, vol. 16, no. 4, pp.1112-1120, April 2007.

Table 5: *The result of performance analysis of noise removal algorithm under five gaussian ambiance.*

Gaussian Noise	**PSNR (dB)**					
Analyzed Images	**Noise Case**	**Noisy Image**	**Noise Removal Algorithm**			
			MF (3×3)	**LF** (3×3)	**BF** (7×7)	**TF** (7×7)
Girl-Tiffany (256×256)	SNR15dB	17.7881	24.1699	20.7095	23.9716	**26.5688**
	SNR20dB	22.4394	27.7728	25.3547	28.2479	**29.3724**
	SNR25dB	27.1071	30.7341	29.8959	32.0362	**32.1506**
	SNR30dB	31.8195	32.4375	34.0632	**35.5470**	35.4600
	SNR35dB	36.7584	33.3822	37.6695	**39.3654**	38.3649
Pepper (256×256)	SNR15dB	19.3439	25.6799	23.0832	27.6464	**27.8945**
	SNR20dB	24.2489	29.0823	27.7753	31.0463	**30.9709**
	SNR25dB	29.2189	31.2985	32.2253	**34.1169**	33.9458
	SNR30dB	34.1491	32.5381	35.7708	**37.2999**	37.0706
	SNR35dB	39.1543	33.1722	38.1625	**40.9889**	40.6838
Baboon (256×256)	SNR15dB	19.9506	22.4160	23.1513	**24.6321**	24.3181
	SNR20dB	24.8470	23.4970	27.0842	**27.5116**	27.0010
	SNR25dB	29.7682	23.9530	29.8602	**31.1151**	30.4085
	SNR30dB	34.6772	24.1216	31.3228	**35.1453**	34.3868
	SNR35dB	39.6675	24.1887	31.9526	**39.9324**	39.7584
House (128×128)	SNR15dB	19.6258	24.9974	23.2755	**26.9374**	26.7154
	SNR20dB	24.6064	27.8589	27.9948	**30.5303**	30.4891
	SNR25dB	29.5790	29.5235	32.2616	**34.0883**	34.0296
	SNR30dB	34.5027	30.1442	35.5054	**37.5081**	37.3013
	SNR35dB	39.4975	30.4456	37.4346	**41.2130**	41.0013
Resolution (128×128)	SNR15dB	18.2220	18.0596	19.5286	**21.0134**	20.9196
	SNR20dB	23.1095	18.8039	22.9997	26.0173	**26.0211**
	SNR25dB	27.9514	18.7726	25.3764	**31.1764**	31.1117
	SNR30dB	32.7527	18.8035	26.6630	**36.1443**	35.9476
	SNR35dB	38.0077	18.7552	27.2679	**41.3833**	39.4809
Lena (256×256)	SNR15dB	22.2535	27.4450	25.8520	**29.6376**	29.1018
	SNR20dB	27.2412	29.8872	30.4495	**32.7669**	32.3235
	SNR25dB	32.1982	31.1745	34.2709	**35.8805**	35.2720
	SNR30dB	37.0853	31.8176	36.8940	**39.1272**	38.2054
	SNR35dB	42.0576	32.0870	38.3551	**43.0502**	42.8932
Airplane (256×256)	SNR15dB	17.8747	24.0342	21.6272	25.9115	**26.8498**
	SNR20dB	22.4779	27.6938	26.1102	**29.9107**	29.7741
	SNR25dB	27.4094	30.2274	30.6678	**33.2643**	33.0985
	SNR30dB	32.3723	31.5596	34.5766	**36.7868**	36.6884
	SNR35dB	37.3720	32.1288	37.4175	**40.4954**	39.2601
Mobile (Frame 10) (352×240)	SNR15dB	20.6966	20.8561	23.3582	**24.6020**	23.5321
	SNR20dB	25.5602	21.6119	26.6155	**28.4430**	27.7090
	SNR25dB	30.5035	21.9052	28.5231	**32.3315**	31.5709
	SNR30dB	35.4145	21.9916	29.4013	**36.6773**	35.7150
	SNR35dB	40.4180	22.0272	29.7144	**41.2216**	41.0209
Pentagon (512×512)	SNR15dB	20.1604	25.3751	23.7962	**27.2974**	27.0356
	SNR20dB	25.1476	27.7145	28.3476	**30.0672**	29.8615
	SNR25dB	30.1209	28.9958	32.2103	**33.3721**	32.9919
	SNR30dB	35.0381	29.5409	34.8223	**36.8605**	36.3214
	SNR35dB	40.0408	29.7910	36.2628	**40.9279**	40.8544

Table 6: *The result of performance analysis of noise removal algorithm under five impulsive ambiance.*

Gaussian Noise	**PSNR (dB)**					
Analyzed Images	**Noise Case**	**Noisy Image**	**Noise Removal Algorithm**			
			MF (3×3)	**LF** (3×3)	**BF** (7×7)	**TF** (7×7)
Girl-Tiffany (256×256)	D=0.10	13.6890	31.5583	17.2817	13.8950	**37.1128**
	D=0.20	10.6567	25.5153	13.9747	10.8134	**30.0798**
	D=0.30	8.8677	20.7738	11.9701	8.9921	**23.7108**
	D=0.40	7.5798	16.5146	10.4604	7.6789	**18.1536**
	D=0.50	6.5712	13.0319	9.2417	6.5793	**14.5233**
Pepper (256×256)	D=0.10	15.3798	30.6116	19.0795	25.0013	**35.5046**
	D=0.20	12.3593	26.5888	15.9804	21.4752	**29.5265**
	D=0.30	10.6242	22.0663	14.1712	18.2898	**23.1200**
	D=0.40	9.3998	18.4321	12.9017	9.4404	**17.6233**
	D=0.50	8.3843	**14.8506**	11.8056	8.4139	13.6447
Baboon (256×256)	D=0.10	15.3487	23.6544	18.7956	21.9311	**28.7082**
	D=0.20	12.3118	22.4812	15.7963	19.7091	**24.5076**
	D=0.30	10.5359	**20.3469**	13.9779	17.3238	19.9880
	D=0.40	9.2209	**17.3112**	12.6149	9.2359	15.9459
	D=0.50	8.2874	**14.4515**	11.6148	8.3008	12.8848
House (128×128)	D=0.10	15.6476	29.0356	19.4351	24.9626	**34.6743**
	D=0.20	12.5750	26.0908	16.2655	21.9734	**28.6723**
	D=0.30	10.8407	21.0572	14.4778	19.1979	**21.6764**
	D=0.40	9.6803	**18.2477**	13.2732	9.6943	17.3795
	D=0.50	8.6874	**15.0785**	12.3042	8.6979	13.5796
Resolution (128×128)	D=0.10	13.4819	17.9425	16.4562	16.7381	**20.6904**
	D=0.20	10.1271	16.2124	13.1233	13.4334	**17.9188**
	D=0.30	8.4430	14.4548	11.2173	11.3067	**16.3248**
	D=0.40	7.3308	12.6223	9.9764	9.7543	**14.3725**
	D=0.50	6.2938	10.4851	8.7248	8.3101	**11.8737**
Lena (256×256)	D=0.10	15.6564	30.7076	19.3727	19.0151	**35.5594**
	D=0.20	12.6389	27.6257	16.3076	15.0831	**29.6911**
	D=0.30	10.8971	23.6811	14.5645	12.7455	**23.6538**
	D=0.40	9.6481	**19.0080**	13.2294	11.0367	17.6732
	D=0.50	8.6553	**15.4758**	12.1926	8.6652	13.6628
Airplane (256×256)	D=0.10	14.8320	29.6532	18.4673	24.8131	**34.3944**
	D=0.20	11.8045	26.4356	15.3268	19.8901	**28.8114**
	D=0.30	10.0510	21.8862	13.4568	16.6337	**23.0129**
	D=0.40	8.8735	17.6412	12.1431	8.9555	**17.9206**
	D=0.50	7.8600	**14.2697**	11.0113	7.9221	14.2382
Mobile (Frame 10) (352×240)	D=0.10	15.1637	21.3601	18.4457	19.9125	**24.4940**
	D=0.20	12.0780	20.1976	15.4208	17.9120	**21.5165**
	D=0.30	10.3465	**18.3435**	13.6399	16.0204	18.2285
	D=0.40	9.0919	**16.1073**	12.3323	14.1858	15.1864
	D=0.50	8.1216	**13.4726**	11.2963	12.5046	12.4693
Pentagon (512×512)	D=0.10	15.7999	28.7784	19.5073	25.2894	**33.8045**
	D=0.20	12.7934	26.5128	16.5176	22.7696	**28.4599**
	D=0.30	11.0668	**22.8646**	14.7752	17.5219	22.7610
	D=0.40	9.8125	**18.9056**	13.5069	11.0668	17.2546
	D=0.50	8.8227	**15.4225**	12.5053	8.8227	13.2195

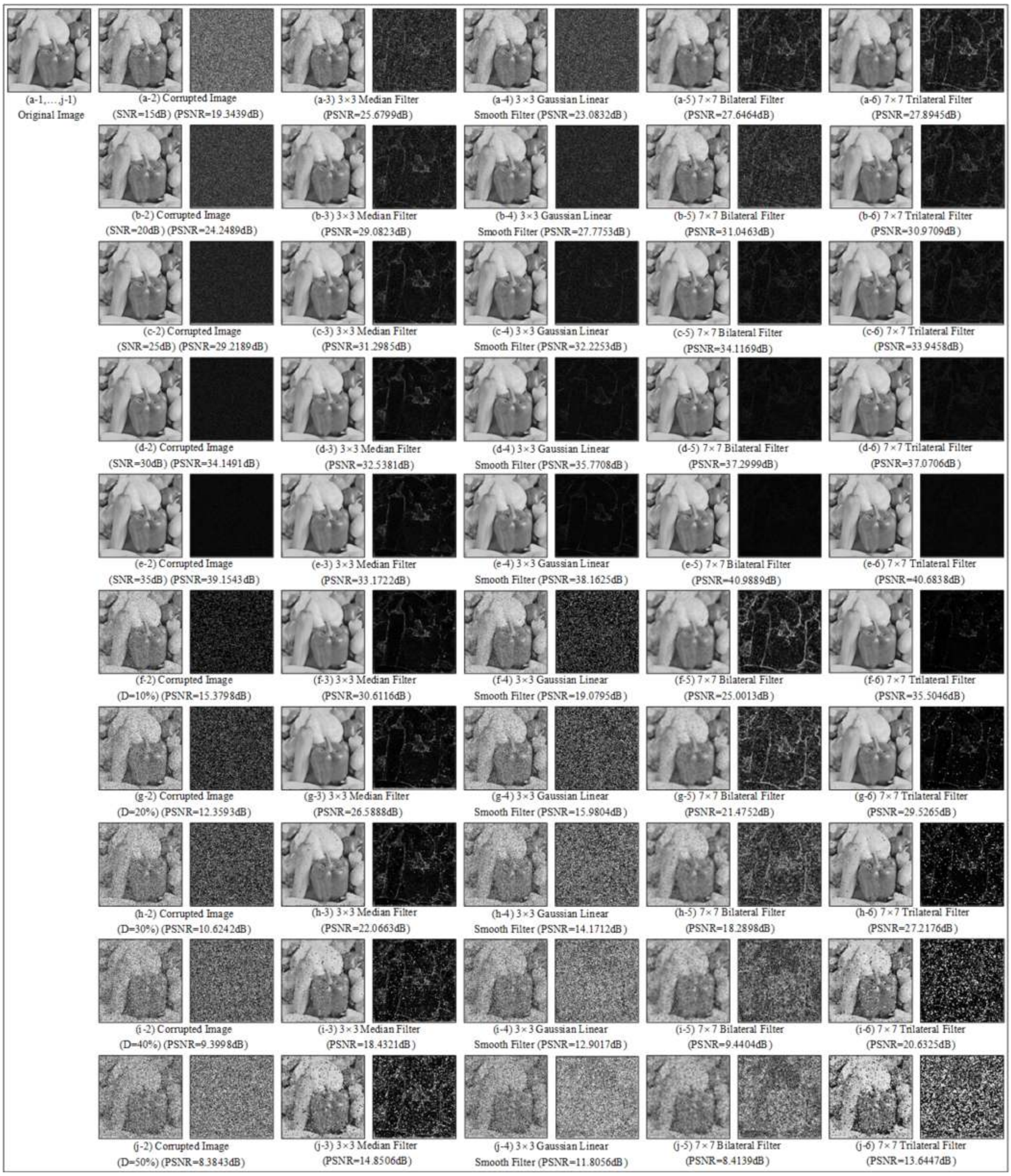

Fig.6: *The simulation performance scrutiny (Pepper) of trilateral filter for noise removed propose (The right image on the performance scrutiny of each sub-graphic is the discrepancy between it's reference left graphic to the original graphic where the discrepancy is strengthen by 5.).*

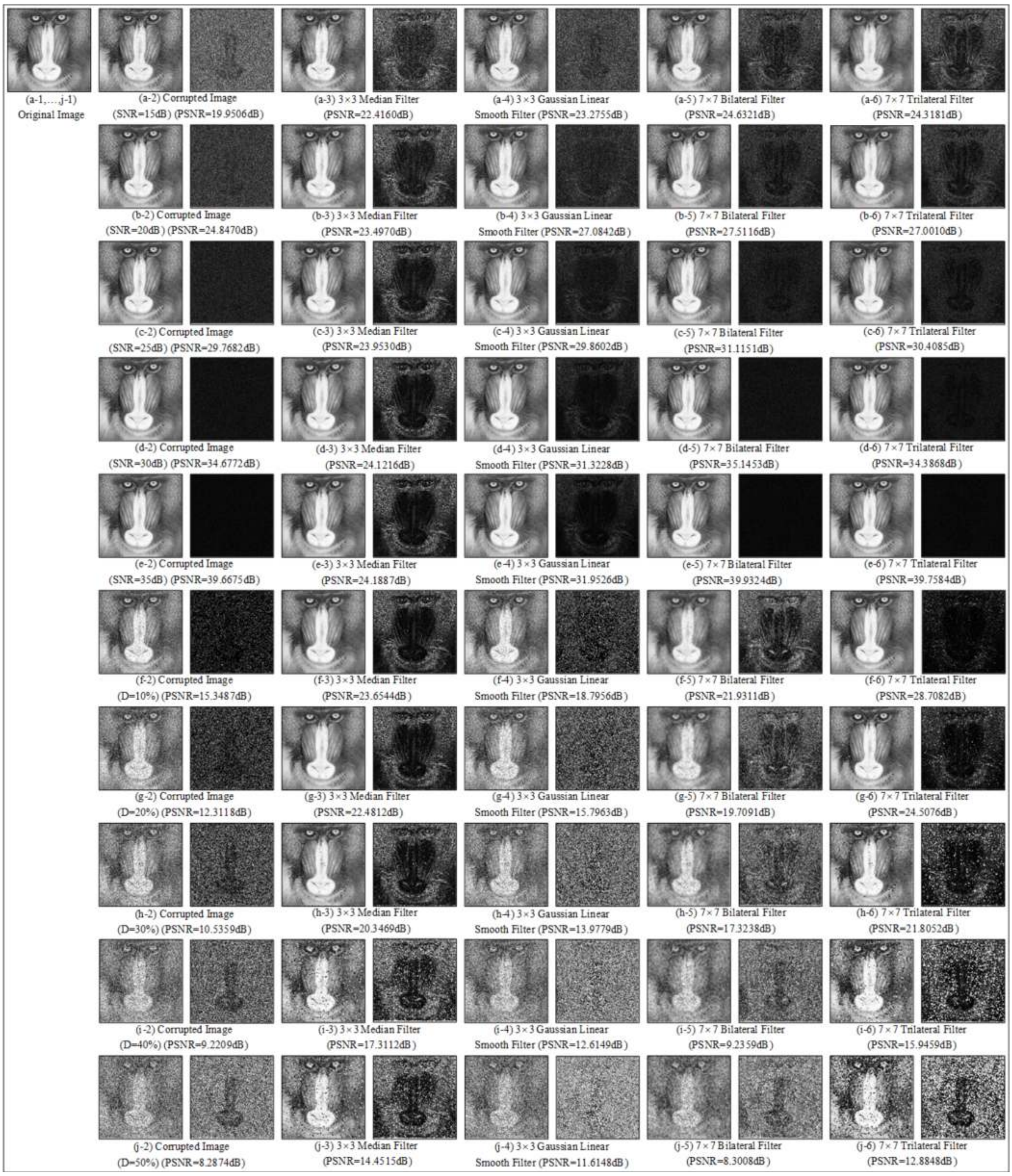

Fig.7: *The simulation performance scrutiny (Baboon) of trilateral filter for noise removed propose (The right image on the performance scrutiny of each sub-graphic is the discrepancy between it's reference left graphic to the original graphic where the discrepancy is strengthen by 5.).*

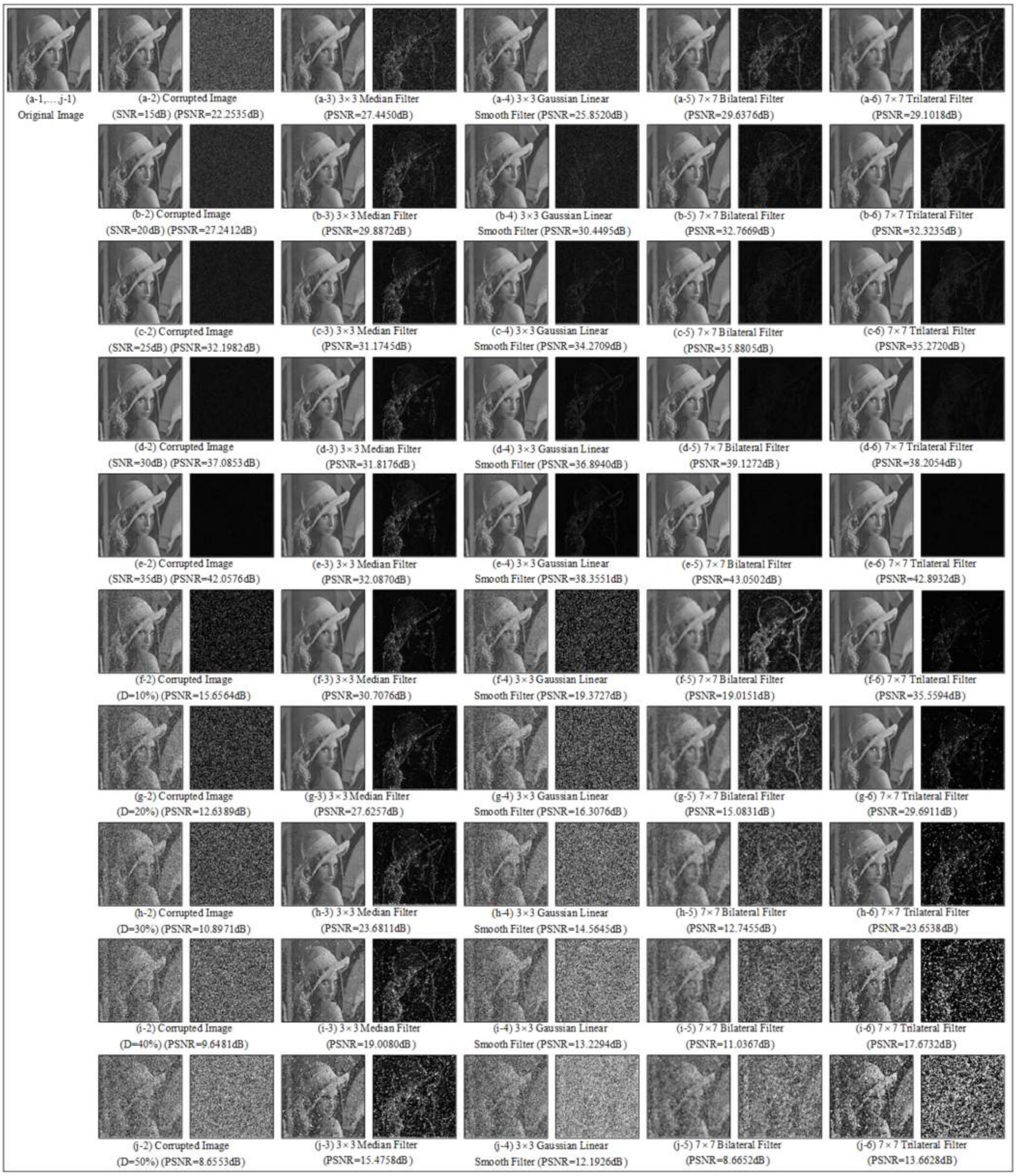

Fig.8: *The simulation performance scrutiny (Lena) of trilateral filter for noise removed propose (The right image on the performance scrutiny of each sub-graphic is the discrepancy between it's reference left graphic to the original graphic where the discrepancy is strengthen by 5.).*

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