IMAGE FILTER FOR EFFICIENT IMPULSE NOISE REMOVAL AND FINE DETAIL PRESERVATION

Oleksiy POGREBNYAK, Pablo MANRIQUE
Instituto Politécnico Nacional, Centro de Investigación en Computación,
Av. Juan de Dios Bátiz s/n, Colonia Nueva Industrial Vallejo, C.P. 07738, México D.F.
olek@pollux.cic.ipn.mx , pmanriq@pollux.cic.ipn.mx

ABSTRACT

A filtering algorithm applicable to image processing is presented. It was designed using rank-ordered mean (ROM) estimator to remove an outlier and robust local data activity estimators to detect the outliers. The proposed filter effectively removes impulse noise and preserve edge and fine details. The filter possesses good visual quality of the processed simulated images and good quantitative quality in comparison to the standard median filter. Recommendations to obtain best processing results by proper selection of the filter parameters are given. The designed filter is suitable for impulse noise removal in any image processing applications. One can use it at the first stage of image enhancement followed by any detail-preserving techniques such as the Sigma filter at the second stage.

KEY WORDS
image processing, nonlinear filters, detail-preserving filtering

1. INTRODUCTION

In practice, the quality of digital images often is not acceptable to provide reliable data interpretation due to random noise presence. It is highly desirable to get the image enhancement providing both effective noise cancellation/suppression and fine detail preservation. Linear filters ensure strong attenuation of Gaussian noise but they fail when data contain the impulse one. On the other hand, nonlinear filters have become very attractive in signal and image processing because of their ability to suppress noise of different nature, in particular, to remove impulse noise. Nonlinear filtering is also a well-known detail-preserving method. However, nonlinear filters are mainly designed to preserve edges of image objects only, but not fine details such as thin lines and small-scale objects. In particular, median, Wilcoxon[1,2] and α-trimmed mean[2,3] filters can remove small size objects considering them as outliers. As a result, they may to be unable to preserve fine details. A class of linear median hybrid (LMH) filters was introduced by Heinonen and Neuvo[4] to provide edge preservation with impulse noise reduction[5,6]. Its subclass, FIR-median hybrid filters (FMH)[7], provides preservation of thin lines as well[5, 6]. Impulse rejecting filters[6] suppress impulse noise effectively and avoid unnecessary distortions of noise-free pixels. These filters use different impulse detectors to decide, if the current pixel is an outlier and should be filtered by some nonlinear filter or it can be unaltered otherwise. To provide simultaneous detail preservation, rather complicated impulse detectors must be used. For example, Mitra et al[8] suggested rank-ordered mean (ROM) impulse rejecting filter with sophisticated fuzzy detector that can be optimized using image training data.

Besides, Sigma[9] and KNN[10] filters can preserve fine details well, but their robustness is insufficient to provide desired suppression of impulse noise[2,5,6]. Since the standard Sigma filter does not have any robustness, it is not able to suppress impulse noise at all. The attempts to get more appropriate robust versions of two latter mentioned techniques known. First, the modified locally adaptive Sigma filter[11] possesses some robust features but it does not perform well for probability of spikes greater than 0.05. Second, the known adaptive KNN filter[12] also provides insufficient impulse noise suppression. Another attempt to get better detail preservation is a weighted median filter[13] that has better detail preservation but lower noise suppression in comparison to the standard median one.

Recently, a robust KNN filter (RM-KNN filter) for efficient impulse noise suppression and good fine detail preservation was designed[14]. The filter uses a robust RM estimator[15,16] derived from R-estimators following from the statistical rank theory and robust M-estimators. The limitation of K nearest neighbors is applied to the data within the filtering window to perform calculations in an recursive manner. The resulted RM-KNN estimator has an adaptive nature: the number of K neighbors is adjusted using some robust estimator of local data activity that acts as outlier detector. The variants of this filter that use the different local data activity estimators were presented[14,17] and investigated.

It was found that this kind of impulse cancellation filter is very sensitive to the quality of the local data activity estimator. Some variants of this filter substitute the RM-KNN estimate by the output of the standard 3x3 median filter in the case when the local data activity is high that results that the central pixel of the filtering window is outlier. In contrast, when the local data activity is too small, the decision may be made to take the central window pixel as the filter output, similar to known impulse rejecting filters[6]. If the activity has intermediate values, the filter performs recursive calculations according to the RM-KNN estimator algorithm[15].

Unfortunately, the processing with the RM-KNN filter is slow because of the recursive nature of the robust estimator used. We found that the computation time may be significantly reduced eliminating the RM-KNN estimator when the data local activity estimator, or outlier detector performs better. Simultaneously, we found by simulations that the output of the ROM filter produces a more robust and more accurate estimate in comparison to the median estimator when the outlier is detected exactly or more or less reliably.

In this way, we designed a new adaptive impulse rejecting filter that uses an enhanced local data activity estimator and behave as an impulse rejecting filter: calculate the ROM estimate in the case when the data activity is high, and preserve the image pixels otherwise. In this paper, we present the designed filter that possesses the cancellation of impulse noise and preserves well image fine details.

2. PROPOSED IMAGE FILTER

Different impulse noise models were proposed and described in the literature[2, 6]. We used the following image degradation model in the case of impulse noise presence[15,17]:

$$\mathrm{u}(x,y)=\mathrm{n}_{\mathrm{im}}(\mathrm{e}(x,y)), \quad (1)$$

where $\mathrm{e}(x,y)=\vec{\mathbf{e}}$ is the vector of an original image, $\mathrm{u}(x,y)=\vec{\mathbf{u}}$ is the vector of a distorted image, and $\mathrm{n}_{\mathrm{im}}(\mathrm{e}(x,y))$ is the functional

$$\mathrm{n}_{\mathrm{im}}(\mathrm{e}(x,y))=\begin{cases}\text{random valued spike with probabilty } P\\ \mathrm{e}(x,y)\text{ otherwise}\end{cases} \quad (2)$$

We assume that the spikes have uniformly distributed random values (0..255 for the byte-represented images). Such assumption makes the problem of impulse noise removal more complicated, because when spikes are represented by maximal and/or minimal values only, one can use some thresholding techniques for their detection and removal. Besides, the impulse noise described by the model (1) is more realistic.

With this model, the problem of impulse noise removal is to derive a robust filtering algorithm that can be able both to remove the outliers and to preserve the fine details well.

The output of the ROM filter can be represented as follows. Let the $\mathbf{w}(n)$ is a vector that represents the data within the 3x3 filtering window that is scanned on the entire image and is centered at i,j pixel excluding this pixel, $u(i,j)$, itself:

$$\mathbf{w}(n)=\{w(1),w(2),w(3),w(4),w(5),w(6),w(7),w(8)\} \quad (3)$$

These samples can be ordered by rank, which defines the vector

$$\mathbf{r}(n)=\{r(1),r(2),r(3),r(4),r(5),r(6),r(7),r(8)\} \quad (4)$$

where $r(1),r(2),\ldots,r(8)$ are the elements of $\mathbf{w}(n)$ arranged in ascending order such that $r(1)\le r(2)\le\cdots\le r(8)$. In this case of even number of data the most robust estimate that corresponds to a Hoghes-Leman estimate by the rank sign test[18] is

$$\hat{e}_{ROM}(i,j)=\frac{r(4)+r(5)}{2} \quad (5)$$

According to the theory of rank tests, the estimate (5) in the case when the vector $\mathbf{w}$ has odd number of elements corresponds to the median of the data, which is more known and widely used in practice.

From the point of view of rank test/estimation theory, the estimator (5) has the same robust properties as the usual median estimator. However, taking into account that the image filter that is based on the estimator (5) excludes the corrupted central pixel of the filtering window, this estimator seems to be more robust.

One can expect that the ROM filter, which implements estimator (5) excluding the central window pixel $u(i,j)$ at the stage of vector $\mathbf{w}(n)$ forming, will perform better than the standard median filter in the case when the pixel $u(i,j)$ is detected as corrupted properly. Therefore, it is highly important to detect the outlier reliably. Besides, the performance of the image rejecting filter depends on the false outlier detection. Thus, we have to design an outlier detector, which has to be able both to detect an outlier well and to minimize the false detection, which is usually occur in the vicinity of small scale fine details of the image.

For the purpose of outlier detection, we modified the local data activity estimator, which was developed and presented previously[19]. This estimator is based on the robust estimate of data scale, the median of absolute deviations from median (MADM) that is known from the theory of robust M-estimators[20]. The calculation scheme of the previous estimator is described as

$$S(u(i,j)) = \frac{\text{med}\{|u(i,j) - u(i+m, j+n)|\}}{\text{MADM}\{u(i,j)\}} \quad (6)$$

where $\text{med}\{|u(i,j) - u(i+m, j+n)|\} = \text{MADCP}(i,j)$ is the median of the of absolute deviations from central filtering window pixel, $k,l = -L..L$, and $\text{MADM}\{u(i,j)\}$ is calculated as

$$\text{MADM}\{u(i,j)\} = \text{med}\{|\text{med}\{u(i+k, j+l)\} - u(i+m, j+n)|\} \quad (7)$$

We found by simulations that the estimator given by Eq.(6) performs well at flat image regions, but in the vicinity of edges it produces the small values. This causes insufficient outlier removal near the object edges in the filtered image. To resolve the problem of insufficient sensitivity of the impulse detector (6) near the edges, it was modified to produce better results in the filtered images. The new version of the local data activity estimator is expressed as

$$S(u(i,j)) = \frac{[a \cdot \text{MADCP}\{u(i,j)\}]^2}{\ln(\text{MADM}\{u(i,j)\})} \quad (8)$$

where the coefficient a varies the sensitivity of the estimator. The estimator (8) performs well both in flat regions and near the image object edges. Unfortunately, it was found by simulation that the direct use of this estimator as impulse detector is insufficient and one has to take into account other features as well. The additional criterion that we used is the difference between the value of the central pixel of the filtering window and ROM estimate (5)

$$dif(i,j) = |u(i,j) - \hat{e}_{ROM}(i,j)| \quad (9)$$

Finally, the proposed impulse rejecting filter can be described as a sequence of the experimentally derived rules, which can be formulated as

$$\hat{e}(i,j) = \begin{cases} u(i,j), & \text{if } dif(i,j) \le 5 \\ \text{else} \begin{cases} \hat{e}_{ROM}(i,j), & \text{if } dif(i,j) > \text{the median of entire image} \\ & \text{or if } \text{MADM}(i,j) \le 1 \text{ and } \text{MADCP}(i,j) > 0 \\ & \text{or if } S(i,j) > 1 \\ & \text{or if } [dif(i,j) \cdot a]^2 / \ln(\text{MADM}(i,j)) > 1 \\ u(i,j) & \text{otherwise} \end{cases} \end{cases} \quad (10)$$

where $\hat{e}(i,j)$ denotes the output of the proposed filter and a is the noise sensitivity coefficient. To possess the fine detail preservation properties, the filter always perform calculation of the ROM estimate in 3x3 filtering window meanwhile the scanning window for local data activity estimator (8) generally can be of the different size. However, the estimator (8) that estimates the data within the window of the same 3x3 size produces the better results as it is shown in the next section.

3. SIMULATION RESULTS

We performed a number of different tests to study the properties of the proposed algorithm (10) and to compare it to the standard median filter. The criterion used for the comparison of the performance of the filters was peak signal to noise ratio (PSNR), which can be expressed as

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{255^2}{\sum[e(x,y) - \hat{e}(x,y)]^2}\right), \quad (11)$$

where $e(x,y)$ denotes the pixels of the original (no corrupted) image and $\hat{e}(x,y)$ denotes the pixel of the filtered corrupted image (restored image).

In simulations, the parameters were varied: the percentage of the impulse noise, the noise sensitivity coefficient value, and the size of the sliding window L for determination of the local median in calculation of the parameters $\text{MADM}\{u(i,j)\}$, $\text{MACP}\{u(i,j)\}$ that are used in estimator (8) and in the filter output (10) forming as well.

To evaluate the deterministic properties of the designed filter, we performed filtering of the artificial test image shown in Figure 1 a) by the standard 3x3 median filter and the proposed one. One can see that in this case of the artificial image processing the proposed filter performs very similar to the median one.

To determine the noise suppression properties of the proposed adaptive ROM filter, the standard 512x512 test images ("Lena" and "Mandrill") shown in Figure 2 were corrupted by the random-valued impulse noise according to Eq.(1).The percentage of impulse noise was varied from 1% up to 15%. The filter parameter a from Eqs.(8),(10) was varied in a wide range as well as estimator (8) window size L was varied from 3 to 7.

Table presents the PSNR values, which were obtained according to (11) on images processed by the proposed filter with the optimal values of the coefficient a. The PSNR values of the standard median filter having different window size 3x3, 5x5, 7x7 are presented as well.

Analyzing these values, one can see that the designed filter performs better and provides significantly larger PSNR values in comparison to the median filter. It can be concluded from the analysis of this Table that the optimal size of the estimator (8) window is 3x3. The PSNR values of the processed "Mandrill" images is smaller than the ones of the "Lena" images that is caused by numerous small scale details contained in the original "Mandrill" image.

The PSNR criterion does not reflects well the quality of the filtered images in the sense of fine detail preservation. That is why it is necessary to check visually both the detail preservation and absence of outliers after filtering. Figure 2 illustrates the impulse noise removal by the designed filter and the median one. Figure 2 (a) shows the noisy test image "Lena", Figure 2 (b) presents the output of the standard 3x3 median filter and Figure 2 (c), (d) show images processed by the proposed filter having estimator (8) window size 3x3 and 7x7. Analyzing this Figure, one can see that the proposed filter possesses both good impulse noise removal and better detail preservation in comparison to the standard median filter.

4. CONCLUSION

We have presented an adaptive impulse rejecting filter for image processing applications. Its deterministic and statistical properties have been analyzed. The proposed filter possesses good impulse noise removal and preserves well edge and fine details in the processed images. The filter optimal parameters have been given. The presented results demonstrate obviously that the designed filter can remove impulse noise even from highly corrupted images. It was established that the optimal impulse detector size as 3x3, the same as the filtering window. This feature allows to simplify the filtering algorithm. The proposed filter can be used for impulse noise removal as well as for information abundance decreasing in image compression applications.

Because the proposed algorithm is strictly non-linear, it not changes the noise-free pixels and not introduces any "new" information. This feature means that the filtered image can be passed through a once trained classifier without the necessity of the new training.

REFERENCES

[1] R.J.Crinon, "The Wilcoxon filter: a robust filtering scheme", in Proc. *IEEE Int. Conf. on Acoustics, Speech, and Signal Processing* 1985, 668-671.

[2] I.Pitas and A.N.Venetsanopoulos, *Nonlinear Digital Filters: Principles and Applications* (Ed.: Kluwer Academic Publisher, 1990).

[3] J.B.Bednar and T.L.Watt, "Alfa-trimmed means and their relationship to median filters," *IEEE Trans. Acoust., Speech, Signal Processing* ASSP-*32*, 1984, 145-153.

[4] P. Heinonen and Y.Neuvo, "Smoothed median filters with FIR substructures," in Proc 1985 *IEEE Int Conf. Acoust., Speech, and Signal Processing* Tampa, March 1985, 49-52.

[5] Y.Fong, C.A.Pomalaza-Ráez, X.Wang. "Comparison study of nonlinear filters in image processing applications". *Opt. Eng. 28*(7), 1989, 749-760.

[6] J.Astola and P. Kuosmanen. *Fundamentals of Nonlinear Digital filtering* (Ed.: Boca Raton-New York: CRC Press, 1997).

[7] A.Neiminen, P. Heinonen and Y.Neuvo, "A new class of detail-preserving filters for image processing," *IEEE Trans. Pat. Anal. Mach. Intell.* PAMI-*9*(1), 1987, 74-90.

[8] Eduardo Abreu, Michael Lightstone, Sanjit K. Mitra, Kaoru Arakawa. "A new Efficient Approach for the Removal of Impulse Noise from Highly Corrupted Images," *IEEE Trans. on Image Processing* *5*(6), 1996, 1012-1025.

[9] J.-S.Lee, "Digital image smoothing and the sigma filter," *Computer Vision, Graphics, and Image Processing, 24,* 1983, 255-269.

[10] L.S.Davis, A.Rosenfeld, "Noise cleaning by iterative local averaging," *IEEE Trans. Syst. Man Cybern* SMC-*8*(9), 1978, 705-710.

[11] V.Lukin, N.N.Ponomarenko, P.Kuosmanen, and J. Astola, "Modified sigma filter for processing of images corrupted by multiplicative and impulse noises," *in Proc. of EUSIPCO-96, III*, Triesto, Italy, 1996, 1909-1912.

[12] Atsushi Teramoto, Isao Horiba, Noburu Sugie, "Improvement of Image Quality in MR and CT Image Using Adaptive K-nearest Neighbor Averaging Filter," *Proceedings of 8th International Conference on Signal Processing Applications & Technology, 1*, San Diego, USA, 1997, 677-681.

[13] D.R.K.Brownrigg, "The weighted median filter," *Commun. ACM, 27*, 1984, 807-818.

[14] Ponomaryov V.I., Pogrebniak A.B. «Novel robust KNN filters with impulsive noise suppression for image processing» *Mathematical Modelling and Estimation Techniques in Computer Vision, Proc. SPIE 3457,* Franqoise Préteux, Jennifer L.Davidson, Edward R.Dougherty, Editors, Orlando, 1998, 19-30.

[15] V.I.Ponomarev, A.B.Pogrebniak. Robust RM filters for radar image processing. Proc. SPIE *2955, Image and Signal Processing for Remote Sensing III,* Jacky Desachy, Ed., 1996, 272-283.

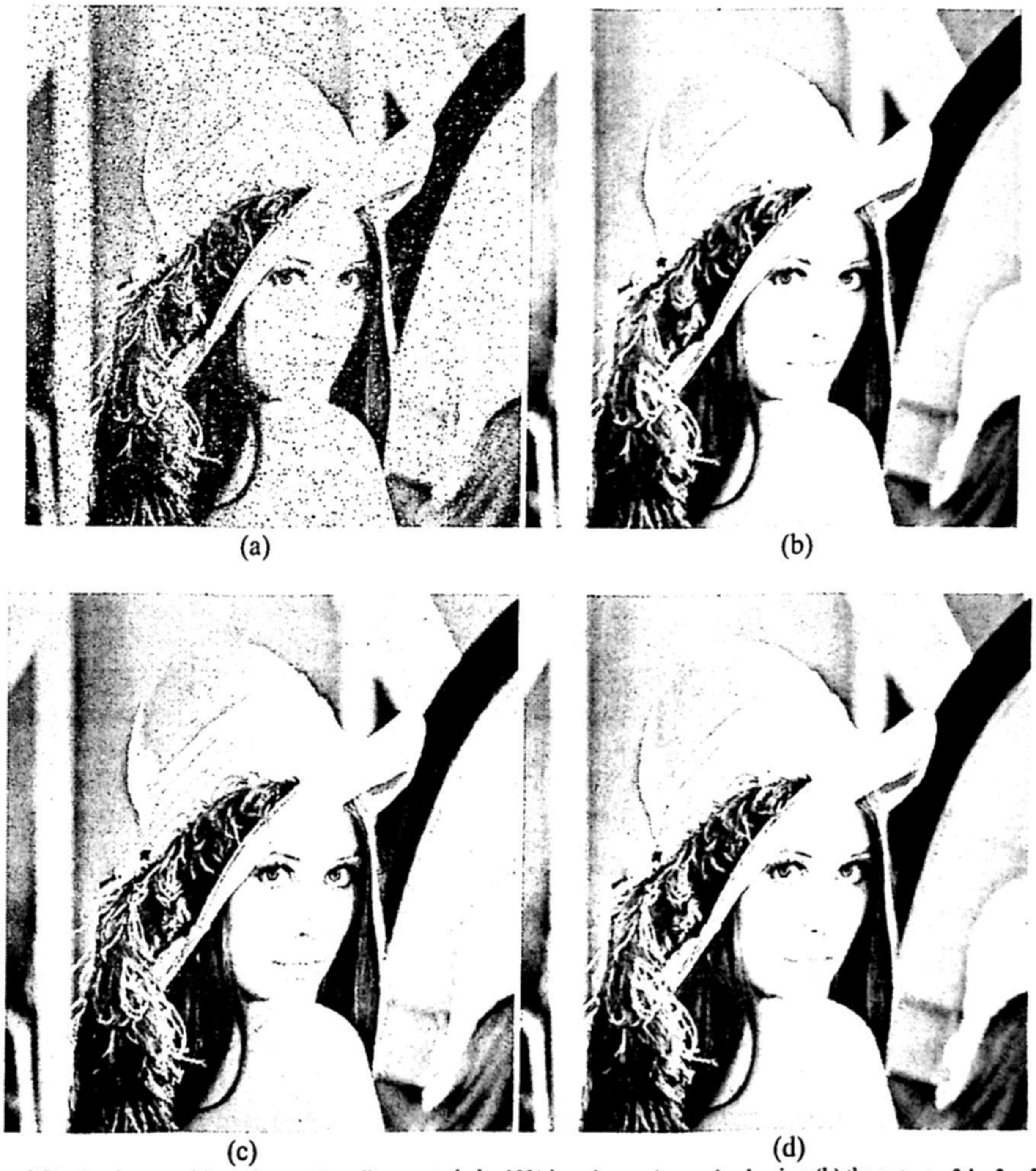
[16] Volodymyr V. Ponomaryov, Oleksiy B. Pogrebnyak. «Novel robust RM filters for radar image preliminary processing». *Journal of Electronic Imaging, 8*(4), 1999, 467-477.

[17] Volodymyr I. Ponomaryov, Oleksiy B. Pogrebnyak, Felipe González Leon "Robust rank detail-preserving filters with noise suppression in image processing applications", *Visual Information Processing VIII*, Stefen K. Park, Richard D. Juday, Chairs/Editors, Proc. SPIE *3716*, Orlando, 1999, 206-211.

[18] T.P.Hettmansperger. *Statistical inference based on ranks* (Ed.: New York Wiley, 1984).
[19] Volodymyr I. Ponomaryov, Luis Niño de Rivera Francisco J.Jallegos Funes, Oleksiy B. Pogrebnyak "Novel detail preserving robust filter for multiplicative and additive noise suppression in the image processing", *Visual Information Processing IX, Proc. SPIE 4041*, Stephen K. Park, Zia-ur Rahman, Chairs/Editors, Orlando, USA, 2000, 172-179.
[20] F.R.Hampel, E.M.Ronchetti, P.J.Roussew, W.A.Stahel. *Robust Statistics. The Approach Based on Influence Function* (Ed.: New York Wiley, 1986).

a) b) c)

Figure 1. a) artificial test image b) 3x3 medi an filter output c) proposed filter output, a=0.05 $L = 3$



(a) (b) (c) (d)

Figure 2. Noisy test and filtering images: (a) test image "Lena" corrupted by 10% impulse random-valued noise; (b) the output of the 3x 3 median filter; (c) the output of the proposed filter (10) with $a = 0.044$ and estimator (8) window size 3x3; (d) the output of the proposed filter (10) with $a = 0.044$ and estimator (8) window size 7x7

Table. Simulation results on impulse noise suppression

Window size of estimator (8) (median filter)	Impulse noise percentage	Lena			Mandrill		
		Filter sensitivity coefficient a	PSNR	PSNR for median filter	Filter sensitivity coefficient a	PSNR	PSNR for median filter
3	1	0.034	45.1	36.4	0.019	34.1	23.64
	2	0.037	43.1	36.2	0.021	31.7	23.58
	3	0.037	42.1	36.1	0.022	30.6	23.53
	4	0.038	41.0	35.9	0.023	29.7	23.48
	5	0.039	40.2	35.8	0.024	28.8	23.42
	6	0.04	39.6	35.6	0.024	28.3	23.38
	7	0.042	39.1	35.4	0.026	27.9	23.34
	8	0.044	38.6	35.3	0.026	27.4	23.27
	9	0.044	38.1	35.0	0.027	27.0	23.24
	10	0.044	37.6	34.8	0.027	26.6	23.18
	11	0.046	37.0	34.6	0.027	26.3	23.13
	12	0.046	36.5	34.3	0.027	26.0	23.06
	13	0.047	36.3	34.2	0.028	25.7	22.98
	14	0.047	35.9	33.9	0.028	25.4	22.94
	15	0.048	35.5	33.7	0.028	25.2	22.88
5	1	0.031	43.7	32.4	0.019	34.1	21.27
	2	0.031	41.7	32.3	0.02	31.8	21.26
	3	0.035	40.9	32.3	0.022	30.1	21.26
	4	0.036	39.8	32.2	0.022	29.6	21.24
	5	0.038	39.2	32.2	0.022	28.8	21.23
	6	0.039	38.7	32.1	0.023	28.2	21.23
	7	0.04	38.3	32.09	0.024	27.8	21.23
	8	0.042	37.8	32.02	0.024	27.3	21.21
	9	0.041	37.4	31.97	0.025	26.9	21.22
	10	0.041	37.0	31.92	0.026	26.5	21.20
	11	0.041	36.6	31.81	0.026	26.2	21.19
	12	0.042	36.2	31.75	0.026	25.9	21.18
	13	0.042	35.9	31.71	0.027	25.6	21.16
	14	0.042	35.6	31.61	0.027	25.4	21.16
	15	0.044	35.3	31.56	0.027	25.1	21.13
7	1	0.027	42.8	30.26	0.019	33.9	20.59
	3	0.034	40.0	30.21	0.02	30.4	20.58
	5	0.039	38.5	30.16	0.022	28.6	20.58
	7	0.041	37.7	30.12	0.024	27.7	20.58
	8	0.041	37.3	30.11	0.024	27.2	20.57
	10	0.044	36.6	30.03	0.025	26.5	20.56
	11	0.047	36.2	29.96	0.025	26.2	20.55
	12	0.044	35.9	29.94	0.025	25.9	20.55
	13	0.046	35.6	29.95	0.026	25.5	20.54
	14	0.046	35.3	29.85	0.026	25.3	20.55
	15	0.044	35.1	29.84	0.027	25.1	20.53