

Combined Image Filter for Robust Fine Detail Preservation and Efficient Noise Suppression

Filtro Combinado sobre Imágenes para la Preservación Robusta de Detalles y la Supresión Eficiente de Ruido

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Article received on June 6, 2000 / accepted on March 11, 2001

Abstract

In this paper, we present a robust image filter that provides preservation of fine details and effective suppression of intensive multiplicative noise. The filter is based on the use of M (robust maximum likelihood) estimators and R (rank) estimators derived from the statistical theory of rank tests. At the first stage, to provide impulsive noise rejection, the presented image filter uses an adaptive spike detector and a re-descending M -estimator combined with the median estimator to remove outliers in the center of the filtering window. At the second stage, to provide the multiplicative noise suppression, a modified sigma filter combined with detail preserving scheme of a Lee filter, is used. Visual and quantitative analysis of the simulation results shows that the proposed image filter demonstrates good preservation of fine details, effective multiplicative noise suppression and impulsive noise removal.

Keywords: Image processing, nonlinear filters, detail preserving image filters.

Resumen

En este trabajo presentamos un filtro robusto para imágenes que permite preservar detalles finos y suprimir de manera efectiva ruido intenso de tipo multiplicativo. El filtro se basa en el uso de estimadores robustos de probabilidad máxima (estimadores tipo M) y estimadores de rango (tipo R) derivados de la teoría estadística de conjuntos ordenados. En una primera etapa, para proporcionar rechazo de ruido tipo impulsional, el filtro presentado usa un detector de picos adaptativo y un estimador tipo M re-descendente combinado con un estimador mediano para remover los valores alejados (outliers) en el centro de la ventana de filtrado. En una segunda etapa, para proporcionar supresión de ruido tipo multiplicativo, se usa un filtro sigma modificado combinado con un filtro preservador de detalles de Lee. Un análisis visual y cuantitativo de los resultados de simulación muestran que el filtro propuesto preserva bastante bien detalles finos, así como la efectiva supresión de ruido multiplicativo y la remoción de ruido impulsional.

Palabras Clave: Procesamiento de imagen, filtros no lineales. Filtros de imagen que preservan detalles.

1 Introduction

In many practical situations the quality of digital images is not acceptable due to random noise presence. It is highly desirable to get a good image enhancement providing both effective noise suppression and fine detail preservation. Linear filters are commonly used to attenuate Gaussian noise in images. However, they fail when the image data contains impulsive noise, they tend also to blur the original image.

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 impulsive 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, the median, Wilcoxon (see Crinon (1985)) and the α -trimmed mean (see Bednar (1984)) filters, which are completely described in the book on nonlinear image filters of Astola (1997), can remove small size objects considering them as outliers. As a result, they often occur to be unable to preserve fine details.

A linear median hybrid (LMH) filter was introduced by Heinonen and Neuvo in 1985 to simultaneously provide edge preservation with impulsive noise removal. Its subclass, the FIR-median hybrid filters (FMH), proposed by Neiminen, Heinonen and Nuevo (1987), provides the preservation of thin lines as well (see Astola (1997)). Impulse rejecting filters, also described in the book of Astola (1997), suppress impulsive noise effectively and avoid unnecessary distortions of noise-free pixels. These filters use different impulse detectors to decide if the current pixel can be classified as an outlier and be filtered by some nonlinear filter or it can be unaltered otherwise. To provide simultaneous detail preservation, rather complicated impulse detectors have to be used. For example, Mitra et al (see Abreu (1996)) suggested

a ROM impulse rejecting filter combined with a sophisticated fuzzy detector that can be optimized using image training data.

Besides, the sigma and Lee filters, proposed by Jong-Sen Lee (see Lee (1980) and (1983)), can preserve fine details well, but their robustness is insufficient to provide desired suppression of impulsive noise, as it was explained in the literature, see Astola (1997), Pitas and Venetsanopoulos (1990) and Fong (1989). Attempts to get more appropriate robust versions of two latter mentioned techniques are known.

For example, the modified locally adaptive sigma filter (see Lukin et al (1996)) possesses some robust features but it does not perform well in the case of spikes with a probability larger than 0.05.

Recently, we introduced the robust KNN-type filters (Ponomaryov (1998)), which provide both good fine detail preservation and appropriate impulsive noise suppression. Unfortunately, they do not possess effective suppression of additive and multiplicative noise. In this paper we present a modification that allows to effectively suppress multiplicative noise as well as impulsive noise removal and to preserve fine details.

2 Image Noise Model

Different impulse noise models were proposed and described in the literature (Pitas and Venetsanopoulos (1990), Astola (1997)). We use the following image degradation model in the case of impulse noise presence (see Ponomaryov (1998))

$$u(x, y) = n_{im}(e(x, y)) \quad (1)$$

where $e(x, y)$ is an original (true) image, $u(x, y)$ is the distorted image, and $n_{im}(e(x, y))$ is the functional

$$n_{im}(e(x, y)) = \begin{cases} \text{random valued spike with probability } P \\ e(x, y) & \text{otherwise} \end{cases}$$

We assume that the spikes have uniformly distributed random values between 0 and 255 for byte-represented images.

On the other hand, the images are often corrupted not only by impulsive noise, but by multiplicative noise as well. From this point of view, the noise model, Equation (1), has to be modified to take this feature into account:

$$u(x, y) = n_m(n_m(x, y) \cdot e(x, y)) \quad (2)$$

where $n_m(x, y)$ denotes the multiplicative noise assumed to be Gaussian.

With this model, the problem of noise removal is to design a robust filtering algorithm able to remove the impulsive noise added to the image, to suppress the multiplicative noise and to preserve fine details as well. From this point of view, the image filter has to be a nonlinear filter and to use a robust mean estimator of pixels within the scanning window instead of the local average.

3 Structure of the Proposed Filter

Recently, we introduced a novel robust image filter that can both remove impulsive noise and preserve fine image details as well (Ponomaryov (1998)). It uses combined robust rank and M estimators to calculate the robust point estimate of the pixels within the filtering window. As it was shown in our previous paper (Ponomaryov (1998)), good results for byte-represented images were provided by the filter modification involving a median estimator combined with an M estimator (the theory of M estimators is completely given in a book of Hampel (1986)). Such a combination of robust estimators is a combined RM estimator, as it was presented in our previous paper dedicated to a study of such estimators (Ponomaryov (1999)). In this paper, we consider the combined RM estimator that uses the redescending function similar to the well known K-nearest neighbor filter (KNN filter), proposed by Davis and Rosenfeld (1978).

The operation of the proposed filter can be described as follows. The filter uses an iterative calculation scheme derived from the basic M estimator. In opposite to a classic M-estimator that uses the median of sample data, the proposed filter uses the value of the central pixel of the filtering window as the initial estimate to provide preservation of image fine details. At the current iteration indexed as q , a sample of the pixels nearest by value to the previous estimate is formed and then the median value of the sample is calculated. Next, the calculated median value is used as the previous estimate at the next iteration with the index $q+1$. The number of the nearest neighbors K_c is calculated before performing the iterations and it does not change in the next iterations. This number reflects the local data activity in the presence of spikes.

Therefore, the K_c value is calculated for every (i, j) pixel to adjust the filter performance to the local image data characteristics that results in better detail preservation. It was shown in the aforementioned paper (Ponomaryov (1998)) that such an image filter effectively removes spikes and preserves fine image details. Additionally, it was determined that the use of the proposed iterative scheme decreases the number of nearest pixels K_c necessary to remove spikes, and with a

lower K_c value, the filter preserves fine details significantly better. The iterations are stopped when the current estimate is equal to the previous one. Usually, 3 to 4 steps are enough to satisfy this condition.

The operation of the proposed image filter, called MM-KNN filter, can be formulated as:

$$\hat{e}_{\text{MMKNN}}^{(q)}(i, j) \text{med}\{g^{(q)}(i+m, j+n)\} \quad (3)$$

where $g^{(q)}(i+m, j+n)$ is a set of K_c pixels within the filter window that are the closest by value to the estimation obtained at the previous step $\hat{e}_{\text{MMKNN}}^{(q-1)}(i, j)$, where $\hat{e}_{\text{MMKNN}}^{(0)}(i, j) = u(i, j)$, $m, n = -L..L$, $(2L+1)^2$ defines the filter scanning window size. The current number of the nearest neighbor pixels, $K_c(i, j)$ is determined as

$$K_c(i, j) = K_{\text{min}} + aS(u(i, j)) \leq K_{\text{max}} \quad (4)$$

where the parameter a controls the filter sensitivity to local data variance in order to provide a proper detail detection.

The minimal number of the neighbors K_{min} determines the filter noise removal ability in homogeneous image regions, and the maximal number of the neighbors K_{max} restricts the edge and detail smoothing. During various simulations, it was found that the filter behavior is very sensitive to the spike detector $S(u(i, j))$ efficiency. Thus, this detector was modified to produce better results in the filtered images as

$$S(u(i, j)) = \frac{\text{med}\{|u(i, j) - u(i+m, j+n)|\}}{\text{MADM}\{u(i, j)\}} + 0.5 \frac{\text{MADM}\{u(i, j)\}}{\text{med}\{u(i+k, j+l)\}} \quad (5)$$

where $\text{med}\{u(i+k, j+l)\}$ is the median of the pixels within the filtering window, $k, l = -L..L$, and MADM (the median of absolute deviations from median in our terms) is calculated as

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

As it was shown before (Ponomaryov, 1998), the window size 5×5 for this filter is optimal for different impulsive noise percentage and different type of images and for this window size the minimal number of the neighbors $K_{\text{min}} = 5$ provides both good fine detail preservation and impulsive noise removal.

To enhance the impulsive noise removal ability of the described filter, one can involve the standard median filter output. Thus, when K_c is high the filter, Eq.(3), output is substituted by the output of the median filter. Using simulations it was found that when $K_c > 7$ the output of the filter can be substituted by the output of the 3×3 median filter and when $K_c > 250$ such a substitution should be done with 5×5 median filter.

The considered filter, Equation (3), is not able to suppress efficiently noise of different nature, in particular multiplicative noise. This leads us to elaborate a new detail preserving robust filter, which is able to both remove spikes and suppress multiplicative noise. For this purpose, the output of the impulsive noise removal filter can be used as the initial estimate for another M-estimator suitable for image filters as it was considered in our paper (Ponomaryov (1999)):

$$\theta_{\mathbf{X}} = \frac{\sum_{i=1}^n X_i \varphi(X_i - \text{med}\{\mathbf{X}\})}{\sum_{i=1}^n 1_{[1, \dots, j]}(\varphi(X_i - \text{med}\{\mathbf{X}\}))} = \frac{\sum_{i=1}^n X_i \varphi(X_i - \text{med}\{\mathbf{X}\})}{\sum_{i=1}^n 1_{[1, \dots, j]}(X_i - \text{med}\{\mathbf{X}\})} \quad (7)$$

where $\theta_{\mathbf{X}}$ is the M-estimate of the sample location parameter θ , φ denotes a normalized function $\varphi: \varphi(X) = X\psi(X)$ and $\mathbf{X}: X_i, i = 1..n$ is a data sample.

The presented estimator is correct with the simplest $\varphi(X)$ functions only, such as Huber's limiter type M estimator or skipped median (see Hampel, 1986).

To supply the proposed image filter the ability of multiplicative noise suppression, we propose to use the following redescending function for M-estimator:

$$\varphi(X) = \begin{cases} X, & X - \theta^{(0)} \leq b \cdot \text{med}\{\mathbf{X}\} \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

where \mathbf{X} is the vector of image data within the filtering window, $\theta^{(0)} = \hat{e}_{\text{MMKNN}}(i, j)$, $\text{med}\{\mathbf{X}\}$ and b is the median of the pixels within 5×5 filtering window. Thus, an M-type

image filter that uses the re-descending defined by Equation (8) can be written as

$$e_M(i, j) = \frac{\sum_{m=-L}^L \sum_{n=-L}^L u(i, j) \psi' \{u(i+m, j+n) - e^{(0)}(i, j)\}}{\sum_{m=-L}^L \sum_{n=-L}^L \psi' \{u(i+m, j+n) - e^{(0)}(i, j)\}} \quad (9)$$

where

$$\psi' \{u(i+m, j+n) - e^{(0)}(i, j)\} = \begin{cases} 1, & |u(i+m, j+n) - e^{(0)}(i, j)| \leq b \cdot \text{med}\{u(i, j)\} \\ 0, & \text{otherwise} \end{cases}$$

$\text{med}\{u(i, j)\}$ is the median of the pixels within the filtering window. Coefficient b controls the multiplicative noise suppression, $m, n = -L..L$, $2(L+1)$ is the filtering window size, $e^{(0)}(i, j) = e_{MMKNN}(i, j)$.

It was proved by simulation that the filter given by Equation (9) possesses good suppression of multiplicative noise. However, it provides inappropriate detail preservation only when the noise level (relative variance) is small. To avoid this drawback an adaptive scheme similar to that one used by the local statistic Lee filter (Lee (1980)) was applied. According to this scheme, the output of the image filter can be represented as

$$\hat{e}(i, j) = e_{MMKNN}(i, j)W(i, j) - (1 - W(i, j))e_M(i, j) \quad (10)$$

where

$$W(i, j) = 1 - \left(c \frac{e_M(i, j)}{\text{med}\{e_M(i, j) - u(i+m, j+n)\}} \right)^2 \quad (11)$$

is a robust estimator of the local data activity. Coefficient c controls the detail preservation and $m, n = -L..L$. Since the estimator $W(i, j)$ has a nonlinear nature, sometimes it gets negative values. Usually, this fact occurs at homogeneous image regions. In such situations, the output of the filter given by Equation (10), should be substituted by the output of the multiplicative noise suppressor given by Equation (9).

With the implementation of the adaptive detail-preserving scheme given by Equation (10), it was found during

simulations that the filtering results do not depend significantly on the value of coefficient c . In order to simplify the adjustment of the filter behavior this parameter can be treated as a constant. It was found that this optimal constant value is $b = 2$.

Thus, the proposed image filter given by Equation (10), represents the consequential connection of two detail-preserving filters: 5x5 MMKNN filter, Equation (3) to (5), for impulsive noise removal, and the M filter, Equation (9), for multiplicative noise suppression. The M filter given by Equation (9), is similar to the well-known detail preserving sigma image filter except the fact that it uses locally adaptive data weighting. Finally, the outputs of these filters are mixed in the way similar to the Lee filter taking into account the image data local activity, Equation (11), to achieve better detail preservation. Figure 1 shows the structure of the proposed filter.

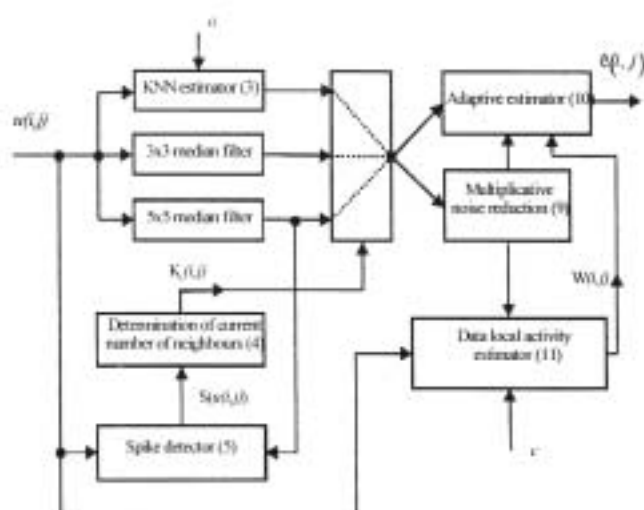


Figure 1. Structure of the proposed filter

4 Simulation Results

We performed a number of different tests to study the properties of the novel algorithms given by Equations (3), (5), (10) and (11), and to compare them to the standard method. The criterion used to compare performance of various filters was the mean square error (MSE).

To determine the noise suppression properties of the proposed filters, the standard test grayscale images "Mandrill" and "Lena" shown in Figure 2(a) and (b) were corrupted by the mixture of multiplicative Gaussian and impulsive noise according to Equation (2). These images were chosen because they are of different type in the sense of small detail percentage. The test image "Mandrill" is characterized by the

presence of a number of small details. Their preservation after filtering has a great influence on the resulting MSE value. On the other hand, the test image "Lena" is characterized by the presence of homogeneous regions. Therefore, the MSE values of the filtered image reflect, mainly, the noise suppression ability of the proposed filter. As a result, the joint analysis of the MSE values of the filtered images gives the possibility to estimate the fine detail preservation and noise suppression properties of the designed filter. This is mainly due to the absence of objective universal criteria to estimate these characteristics in general and to measure filter performance in fine detail preservation in particular.

The parameters of the contaminating noise mixture were varied: the percentage of impulsive noise and the relative variance of the multiplicative noise. Filter parameters a from Equation (4) and c from Equation (11) were varied in each case to adjust filter characteristics and to find the optimal (in minimum MSE sense) filtered images, both "Mandrill" and "Lena".

The minimal MSE values were determined by simulations and analyzed. Their analysis shows that the optimal (in the MSE sense) values of parameters a, c have almost the same values for both images of different local data activity. However, the analysis detected small differences in coefficient values in the case of low variance of multiplicative noise. The optimal values of parameter c for the filtered "Lena" image were a little greater than the values of the filtered "Mandrill" image. Such a performance of the filter can be explained by the fact that greater c values provide better multiplicative noise suppression in homogeneous areas and result in a smaller MSE value, while the fine detail preservation performance is almost not decreased and not influence much in this case. In the other hand, since the image "Mandrill" has much more fine details, the decrease of the fine detail preservation performance is much sensible in the resulting MSE value.

The same situation occurred with the values of coefficient a when the variance of the multiplicative noise was high (≥ 0.1). This can be explained by the fact that in the case of strong multiplicative noise, the impulsive noise suppression part of the filter treats some of the noisy pixels as outliers and is able to remove them. In such conditions, the noise loses its Gaussian nature because of the restricted dynamic range of byte-represented images. Under such restrictions, the noise distribution changes from an exponential distribution at dark regions to salt-and-paper noise at bright regions. Generally, the proposed image filter does not take into account the specific features of the aforementioned distortions. In such conditions, image enhancement is provided due to the robust properties of the designed filter that results in greater values of the coefficient a .

Thus, the minimal MSE values of the filtered "Lena" images result in slightly greatest values for a in comparison to those of the image "Mandrill" to provide better multiplicative noise suppression ability when the noise variance is high. With respect to the fine detail preservation, in this paper are presented the lowest values of the coefficients a and c . Those correspond to the optimal results of the filtering of the image "Mandrill".

Impulse noise percentage	Variance of multiplicative Gaussian noise			
	0	0.05	0.1	0.25
0	0(0)	0.01(0.16)	0.02(0.25)	0.03(0.4)
1	0.01(0)	0.035(0.17)	0.07(0.25)	0.08(0.41)
5	0.07(0)	0.06(0.18)	0.075(0.27)	0.095(0.42)
10	0.12(0)	0.18(0.2)	0.08(0.29)	0.15(0.45)
15	0.41(0)	0.4(0.22)	0.28(0.32)	0.75(0.45)

Table 1. Optimal values of filter parameters (Equation (4)) and (in parenthesis, Equation (9))

Test image	Impulse noise percentage	Variance of multiplicative Gaussian noise			
		0	0.05	0.1	0.25
Mandrill	0	24.7	324.3	469.1	745.7
	1	39.1	334.4	476.4	750.8
	5	100.2	377.1	510.2	781.2
	10	175.5	430.3	550.5	813.9
	15	239.9	494.5	601.4	849.6
Lena	0	3.4	81.7	116.9	268.4
	1	6.4	79.2	120.8	265.9
	5	16.8	92.2	127.1	280.2
	10	31.9	104.5	143.1	288.2
	15	30.6	115.1	155.3	297.4

Table 2. MSE values determined by simulations with the designed image filter corresponding to the values of filter parameters and given in Table 1

Test image	Impulse noise percentage	Variance of multiplicative Gaussian noise			
		0	0.05	0.1	0.25
Mandrill	0	484.5	555.1	622.1	802.2
	1	484.9	556.5	623.5	803.4
	5	489.5	563.7	632.6	813.9
	10	493.8	572.6	643.5	826.8
	15	500.7	587.9	662.8	850.6
Lena	0	37.5	87.0	129.8	250.4
	1	37.8	87.7	130.8	251.6
	5	39.5	91.1	135.5	258.0
	10	41.8	96.0	142.3	266.5
	15	45.4	103.8	153.0	282.1

Table 3. MSE values determined by simulations with 5x5 median filter

The optimal values for the parameters a, c are shown in Table 1. The MSE values determined by the simulations for filtering noised images "Mandrill" and "Lena" are presented in Tables 2 and 3, respectively. To make the quantitative comparison of the characteristics of the designed filter, Table 3 shows the results of noise suppression when a 5x5 median filter is applied.

Analyzing Tables 2 and 3 one can see that the proposed filter provides better quantitative results (in comparison to the standard median filter), when the relative variance of the multiplicative noise is less than 0.25. However, when the relative variance of the multiplicative noise is significantly large (0.25 and more), the proposed filter does not suppress the noise well enough. This fact can be explained by the strictly nonlinear structure of the proposed filter, which fails when

the neighbor pixels take min/max dynamic range values too often, i.e. when the noise relative variance is too large. The filter "recognizes" these corrupted regions as the image objects trying to preserve these "false" fine details. These "mistakes" can be observed in a filtered image as dark and bright dots. In other words, the proposed filter possesses the robust properties but they are not sufficient enough in the case of very intensive multiplicative noise.

Figure 3 shows the noisy versions of the test images shown in Figure 2. Figures 4 shows the output of the standard 5x5 median filter, while Figure 5 presents the resulting images processed by means of the proposed filter. Analyzing these figures, one can see that the designed filter provides more effective noise suppression in homogeneous image regions in comparison to the median filter. The fine details of the image are preserved significantly better as well.

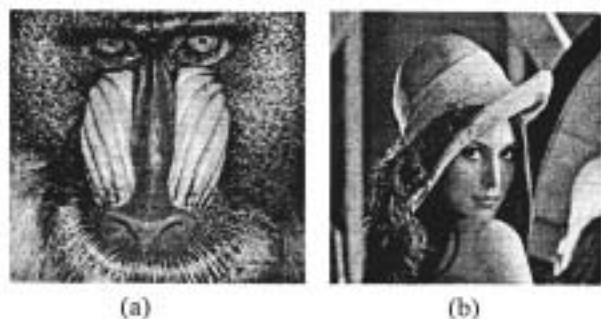


Figure 2. Test images used in simulations:
(a) «Mandrill» and (b) «Lena»



Figure 3. Noisy versions of the test images of Figure 2.
Parameters of noise mixture: 5% impulsive noise, multiplicative
Gaussian noise of variance 0.1



Figure 4. Results obtained by means of a 5x5 median filter



Figure 5. Results obtained by means of the proposed filter using
the parameter values given in Table 1.

5 Conclusions and future work

A robust RM-type filter for image processing applications has been presented. The designed filter is able both to remove complex noise mixture and to preserve edge and fine details.

The statistical properties of the filter are described. The filter optimal parameters for different parameters of the noise mixture are obtained and given.

The designed filter provides good visual quality of the processed images when the variance of the multiplicative noise

is not too large, and the impulsive noise percentage is at the middle level. To improve the filter performance, the methods for impulsive noise removal from highly corrupted images can be also used, for example, the running Min and Max operation (see Han (1997)) or the ROM filter, proposed in Abreu (1996).

Another way to improve the filter performance is to apply better spike detectors and data local activity estimators, and to take into account the peculiarities of the multiplicative noise with high values of the relative variance that can be certainly a subject for further investigations.

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