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Performance enhancement of image impulse noise filters by image rotation and fuzzy processing

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Abstract

A novel filtering approach for improving the performances of recursive impulse noise filters is proposed. The method is based on the fact that the output of a recursive image filter varies depending on the orientation of the input image. Hence, the proposed method generates four input images by rotating the noisy input image at integer multiples of 90°, obtains four restored images by processing these images by the noise filter, and then computes the enhanced output image from these filtered images by using a fuzzy system. Internal parameters of the fuzzy system are determined by training by using simple artificial training images. The validity of the proposed method is demonstrated by extensive filtering experiments, which are conducted for four different impulse noise filters, four different test images and three different noise densities. The results show that the proposed method can efficiently be used for improving the performance of any recursive impulse noise filter to obtain significantly enhanced output images.

Keywords: Image processing; Image rotation; Noise filtering; Nonlinear filters; Fuzzy systems

1. Introduction

One of the most common problems encountered in image acquisition and/or transmission is the contamination of the image by impulse noise due to various imperfections in image sensors and communication media. The noise in the image data severely degrades the performances of further image processing operations (such as edge detection, image segmentation, object recognition, etc.) that are to be performed on the acquired/received image data. Therefore, it is of vital importance to restore the corruptions in the image data caused by the noise before performing any subsequent image processing task on the image data.

In the last decade, a large number of methods have been presented for the removal of impulse noise from digital images. A considerable number of these methods are based on order statistics filters, which exploit the rank order information of the pixels contained in a given filtering window. The *standard median filter* [1] attempts to remove impulse noise from the center pixel of a given filtering window by altering this pixel with the median of the pixels within the window. This simple approach has the advantage of being computationally very efficient and provides a reasonable

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noise removal performance but it also has the disadvantage of removing thin lines and blurring image details even at low noise densities. The modified versions of the standard median filter, the *weighted median filter* [2] and the *center-weighted median filter* [3], which give more weight to certain pixels in the filtering window, have been proposed to avoid the inherent drawbacks of the standard median filter. These filters usually offer better detail preservation performance than the median filter, but at the expense of reduced noise removal performance.

The standard, the weighted and the center-weighted median filters are *spatially invariant* operators making no distinction between the noisy and the noise-free pixels of the input image regarding filtering behavior. This results in undesirable distortions and blurrings in the output image and also causes the loss of valuable information from the image data.

In an attempt to avoid this problem, a number of methods [4–23] combine the noise filter with an *impulse detector* that aims to determine whether the center pixel of a given filtering window is noisy or not. If the center pixel is classified by the impulse detector as a noisy pixel, its restored value is obtained by processing the pixels in the filtering window by the filter. If the center pixel is classified as noise-free, it is left unchanged. Although this approach significantly enhances the performance of the noise filter by reducing its distortion effects, its performance inherently depends on the performance of the impulse detector. Hence, several different impulse detection approaches utilizing median filters [4–7], center-weighted median filters [8–11], boolean filters [12], edge detection kernels [13], homogeneity level information [14], statistical tests [15,16], classifier based methods [17], rule based methods [18], level detection methods [19], pixel counting methods [20] and soft computing methods [21–23] have been proposed.

In addition to the median-based filters mentioned above, various types of mean filters are successfully utilized for impulse noise removal from digital images [24–29]. These filters usually exhibit better filtering performance compared to the median-based filters. However, their computational complexity is, in general, higher too.

There are also a number of nonlinear filters based on soft computing methodologies such as neural networks [30,31], fuzzy systems [32–36] and neuro-fuzzy systems [37–39] as well as many hybrid filters [40–49] constructed by combining the desired properties of the above mentioned filters. These filters are usually more complex than the above mentioned median- and the mean-based filters, but they usually offer much better noise suppression and detail preservation performance.

Naturally, none of the impulse noise removal methods mentioned above is 100% efficient. They leave some of the noisy input pixels unfiltered, causing noise spikes at the output image, and filter some of the noise-free pixels, causing undesirable distortions at the output image. This is mainly due to the uncertainty introduced by the noise corrupting the input image.

In the last few decades, fuzzy systems have been shown to be very successful at handling uncertainty and imprecision in many different problems encountered in various areas of science and technology. Hence, fuzzy systems may be employed to deal with the uncertainty encountered in impulse noise removal from digital images and may be used to improve the performances of impulse noise filters provided that appropriate network topologies and processing strategies are adopted.

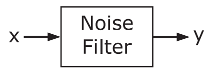
In this paper, a novel filtering approach for improving the performances of image impulse noise filters is proposed. The method exploits the fact that the output image of a recursive image filter varies depending on the orientation of the input image. Hence, the proposed method generates four input images by rotating the noisy input image at integer multiples of 90°, obtains four restored images by processing these images by the noise filter, and then computes the enhanced output image from these filtered images by using a fuzzy system. The validity of the proposed method has been demonstrated by extensive simulation experiments covering four different impulse noise filters, four different test images and three different noise densities.

The rest of the paper is organized as follows: Section 2 explains the motivation behind the proposed method and describes the building blocks used to implement it. Section 3 discusses the application of the proposed method with selected impulse noise filters from the literature. Results of the filtering experiments conducted to evaluate the performance improvements obtained by using the proposed method and comparative discussion of these results are also presented in this section. Section 4, which is the final section, presents the conclusions.

2. The proposed method

Fig. 1 shows a conventional noise filter and two typical filtering windows. In most filtering applications, the noisy input image is processed by sliding one of these two filtering windows on the image. Here the window size is chosen as 3×3 pixels, corresponding to the minimum window size. The window is usually started from the upper-left corner of the image, moved sideways, and progressively downwards in a *raster scanning* fashion. For each filtering window, the filtered (restored) value of the input pixel located at the center of the filtering window is computed by appropriately processing the pixels contained within the window. The operation performed on the pixels within the window to compute the restored value of the center pixel depends on how the noise filter is applied to the noisy input image.

For the non-recursive case, the filtering window in Fig. 1b is used. In this way, the filtered value of the input pixel located at the center of the filtering window depends



a

x[l-1,c-1]	x[l-1,c]	x[l-1,c+1]
x[l,c-1]	x[l,c]	x[l,c+1]
x[l+1,c-1]	x[l+1,c]	x[l+1,c+1]

b

y[l-1,c-1]	y[l-1,c]	y[l-1,c+1]
y[l,c-1]	x[l,c]	x[l,c+1]
x[l+1,c-1]	x[l+1,c]	x[l+1,c+1]

c

Fig. 1. (a) A conventional noise filter, (b) A 3×3 pixel non-recursive filtering window centered at location (l, c), (c) A 3×3 pixel recursive filtering window centered at location (l, c).

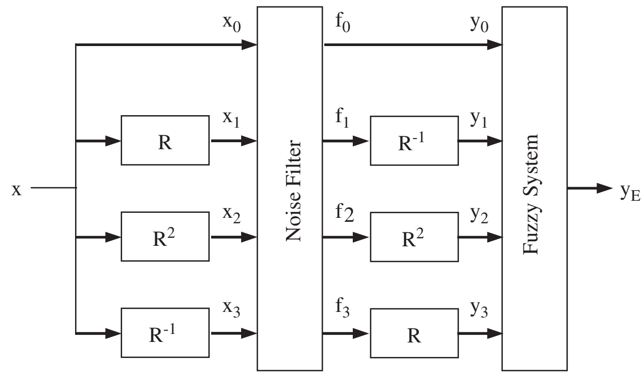


Fig. 2. Schematic representation of the proposed method.

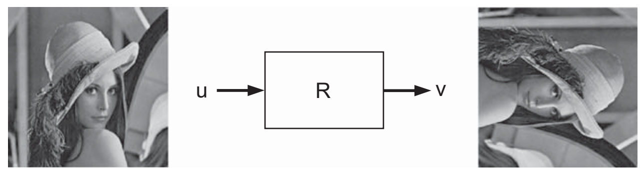


Fig. 3. Operation of the image rotation operator. The operator rotates its input image by 90° in clockwise direction.

only on the pixels of the noisy input image contained in the filtering window.

If the filter is applied recursively, however, the filtering window in Fig. 1c is used. In this case, the filtered value of the input pixel located at the center of the filtering window will depend on pixels of both the noisy input image and the filtered (restored) output image. It should be noted that the pixels of the restored output image contained in the recursive filtering window in Fig. 1c represent the past outputs of the noise filter. Hence, the output of an image filter, when it is applied recursively, is usually better than the case when it is applied nonrecursively. It should further be observed that the output of a recursive image filter depends on the order in which the pixels of the noisy input image are processed. This property of recursive image filters constitutes the fundamental idea behind the method proposed in this paper. It should finally be emphasized that any impulse noise filter can be used recursively or nonrecursively on a noisy input image. Therefore, the filtering approach proposed in this paper is valid for all impulse noise filters provided that they are applied recursively.

Fig. 2 shows a schematic representation of the proposed method for improving the performance of a recursive noise filter for enhancing its output image. There are three main blocks in this figure: the noise filter, the image rotation operator and the fuzzy system. We will now describe these blocks, as well as the application of the proposed method to a noisy image, in more detail.

2.1. The noise filter

The noise filter is the filter whose filtering performance is to be improved to yield an enhanced output image. The only restriction on the noise filter is that it must be recursive. The proposed method may be applied with any recursive noise filter since its operation is independent of the operation of the noise filter.

2.2. The image rotation operator

The image rotation operator is an image filter whose output image is obtained by rotating its input image by 90° in *clockwise* direction. Fig. 3 illustrates the operation of the rotation operator. The operator may formally be defined as follows:

Let $R(.)$ denote the image rotation operator. Let u denote a digital image applied to the input of the rotation operator, and $u[l, c]$ denote a pixel of this image at the coordinates (l, c). Here l and c represent the line and the column indices, respectively, with $1 \leqslant l \leqslant L$ and $1 \leqslant c \leqslant C$ for an input image u having the size of $L \times C$ pixels. Similarly, let v denote the image obtained at the output of the rotation operator, that is $v = R(u)$. Based on these definitions, v is the rotated version of u by 90° in *clockwise* direction, and the pixels of v are obtained from the pixels of u as follows:

$$v[c, l] = u[L - l + 1, c] \tag{1}$$

with $l = 1, 2, \ldots, L$ and $c = 1, 2, \ldots, C$.

It should be noted that the output image v has the dimension of $C \times L$ pixels (C lines and L columns) since the input image u has the dimension of $L \times C$ pixels (L lines and C columns).

We will use the notation of $R^2(u)$ to briefly represent the successive rotations of the input image u for 2 times. Hence $R^2(u)$ is identical to $R(R(u))$.

The definition of the $R^{-1}(.)$ operator is straightforward from the above definitions and it corresponds to the rotation of the input image by 90° in *counterclockwise* direction.

2.3. The fuzzy system

The fuzzy system used in the structure of the proposed scheme is a first order Sugeno type fuzzy system with four inputs and one output [50]. Each input has two membership functions. The input–output relationship of the fuzzy system may be defined as follows:

Let $X_0, \ldots, X_3$ denote the inputs of the fuzzy system and Y denote its output. Hence, the images $y_0, \ldots, y_3$ are applied to the inputs $X_0, \ldots, X_3$ and the enhanced image y_E is obtained at the output Y during operation. Each possible combination of inputs and their associated membership functions is represented by a rule in the rule base of the fuzzy system. Since the fuzzy system has four inputs and each input has two membership functions, the rule base contains a total of 16 (2^4) rules, which are as follows:

1. if (X_0 is I_{01}) and (X_1 is I_{11}) and (X_2 is I_{21}) and (X_3 is I_{31}), then $R_1 = O_1(X_0, X_1, X_2, X_3)$.
2. if (X_0 is I_{01}) and (X_1 is I_{11}) and (X_2 is I_{21}) and (X_3 is I_{32}), then $R_2 = O_2(X_0, X_1, X_2, X_3)$.
3. if (X_0 is I_{01}) and (X_1 is I_{11}) and (X_2 is I_{22}) and (X_3 is I_{31}), then $R_3 = O_3(X_0, X_1, X_2, X_3)$.
4. if (X_0 is I_{01}) and (X_1 is I_{11}) and (X_2 is I_{22}) and (X_3 is I_{32}), then $R_4 = O_4(X_0, X_1, X_2, X_3)$.
5. if (X_0 is I_{01}) and (X_1 is I_{12}) and (X_2 is I_{21}) and (X_3 is I_{31}), then $R_5 = O_5(X_0, X_1, X_2, X_3)$.

$\vdots$

16. if (X_0 is I_{02}) and (X_1 is I_{12}) and (X_2 is I_{22}) and (X_3 is I_{32}), then $R_{16} = O_{16}(X_0, X_1, X_2, X_3)$.

where I_{ij} denotes the jth membership function of the ith input, R_k denotes the output of the kth rule, and O_k denotes the kth output membership function. The input membership functions are generalized bell type and the output membership functions are linear

$$I_{ij}(X_i) = \frac{1}{1 + \left|\frac{X_i - a_{ij}}{b_{ij}}\right|^{2c_{ij}}} \tag{2}$$

$$O_k(X_1, X_2, X_3, X_4) = d_{k0}X_0 + d_{k1}X_1 + d_{k2}X_2 + d_{k3}X_3 + d_{k4} \tag{3}$$

with $i = 0, 1, 2, 3$, $j = 1, 2$ and $k = 1, 2, \ldots, 16$.

Here the parameters a, b, c and d are constants that characterize the shape of the membership functions. The optimal values of these parameters are determined by training, which will be discussed in detail later on.

The output of the fuzzy system is the weighted average of the individual rule outputs. The weighting factor, w_k, of each rule is calculated by evaluating the membership expressions in the antecedent of the rule. This is accomplished by first converting the input values to fuzzy membership values by utilizing the input membership functions and then applying the *and* operator to these membership values. The *and* operator corresponds to the multiplication of input membership values. Hence, the weighting factors of the rules are calculated as follows:

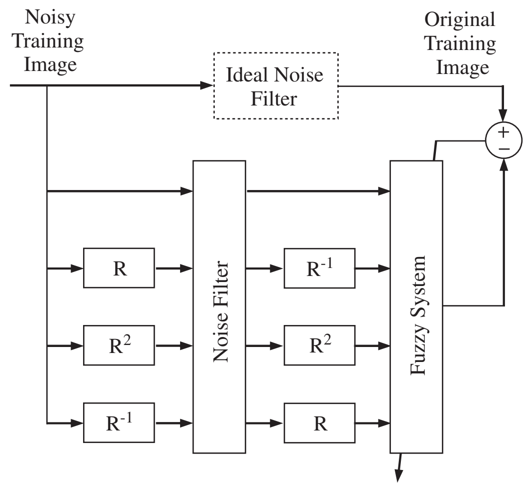


Fig. 4. Training of the fuzzy system.

$$\begin{aligned}
w_1 &= I_{01}(X_0)I_{11}(X_1)I_{21}(X_2)I_{31}(X_3)\\
w_2 &= I_{01}(X_0)I_{11}(X_1)I_{21}(X_2)I_{32}(X_3)\\
w_3 &= I_{01}(X_0)I_{11}(X_1)I_{22}(X_2)I_{31}(X_3)\\
w_4 &= I_{01}(X_0)I_{11}(X_1)I_{22}(X_2)I_{32}(X_3)\\
w_5 &= I_{01}(X_0)I_{12}(X_1)I_{21}(X_2)I_{31}(X_3)\\
&\vdots\\
w_{16} &= I_{02}(X_0)I_{12}(X_1)I_{22}(X_2)I_{32}(X_3)
\end{aligned} \tag{4}$$

Once the weighting factors are obtained, the output of the fuzzy system can be found by calculating the weighted average of the individual rule outputs

$$Y = \frac{\sum_{k=1}^{16} w_k R_k}{\sum_{k=1}^{16} w_k} \tag{5}$$

The internal parameters of the fuzzy system are optimized by training. Fig. 4 shows the arrangement used for training. Here, the parameters of the fuzzy system are iteratively optimized so that its output converges to the output of the *ideal noise filter* which, by definition, can completely remove the noise from the image. *The ideal noise filter is conceptual only and does not necessarily exist in reality.* It is only the output of the ideal noise filter that is necessary for training, and this is represented by the original (noise-free) training image.

Fig. 5 shows the training images, which are simple artificial images easily generated by computer. The image shown in Fig. 5a is the *original* (*noise-free*) *training image*, which is a 128-by-128 pixel artificial image that can easily be generated in a computer. Each square box in this image has a

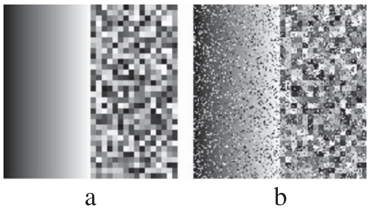


Fig. 5. The training images: (a) original training image, and (b) noisy training image.

size of 4-by-4 pixels and the 16 pixels contained within each box have the same luminance value, which is a random integer number uniformly distributed in [0, 255]. The image in Fig. 5b is the *noisy training image* and is obtained by corrupting the original training image by impulse noise of 30% noise density. Although the density of the corrupting noise is not very critical regarding training performance, it is experimentally observed that the operator exhibits the best performance when the noise density of the input training image is equal to the noise density of the noisy input image to be restored. It is also observed that the performance of the operator slightly decreases as the difference between the two noise densities increases. Hence, in order to obtain a stable filtering performance for a wide range of filtering noise densities, very low and very high values for training noise density should be avoided since it is usually impossible to know the actual noise density of a corrupted image in a real practical application. Results of extensive simulation experiments indicate that very good filtering performance is easily obtained for all kinds of images corrupted by impulse noise with a noise density between 0% and 80% provided that the input training image has a noise density between 20% and 50%.

The images in Figs. 5a and b are employed as the *target* (*desired*) and the *input* images during training, respectively, yielding a training set of 16 384 samples. The parameters of the fuzzy system are then iteratively adjusted by using the Levenberg–Marquardt optimization algorithm [50–52] so as to minimize the learning error. Once the training of the fuzzy system is completed, its internal parameters are fixed and it is used within the structure of the proposed scheme, as shown in Fig. 2. The time training takes depends on the computer that the training is performed. It takes less than 10 minutes on a machine with a Core™ 2 Duo processor running at 2.2 GHz. However, the response of the trained system is quite fast being less than 1 second.

Readers interested in the details of fuzzy systems may refer to an excellent book on this subject [50].

2.4. Processing of the noisy image

Based on the schematic representation of the proposed method given in Fig. 2 and the definitions given so far, the application of the proposed method may be summarized as follows:

Let $F(.)$ denote a recursive filtering operator, whose performance is to be improved to obtain an enhanced output image. Let x denote a noisy digital image having a size of $L \times C$ pixels, and $x[l, c]$ denote a pixel of this image located at the coordinates (l, c) with $1 \leqslant l \leqslant L$ and $1 \leqslant c \leqslant C$. Similarly, let y denote the filtered version of the noisy input image x, which is obtained by processing x using the filter F, that is $y = F(x)$.

The proposed method aims to produce an enhanced image y_E that is expected to be better than y. The proposed method comprises the following steps:

(1) Construct four source images x_k $(k = 0, 1, 2, 3)$ by appropriately rotating the noisy input image x:

$$x_0 = x$$

$$x_1 = R(x)$$

$$x_2 = R^2(x)$$

$$x_3 = R^{-1}(x)$$

It should be noted that the images x_0 and x_2 have the size of $L \times C$ pixels, which is the size of the noisy input image x, whereas the images x_1 and x_3 have the size of $C \times L$ pixels.

(2) Filter the four source images x_k by using the noise filter $F(.)$ and obtain the four filtered images f_k:

$$f_k = F(x_k), \quad k = 0, 1, 2, 3$$

(3) Appropriately rotate the four filtered images f_k to obtain the four output images y_k:

$$y_0 = f_0$$

$$y_1 = R^{-1}(f_1)$$

$$y_2 = R^2(f_2)$$

$$y_3 = R(f_3)$$

It should again be noted that the images y_1, y_2, y_3 and y_4 have the same size of $L \times C$ pixels.

(4) Compute the enhanced output image y_E from the output images y_k $(k = 0, 1, 2, 3)$ by using the fuzzy system.

3. Results and discussion

The proposed method has been implemented and tested on four impulse noise filters from the literature. These are the *multi-state median filter* (MSMF) [10], the *Jarque-Berra test based filter* (JBF) [15], *signal dependent rank ordered mean filter* (SDROMF) [24] and the *two-output nonlinear filter* [45] (TONF).

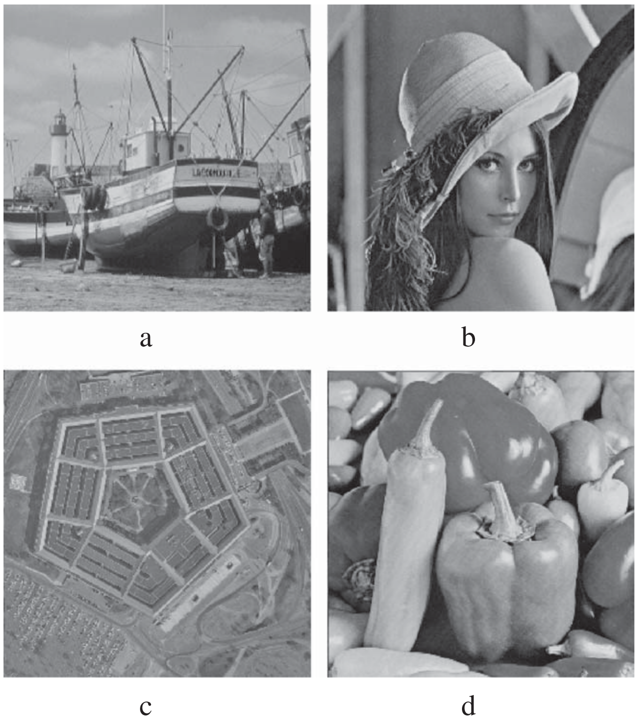


Fig. 6. Test images used in the filtering experiments: (a) Boats, (b) Lena, (c) Pentagon, and (d)Peppers.

Simulation experiments have been conducted on four popular test images from the literature including the *boats*, *Lena*, *pentagon* and *peppers* images, which are shown in Fig. 6. All images are 8-bit gray level images.

The noisy experimental images are obtained by individually corrupting each of the four test images by impulse noise with noise densities of 25%, 50% and 75%, respectively, producing 12 experimental images in total. Each of these noisy images are then processed by each of the four impulse noise filters *without* and *with* the proposed method. The improvement obtained by using the proposed method is evaluated by utilizing the *mean squared error* (*MSE*) criterion, which is defined as follows:

$$\mathrm{MSE} = \frac{1}{RC}\sum_{r=1}^{R}\sum_{c=1}^{C}(s[r,c]-y[r,c])^2 \tag{6}$$

where $s[r,c]$ and $y[r,c]$ denote the original (noise-free) and the restored versions of a test image, respectively.

Since noise is a random process, every realization of the same experiment yields different results even if the experimental conditions are the same. Hence, each individual filtering experiment for a given {noise filter/test image/noise density} combination is repeated for 10 times, and the resulting MSE values are averaged to obtain the representative MSE value for that combination.

Fig. 7 shows the output images of the filters for the uses without and with the proposed method for the *boats* image corrupted by 50% impulse noise. In each image pair, the image on the left shows the direct output of the filter *without* using the proposed method, whereas the image on the right shows the enhanced output image obtained *with* the proposed method. It is easily observed that the proposed method significantly improves the performances of the filters and enhances their output images. Specifically, undesirable noise blotches that are easily visible in the direct output images

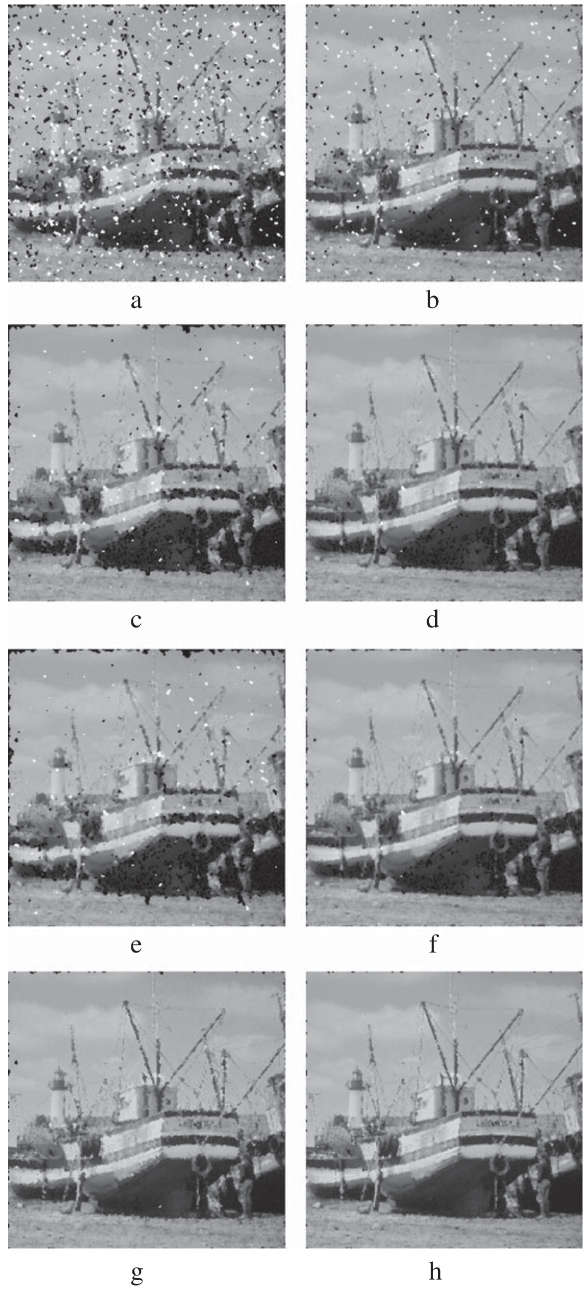


Fig. 7. Comparison of the direct and the proposed use of the noise filters: (a, b) MSMF, (c, d) JBF, (e, f) SDROMF, (g, h) TONF. In each image pair, the image on the left shows the direct output of the filter and the image on the right shows the enhanced output image obtained by using the proposed method.

Table 1. Comparison of the MSE values obtained for the direct and the proposed use of the noise filters.

	Boats			Lena			Pentagon			Peppers			Average		
	25%	50%	75%	25%	50%	75%	25%	50%	75%	25%	50%	75%	25%	50%	75%
MSMF															
Direct	283	1979	9107	260	1932	9103	314	1925	8574	185	1933	8749	260	1942	8883
Proposed	144	753	2789	129	822	3332	179	902	3470	92	810	3391	136	822	3241
Reduction (%)	*49*	*62*	*69*	*50*	*57*	*63*	*43*	*53*	*60*	*50*	*58*	*61*	*48*	*58*	*63*
JBF															
Direct	148	375	1259	108	297	1068	188	365	1038	80	256	1061	131	324	1106
Proposed	81	168	519	60	139	422	97	163	405	46	119	386	71	147	433
Reduction (%)	*45*	*55*	*59*	*44*	*53*	*60*	*48*	*55*	*61*	*43*	*54*	*64*	*45*	*54*	*61*
SDROMF															
Direct	269	809	4127	182	665	3628	240	592	3537	131	623	4251	206	672	3886
Proposed	140	375	1773	99	302	1533	145	311	1721	76	333	2133	115	330	1790
Reduction (%)	*48*	*54*	*57*	*46*	*55*	*58*	*40*	*47*	*51*	*42*	*47*	*50*	*44*	*51*	*54*
TONF															
Direct	84	286	1203	75	258	1406	96	298	1119	66	236	1387	80	269	1279
Proposed	53	164	641	45	131	607	61	177	622	43	128	664	51	150	634
Reduction (%)	*37*	*43*	*47*	*40*	*49*	*57*	*37*	*41*	*44*	*35*	*46*	*52*	*37*	*45*	*50*

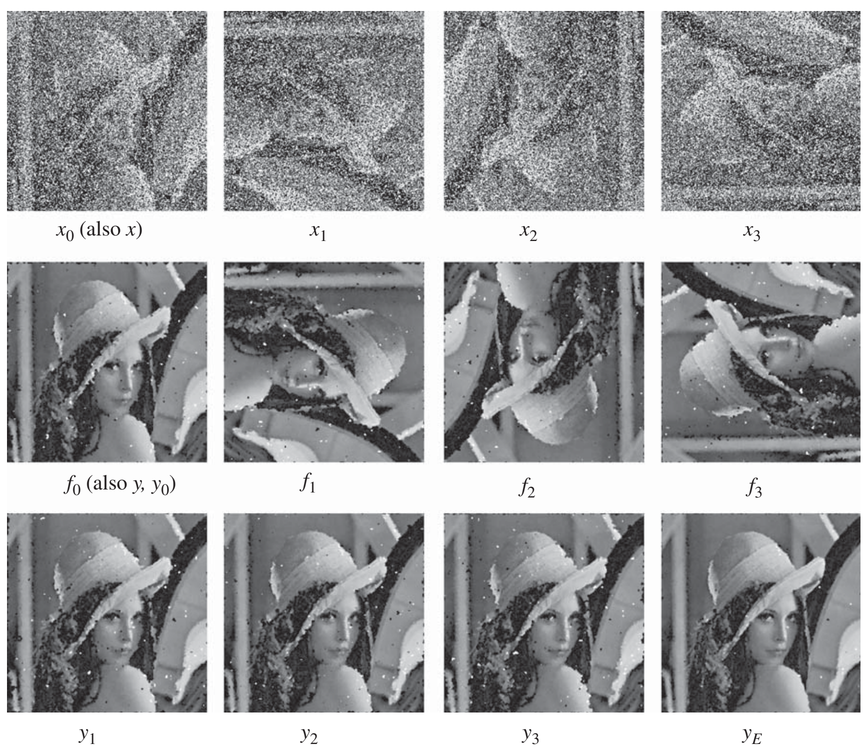


Fig. 8. The images created during the application of the proposed method with the JBF operator for the Lena image corrupted by 50% noise density. The relationship between these images is depicted in Fig. 2.

of the filters, which are shown on the left side, greatly disappear when the filters are used with the proposed method, yielding visually much more pleasing images. This shows that the proposed method efficiently improves the noise suppression ability of the filters. It is also observed that small details that are blurred or severely degraded in the direct output images of the filters are effectively preserved when the filters are used with the proposed method. This indicates that the proposed method also improves the detail preservation capability of the filters. The difference in detail preservation obtained by using the proposed method may easily be observed by carefully comparing the appearance of thin lines, edges and object boundaries in the images on the left to the images on the right.

For a more objective evaluation, Table 1 shows the comparative MSE values calculated for the output images of the filters obtained without and with the proposed method, respectively. In this table, each cell contains three numbers. The first number (labeled as "direct") represents the MSE value of the *direct* output image of the filter obtained *without* the proposed method. The second number (labeled as "proposed") represents the MSE value of the improved output image of the filter obtained *with* the proposed method. The third number (labeled as "reduction (%)") represents the reduction in MSE value achieved by using the proposed method, which is calculated by

$$\text{Reduction} = \frac{\text{MSE}^{(\text{direct})} - \text{MSE}^{(\text{proposed})}}{\text{MSE}^{(\text{direct})}} \times 100 \tag{7}$$

Results presented in this table also confirm that the proposed method significantly improves the performances of the filters for all test images.

In order to enable the reader to have a deeper understanding of the operation of the proposed method, Fig. 8 shows all the images created during the application of the proposed method with the JBF operator for the Lena image corrupted by 50% noise density. The relationship between these images has already been depicted in Fig. 2 and also described in detail in Section 2. It should be noted that the image x_0 is the noisy input image, f_0 is the direct output image of the JBF obtained by using the filter *without* the proposed method, as illustrated in Fig. 1a, and y_E is the enhanced output image obtained by using the filter *with* the proposed method, as illustrated in Fig. 2.

4. Conclusion

A novel method for improving the performances of recursive impulse noise filters is presented. The method is very simple, yet it provides a significant increase in the performances of the filters. Furthermore, it may be used with any recursive impulse noise filter since its operation is independent of the operation of the filter.

Based on these observations and the experimental results presented in the previous section, it is concluded that the proposed method can be used with any type of recursive impulse noise filter to significantly improve its performance.

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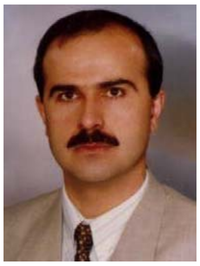

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