An adaptive median filter for colour image processing

Frédérique Robert-Inacio[1], Éric Dinet[2]
[1]*ISEN - Toulon, L2MP UMR CNRS 6137, Toulon, France*
[2]*LIGIV, Saint-Étienne, France*

Abstract

Colour image filtering is not an obvious task when considering rank order filters. In this paper, an original way of setting up a spatially adaptive median filter is described. The proposed methodology is based on the computation of a colour distance map. Such a map allows the estimation of the optimal width of the filtering window at each point of the image to process. The sort of colour vectors, inherent to a median filtering approach, is achieved by using a bit-mixing paradigm. Finally, experimental results reported in this paper show that the proposed method is able to remove noise whereas fine details and edges are preserved. At the same time, the method is computationally efficient and very easy to implement.

Introduction

Images are often corrupted by noise that may bias and compromise the image processing stages required by computer vision applications. Then, noise filtering is a very important task in the pre-processing methods. The quality of its results has a direct influence on the main image processing algorithms such as segmentation or pattern analysis. Inappropriate and coarse results may strongly deteriorate the relevance and the robustness of a computer vision application. The main challenge in noise removal consists in suppressing the corrupted information while preserving the integrity of image structures in order to build reliable automatic analysis processes.

Several and well established techniques, such as median filtering, have successfully been used in grey scale imaging. The median filter is a non linear operator of the class of rank filters [1]. It was shown that median filters present the advantage to remove noise without blurring edges. Futhermore, their output is one of the original grey values.

The extension of the concept of median filtering to colour images is not a simple task. Componentwise (marginal) techniques that separately process on colour channels generally lead to strong artifacts because colour channels are inherently correlated [2]. Then vector (multivariate) approaches that work on the complete colour information of each pixel of an image are largely preferred. The main difficulty in defining a rank filter in vector approaches is that there is no "natural" and unambiguous order in data. During the last years, different methods were proposed to overcome this problem [3, 4].

The main reference in vector filtering was probably introduced by Astola *et al.* in 1990 [5]. In such a class of filters, so called vector median filters (VMF), the ordering problem is achieved by minimizing vector distances. VMF uses the L_1 or L_2 norm to order vectors according to their relative magnitude differences [6, 7]. Another class of filters classically found in the literature orders vectors according to their relative orientation differences hence the name vector directional filter (VDF) [8].

Many approaches were proposed to evaluate differences and it makes difficult the selection of a filter for a given set of colour images. To overcome this problem another option can be considered for RGB images. It consists in defining a total order on the three-dimensional colour space [2]. Such a total order can be achieved through a bijective transform based on a *bit-mixing paradigm* as proposed in [9]. As explained further, the basic principle is to mix the 8 bits of the three channels R, G and B to get a 24-bit scalar data.

Whatever the vector filtering method, the challenge is to detect and replace noisy pixels whereas the relevant information is preserved. But it is recognized that in some image areas most of vector filters blur thin details and image edges [10, 11]. Even if many works such as Khriji and Gabbouj [12], Lucat *et al.* [13] and Lukac *et al.* [14, 15] propose to improve the quality of the output images, it is often by using constraints, restrictions and optimization stage more or less difficult to set up and control.

In this paper we present an adaptive median filter that preserves fine image details without introducing colour artifacts when removing noise. Besides these noticeable characteristics, the method we propose is simple and very efficient that is a great advantage because the computational cost can be a serious problem in several industrial computer vision applications.

Determination of the colour distance map

The first stage of the adaptive median filter we propose corresponds to the computation of a colour distance map which outlines the highest colour differences in the image to process. The underlying idea is to adjust and to optimise the width of the filter window on the colour difference information.

Figure 1. *Original colour image*

First of all, two directional maps are computed from the original image (see example in Figure 1) by using the Euclidean distance between colours in the RGB space. The first map corresponds to the colour distance between a point and its closest right neighbour (X-map) and the second one to the colour distance between this point and its closest top neighbour (Y-map) (Figure 2).

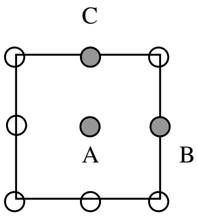

Figure 2. *Points of the neighbourhood used to compute the directional maps : A and B for the X-map and A and C for the Y-map*

These two directional maps are mixed according to a selected threshold in order to determine the greatest colour differences in horizontal and vertical directions. Figure 3 shows two examples of colour distance maps computed from the original image of Figure 1 respectively for a threshold value of 10 and of 30 when the maximal distance value is equal to 216. This map does not accurately delineate edges but it gives points where the colour differences are the most representative.

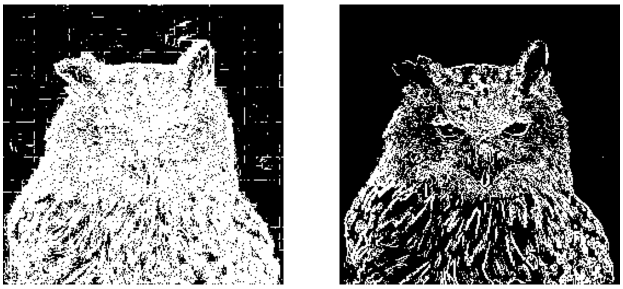

Figure 3. *Colour distance maps: the threshold value is equal to 10 on the left and to 30 on the right*

Determination of the width of the local filtering window

Because of the shape of its “circles”, the distance presenting the best properties to determine the width of the local window for a spatially adaptive filter is defined by the following relation :

$$d_{ch}(M,P)=max(|x_M-x_P|,|y_M-y_P|) \tag{1}$$

for two points M and P with position vectors (x_M, y_M) and (x_P, y_P). Equation (1) describes the definition of the chessboard distance between two arbitrary points M and P. For the chessboard distance, “circles” or equidistant sets of points are located on a square (Figure 4). This property ensures that each point of the square is at a distance less or equal to r, the radius of the corresponding circle.

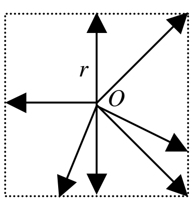

Figure 4. *"Circles" for the chessboard distance: every point of the square perimeter is at a distance r from the centre O*

A generalization of the distance computation consists of the elaboration of the corresponding distance map from a binary image. This binary image is supposed to include two classes : the object class and the background class. For our application, a chessboard distance map is computed from the colour distance map. Points where the colour differences are greater than the given threshold are considered as objects. For each point of the background, the distance to the nearest object can be evaluated.

The chessboard distance map is then computed according to the following algorithm by scanning twice the colour distance map.

Algorithm

Initialise the distance map D by setting points of the objects to 0 and those of the background to $+\infty$
For each line i of the distance map D, from top to bottom,
For each point (i, j) of the current line, from left to right,
Set the distance D(i, j) to the minimal value between
D(i, j), D(i+1, j)+1,D(i+1, j+1)+1
and D(i, j+1)+1
For each line i of the distance map D, from bottom to top,
For each point (i, j) of the current line, from right to left,
Set the distance D(i, j) to the minimal value between
D(i, j), D(i-1, j)+1, D(i-1, j-1)+1
and D(i, j-1)+1

Table 1. Numerical example of a chessboard distance map

2	2	2	2	2	2	2	3	4	4	5	4	3	2	1	0	1	2	3	4
2	1	1	1	1	1	2	3	3	4	5	4	3	2	1	0	1	2	3	4
2	1	0	0	0	1	2	2	3	4	5	4	3	2	1	0	1	2	3	4
2	1	1	1	0	1	1	2	3	4	5	4	3	2	1	0	1	2	3	4
2	2	2	1	1	0	1	2	3	4	5	4	3	2	1	0	1	2	3	4
3	3	2	2	1	1	1	2	3	4	5	4	3	2	1	0	1	2	3	4
4	3	3	2	2	2	2	2	3	4	4	4	3	2	1	1	1	2	3	4
4	4	3	3	3	3	3	3	3	3	3	4	3	2	2	2	2	2	3	4
5	4	4	4	3	2	2	2	2	2	3	3	3	3	3	3	3	3	3	4
5	5	5	4	3	2	1	1	1	2	3	2	2	2	2	2	2	2	3	4
6	6	5	4	3	2	1	0	1	2	3	2	1	1	1	1	1	2	3	4
7	6	5	4	3	2	1	1	1	2	3	2	1	0	0	0	1	2	3	4
6	6	5	4	3	2	2	2	2	2	3	2	1	0	1	0	1	2	3	4
5	5	5	4	3	3	3	3	3	3	3	2	1	0	0	0	1	2	3	4
4	4	4	4	4	4	4	4	4	4	3	2	1	1	1	1	1	2	3	4
3	3	3	3	3	3	3	4	5	4	3	2	2	2	2	2	2	2	3	4
3	2	2	2	2	2	3	4	5	4	3	3	3	3	3	3	3	3	3	4
3	2	1	1	1	2	3	4	5	4	4	4	4	4	4	4	4	4	4	4
3	2	1	0	1	2	3	4	5	5	5	5	5	5	5	5	5	5	5	5
3	2	1	1	1	2	3	4	5	6	6	6	6	6	6	6	6	6	6	6

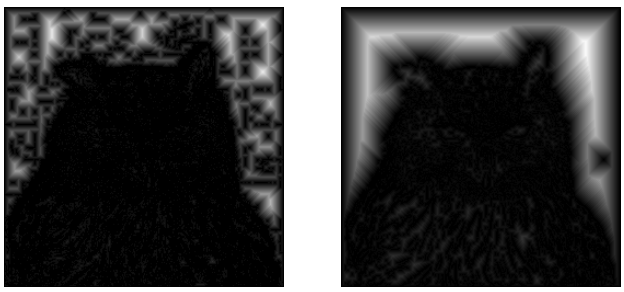

Figure 5. *Chessboard distance maps: the threshold value for the colour distance map is equal to 10 on the left and to 30 on the right*

This process consists in minimizing the distance between a given point *B* of the background and points of the objects. Information about object position is propagated from background points to their neighbours by considering an update of distance values on the V8 neighbourhood.

In this way, the example of the chessboard distance map described in Table 1 gives, for each point of the background, its distance to the nearest object. In Figure 5, the object class is made of the information provided by the colour distance map and by the first and last columns and rows of the image. Actually it is necessary to consider these columns and rows as boundaries for the chessboard distance map, as filter windows cannot overflow the image frame. The chessboard distance map provides the half-width of the maximal square included in the background and reaching the objects at least at one point (Figure 6). Thus, we simply obtain the width of the filtering window with the evaluation of the distance to the objects derived from the colour distance map. The width $W(i, j)$ of the filtering window at a point (i, j) of the background is then equal to twice the distance $D(i, j)$ plus 1 (see relation (2)).

$$W(i,j)=2.D(i,j)+1 \tag{2}$$

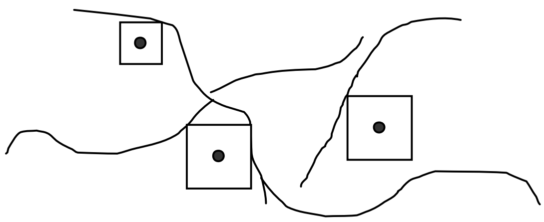

Figure 6. *Filtering windows at different points of the background*

Median value computation

The last stage of the adaptive median filter we propose consists in computing the median vector for each window previously defined. The colour order is based on a bit-mixing paradigm (Figure 7) that combines the 8 bits of the three RGB components to get 24 bit scalar data [9]. In this way, a 24 bit integer value is associated with each colour vector, so that colours can be sorted to complete the median filtering process.

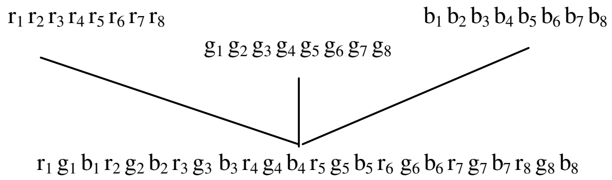

Figure 7. *Bit-mixing paradigm*

For example, if the filtering window is of n-width, the n^2 colour vectors are sorted according to their associated 24 bit scalar values. Then, the median scalar value, i.e. the $(1+n^2/2)$th one, corresponds to the median colour vector. Such a vector gives the three RGB components of the output colour of the filter.

Experimental results

Since noise filtering techniques are designed to enhance the image quality, we chose to discuss the performance of the method we propose regarding the two following criteria : criterion 1 that considers visual impression and criterion 2 that considers objective measures. Our adaptive median filter and a classical median filtering approach based on a bit-mixing paradigm have been applied to the original colour image of Figure 1.

Figure 8 shows the evolution of the adaptive median filter for different threshold values used during the computation of the colour distance map. Figure 9 shows the evolution of the classical median filtering approach for different sizes of the filtering window.

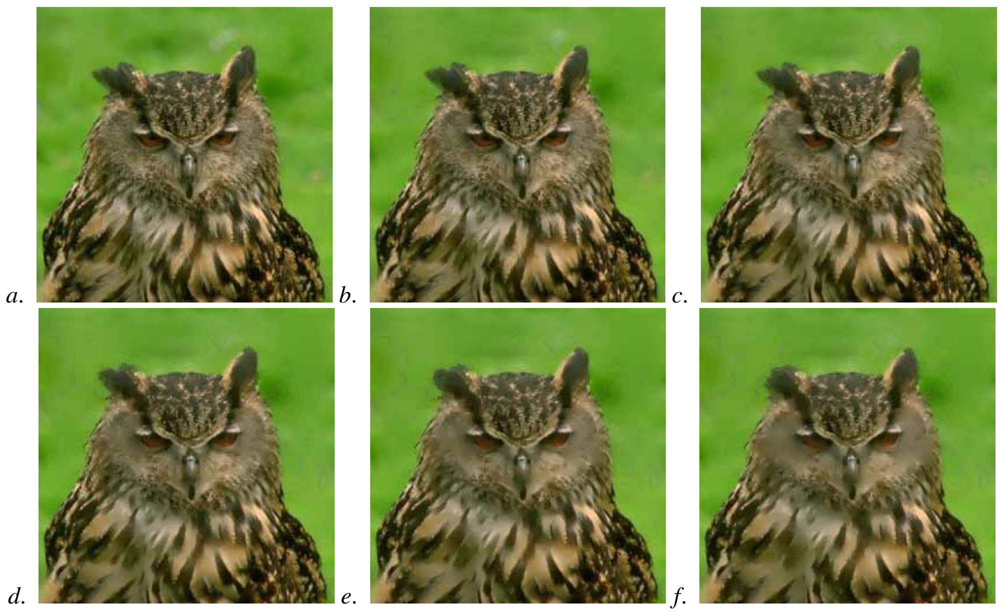

Figure 8. *Results of adaptive median filter, when the threshold is respectively equal to 10 (a), 20 (b), 30 (c), 40 (d), 50 (e) and 60 (f) during the computation of the colour distance map*

a. b. c. d. e. f.

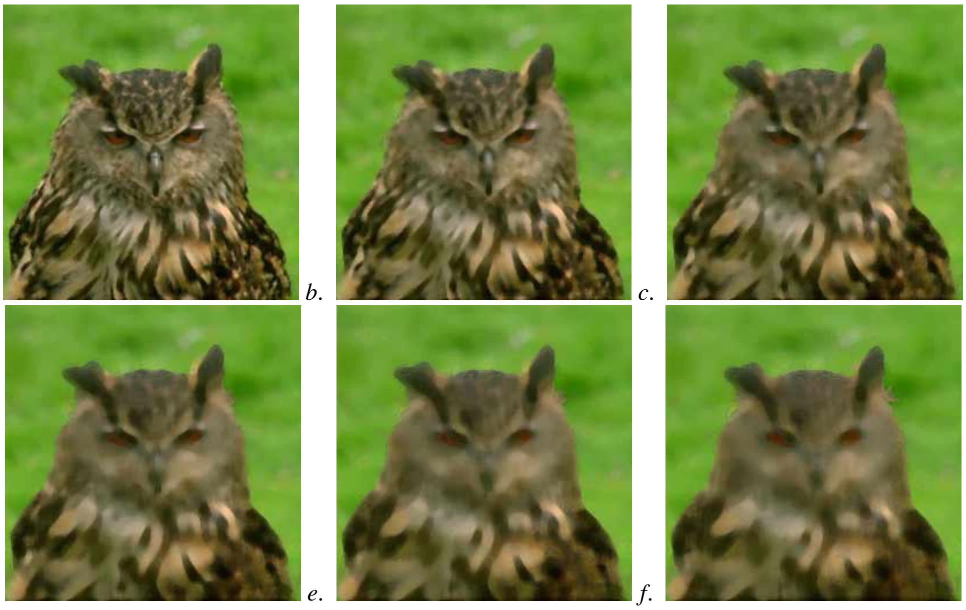

Figure 9. *Results of median filtering based on the bit-mixing paradigm respectively with a size of filter window equal to 3 × 3 (a), 5 × 5 (b), 7 × 7 (c), 9 × 9 (d), 11 × 11 (e) and 13 × 13 (f)*

Regarding criterion 1, we can clearly see that the adaptive median filter performs best. Small details and fine spatial structures of the original image are well preserved even for high values of the threshold used during the computation of the colour distance map. For example, Figure 8c shows that the green background is really smoothed as there is almost no high colour difference in this area of the original image and all details of feathers are preserved on the owl. On the contrary, results visualized in Figure 9 illustrate limitations of classical techniques for which the size of the filtering window is constant whatever the features of data to be processed. For example, Figure 9b shows that, even for a small size of the filtering window, fine details are degraded. Feathers are too strongly filtered and the image appears blurred.

a. b. c. d. e. f.

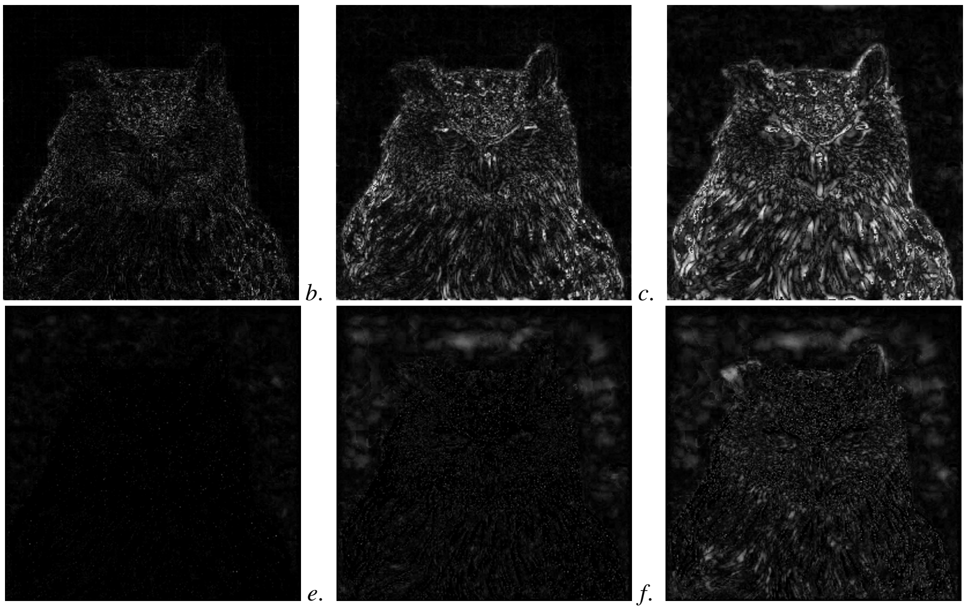

Figure 10. *Top: absolute error of median filtering based on the bit-mixing paradigm respectively with a size of filter window equal to 3 × 3 (a), 7 × 7 (b) and 13 × 13 (c). Bottom: absolute error of adaptive median filtering when the colour distance map is computed respectively with a threshold equal to 10 (d), 30 (e) and 60 (f)*

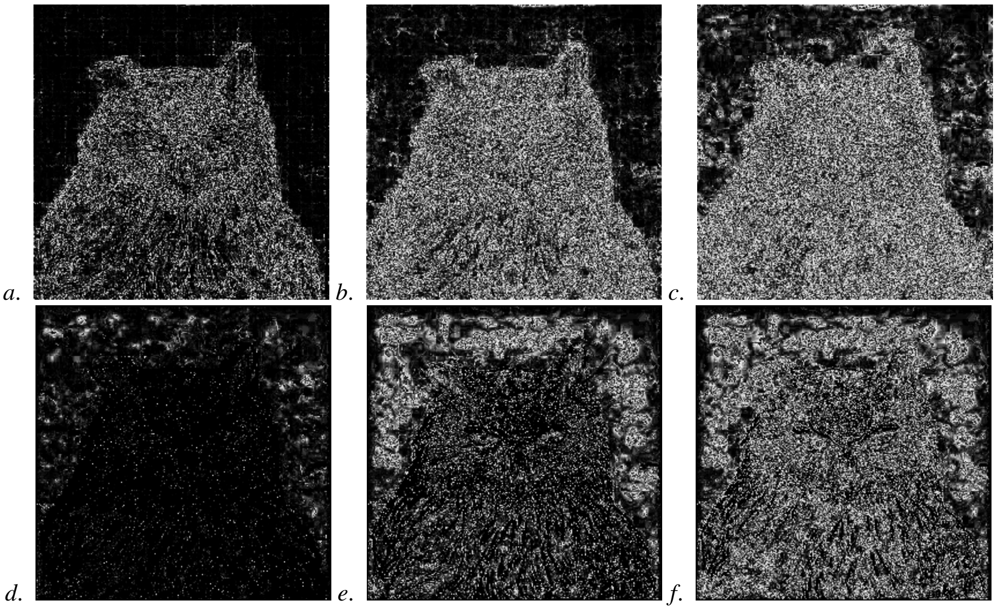

***Figure 11.** Top: square error of median filtering based on the bit-mixing paradigm respectively with a size of filter window equal to 3 × 3 (a), 7 × 7 (b) and 13 × 13 (c). Bottom: square error of adaptive median filtering when the colour distance map is computed respectively with a threshold equal to 10 (d), 30 (e) and 60 (f)*

Regarding criterion 2, measures such as absolute error (AE) and square error (SE) that quantify differences between two digital images have been used. The AE and the SE are given by :

$$\mathrm{AE}(i,\ j) = \left| I_{i,\ j} - O_{i,\ j} \right| \tag{3}$$

$$\mathrm{SE}(i,\ j) = \left(I_{i,\ j} - O_{i,\ j} \right)^2 \tag{4}$$

where $I_{i,j}$ is the value of the pixel (i, j) of the input image and $O_{i,j}$ the value of the pixel (i, j) of the filtered (output) image. For RGB images, AE is computed as the mean over channels and SE as the Euclidean norm over channels.

Figure 10 and Figure 11 respectively present the AE and the SE between the original test image (Figure 1) and different filtered versions. It correlates with the previous observations and the visual impression. Our adaptive technique preserves fine details while techniques with a fixed window size do not. Figure 10a and Figure 11a show that even with the smaller size of the filtering window the relevant information is degraded.

When the size of the filtering window is locally adapted to the spatial organization of images, textured areas are more efficiently preserved. The highest differences between the original image and the filtered one are concentrated in smooth areas where colour differences are small (see Figure 10e and Figure 11e for example). It means that an adaptive technique is better in a perceptual point of view and for signal processing considerations.

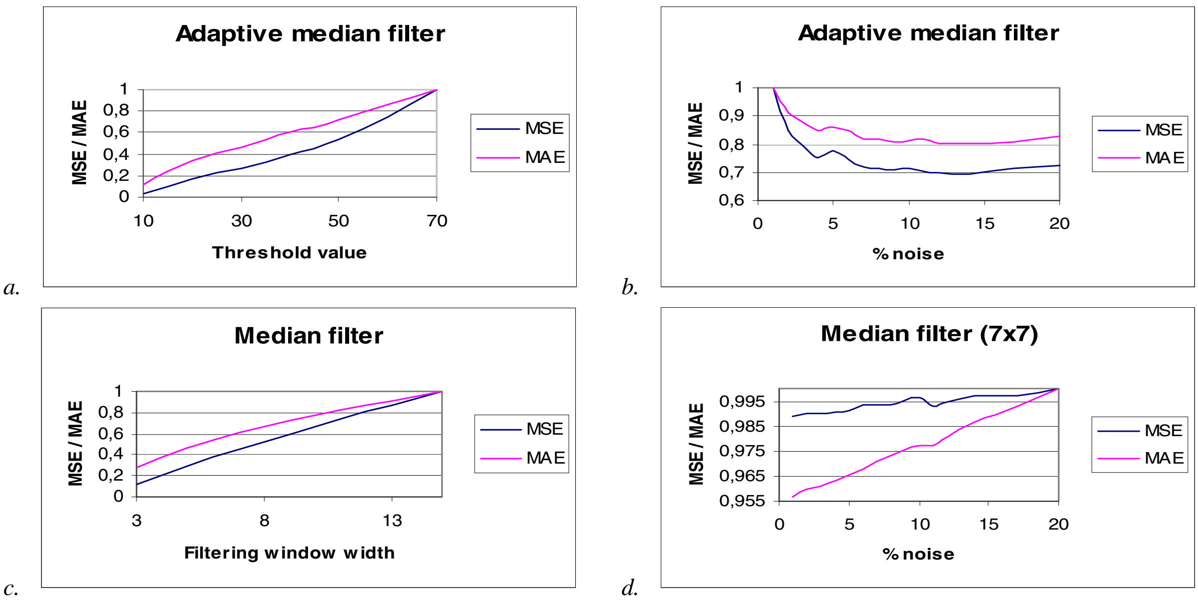

***Figure 12.** Comparative results from the original colour image in Figure 1. (a) and (c) : the filtering strength is increased. (b) and (d) : for a given filtering strength, the rate of colour impulse noise is increased.*

For a global quantitative comparison of the performance of the filters we can mean the AE and mean the SE in order to respectively obtain the mean absolute error (MAE) and the mean square error (MSE) expressed by :

$$\mathrm{MAE} = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\mathrm{AE}(i,\ j) \tag{5}$$

$$\mathrm{MSE} = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\mathrm{SE}(i,\ j) \tag{6}$$

where N, M characterize image size. Figures 12a and 12c show the evolution of the MAE and the MSE normalized values for both compared methods. Obviously the normalized MAE and MSE values increase when :

1. the threshold value, used during the computation of the colour difference map, increases in our adaptive technique,
2. the size of the filtering window increases in the classical approach.

At first glance, performances of the two filtering methods seem very similar. But plots of Figures 12a and 12c must be compared to each other while keeping in mind that they do not take into account the spatial repartition of differences. As previously explained and as illustrated by Figure 10 and by Figure 11, the two filtering methods do not affect the same parts of the original image. More precisely, for a given size of the filtering window used in the classical approach, it is possible to find a threshold value in our adaptive technique that leads to similar MAE and MSE (for example at a size of 7×7 corresponds a threshold value equal to 30). Similar MAE and MSE indicate that the global differences between original image and its filtered version are similar but do not precise the spatial distribution of differences. As clearly shown by Figures 8, 9, 10 and 11, such a spatial distribution of differences is extremely important regarding the quality and the performance of the filtering method.

Plots of Figures 12b and 12d show the variation of the normalized error criteria when the density of noise increases. Two parameters that lead to similar MAE and MSE from the noise free original test image have been chosen. For the classical median filtering method, the size of the filtering window has been set up to 7×7 and, for our adaptive median filtering method, the threshold value for the computation of the colour distance map has been set up to 30. The colour impulse noise rate indicates the absolute value by which the concerned pixel is changed. In Figures 12b and 12d we can clearly see that our adaptive approach performs best when the noise rate increases. The adaptive technique we propose combines better MAE and MSE with the preservation of fine details of the image to process.

Conclusion

An adaptive median filtering method for colour images has been described and analyzed. The proposed method is based on the computation of a colour distance map that allows the adaptive control of the width of the filtering window. The problem of colour ordering necessary to determine the median vector is overcame by using a bit-mixing paradigm.

The achieved results show excellent properties as well as regarding visual appearance as objective quality measures. Fine details and small structures are better preserved by the adaptive method we propose than by its non-adaptive form. Moreover our adaptive method is simple to implement and very efficient.

References

[1] R.M. Hodgson, D.G. Bailey, M.J. Naylor, A.L.M. Ng, S.J. McNeill, Properties, implementations and applications of rank filters, Image Vision Comput. 3, pg. 3-14. (1985).

[2] P. Lambert and L. Macaire, Filtering and segmentation : the specificity of color images, Proc. Conference on Color in Graphics and Image Processing, Saint-Étienne, pg. 57-64. (2000).

[3] R. Lukac, B. Smolka, K. Plataniotis and A. Venetsanopoulos, Selection weighted vector directionnal filters, Computer Vision and Image Understanding 94, pg. 140-167. (2004).

[4] M.I. Vardavoulia, I. Andreadis and Ph. Tsalides, A new median filter for colour image processing, Pattern Recognition Letters 22, pg. 675-689. (2001).

[5] J. Astola, P. Haavisto and Y. Neuvo, Vector median filters, Proc. IEEE 78, pg. 678-689. (1990).

[6] B. Smolka, K.N. Plataniotis, A. Chydzinski, M. Szczepanski, A.N. Venetsanopoulos and K. Wojciechowski, Self-adaptive algorithm of impulsive noise reduction in color images, Pattern Recognition 35, pg. 1771-1784. (2002).

[7] I. Pitas and P. Tsakalides, Multivariate ordering in color image processing, IEEE Trans. Circuits Syst. Video Technol. 1, pg. 247-256. (1991).

[8] P.E. Trahamias and A.N. Venetsanopoulos, Vector directional filters: A new class of multichannel image processing filters, IEEE Trans. Image Process. 2, pg. 528-534. (1993).

[9] J. Chanussot and P. Lambert, Total ordering based on space filling curves for multivalued morphology, Proc. 4th ISMM, pg. 51-58 (1998).

[10] R. Lukac, Adaptive vector median filtering, Pattern Recognition Letters 24, pg. 1889-1899. (2002).

[11] A. Koschan and M. Abidi, A comparison of median filter techniques for noise removal in color images, Proc. 7th german workshop on color image process. 34, No. 15, pg. 69-79. (2001).

[12] L. Khriji and M. Gabbouj, Vector median-rational hybrid filters for multichannel image processing, IEEE Signal Procees. Letters, Vol. 6, No. 7, pg. 186-190. (1999).

[13] L. Lucat, P. Siohan and D. Barba, Adaptive and global optimization methods for weighted vector median filters, Signal Process.: Image Commun. 17, pg. 509-524. (2002).

[14] R. Lukac, K.N. Plataniotis, A.N. Venetsanopoulos and B. Smolka, A statistically-switched adaptive vector median filter, J. Intell. And Robotic Sys. 42, pg. 361-391. (2005).

[15] R. Lukac, B. Smolka, K.N. Plataniotis and A.N. Venetsano-poulos, Vector sigma filters for noise detection and removal in color images, J. Vis. Commun. Image R. 17, pg. 1-26. (2006).

Author biography

Frédérique Robert-Inacio received her Master degree in applied mathematics in 1988 and her PhD in image processing in 1992 from University Jean Monnet, Saint-Étienne, France. She worked as a re-searcher at the University of Sherbrooke, Canada, from 1993 to 1994, and since September 1994 at the ISEN. Her present spots of interest concern pattern recognition, colour imaging and computer vision, and more accurately image processing furthering the estimation of para-meters characterizing geometrical features for shape classification.

Éric Dinet received a Master degree in computer science in 1991 and a PhD in image processing in 1994 from University Jean Monnet, Saint-Étienne, France. From 1994 to 1999 he was an Assistant Professor in field of image processing at University Jean Monnet. In 1999 he took part in the creation of the laboratory LIGIV where he works today. His research interests include colour science and colour perception.

.