Journal of Electronic Imaging 7(2), 333–338 (April 1998).

Rational unsharp masking technique

Giovanni Ramponi
Andrea Polesel
University of Trieste
DEEI
via A. Valerio 10
I-34127 Trieste, Italy
E-mail: ramponi@univ.trieste.it

Abstract. *The linear unsharp masking technique used in image contrast enhancement is modified in this article by introducing a control term expressed as a rational function of the local input data. In this way noise amplification is avoided and, at the same time, overshoot effects on sharp edges are limited. Experimental results support the validity of the method, even as a preprocessor for interpolation systems.* © *1998 SPIE and IS&T.* [S1017-9909(98)00702-8]

1 Introduction

The technique of unsharp masking (UM) was introduced in photography to improve the quality of pictures by making their details crisper; it consisted in optically subtracting a blurred copy of an image from the image itself. Its digital version, due to its simplicity and relative effectiveness, has become a tool of widespread use in the image processing community, described in any textbook[1] and included in many available software packages (e.g., Ref. 2). In digital image manipulation, it can be realized as shown in Fig. 1, by processing the image with a highpass filter (usually a Laplacian), multiplying the result by a scaling factor, and adding it to the original data.

Notwithstanding its popularity, this technique suffers from two drawbacks which can significantly reduce its benefits: noise sensitivity and excessive overshoot on sharp details. The former problem comes from the fact that the UM method assigns an emphasis to the high frequency components of the input, amplifying a part of the spectrum in which the signal-to-noise ratio (SNR) is usually low. On the contrary, wide and abrupt luminance transitions in the input image can produce overshoot effects; these are put into further evidence by the human visual system through the Mach band effect.[1]

Various modifications have been introduced in the basic UM technique, in particular to reduce the noise amplification problem. A quite trivial approach consists of substituting a bandpass filter for the highpass one in Fig. 1. This of course reduces noise effects, but also precludes effective detail enhancement in most images. In more sophisticated approaches, nonlinear operators (order statistics, polynomial, logarithmic) are used to generate the correction signal which is added to the image; we will cite a few of them, without attempting a thorough overview of the field.

A modified Laplacian filter, called the order statistics (OS) Laplacian, is proposed in Ref. 3; its output is proportional to the difference between the average and the median of the pixels in a window. The resulting OS-UM algorithm is evaluated for its performance on a convex/concave edge model and on white Gaussian noise input signal, showing its robustness and its enhancing characteristics.

Alternatively, a polynomial approach can be used. In Ref. 4, the Laplacian filter is replaced by a simple operator based on a generalization of the so-called Teager's algorithm. Under reasonable hypotheses, this operator approximates the behavior of a local-mean-weighted highpass filter, having reduced high-frequency gain in dark image areas. According to Weber's law,[1] the sensitivity of the human visual system is higher in dark areas; hence the proposed filter introduces a perceptually smaller noise amplification, without diminishing the edge–enhancing capability of the UM method. Another polynomial method, the cubic UM (CUM) technique, has been devised:[5] its purpose is to amplify only local luminance changes due to true image details. This is achieved by multiplying the output of the Laplacian filter by a control signal obtained from a quadratic edge sensor. Still in the polynomial framework, a class of quadratic filters is defined in Ref. 6, where the filter coefficients at a given position in the image are calculated by taking into account the gray level distribution of the surrounding pixels. A Gaussian or an exponential function is used to reduce the contribution of pixel values the luminance of which is different from that of the center pixel.

Finally, to acquire a better control on the range of the image brightness, the UM method can be coupled to homomorphic filtering[1]: in this case, the image is first converted to the logarithmic domain, then UM is performed and the output is exponentiated and scaled.[7]

To try and cope with both the drawbacks indicated above, i.e., noise amplification and excessive overshoots, a linear adaptive operator is proposed in Ref. 8. The least-mean-squares (LMS) technique is used to change the value of the scaling factor (λ in Fig. 1) at each location of the image; to this purpose, the pixel to be processed is labeled as belonging to a smooth area or to a medium- or high-

Paper 97-027 received Aug. 9, 1997; revised manuscript received Nov. 4, 1997; accepted for publication Nov. 19, 1997.
1017-9909/98/$10.00 © 1998 SPIE and IS&T.

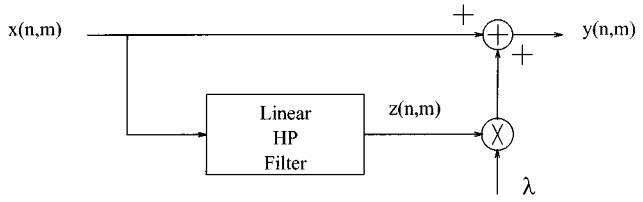


Fig. 1 Structure of the unsharp masking operator.

contrast area. Good quality results can be achieved at the expense of a relatively high computational complexity. In this article we attempt to obtain a similar result with a simpler, nonadaptive method. The basic UM scheme is still used here, but a *rational function* (the ratio of two polynomials in the input variables) is introduced in the correction path. Employing such a function, selected details having low and medium sharpness are enhanced; on the other hand, noise amplification is very limited and steep edges, which do not need further emphasis, remain almost unaffected. From a computational viewpoint, it must be stressed that the proposed solution maintains almost the same simplicity as the original linear UM method. The filter we propose belongs to the class of the rational operators, which have been recently used in the image processing field to develop simple and effective techniques for edge-preserving noise smoothing.[9–12]

This article is organized as follows: in Sec. 2 the enhancement algorithm is presented in detail in the one-dimensional (1D) case, while Sec. 3 describes the 2D formulation which has been used. Experiments and comparisons are discussed in Sec. 4.

2 The 1D Sharpening Operator

We first introduce for simplicity the 1D operator. If $x(n)$ is the input at time n, the enhanced signal $y(n)$ obtained from the UM scheme is

$$y(n)=x(n)+\lambda z(n), \tag{1}$$

where $z(n)$ is the correction term computed as the output of a suitable enhancing filter and λ is a positive scaling factor. A common choice in the linear case is to employ the Laplacian of $x(n)$ as the signal $z(n)$, that is,

$$z(n)=L(n)=2x(n)-x(n-1)-x(n+1). \tag{2}$$

We propose a modified $z(n)$ signal obtained as the product of the Laplacian and a rational control term $c(n)$. The output of the filter is then computed as

$$y(n)=x(n)+\lambda c(n)L(n), \tag{3}$$

where

$$c(n)=\frac{g(n)}{kg^2(n)+h}; \tag{4}$$

$g(n)$ is a measure of the local activity of the signal which will be discussed in the following, while k and h are proper positive factors.

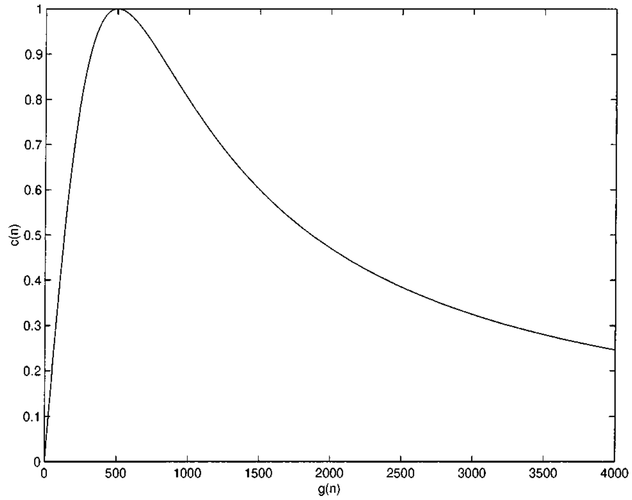


Fig. 2 Plot of the control function $c(n)$ for $k=250$, $h=0.001$.

In Fig. 2 the control term $c(n)$ is shown as a function of $g(n)$ for a specific choice of k and h ($k=250$, $h=0.001$). The presence of a *resonance peak* at the abscissa $g_0=500$ should be noted: this characteristic makes the operator able to emphasize details which are represented by low- and medium-amplitude luminance transitions. At the same time, steep and strong edges will yield high values of activity $g(n)$ (larger than g_0) and hence will undergo a more delicate amplification: in this way, undesired overshoots in the output image will be avoided. At the other end of the diagram, we expect that the noise which is always present in an image will yield small values of $g(n)$ (smaller than g_0), so that $c(n)$ will be small, too; hence, the noise itself will not affect the correction signal $z(n)$ in homogeneous areas. By selecting the position g_0 of the resonance, the user can achieve the best balance among these effects.

To better illustrate the proposed technique, we first establish some relations between the parameters of the operator. It is easy to verify that the coordinates of the resonance are

$$g_0=\sqrt{\frac{h}{k}}, \quad c_0=\frac{1}{2\sqrt{hk}}. \tag{5}$$

From Eqs. (5) it can be seen that different values of g_0 could yield different amplitudes for the peak c_0. This would make the overall strength of the UM action a function of the selected g_0, hampering the tuning of the operator. It is convenient to avoid this effect; to this purpose, we normalize $c(n)$ using the following constraint:

$$\sqrt{hk}=\tfrac{1}{2}, \tag{6}$$

so that the peak height is equal to one for any value of g_0. Now, using Eq. (6) and the first of Eqs. (5), we can determine the values of h and k that are to be used to place the resonance peak in g_0:

$$h=\frac{g_0}{2}, \quad k=\frac{1}{2g_0}. \tag{7}$$

In this way, the action of the $c(n)$ term is controlled by a single parameter, i.e., g_0. It is interesting to observe that once g_0 is set we can freely adjust the intensity of the enhancement using the parameter λ; this choice will not affect the width Δ of the resonance peak. Indeed, Δ can be defined as

$$\Delta = g_2 - g_1, \tag{8}$$

where g_1 and g_2 are such that

$$c(g_1) = c(g_2) = \tfrac{1}{2}, \quad g_2 > g_1; \tag{9}$$

it is easy to verify that

$$\Delta = 2 g_0 \sqrt{3}. \tag{10}$$

Practical experiments, some of which are shown in Sec. 4, have indicated that the choice of the parameters g_0 and λ is not critical.

It is apparent that the overall performance of the system can be satisfactory only if the activity measure $g(n)$ is capable of representing important image features, without being deceived by noise. Moreover, even very small details should be sensed by $g(n)$ to achieve an effective sharpening action. For this task, a possible candidate could be the local variance, but its response to noise is too strong. Alternatively, the magnitude of the so called Teager's operator could be used:[13]

$$g(n) = |x^2(n) - x(n+1)x(n-1)|; \tag{11}$$

the latter was proposed for estimating the energy of a signal and was also used in a nonlinear UM technique.[4] Its main advantage is that its output increases with the average luminance of the signal; hence, it complies with the Weber's law for the response of the human visual system.[5] However, even for this operator the sensitivity to noise is too high: including it in the processing mechanism described above, a considerable part of the input noise becomes more visible in the output image. This problem can be alleviated by the use of an even simpler $g(n)$ function. In this article, a squared bandpass filter of the type

$$g(n) = [x(n+1) - x(n-1)]^2 \tag{12}$$

will be adopted. The same operator has also been successfully employed in Ref. 5; moreover, it is used with the name of Brenner function as a criterion for sharpness in autofocusing techniques.[14]

3 The 2D Sharpening Operator

We can extend the results of the previous section to multidimensional data by considering the separate effects of the control signal $c(n)$ along the horizontal and vertical directions: this choice, apart from being the simplest, is also justified by the fact that the eye is more sensitive to lines and edges having these orientations.[1] To this purpose, let us define the two control signals:

$$c_x(n,m) = \frac{g_x(n,m)}{k g_x^2(n,m) + h}, \quad c_y(n,m) = \frac{g_y(n,m)}{k g_y^2(n,m) + h}, \tag{13}$$

where

$$g_x(n,m) = [x(n,m+1) - x(n,m-1)]^2,$$
$$g_y(n,m) = [x(n+1,m) - x(n-1,m)]^2. \tag{14}$$

The output of the filtering is then obtained as

$$y(n,m) = x(n,m) + \lambda[z_x(n,m)c_x(n,m) + z_y(n,m)c_y(n,m)], \tag{15}$$

where

$$z_x(n,m) = 2x(n,m) - x(n,m-1) - x(n,m+1),$$
$$z_y(n,m) = 2x(n,m) - x(n-1,m) - x(n+1,m). \tag{16}$$

4 Experimental Results

The proposed algorithm has been tested using different images: examples of the results are presented in this section. First, we examine the effects of different choices for the parameters. Then, we compare our algorithm to other ones which can be found in the literature. Finally, we verify the results achievable using our method as a preprocessor for images to be interpolated.

As usual when dealing with sharpening techniques, when no ideal image is available for comparison, the most reliable quality criterion is the visual appearence; however, we also introduce here an objective measure. The measure we use is described in detail in Ref. 15 and used also in Ref. 5; it is formed by two figures of merit representing an estimate of the local variance of an image. The estimate is performed separately in detail zones [detail variance, (DV)] and in relatively uniform zones [background variance (BV)] of an original or processed image. We should expect reasonably high values of DV in the enhanced images, while the BV value should remain low in order to indicate limited noise amplification. As we shall verify, DV and BV values cannot completely characterize the visual quality of an image, but constitute in general a useful comparison tool.

Figure 3(a) shows the 256×256 central portion of the ''Lena'' image; its enhanced version using the proposed technique [Eq. (15), $\lambda = 1.2$, $g_0 = 400$] is shown in Fig. 3(b). It can be seen that medium-contrast details have been enhanced without incurring significant noise amplification. At the same time, the typical black or white stripes which are present along strong image edges when conventional techniques are used, and which are due to overshoots of the correction term $z(n,m)$, are almost absent.

As claimed previously, the values of the parameters are not critical; we demonstrate this fact showing first the effects of different choices, then using the same parameters

(a) (b)

Fig. 3 Original test image ''Lena'' (a), and result of the proposed algorithm (b).

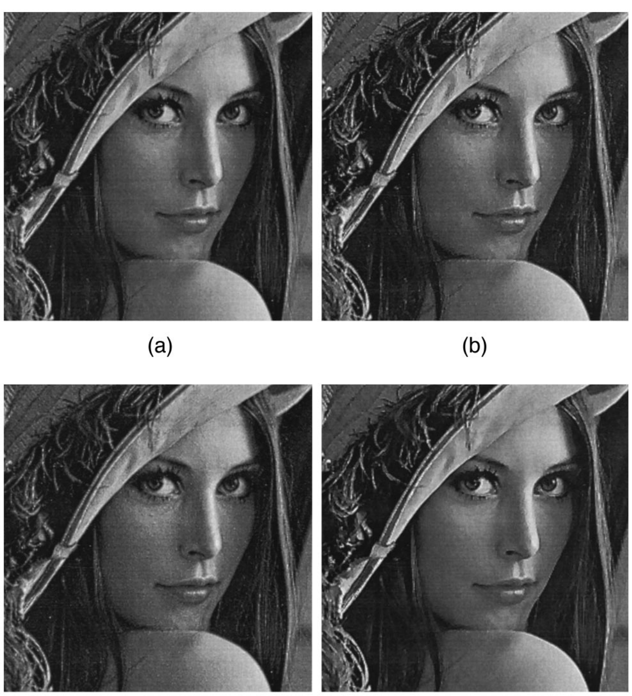
as in Fig. 3 on a different image. Figures 4(a) and 4(b) report the processed ''Lena'' image when $g_0=400$ (as above) but λ is changed to 0.9 and 1.5, respectively. As expected, the intensity of the sharpening effect is reduced in the former case and may be excessive in the latter, but no specific defects arise. More interestingly, Figs. 4(c) and 4(d) indicate the effects of a change in g_0, which is equal to 100 in the former image, to 1600 in the latter (in both cases $\lambda=1.2$, as above). Since the peak of the contrast amplification is moved towards small luminance differences, noise is more visible in Fig. 4(c); on the contrary, in Fig. 4(d) noise is almost absent but strong luminance differences are unduly amplified and overshoots appear in some details (see, e.g., the left cheek–hair and the shoulder–hair borders). Again, and notwithstanding the strong variation of the parameter g_0, the quality of the processed images is in all cases acceptable.

The best visual quality is obtained for ''Lena'' using $\lambda=1.2$, $g_0=400$ as in Fig. 3(b). The same parameters have been used for processing a 256×256 version of ''Boats.'' The original and the processed images are reported in Figs. 5(a) and 5(b), respectively, and the results appear satisfactory.

We have also made a number of experiments using the operators described in Sec. 1. Applying a conventional linear UM operator to the original image ($\lambda=1$), Fig. 6(a) results. The processed image is sharp, but the noise is very visible in the uniform areas such as the cheek. In Fig. 6(b) the results of the cubic UM method ($\lambda=0.001$) show an improvement of the quality in homogeneous areas; nevertheless, details of intermediate strength, such as those

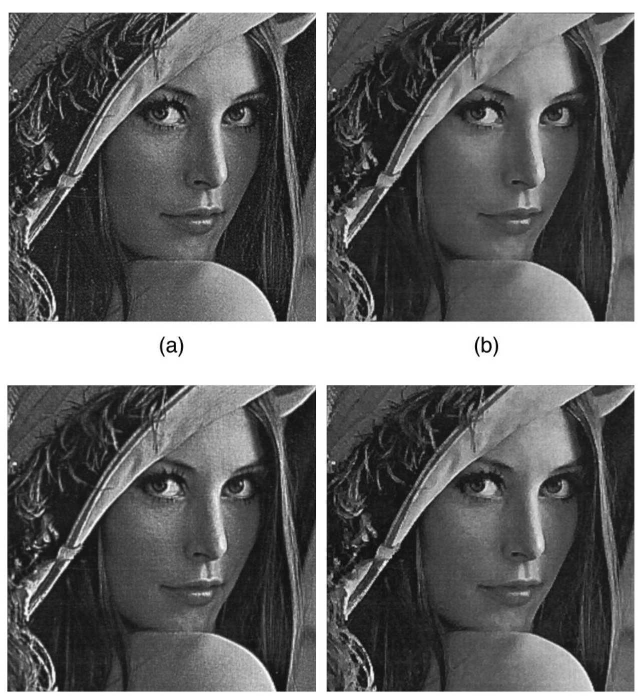
(a) (b)

Fig. 5 Original test image ''Boats'' (a), and result of the proposed algorithm (b).



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

Fig. 4 Enhanced image after processing with the rational UM technique with different values for the parameters.



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

Fig. 6 Enhanced image after processing with the conventional UM (a), cubic UM (b), Teager-based UM (c), OS-UM (d) operators.

Table 1 DV and BV of the original and processed images.

Filter	Parameters	Figure	DV	BV
none		3(a)	365	14
linear UM	$\lambda=1$	6(a)	1995	276
linear UM	$\lambda=0.55$		1181	118
Teager-based	scale=256	6(c)	1124	87
cubic UM	$\lambda=0.001$	6(b)	1263	25
OS-UM	$\lambda=1$	6(d)	1188	56
rational UM	$\lambda=1.2,\ g_0=400$	3(b)	1169	57

which are present on the top of Lena's hat, are not as well defined as in the previous case. Moreover, significant overshoots are recognizable. When the Teager–based operator[4] (scaling factor=256) is used, Fig. 6(c) is obtained; it may be observed that the noise is amplified. The latter effect is less annoying using the OS-UM technique, as it can be observed in Fig. 6(d) ($\lambda=1$); here, however, the typical ''patchwork'' effect of OS methods is recognizable in uniform areas.

The DV and BV figures of merit have been estimated for the above images and are reported in Table 1. Taking as a reference the unprocessed ''Lena'' image, it is seen that all the techniques are able to significantly improve the DV, at the expense of an increase in the BV. In more detail:

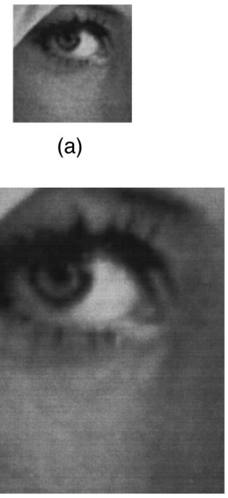
(i) The linear UM method strongly amplifies the detail variance, but is also very sensitive to noise; it should be observed that the extremely high value of DV is also due to the overshoot effects recognizable in Fig. 6(a). If we reduce the value of λ in this technique to 0.55, we obtain a DV value similar to the one of the other methods, but the BV is still very high.

(ii) The Teager-based method is capable of yielding DV growth to a degree similar to the UM method for $\lambda=0.55$; however, the value of the BV indicates that the noise amplification is smaller.

(iii) The cubic UM method yields a slightly higher value of DV, with a very good behavior with respect to noise. Actually, it should be observed that the small BV value achieved is also due to the fact that medium-contrast details are poorly sharpened by this operator, as recognizable in Fig. 6(b).

(iv) The OS-UM and the rational UM yield similar values of DV and BV. However, the figures of merit do not take into account the better enhancement of medium-contrast details obtained using the proposed approach.

Due to its characteristics the proposed operator can also be successfully employed as a preprocessor for images which are to be interpolated. It is well known that interpolation introduces some blurring effects due to the presence of the anti-aliasing lowpass filter;[1] the basic idea we can use to obtain more visually pleasant results is then to give a little emphasis to fine details before the interpolation. If the conventional UM algorithm is used for this purpose, two main drawbacks can be observed: the first is an undesirable



(a)

(b)

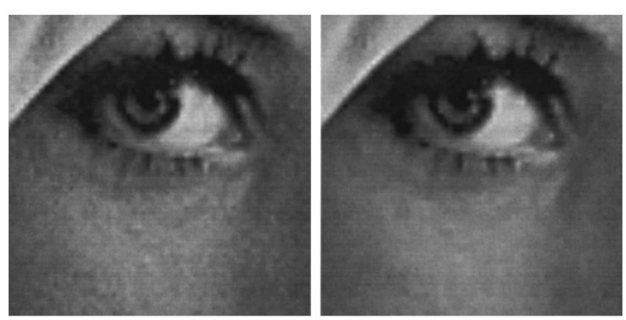
Fig. 7 64×64 detail to be interpolated (a); interpolated image without preprocessing (b).

amplification of the background noise, and the second is the introduction of some overshoot effects in the neighborhood of the details which already have quite a good contrast. On the contrary, by the use of the proposed algorithm we can avoid these unpleasant artifacts performing a sharpening action only where it is needed and leaving the rest of the image almost unchanged.

As an example, Fig. 7(a) shows a 64×64 detail of the original image; Fig. 7(b) reports the image resulting from interpolation by a factor of 4; the bicubic operator[16] has been used. A loss of contrast can be noted in the details. In Fig. 8(a) the 64×64 image is processed with the linear UM technique ($\lambda=0.3$) before interpolation: the result is clearly sharper than the previous one, however, the background noise has also been increased. Finally, in Fig. 8(b) the rational UM preprocessing ($\lambda=0.5$, $g_0=1000$) produces a good improvement in the contrast, while the homogeneous areas are still clean.

5 Conclusions

A new nonlinear rational UM algorithm has been proposed in this contribution; despite its simple formulation, it is able



(a) (b)

Fig. 8 Interpolated detail with linear UM (a), and rational UM (b) preprocessing.

to produce a good noise-insensitive sharpening action without introducing unpleasant overshoot artifacts. Moreover, its characteristics permit one to successfully employ it also to improve the quality of interpolated images.

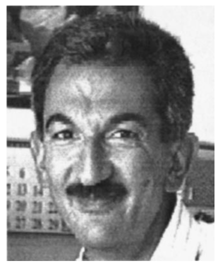
The 2D operator is derived as a straightforward extension of its 1D counterpart. Future research work could be devoted to improving the obtainable performance by studying non-separable filtering masks.

Acknowledgments

This work has been partially supported by the European ESPRIT Project No. LTR 20229—Noblesse and by a 60% grant from the University of Trieste.

References

1. A. K. Jain, *Fundamentals of Digital Image Processing*, Prentice-Hall, Englewood Cliffs, NJ (1989).
2. L. Gozum, *VidFun* Multimedia viewer, v.2.2 for Windows, http://www.rose.com/~lgozum.
3. Y. H. Lee and S. Y. Park, ''A study of convex/concave edges and edge-enhancing operators based on the Laplacian,'' *IEEE Trans. Circuits Syst.*, **37**, 940–946 (July 1990).
4. S. K. Mitra, H. Li, I. Li, and T. Yu, ''A new class of nonlinear filters for image enhancement,'' *Proc. IEEE Int. Conf. on Acoustic, Speech and Signal Processing, ICASSP-91*, Toronto, Canada, pp. 2525–2528 (May 14–17, 1991).
5. G. Ramponi, N. Strobel, S. K. Mitra, and T-H. Yu, ''Nonlinear unsharp masking methods for image contrast enhancement,'' *J. Electron. Imaging* **5**(3), 353–366 (1996).
6. S. Guillon, P. Baylou, and M. Najim, ''Robust nonlinear contrast enhancement filter,'' *Proc. Third IEEE Int. Conf. on Image Processing, ICIP-96*, Lausanne, Switzerland (Sept. 16–19, 1996).
7. *Washington State University's Digital Image Processing Instructional Database*, R. Bamberger, Ed., http://www.eecs.wsu.edu/IPdb/Enhancement/homo_filtering.html.
8. A. Polesel, G. Ramponi, and V. J. Mathews, ''Adaptive unsharp masking for contrast enhancement,'' *Proc. Fourth IEEE Int. Conf. on Image Processing, ICIP-97*, Santa Barbara, CA (Oct. 26–29, 1997).
9. G. Ramponi, ''The rational filter for image smoothing,'' *IEEE Signal Process. Lett.* **3**, 63–65 (March 1996).
10. R. Castagno and G. Ramponi, ''A rational filter for the removal of blocking artifacts in image sequences coded at low bitrate,'' *Proc. Eighth European Signal Processing Conf., EUSIPCO-96*, Trieste, Italy (Sept. 10–13, 1996).
11. G. Ramponi and C. Moloney, ''Smoothing speckled images using an adaptive rational operator,'' *IEEE Signal Process. Lett.* **4**, 68–71 (March 1997).
12. F. Cocchia, S. Carrato, and G. Ramponi, ''Design and real-time implementation of a 3-D rational filter for edge preserving smoothing,'' *IEEE Int. Conf. on Consumer Electronics, ICCE-97*, Chicago, IL (June 1997).
13. T. F. Kaiser, ''On a simple algorithm to calculate the 'energy' of a signal,'' *Proc. IEEE Int. Conf. on Acoustic, Speech and Signal Processing*, Albuquerque, NM, No. 1, pp. 381–384 (May 1990).
14. T. T. E. Yeo, S. H. Ong, R. Jayasooriah, and R. Sinniah, ''Autofocusing for tissue microscopy,'' *Image Vis. Comput.* **11**, 629–639 (1993).
15. A. Vanzo, G. Ramponi, and G. L. Sicuranza, ''An image enhancement technique using polynomial filters,'' *Proc. First IEEE Int. Conf. on Image Processing, ICIP-94*, Austin, TX (Nov. 13–16, 1994).
16. R. G. Keys, ''Cubic convolution interpolation for digital image processing,'' *IEEE Trans. Acoust., Speech, Signal Processing* **ASSP-29**, 1153–1160 (1981).



Giovanni Ramponi received a degree in electronic engineering (*summa cum laude*) in 1981 from the University of Trieste, Italy. In 1983 he joined the Department of Electronics of the University of Trieste as a research engineer; in 1986 he was appointed Senior Research Engineer and, in 1992, Associate Professor of Electronics. Professor Ramponi has contributed to several undergraduate and graduate courses on analog and digital electronics and on digital signal processing. His research interests include nonlinear digital signal processing, enhancement and feature extraction in images and image sequences, and image compression. Professor Ramponi is an Associate Editor of the *Journal of Electronic Imaging* and was Chairman of the Technical Programme of Eusipco-96. He is a Member of the IEEE.

Andrea Polesel graduated with a degree in electronic engineering (*summa cum laude*) in 1997 from the University of Trieste, where he continues to develop his thesis work on image processing under a research contract.