ADAPTIVE UNSHARP MASKING FOR CONTRAST ENHANCEMENT

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ABSTRACT

A new scheme of unsharp masking for image contrast enhancement is presented in this paper. An adaptive algorithm is introduced so that a sharpening action is performed only in locations where the image exhibits significant dynamics. Hence, the amplification of noise in smooth areas is reduced. An adaptive directional filtering is also performed so as to provide suitable emphasis to the different directional characteristics of the detail. Because it is capable of treating high-detail and medium-detail areas differently, this algorithm also avoids unpleasant overshoot artifacts in regions of sharp transitions. Experimental results demonstrating the usefulness of the adaptive operator in an application involving preprocessing of images for enhancement prior to zooming are also included in the paper.

1. INTRODUCTION

Linear unsharp masking (UM) is a widely used technique for improving the perceptual quality of an image by emphasizing its high-frequency components. In this scheme, a highpass filtered, scaled version of the input signal is added to the signal itself to form the enhanced image. Even though this method is simple to implement, the presence of the linear highpass filter makes the system extremely sensitive to noise. This results in perceivable and undesirable distortions, particularly in uniform areas of the images. Furthermore, medium-contrast details are not enhanced as well as high-contrast details in the image. Consequently, to provide medium-contrast detail areas with a good sharpening, the parameter of the linear unsharp masking algorithm must be set so as to emphasize the high-contrast areas excessively. Therefore, unpleasant overshoot artifacts appear in the output images. A number of approaches have been devised to overcome the noise sensitivity of the linear UM scheme. Most of such methods are based on the introduction of nonlinear operators in the correction path. Different polynomial-based methods were suggested in [1]. A technique based on the order statistics Laplacian operator was presented in [2]. An approach based on adaptive quadratic filtering was proposed in [3]. An adaptive filter that provides good sharpening to medium-contrast details was introduced in [4].

This paper introduces an adaptation algorithm in the correction path so as to emphasize medium-contrast details more than large-contrast details such as abrupt edges, without introducing overshoot artifacts in the output image. Furthermore, the adaptation reduces the noise sensitivity, since the sharpening action is relatively mild when the input pixel belongs to a smooth area.

2. THE ALGORITHM

In the linear UM algorithm, the enhanced image $y(n,m)$ is obtained from the input image $x(n,m)$ as

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

where $z(n,m)$ is the correction signal computed as the output of a linear highpass filter, and λ is a suitable positive scaling factor which controls the contrast enhancement at the output. A common choice is to employ a two-directional Laplacian of the input image as $z(n,m)$. In this paper, we propose to use an adaptive algorithm to change the value of the scaling factor λ at each location. Furthermore, to achieve directional filtering capabilities, we separate the correction signal into two orthogonal components. Thus, the output of our system is obtained by modifying (1) as

$$\begin{aligned} y(n,m) &= x(n,m) + \lambda_x(n,m)\, z_x(n,m) + \\ &+ \lambda_y(n,m)\, z_y(n,m) \,, \end{aligned} \tag{2}$$

where $z_x(n,m)$ and $z_y(n,m)$ respectively are the outputs of a linear one-dimensional operator applied horizontally and vertically to the input image, and $\lambda_x(n,m)$ and $\lambda_y(n,m)$ are the scaling factors for these signals, and are recursively updated by the adaptation algorithm. The two directional highpass operators employed in our system are based on the one-dimensional

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Laplacian operators that are described by the input-output relationships

$$z_x(n,m) = 2\,x(n,m) - x(n,m-1) - x(n,m+1) \quad (3)$$

and

$$z_y(n,m) = 2\,x(n,m) - x(n-1,m) - x(n+1,m)\ . \quad (4)$$

By defining the scaling vector $\Lambda(n,m)$ and the correction vector $Z(n,m)$ as

$$\Lambda(n,m) = [\lambda_x(n,m)\ ,\ \lambda_y(n,m)]^T \quad (5)$$

and

$$Z(n,m) = [z_x(n,m)\ ,\ z_y(n,m)]^T, \quad (6)$$

respectively, (2) can be rewritten as

$$y(n,m) = x(n,m) + \Lambda^T(n,m)\,Z(n,m)\ . \quad (7)$$

The objective of the adaptive filter is to change the scaling vector $\Lambda(n,m)$ at each spatial location so that the contribution of the correction vector varies according to a measure of the *local activity* of the image. In this work, we employ the local variance $V_l(n,m)$ computed over a 3×3-pixel area as

$$V_l\,(n,m) = \frac{1}{9}\sum_{i=n-1}^{n+1}\sum_{j=m-1}^{m+1}(x(i,j) - \bar{x}(n,m))^2 \quad (8)$$

as a measure of the local activity in the neighborhood of the processed sample. In the above equation, $\bar{x}(n,m)$ is the average luminance level over the 3×3-pixel block under consideration. The adaptation algorithm accomplishes our objective by attempting to minimize the cost function

$$\begin{aligned} J(n,m) &= E[e^2(n,m)] \\ &= E[(g_d(n,m) - g_y(n,m))^2] \end{aligned} \quad (9)$$

at each location, where $g_d(n,m)$ and $g_y(n,m)$ represent the desired *local dynamics* and the actual local dynamics, respectively, of the output image at the spatial location (n,m). For ease of implementation and analytical tractability, we have defined a measure for the local dynamics of an image as the output of a simple linear highpass filter (a 3×3 Laplacian operator has been chosen). Let $g_x(n,m)$ be the measure of the local dynamics of the input image $x(n,m)$. Similarly, let $g_{z_x}(n,m)$ and $g_{z_y}(n,m)$ represent measures of the local dynamics of $z_x(n,m)$ and $z_y(n,m)$, the output signals of the directional filters. Assuming that $\Lambda(n,m)$ varies slowly in the 3×3-pixel neighborhood of the processed pixel, we can express the activity measure $g_y(n,m)$ of the output signal approximately as

$$g_y(n,m) = g_x(n,m) + \Lambda^T(n,m)\,G(n,m), \quad (10)$$

where

$$G(n,m) = [g_{z_x}(n,m)\ ,\ g_{z_y}(n,m)]^T. \quad (11)$$

Substituting this result in (9) yields

$$e(n,m) = g_d(n,m) - g_x(n,m) - \Lambda^T(n,m)\,G(n,m)\ . \quad (12)$$

For the purpose of image enhancement, we define the desired output dynamics $g_d(n,m)$ as

$$g_d(n,m) = \alpha(n,m)g_x(n,m)\ , \quad (13)$$

where $\alpha(n,m)$ is a variable gain computed by means of the following mapping:

$$\alpha(n,m) = \begin{cases} 1 & V_l(n,m) < T_1 \\ \alpha_{dh} & T_1 \le V_l(n,m) \le T_2 \\ \alpha_{dl} & V_l(n,m) > T_2. \end{cases} \quad (14)$$

The mapping defined in (14) provides a classification of the input samples based on the local activity of the input image. Any pixel located in a region with local variance lower than T_1 is considered as part of a smooth area. Consequently, the local dynamics in the input image need no improvement in that location, and therefore, we set $\alpha(n,m) = 1$ at that location. On the other hand, if $V_l(n,m)$ belongs to the range $[T_1\ ,\ T_2]$, the corresponding pixel is classified as belonging to a medium-contrast detail area. Thus, a relatively strong enhancement is required, and therefore, we employ the highest amplification factor α_{dh} for this case. Finally, if $V_l(n,m)$ is larger than T_2, the pixel is considered as belonging to a region where the local activity is already quite large. Consequently, a sharpening action is necessary, but not as marked as in the previous case. On the basis of this rationale, we set α_{dl} to be somewhat smaller than α_{dh}. The threshold values T_1 and T_2 and the gains α_{dl} and α_{dh} are selected as a function of the desired level of the contrast enhancement at the output. We assume in our discussions that the image is scanned along its rows, and the scaling vector $\Lambda(n,m)$ is updated using a Gauss-Newton algorithm given by [5]:

$$\Lambda(n,m+1) = \Lambda(n,m) - \mu\,R^{-1}(n,m)\,\nabla_\Lambda\left(e^2(n,m)\right)\ . \quad (15)$$

$R(n,m)$ is a recursive estimate of the least-squares autocorrelation matrix of the input vector $G(n,m)$, and is given by

$$R(n,m) = (1-\beta)\,R(n,m-1) + \beta\,G(n,m)\,G^T(n,m)\ . \quad (16)$$

Substituting (12) in (15) yields the update rule

$$\Lambda(n,m{+}1) = \Lambda(n,m){+}2\,\mu\,e(n,m)\,R^{-1}(n,m)\,G(n,m)\ .$$

The constant β in (16) is a positive convergence parameter that is smaller than one. The parameter μ in the update equation is a small, positive step size, and it controls the speed of convergence of the adaptive filter.

3. EXPERIMENTAL RESULTS

The image we employed to test the enhancement capabilities of our adaptive algorithm is a 256 × 256-pixel portion of the image "Lena"; it is shown in Figure 1.a.

3.1. Image Sharpening

Figure 1.b displays the output of the fixed UM operator ($\lambda = 0.5$). It can be seen from this figure that the sharpening is effective, especially for medium-contrast details. However, the background noise is amplified in smooth areas. Figure 1.c shows the output produced by the order statistics-based operator ($\lambda = 0.92$) [2]. Its effectiveness is reduced in the presence of fine details, even though it yields better results than standard linear unsharp masking in uniform regions. Finally, Figure 1.d presents the result obtained using the adaptive operator of this paper. The homogeneous areas are less noisy than in the case of the linear operator. Nevertheless, a good sharpening is achieved in the detail areas. The adaptive algorithm also overcomes the problems of the order statistics-based scheme in the sense that medium-contrast details are better enhanced. The parameters employed by the adaptive operator were the following: $T_1 = 60$, $T_2 = 200$, $\alpha_{dh} = 4$, $\alpha_{dl} = 3$, $\mu = 0.1$ and $\beta = 0.5$. Experiments conducted on other images have suggested that the above values for T_2, α_{dh}, α_{dl}, μ, β provide satisfactory levels of enhancement for a large class of input images. The parameter T_1 depends on the noise level of the input image and usually takes values in the range [30 , 60].

3.2. Preprocessing for Interpolation

Because of its enhancement capabilities, our operator can also be employed as a preprocessor for images which are to be interpolated. Interpolation introduces some blurring effects in the output images due to the presence of non-ideal anti-aliasing lowpass filter that partially suppresses useful frequency components in the interpolated images. This effect can be seen in Figure 2.a. Better results can be obtained by providing a high-frequency emphasis to the image before the interpolation, as done, for example, in [6]. If the fixed UM algorithm is used for this purpose, the system suffers from two main drawbacks. There is an undesirable amplification of the background noise and the method also introduces some overshoot effects. By using the adaptive algorithm of this paper, we can avoid these unpleasant artifacts and perform a sharpening action only where it is needed. We can see from Figure 2.c that the adaptive algorithm provides much improved enhancement over the fixed scheme without amplifying the noise in the smooth areas as in Figure 2.b.

In the experimental results that we presented, we employed bicubic interpolation [7] to increase the spatial resolution of a detail from 64 × 64 to 256 × 256 pixels.

4. CONCLUDING REMARKS

An adaptive recursive two-dimensional filter for image sharpening was presented in this paper. The algorithm employs two directional filters whose coefficients are controlled by the Gauss-Newton algorithm. Experimental results demonstrated that the algorithm performs well compared to standard approaches to image contrast enhancement. The proposed operator is also suitable for preprocessing images prior to interpolation.

Acknowledgements

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5. REFERENCES

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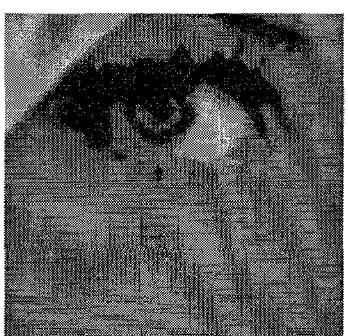
(a)

(b)

(c)

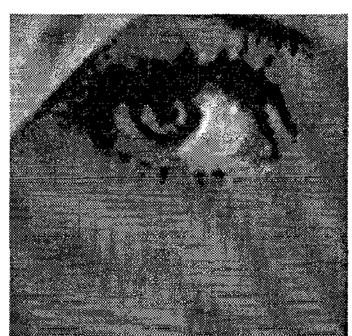
(d)

Figure 1: (a): original image; (b): linear UM; (c): order statistic UM; (d): adaptive UM.



(a)

(b)



(c)

Figure 2: (a): zoom without preprocessing; (b): linear UM preprocessing; (c): adaptive preprocessing.