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Simple Fuzzy Technique Combining Sharpening and Noise Reduction for Color Images

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***Abstract*— The development of digital techniques for color image enhancement is very important because color pictures include information that is essential in many research and application fields. Color image enhancement, however, is not a trivial problem, because it typically deals with conflicting operations such as data sharpening and smoothing. The challenging goals consist in avoiding noise amplification, chroma distortion and excessive overshoot on object edges. This paper presents a novel technique for the enhancement of RGB images that is designed to address all these issues. The proposed approach consists in a two-stage recursive operator that adopts fuzzy processing in order to gradually perform smoothing and sharpening of noisy color data. In this approach, chroma distortion is avoided by choosing vector smoothing of RGB data and by applying the sharpening to the luminance channel only. Computer simulations show that the method combines simplicity and effectiveness. It can sharpen the image details and reduce the noise without generating false colors, whereas other techniques cannot. The method is easy to use too. The behavior of the operator is easily controlled by choosing a few parameter values.**

Keywords*— *image processing, image enhancement, image sharpening, nonlinear filters, fuzzy models.

I. INTRODUCTION

It is known that methods for image enhancement are widely used in many research and application fields such as robotics, medical systems, remote sensing, video surveillance, biometrics and consumer electronics. In all these areas, digital images represent a key source of information, so highlighting important features embedded in the image data is of paramount importance. A large body of scientific literature deals with the enhancement of grayscale images. In this framework, the most compelling issue is represented by the noise amplification typically generated by the sharpening process, such as in the linear *unsharp masking* (UM) method [1-2]. A variety of nonlinear approaches have been proposed in order to control the noise increase during detail sharpening and possibly avoid excessive overshoot on object edges [3-7]. Such approaches include operators based on weighted medians (WM) [8], permutation weighted medians (PWMs) [9-10], polynomial UM techniques [11-15], fuzzy model-based operators [16-17], piecewise linear functions [18-19], bilateral smoothers [20], non-local means (NLM) [21], anisotropic diffusion filters [22]. In this framework, the simplest approach to the enhancement of color images is to enhance each image channel independently by adopting a grayscale (i.e, scalar) algorithm (*marginal approach*). Although conceptually simple and computationally light, this choice does not take into account the correlation among color components and the result is typically affected by color artefacts. More accurate methods avoid chroma distortion by considering the color dependence (*vector approaches)* or by applying the sharpening effect to the *luminance* channel only [23-27].

In this paper we present a new method for the enhancement of color images that can avoid noise amplification, chroma distortion and excessive overshoot on object edges. The proposed method is a two-stage recursive operator that resorts to fuzzy model-based processing to gradually apply smoothing and sharpening to noisy color data. The operator performs vector filtering of RGB data and sharpening of the luminance channel, after conversion from the RGB to the YC_bC_r color space. Thus, it can sharpen the image details and reduce the noise without generating false colors. Furthermore, its behavior can be easily controlled by a few parameters only. This is a key aspect of the novel method. This paper is organized as follows. Section II describes the two-stage recursive enhancement system, Section III discusses the results of some computer simulations and, finally, Section IV reports conclusions.

II. PROPOSED ENHANCEMENT SYSTEM

The proposed enhancement system operates in the pixel window W depicted in Fig.1. The operation is recursive and involves two processing stages addressing the subsets of pixel coordinates W_1 and W_2, respectively.

A. Fuzzy Model-Based Vector Smoothing

The first stage performs fuzzy model-based smoothing in the RGB color space. The goal is to reduce Gaussian noise possibly affecting the input data. Let $\mathbf{x}(i,j)=[x_1(i,j), x_2(i,j),x_3(i,j)]^T$ be the vector (in the RGB color coordinate system) denoting the pixel at spatial location (i,j) in the noisy

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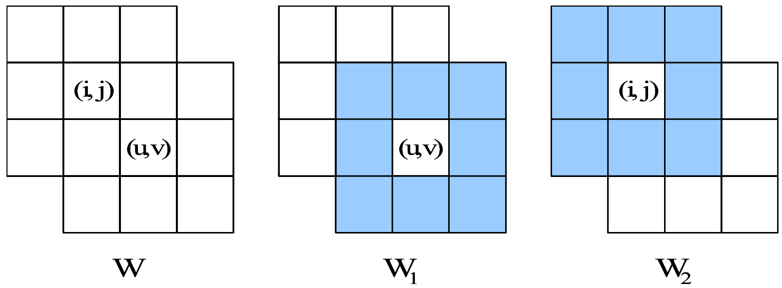


Figure 1. Decomposition of the pixel window W into subwindows W_1 and W_2

image (i=1,…, N_1; j=1,…, N_2), where x_1, x_2 and x_3 briefly represent the R, G and B components, respectively. Let each component be digitized by using L different levels: $0 \le x_k \le L-1$ (L=256 for a 24-bit RGB color picture). Let **x**(u,v) be the vector pixel at spatial location (u,v), where u=i+1 and v=j+1 (Fig.1). The output $\mathbf{y}(u,v)=[y_1(u,v), y_2(u,v), y_3(u,v)]^T$ of this stage is defined by the following relationships:

$$y_k(u,v) = x_k(u,v) - f_k(u,v) \tag{1}$$

$$f_k(u,v) = \frac{1}{8} \sum_{(m,n)\in W_1} \mu_{SM}\left(d(m,n)\right)\left[x_k(u,v) - x_k(m,n)\right] \tag{2}$$

where $d(m,n) = \left\| x(u,v) - x(m,n) \right\|$ is the Euclidean distance of two vector pixels **x**(u,v) and **x**(m,n), and μ_{SM} is the parameterized membership function that describes the fuzzy set "small":

$$\mu_{SM}(d) = \begin{cases} 0 & d \ge 4a_1 \\ \dfrac{4a_1 - d}{3d} & a_1 \le d < 4a_1 \\ 1 & 0 \le d \le a_1 \end{cases} \tag{3}$$

where a_1 is a parameter ($0 < a_1 < L$). The detail-preserving smoothing defined by (1-3) operates as follows. The term $\mu_{SM}\left(d(m,n)\right)$ basically represents a weight. In order to avoid detail blur, the algorithm focuses on small pixel distances (possibly produced by Gaussian noise) and excludes pixel values with large distances because they very likely represent object borders. The approach assumes that only noise is present if all distances are small ($d \le a_1$), In this case, the result is the arithmetic mean of the pixel values that performs strong smoothing, as it should be. Conversely, large distances ($d > 4a_1$) denote image edges and thus their contribution is zero. The fuzzy membership function μ_{SM} is designed to perform a gradual transition between these opposite actions. In the proposed model, the parameter a_1 controls how much a pixel distance represents noise to be reduced or information to be preserved. The choice of this parameter clearly depends upon the noise variance. The processing is recursive, i.e., the new value **y**(u,v) is immediately assigned to **x**(u,v) and re-used for further processing.

B. *Fuzzy Model-Based Sharpening*

The second stage performs fuzzy model-based sharpening dealing with the pixel subset W_2 centered on **x**(i,j). Since the filtering is recursive and the window scans the image from left to right and from top to bottom, all values in W_2 are the results of previous smoothing. Let $x_{lum}(i,j)$ be the luminance of the pixel at location (i,j) after conversion from the RGB to the YC_bC_r color coordinate system. The output $y_{lum}(i,j)$ is yielded as follows:

$$y_{lum}(i,j) = MIN\left\{ x_{lum}(i,j) + \lambda f_{lum}(i,j),\ L-1 \right\} \tag{4}$$

where λ is the parameter that controls the overall amount of sharpening (λ>0) and $f_{lum}(i,j)$ is the output of the pseudo high-pass filter defined by the following relationship:

$$f_{lum}(i,j) = \frac{1}{8} \sum_{(m,n)\in W_2} \mu_{LA}\left(\Delta(m,n)\right)\left[x_{lum}(i,j) - x_{lum}(m,n)\right] \tag{5}$$

where $\Delta(m,n) = x_{lum}(i,j) - x_{lum}(m,n)$ is the luminance difference of two pixels $x_{lum}(i,j)$ and $x_{lum}(m,n)$, and μ_{LA} is the parameterized membership function that describes the fuzzy set "large":

$$\mu_{LA}(\Delta) = \begin{cases} \dfrac{|\Delta| - a_2}{a_3 - a_2} & a_2 \le |\Delta| < a_3 \\ 1 & a_3 \le |\Delta| < 2a_3 - a_2 \\ \dfrac{4a_3 - 3a_2 - |\Delta|}{2(a_3 - a_2)} & 2a_3 - a_2 \le |\Delta| < 4a_3 - 3a_2 \\ 0 & otherwise \end{cases} \tag{6}$$

(a) (b)

Figure 2. Modified 24-bit RGB test pictures with superimposed uniform regions of interest (ROI) for noise measurements: (a) "Girl", (b) "Window".

and a_2 and a_3 are parameters ($0 \le a_2 < a_3$). The function $\mu_{LA}(\Delta)$ is useful to sharpen image details because it can highlight the (large) luminance differences among pixel values. The design of the novel membership function $\mu_{LA}(\Delta)$ is based on our previous research work [17] and aims at reducing the number of necessary parameters. In the novel design, the parameter a_2 controls the sensitivity to noise. Indeed, no sharpening is activated if $|\Delta| \le a_2$. The parameter a_3 controls the overshoots along the object borders. Large values of this parameter can be chosen in order to limit this effect.

III. Results of Computer Simulations

We performed many computer simulations in order to analyze the performance of the new fuzzy operator. In these experiments, we chose two 24-bit color images whose size is 512-by-512 pixels. We slightly modified them by superimposing a small uniform region (R=G=B=128) in the proximity of the upper right corner in order to ease the measurement of residual noise after sharpening. The resulting test pictures are shown in Fig.2a ("Girl") and Fig.2b ("Window").

According to (1-6), the overall behavior of the fuzzy operator is controlled by four parameters a_1, a_2, a_3 and λ, where a_1, a_2 specifically address the case of noisy input data. If the input image is not corrupted by noise, a_1 and a_2 should be set as follows: $a_1<1$, $a_2=0$. In this case, the sharpening is controlled by a_3 and λ only. For a given value of λ (determining the overall amount of sharpening), the effects of different choices of a_3 are reported in Fig.3. A portion of the original "Girl" image is depicted in Fig.3a. Examples of processed data are shown in Fig.3b (a_3=20), Fig.3c (a_3=50) and Fig.3d (a_3=150). We chose λ=3 in all examples. Low values of a_3 typically increase the ability to sharpen fine details. On the other hand, large values of this parameter can limit the excess of overshoots on image edges. A tradeoff between these effects is necessary to obtain a well balanced result. For a given value of a_3, the effects of different choices of λ are reported in Fig.4. A portion of the original "Window" image is depicted in Fig.4a. Examples of processed data are shown in Fig.4b (λ=2), Fig.4c (λ=4) and Fig.4d (λ=6). We chose a_3=20 in all examples. Clearly, the edge sharpening becomes stronger as the value of λ increases. Too large values however should be avoided because they typically lead to annoying overshoots on object borders, regardless of the choice of a_3. In order to study the overall performance of the proposed method, we corrupted the test images by adding Gaussian noise. A portion of the "Girl" picture degraded by Gaussian noise with variance σ^2=100 is depicted in Fig.5a. The result yielded by the novel fuzzy operator is shown in Fig.5b (a_1=20, a_2=15, a_3=100, λ=3). For a comparison, the results given by our previous fuzzy sharpener [17] and by the classical linear unsharp masking operator are reported in Fig.5c and 5d, respectively. Both operators are scalar algorithms, so we applied them to the RGB channels. From visual inspection, we can see that the proposed fuzzy technique can perform noise cancellation and detail sharpening as well. Conversely, some noise increase is apparent in the picture processed by our previous method. The noise amplification is very annoying if we observe the data processed by the linear operator. We can obtain a quantitative estimate of the amplified/residual noise by evaluating the *color peak signal-to-noise ratio* (CPSNR) [28] in the uniform region of interest (ROI) located at the

Figure 3. Portion of the original noise-free "Girl" image (a), sharpening yielded by a_3=20 (b), a_3=50 (c), a_3=150 (d).

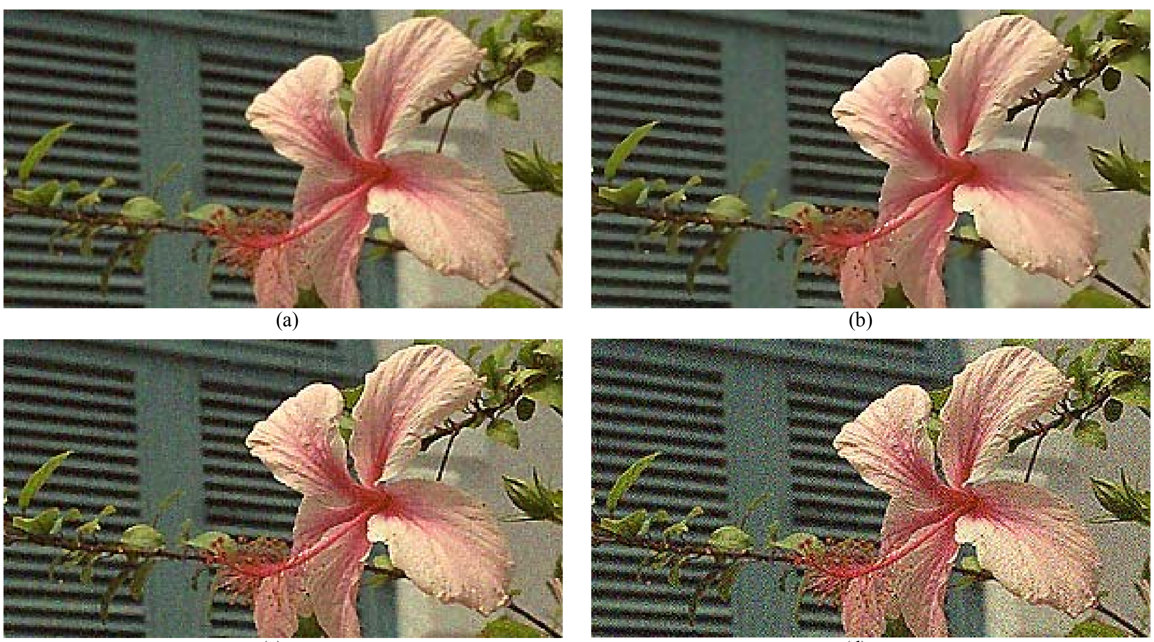
Figure 4. Portion of the original noise-free "Window" image (a), sharpening yielded by λ=2 (b), λ=4 (c), λ=6 (d).

upper-right corner of the modified test images. The $CPSNR_{ROI}$ evaluations are: 33.35 dB (proposed method), 22.96 dB (previous sharpener [17]) and 15.44 dB (linear unsharp masking).

Finally, a portion of the "Window" picture corrupted by Gaussian noise with variance σ^2=150 is reported in Fig.6a. The result given by the novel fuzzy operator is shown in Fig.6b

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

Figure 5. Portion of the "Girl" image corrupted by Gaussian noise with variance σ^2=100 (a), results yielded by the proposed method (b), by our previous sharpener (c) and by the linear unsharp masking operator (d).



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

Figure 6. Portion of the "Window" image corrupted by Gaussian noise with variance σ^2=150 (a), results yielded by the proposed method (b), by our previous sharpener (c) and by the linear unsharp masking operator (d).

(a_1=25, a_2=10, a_3=100, λ=2). The results given by our previous fuzzy technique and by the linear unsharp masking operator are reported in Fig.6c and 6d, respectively. The better performance of the new operator is apparent in this case too. It can reduce the noise and sharpen the color data without chroma distortion. The $CPSNR_{ROI}$ evaluations are: 34.0 dB (proposed method), 24.21 dB (previous sharpener) and 16.17 dB (linear unsharp masking).

IV. CONCLUSIONS

A simple technique for the sharpening of noisy color images has been presented. The proposed approach is based on a recursive architecture that adopts fuzzy models in order to reduce the noise and to sharpen the image details. The novel aspect of the method is the combination of vector filtering of RGB data and sharpening of the luminance information. This avoids the generation of false colors during the enhancement of color image data. Results of computer simulations have shown that the novel method outperforms other techniques and is easy to use. Indeed, the behavior of the operator can be easily controlled by choosing a few parameter values.

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