Image sharpening based on spatiochromatic properties of the human vision system

María S. Millan, Edison Valencia; Dep. of Optics and Optometry - Technical University of Catalonia; Terrassa, Barcelona / Spain

Abstract

We introduce a new method for color image sharpening based on S-CIELAB extension. S-CIELAB involves a series of smoothing spatial filters in the opponent color space to approximate the contrast sensitivity functions of the human vision system. The filters are linear combinations of Gaussian masks. We combine these spatial filters with the Laplacian operator in each opponent channel to obtain the sharpened image. The Laplacian of the smoothed components can be simplified by introducing the Laplacian of Gaussian (LoG) operator. Alternatively, the LoG operator can be approximated by the difference of Gaussians (DoG) operator. Moreover, the use of DoG operator can be justified since it is used to model the receptive field performance in early human vision. The resulting image is subtracted from the image in each opponent channel and then back transformed to the device independent representation space (XYZ) to obtain the final sharpened image.

The method is tested and applied to digital color images. The results are compared with other results obtained by applying the LoG operator to the intensity channel only (keeping the chromatic components unchanged), or by applying the simple Laplacian to the image components in two representations (opponent color space and RGB).

Introduction

Edges and object contours in images are usually noisy and badly defined areas as a consequence of several possible reasons: the point to spread function of the camera lens, the sensor and/or display resolution, viewing conditions, digital operations such as image compression, halftone patterns, etc. There are a large number of applications for which image edges or the differences between adjacent light and dark sample points in an image need to be emphasized or sharpened. But image sharpening is a double-edged sword: it may wonderfully enhance an image but, on the other hand, an improper or excessive use of it affects the image producing artifacts such as overly contrasted contours, edges that look like halos around objects, jagged edges, and specked or mottled areas, increasing noise, etc. On the other hand, there are evidences that show that smoothing and sharpening spatial filters are in the basis of the receptive field performance of the primary stages of the human vision.

The use of the Laplacian operator to enhance grayscale images by edge sharpening is widely known. The digital application of this operator is made by convolving a mask whose kernel computes the addition of the weighted gray-level differences between a pixel and its neighbors. The operator has been extended to color images by applying it to each R, G, B component separately and combining the result to yield the sharpened color image [1]. Other linear filters based on first-order and second-order derivatives that perform as operators for edge detection in grayscale images have been also extended to color images in the same way. As it has been reported, the simple extension of classical gray level methods to the RGB channels is not the best solution. [2-7] In fact, reasonably good results can be obtained by sharpening edges just in the intensity component while keeping unchanged the chromatic components of hue and saturation [8]. In the work of Di Zenzo [2] color images are treated as multivalued functions for which the tensor gradient is used in a more effective edge detection. A more abstract treatment was done by Sochen et al. [4,5]. They viewed images as embedding maps that flow toward minimal surfaces. They considered a color image as a 2-D surface in a 5-D space (x, y, R, G, B). Their geometric framework led to build powerful smoothing and scale space algorithms. In the mathematics developed in Refs. [2-7] the feature coordinates of a color image are the intensity R, G, B values, although the authors of Ref. [5] mentioned the possibility of using a Euclidean space like the CIELAB. This space has been also used as a basis to define a color difference based Laplacian operator for color image sharpening in Ref. [9]. But CIELAB, as well as other standard systems, was tested against data from color appearance judgments of large uniform patches. In consequence, it should not be used to determine the color difference between images on a pixel-by-pixel basis because a point-by-point computation of the CIELAB error tends to produce larger errors at most image points than the perceived ones [10].

Zhang and Wandell described a spatial extension to the CIELAB color metric, known as the S-CIELAB metric [10], which can be applied to complex stimuli such as digital images, when they are viewed at different distances. They use a series of spatial filters in the opponent color space AC_1C_2, containing one luminance channel (A) and two chrominance channels (C_1,C_2). The filters are smoothing filters consisting of a linear combination of Gaussian masks that approximate the contrast sensitivity functions of the human vision system. The filtered image is then back transformed to the CIELAB representation. S-CIELAB allows one to measure the perceived color differences by applying the standard CIELAB formula ΔE to the filtered images pixel-by-pixel. S-CIELAB has been used to measure color reproduction errors in images [10], to predict texture visibility of printed halftone patterns [11], to evaluate the effects of image compression [10] and to segment color images [12]. This technique can be implemented in both the spatial and the frequency domains [13]. The CIEDE2000 color difference formula combined with S-CIELAB has been compared with other existing CIE color difference formula and three different viewing conditions in Ref. [13]. Recently, a new model of the contrast sensitivity functions that is specifically designed for use in image-difference and image-quality models has been introduced [14].

In this work, we introduce a new method for color image sharpening based on S-CIELAB, which offers an interesting approach to deal with digital color images by introducing the models of the human vision system. We combine the spatial filtering with the Laplacian operator in each channel of the opponent space to obtain the sharpened image (Figure 1). Since the spatial filters used in S-CIELAB are linear combinations of weighted Gaussian functions, the application of the Laplacian operator to the spatially filtered components can be further simplified by introducing the Laplacian of Gaussian (*LoG*) operator [15]. This operator takes advantage of the properties of convolution and derivatives and is widely used as an edge detector with reduced sensitivity to noise. The *LoG* operator can be approximated by the difference of Gaussians (*DoG*) operator that can be computed by applying two Gaussian operators with different spread values to an image and forming the difference of the resulting two smoothed images [15]. The use of *DoG* operator can be justified since it has been considered to model the receptive fields in early human vision.

Summarizing, a modified linear combination of Gaussian functions in the opponent channels will allow us to combine the S-CIELAB transformation with the *DoG* operator. The resulting image can be subtracted from the image component in each opponent channel and then back transformed to the device independent representation space XYZ.

As far as we know, this compact combination of S-CIELAB with derivative edge detectors in the opponent color space to obtain color sharpening of digital images is a new method for color image sharpening. It considers human vision models and viewing conditions. The method outlined is tested and applied to several digital color images. The results are compared with other obtained by applying the Laplacian operator to the intensity channel only (keeping the chromatic components unchanged), or to the image components in other representations such as RGB.

Method

Let us consider an image *I* expressed into a device independent color space, such as CIE 1931 XYZ, that is linearly transformed into the opponent channels AC_1C_2 space [10]. Then, the image is spatially filtered, via convolution in the spatial domain, using filters that approximate the contrast sensitivity functions of the human visual system. In each opponent channel *i*, where $i=\{0,1,2\}$ indicates the opponent channel $\{A,C_1,C_2\}$, the filter F_{di} is a linear combination of weighted Gaussian functions G_{ij} whose kernel sums to one. The kernel of each spatial filter is given by

$$F_{di}(x,y)=\sum_j w_{ij}G_{ij}\left(x,y,\frac{d\sigma_{ij}}{\sqrt{2}}\right), \tag{1}$$

where d (pixels/degree of vision angle) indicates the scale, $d\sigma_{ij}/\sqrt{2}$ is the spread of the Gaussian functions and it represents the decreasing in sensitivity that occurs in the human vision system when the viewing distance increases. The values of the weights w_{ij} and the spreads σ_{ij} expressed in degrees of visual angle that are used in S-CIELAB can be found in Refs. [10,13]. The components I_{di} of the spatially filtered image in the opponent color space are obtained by convolving the spatial filters F_{di} with the input image components I_i

$$I_{di}(x,y)=F_{di}(x,y)*I_i(x,y), \tag{2}$$

The filtered components in the opponent channels I_{di} are then back transformed into CIE XYZ space to give $I_{d(XYZ)}$ that are transformed in turns into the CIELAB space, using standard equations, to give $I_{d(CIELAB)}$. Once the CIELAB coordinates are calculated for all the pixels, color differences between two filtered images obtained in this way can be computed on a pixel-by-pixel basis.

When performing operations that involve second derivatives, such as edge detection or image sharpening, it is a common practice to smooth the image first by convolution with a Gaussian kernel of spread *s* to reduce noise before computing a second derivative or Laplacian. Taking into account the properties of derivative, Gaussian function and convolution, it is verified that $\nabla^2\left[G(x,y,s)*I(x,y)\right]=\nabla^2G(x,y,s)*I(x,y)$, where the Laplacian of Gaussian is often just named *LoG*. A sharpened version *ShI* of a given image *I* can be obtained by computing

$$ShI(x,y)=I(x,y)-LoG*I(x,y). \tag{3}$$

In this work, we propose to sharpen the components of the spatially filtered image in the color opponent space taking into consideration the linear combination of weighted Gaussian functions that compose the spatial filters F_{di} to build the *LoG* operator. Thus, we use

$$LoG\{F_{di}(x,y)\}=\sum_j w_{ij}\nabla^2G_{ij}\left(x,y,\frac{d\sigma_{ij}}{\sqrt{2}}\right) \tag{4}$$

to calculate the sharpened image as it would be perceived

$$ShI_{di}(x,y)=I_{di}(x,y)-kLoG\{F_{di}\}*I_{di}(x,y). \tag{5}$$

Since the perceived sharpened image can be also expressed by $ShI_{di}(x,y)=F_{di}(x,y)*ShI_i(x,y)$, we derive that the sharpened image to display should be

$$ShI_i(x,y)=I_i(x,y)-kLoG\{F_{di}\}*I_i(x,y). \tag{6}$$

Parameter *k* has been introduced to control the sharpening depth. Note that the image to display, given by Eq. 6, has been sharpened taking into account that it is to be seen with viewing conditions given by *d*.

For the sake of comparison, if we alternatively consider that the *LoG* operator is convolved by the image component I_i without spatial filtering in Eq. 5, we obtain

$$ShI_{di}(x,y)=I_{di}(x,y)-kLoG\{F_{di}\}*I_i(x,y), \tag{7}$$

and, in such a case, the components of the corresponding displayed sharpened image would be

$$ShI_i(x,y)=I_i(x,y)-k\nabla^2I_i(x,y), \tag{8}$$

which corresponds to a conventional Laplacian based sharpening that does not smooth the image with any Gaussian function before sharpening.

Results

Figure 1 shows the image test.

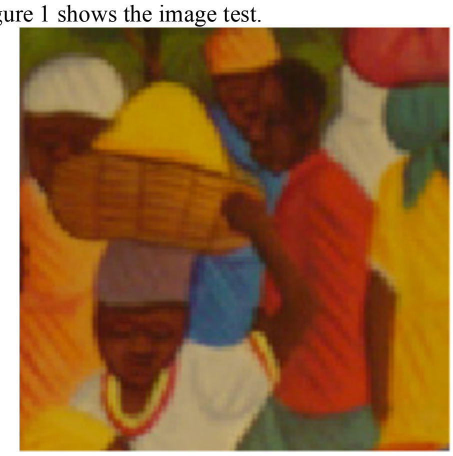

Figure 1. *Test*

Figure 2 shows the test spatially filtered according to SCIELAB, with d=25, 50, 100 pixels per degree of visual angle and their reduced versions. Figure 3 shows an arrangement of spatially filtered images: on the left, the original images; in the centre, the sharpened images according the method proposed (Eqs. 5,6), and on the right, the sharpened images according the simple Laplacian (Eqs. 7,8). Parameter k was set to k=7.5 in all the sharpened images of Figure 3. The advantages of applying the method proposed are clear. Figure 4 shows the results of several experiments. It compares a set of images spatially filtered for d=25 pixels/degree. The simple Laplacian operator applied onto the RGB image components gives bad results *(b)*. The image sharpened according to the proposed method gives good results *(c)*, but these results do not worsen significantly if the method is only applied to the achromatic channel A *(d)*.

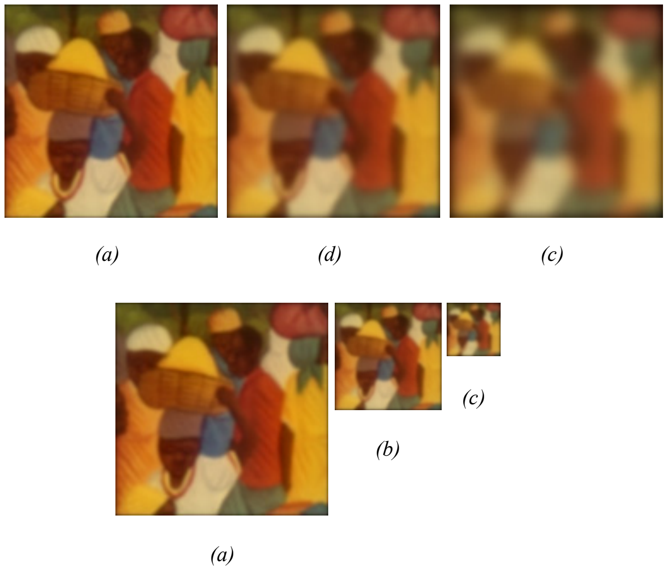

Figure 2*. Spatially filtered test at (a) d=25, (b) d=50, and (c) d=100 pixels per degree. Top file:filtered images displayed at the same scale. Bottom file: Reduced versions of the filtered images according d.*

Figure 3. *Comparison between the original image at different distances (left) and the sharpened images resulting from the method proposed (center) and the simple Laplacian operator (right) applied to the color opponent image components*

Figure 4. *Comparison of several spatial filtered images with d=25 pixels/degree: (a) Original image, (b) Image sharpened using the simple Laplacian operator onto the RGB image components, (c) image sharpened according the proposed method, and (d) sharpened imaged according the method but only applied to the achromatic channel A .*

Conclusions

A method to sharpen digital colour images that takes into consideration viewing conditions and human vision models has been described. The method combines the Laplacian of Gaussian (*LoG*) operator with the spatial filters that approximate the contrast sensitivity functions of human visual systems. The sharpening operation is introduced in the opponent color space, following the scheme proposed in S-CIELAB. With this method we deduce the modification to introduce in the original image to have the spatially filtered image (that approaches the perceived image) *LoG*-sharpened for a given viewing conditions. The results obtained are good. When the sharpening operation is limited to the achromatic channel, the results are still good. An image sharpening based on just the Laplacian of the original is not sensitive to variations of viewing conditions, tends to increase noise, and the appearance deteriorates rather fast.

Acknowledgements

The authors acknowledge the financial support of the Spanish Ministerio de Educación y Ciencia and FEDER funds under project DPI2003-03931.

References

[1] R.C. González, R.E. Woods, S.L. Eddins, *Digital Image Processing using MATLAB*, Pearson Prentice Hall, Upper Saddle River, NJ [2004].

[2] S. Di Zenzo, "A note on the gradient of a multi-image", Computer Vision, Graphics, and Image processing **33**, 116-125 (1986).

[3] J. Weickert, "Coherence-enhancing diffusion of colour images," Image & Vision Computing **17**, 201 (1999).

[4] N. Sochen, R. Kimmel, R. Malladi, "A general framework for low level vision," IEEE Trans. Image Processing **7**, 310-318 (1998).

[5] R. Kimmel, R. Malladi, N. Sochen, "Images as embedded maps and minimal surfaces: movies, color, texture, and volumetric medical images," Int. J. of Computer Vision 39, 111-129 (2000).

[6] C-K. Yang, T-C. Wu, J-C. Lin, W-H. Tsai, "Color image sharpening by moment-preserving technique", Signal processing **45**, 397-403 (1995).

[7] M. Vanrell, R. Baldrich, A. Salvatella, R. Benavente, F. Tous, "Induction operators for a computational colour-texture representation", Computer Vision and Image Understanding 94, 92-114 (2004).

[8] J. C. Russ, *The Image Processing Handbook* 4th Edition, CRC Press, 2002.

[9] M. S. Millán, E. Valencia, "Colour image sharpening using color difference based operators", in *Proceedings of the 10th Congress of the International Colour Association*, Granada (Granada, 2005), pp. 1055-1058.

[10] X. Zhang and B.A. Wandell, "A spatial extension of CIELAB for digital color image reproduction", Soc. for Info. Disp. Symp. Tech. Digest **27**, 731-734 (1996).

[11] X. Zhang, D.A. Silverstein, J.E. Farrell, B.A. Wandell. "Color image quality metric S-CIELAB and its application on halftone texture visibility," Proceedings of IEEE COMPCON 97, p. 44-51, 1997.

[12] M. Mirmehdi, M. Petrou, "Segmentation of color textures", IEEE Transactions on Pattern Analysis and Machine Intelligence 22 (2), 142-159 (2000).

[13] G. M. Johnson, M. D. Fairchild, "A top down description of S-CIELAB and CIEDE2000", Color Research and Application **28** (6), 425-435 (2003).

[14] S. Westland, "Models of the visual system and their application to image-quality assessment", in *Proceedings of the 10th Congress of the International Colour Association*, Granada (Granada, 2005), pp. 309-312.

[15] D. Marr, E. Hildreth, "Theory of Edge Detection", Proc. R. Soc. Lond., **B207**, 187-217 (1980).

Author Biography

Maria S Millán is PhD in Physics Sciences since 1990 and professor of the School of Optics and Optometry at the Technical University of Catalonia (Spain). Her academic activities involve lecturing on Fundamentals of Optics and Image Processing and research on Image Processing. The main lines of research work include optoelectronic information processing, pattern recognition, machine vision, color imaging, automatic inspection, programmable diffractive optical elements. She is member of SPIE, OSA, EOS and SEDO.

Edison Valencia received the system engineering degrees from Universidad EAFIT (Colombia) in 1997 and MS degree in system engineering and computer science from Universidad de Los Andes (Colombia) in 2000. He has been a professor in EAFIT University, and at the moment, he is achieving the degree PhD in optic engineering in the Universitat Politècnica de Catalunya (Spain). Him fields of research involve colour metrology, image processing and pattern recognition. He is member of SEDO.