Color Image Sharpening by Moment-Preserving Technique†

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Abstract

A new approach to sharpening color images using the moment-preserving technique is proposed. An input image is processed pixel by pixel. By preserving some color moments of the n×n neighborhood of each pixel, analytic formulas are derived to compute two sets of (R, G, B) tristimulus values, and one of them is assigned to the pixel as the sharpening result. The proposed sharpening operation can also be applied iteratively to the input image to get better sharpening effect. Experimental results show that the proposed approach is effective for color image sharpening.

1. Introduction

Image sharpening is useful in many image processing applications. Many operators for image sharpening can be found in the literature [1, 2]. The differencing operator and the highpass spatial filter are two common ones [1, 2]. Rowe [3] proposed some nonlinear operators which sharpen image detail better than the differencing operator. Chen and Tsai [4] developed another method to sharpen images using the moment-preserving principle. However, these existing methods were proposed for sharpening gray-scale images

On the other hand, many color image enhancement techniques can be found in literature [2, 5, 6] although they were not proposed directly for the purpose of color image sharpening. Typically, color images are processed in the RGB color space. Several color image enhancement algorithms actually were applied only to the luminance or lightness component. But this approach needs additional time to transform the RGB color values into a desired color space and convert the processing result back to RGB color space again for display.

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In this paper, we propose a new approach to sharpening color images based on the moment-preserving principle that has also been applied to some other image processing tasks [7, 8]. The proposed method is directly applied to an observed image in the RGB color space without transforming the image into the luminance-chroma space or the lightness-chroma space. Its effectiveness is verified by experimental results.

The remainder of this paper is organized as follows. The proposed moment-preserving sharpening method for color images is presented in Section 2. In Section 3, an iteration process based the proposed method with some further illustrative examples are included. Finally, some conclusions are made in Section 4.

2. Proposed Color Image Sharpening by Moment-Preserving Technique

Given an image G to be sharpened and a pixel p in G with (r, g, b) tristimulus values, let F be the n×n neighborhood of p and p_i be a pixel in F with (r_i, g_i, b_i) tristimulus values. Suppose that H is the desired sharpened version of F and has only two representative colors, or equivalently, two sets of representative tristimulus values (R_1, G_1, B_1) and (R_2, G_2, B_2). Let p_1 be the fraction of pixels with the (R_1, G_1, B_1) tristimulus values in H, and p_2 the fraction of pixels with the (R_2, G_2, B_2) tristimulus values in H.

The proposed algorithm for color image sharpening by the moment-preserving technique (abbreviated as CISMP) is described as follows.

Algorithm CISMP

Step 1: Read in an M×N color image G which is to be sharpened.

Step 2: For each pixel p in G perform the following steps:

(a) take the n×n neighborhood F of p;

(b) compute a set of the moments of F;

(c) evaluate the number of uniform spectral bands based on the color variance in F;

(d) decide which method to use to compute the two sets of representative tristimulus values:

0-spectral case: use the means;

1-spectral case: use the technique proposed by Tsai [4];

2-spectral case: use the technique proposed by Lin and Tsai [10];

3-spectral case: use the technique proposed in this paper:

(1) preserve the moments and solve the resulting equations;

(2) resolve the sign ambiguities; and

(3) compute the new tristimulus values for p using the Euclidean distance [9].

Step 3: Do a few iterations of Steps 1 and 2 if necessary.

Based on the moment preserving methods [11, 12] and our color image processing experience, we select the following set of color moments of F mentioned in Step 2(b) to be preserved:

$$
\begin{aligned}
&m_r = \sum_i p_i \mathrm{r}_i,\ m_g = \sum_i p_i \mathrm{g}_i,\ m_b = \sum_i p_i \mathrm{b}_i, \\
&m_{r'} = \sum_i p_i \mathrm{r}_i^2,\ m_{g'} = \sum_i p_i \mathrm{g}_i^2,\ m_{b'} = \sum_i p_i \mathrm{b}_i^2, \quad (1) \\
&m_{rgb} = \sum_i p_i \mathrm{r}_i \mathrm{g}_i \mathrm{b}_i,
\end{aligned}
$$

where $p_i = \dfrac{1}{N}$ for all i, N is the total number of pixels in F, and m_r, m_g, and m_b are the means of the (r, g, b) tristimulus values, respectively, m_{r^2}, m_{g^2}, and m_{b^2} are related to the variances of the (r, g, b) tristimulus values, respectively, and m_{rgb} is related to the correlation within the (r, g, b) tristimulus values. Note that this set of color moments has not been proposed by other investigators before for moment preserving.

By preserving the above selected moments of F (the input neighborhood) in H (the desired output), we get the following equations:

$$
\begin{aligned}
&p_1 \mathrm{R}_1 + p_2 \mathrm{R}_2 = m_r, \quad p_1 \mathrm{R}_1^2 + p_2 \mathrm{R}_2^2 = m_{r'}, \\
&p_1 \mathrm{G}_1 + p_2 \mathrm{G}_2 = m_g, \quad p_1 \mathrm{G}_1^2 + p_2 \mathrm{G}_2^2 = m_{g'}, \\
&p_1 \mathrm{B}_1 + p_2 \mathrm{B}_2 = m_b, \quad p_1 \mathrm{B}_1^2 + p_2 \mathrm{B}_2^2 = m_{b'} \quad (2) \\
&p_1 + p_2 = m_0, \\
&p_1 \mathrm{R}_1 \mathrm{G}_1 \mathrm{B}_1 + p_2 \mathrm{R}_2 \mathrm{G}_2 \mathrm{B}_2 = m_{rgb},
\end{aligned}
$$

where all the terms on the left-hand sides of the equalities are the moments of H and all the terms on the right-hand sides are the corresponding ones of F. There are eight unknowns p_1, p_2, R_1, G_1, B_1, R_2, G_2, and B_2. Note that we define m_0=1 so that $p_1 + p_2 = 1 = m_0$. Without loss of generality, we shift the values of the tristimulus values such that the three mean values m_r, m_g, and m_b are zero. After (R_1, G_1, B_1) and (R_2, G_2, B_2) are obtained from solving (2), these values of color components should be translated back by adding to them the mean values m_r, m_g, and m_b, respectively.

Let om_{r^2}, om_{g^2}, om_{b^2}, and om_{rgb} denote the shifted moments of m_{r^2}, m_{g^2}, m_{b^2}, and m_{rgb}, respectively. Assume that $p_1 \geq p_2$. Then (R_1, G_1, B_1), (R_2, G_2, B_2), p_1, and p_2 can be solved (with details omitted) to be:

$$
\begin{aligned}
&p_1 = \frac{1}{2} + \frac{1}{2}\sqrt{\frac{om_{rgb}^2}{om_{rgb}^2 + 4 om_{r'}^2 om_{g'}^2 om_{b'}^2}}, \\
&p_2 = 1 - p_1, \\
&\mathrm{R}_2 = \pm\sqrt{om_{r'} k}, \quad \mathrm{G}_2 = \pm\sqrt{om_{g'} k}, \\
&\mathrm{R}_1 = -\frac{om_{r'}}{\mathrm{R}_2}, \quad \mathrm{G}_1 = -\frac{om_{g'}}{\mathrm{G}_2}, \\
&\mathrm{B}_2 = \pm\sqrt{om_{b'} k}, \\
&\mathrm{B}_1 = -\frac{om_{b'}}{\mathrm{B}_2}, \qquad (3)
\end{aligned}
$$

where

$$
k = \frac{om_{rgb}^2 + 2 om_{r'}^2 om_{g'}^2 om_{b'}^2 + \sqrt{om_{rgb}^4 + 4 om_{r'}^2 om_{g'}^2 om_{b'}^2 om_{rgb}^2}}{2 om_{r'}^2 om_{g'}^2 om_{b'}^2}.
$$

The values of (R_1, G_1, B_1) and (R_2, G_2, B_2) are still undetermined because of the undetermined signs. For example, the formulas do not show whether R_2 is positive or negative. But note that the signs of R_1 and R_2 are opposite, so are the signs of G_1 and G_2, and those of B_1 and B_2. The signs of (R_1, G_1, B_1) and (R_2, G_2, B_2) can be determined by a pixel counting method. The method is described as follows.

(1) When $p_1 > p_2$, the tristimulus values (R_1, G_1, B_1) must be the representation of the larger group of data. Let

$$\begin{aligned} r\_count &= C_{pr} - C_{nr}, \\ g\_count &= C_{pg} - C_{ng}, \\ b\_count &= C_{pb} - C_{nb}, \end{aligned} \tag{4}$$

where C_{pr}, C_{pg}, and C_{pb} are the number of pixels in F with positive shifted color component values R, G, and B, respectively, and C_{nr}, C_{ng}, and C_{nb} are the number of pixels in F with negative shifted color component values R, G, and B, respectively. Then, the rules for determining the signs are listed as follows:

if r_count ≥ 0, then
    R_1 is positive and R_2 is negative,
else R_1 is negative and R_2 is positive;
if g_count ≥ 0, then
    G_1 is positive and G_2 is negative,
else G_1 is negative and G_2 is positive;
if b_count ≥ 0, then
    B_1 is positive and B_2 is negative,
else B_1 is negative and B_2 is positive. (5)

(2) If p_1 and p_2 are very close, then there exist situations where one or more than one of r_count, g_count, and b_count is close to zero. Artificial color will emerge if any of the sign assignments is wrong. In such a case we need three additional counting variables to resolve the ambiguous situations:

$$\begin{aligned} rg\_count &= \begin{cases} rg\_count + 1, & \text{if } r_i * g_i > 0 \\ rg\_count - 1, & \text{if } r_i * g_i < 0 \end{cases} \\ gb\_count &= \begin{cases} gb\_count + 1, & \text{if } g_i * b_i > 0 \\ gb\_count - 1, & \text{if } g_i * b_i < 0 \end{cases} \\ rb\_count &= \begin{cases} rb\_count + 1, & \text{if } r_i * b_i > 0 \\ rb\_count - 1, & \text{if } r_i * b_i < 0 \end{cases} \end{aligned} \tag{6}$$

where (r_i, g_i, b_i) are the tristimulus values of p_i in F. Initially, rg_count, gb_count, and rb_count are set to zero. The final values are found by scanning the pixels in the entire image. These counting variables are related to the information of correlation between the color component values. For example, if rg_count is positive, then R_1 and G_1 should have the same sign; otherwise, they should have opposite signs. Without loss of generality, we assume that *abs*(r_count) is the maximum of {*abs*(r_count), *abs*(g_count), *abs*(b_count)} where *abs*( ) represents the absolute value function. The corresponding rules turn out to be:

if r_count ≥ 0, then
    R_1 is positive and R_2 is negative,
else R_1 is negative and R_2 is positive;
if rg_count ≥ 0, then
    G_1 is of the same sign of R_1, and
    G_2 is of the same sign of R_2,
else G_1 is of the opposite sign of R_1,
and G_2 is of the opposite sign of R_2;
if rb_count ≥ 0, then
    B_1 is of the same sign of R_1, and
    B_2 is of the same sign of R_2,
else B_1 is of the opposite sign of R_1,
and B_2 is of the opposite sign of R_2. (7)

After the signs and values of (R_1, G_1, B_1) and (R_2, G_2, B_2) are computed, the two sets of tristimulus values are shifted back as follows:

$$\begin{aligned} &R_1 \Rightarrow R_1 + m_r\ ,\ R_2 \Rightarrow R_2 + m_r; \\ &G_1 \Rightarrow G_1 + m_g,\ G_2 \Rightarrow G_2 + m_g; \\ &B_1 \Rightarrow B_1 + m_b\ ,\ B_2 \Rightarrow B_2 + m_b. \end{aligned} \tag{8}$$

In Step 2(c) of Algorithm CISMP, when the formulas of (3) are applied to a small image block, it is possible that some of om_{r2}, om_{g2}, and om_{b2} are zero so that k cannot be computed. Such a condition will result in infinitely many solutions. Take om_{r2}=0 as an example. It shows that the red component value of the pixels are uniformly distributed. So we need another mechanism to distinguish how many color components or "spectral bands" of F are uniform. The employed rules are:

$$\begin{aligned} &Var(R) = om_{r'} \le R_t \ \Rightarrow \text{R-component is uniform,} \\ &Var(G) = om_{g'} \le G_t \ \Rightarrow \text{G-component is uniform,} \\ &Var(B) = om_{b'} \le B_t \ \Rightarrow \text{B-component is uniform,} \end{aligned} \tag{9}$$

where R_t, G_t, and B_t are three given thresholds for detecting the least perceptible variances of the R, G, and B components. In this study, R_t, G_t, and B_t are set to be 0.02. Then, we use different techniques for different conditions as follows.

(1) 3-spectral case (none of the R, G, and B spectral bands are uniform):

Use the formulas of (3) to compute the (R_1, G_1, B_1) and (R_2, G_2, B_2) tristimulus values. Then the desired (R, G, B) tristimulus values for the currently-processed pixel p in H are computed according to the minimum Euclidean distance criterion as follows. First compute the following two Euclidean distance measures :

$$\begin{aligned} d_1 &= (R_1 - r)^2 + (G_1 - g)^2 + (B_1 - b)^2 \\ d_2 &= (R_2 - r)^2 + (G_2 - g)^2 + (B_2 - b)^2 \end{aligned} \tag{10}$$

where (r, g, b) are the original tristimulus values of p. Then, p is assigned the tristimulus values of either (R_1, G_1, B_1) or (R_2, G_2, B_2) according to which value of d_1 and d_2 is smaller.

(2) 2-spectral case (one of the R, G, and B spectral bands is uniform):

Preserve another set of moments to compute the desired color components values of the two non-uniform planes for the currently-processed pixel p in H (e. g., compute R_1, G_1 and R_2, G_2 if the B spectral band is uniform). The details can be derived from the method proposed by Lin and Tsai [10]. The color component value of the uniform plane for p is taken to be the mean of the original color component values in F.

(3) 1-spectral case (two of the R, G, and B spectral bands are uniform):

The given image block F includes only one non-uniform color plane. The method of Tsai [4] is applied to compute the color component value of the non-uniform plane for the currently-processed pixel p in H. The color component values of the two uniform planes for p are taken to be the means of the respective original tristimulus values in F.

(4) 0-spectral case (all of R, G, and B spectral bands are uniform):

The given image block is totally uniform. Hence the (R, G, B) tristimulus values for the currently-processed pixel p in H is taken to be the means of all the original (r, g, b) tristimulus values in F, respectively.

In the previous discussion, nothing is said about how to select the neighborhood size n. In fact, n determines the sharpening effect. If the blurred objects resemble fine-grained features like thin lines, then n need not be too large. In other words, the smaller n is chosen, the better the sharpening result is. From our experimental experience, we choose the number n to be less than 9.

3. Iteration of Moment-Preserving Sharpening for Color Images

In the above discussions, moment-preserving sharpening for color images is applied to each pixel of an input image for a single time. It is found in this study that if the sharpening operation is applied to the image repetitively, the sharpening effect can be improved. At each iteration step, we use the prior result as the input image. As the number of iterations increases, the sharpening effect is strengthened gradually. Some illustrative examples are shown next to illustrate the effectiveness of this process.

The proposed approach has been tested on an IRIS Indigo workstation for several color images. Fig. 1 shown includes a test image in (a) and the sharpening results in (b) with neighborhood size n=5. Figs. 2 and 3 shown include a test image in (a), and the sharpening results of iterations 1 and 3 in (b) and (c), respectively. Figs. 2 and 3 shows the results of the images "Lena" and "pepper" with neighborhood size n=3, respectively. We see that the iterative process indeed can improve the sharpening effect. It is seen that only a few iterations of the proposed method are necessary before the result becomes satisfactory.

4. Conclusion

A color image sharpening technique based on the moment-preserving principle has been proposed. The image is processed pixel by pixel. First, the moments of the $n \times n$ neighborhood of each pixel are computed. The number of uniform spectral bands is evaluated according to the color variance of the pixel neighborhood. Different techniques are applied for different spectral cases. Two sets of (R, G, B) tristimulus values are computed accordingly using analytic formulas. One of them is assigned to the pixel as the sharpening result for the 3-spectral case. The proposed method preserves the spatial details in the image content and requires little memory and small computational load. The neighborhood size should not be too large. Better sharpening results can be obtained by applying the proposed method repetitively. The method is applicable not only to the RGB model but also to any other trichromatic model. The experimental results reveal the feasibility and efficiency of the proposed approach.

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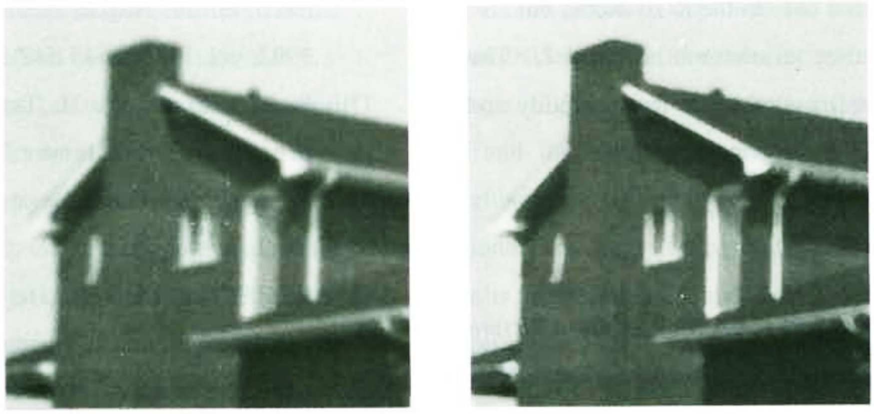

(a) (b)

Fig. 1 Noniterative sharpening result of a house image: (a) the input image; (b) the sharpening result for block size n=5.

(a) (b) (c)

Fig. 2 Iterative sharpening results of a lady image "Lena" with block size n=3; (a) the input image; (b) the result of iteration 1; (c) the result of iteration 3;

(a) (b) (c)

Fig. 3 Iterative sharpening results of the pepper image with block size n=3; (a) the input image; (b) the result of iteration 1; (c) the result of iteration 3;