COLOR IMAGE ENHANCEMENT USING SPATIALLY ADAPTIVE SATURATION FEEDBACK

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ABSTRACT

One way of enhancing color image contrast is to feed back high-frequency spatial information from the saturation component into the luminance component. A new algorithm, which uses a spatially variant measure of salience, is presented. This method offers key improvements to a previous saturation feedback technique. Experimental results confirm that improved color image enhancement is achieved.

1. INTRODUCTION

The trichromatic nature of color image data invites new approaches to image enhancement. One such approach makes use of the luminance, hue, and saturation (LHS) description [2] of a color image. When viewed as distinct monochrome images, the luminance and saturation components frequently exhibit strong similarities. This is particularly true for the negative image of the saturation component, as can be seen in Fig. 1.

An analysis by Strickland et al. [6] has shown that the saturation component often contains more high-frequency spectral energy, i.e. image detail, than its luminance counterpart. This prompted the development of a new approach to color image enhancement in which high-pass information from the saturation component is fed back into the luminance component as a means of supplementing color image sharpness and contrast. This technique of "saturation feedback" can serve to bring out image details that have low luminance contrast.

A number of researchers [4, 6, 8] have undertaken work based on this processing strategy. Unfortunately, little effort has been made to discriminate precisely where feedback into the luminance component is appropriate and to what degree. A further issue involves the feedback of information having opposite polarity which can lead to artifacts. Both of these issues can be succinctly addressed using notions adopted from the image fusion literature. A new, more robust algorithm results which is described in Section 4. The experimental results of Section 5 confirm that the new algorithm produces improved color image enhancement.

2. ORIGINAL ALGORITHM

The original saturation feedback algorithm proposed by Strickland et al. [6] can be expressed as

$$L_{enh}(x,y) = L(x,y) + k_1\left[L(x,y) - \bar{L}(x,y)\right] - k_2\left[S(x,y) - \bar{S}(x,y)\right] \quad (1)$$

where the barred quantities represent blurred versions of the respective components, and k_1 and k_2 are scaling constants. The negative sign preceding the third term reflects the use of negatively scaled saturation data as prescribed in [6].

The two bracketed terms of (1) lead to unsharp masking of the luminance and saturation components. Unsharp masking (USM) is known to produce two simultaneous effects: an increase in perceived contrast along with an increase in perceived sharpness [5]. When $k_2 = 0$, traditional USM is performed. When $k_2 > 0$, a novel form of cross-component USM results. This approach has been demonstrated with particular effectiveness on color images of natural scenes.

3. KEY ISSUES

Though novel in its use of cross-component information, the saturation feedback approach of (1) suffers from two key drawbacks. First, it makes no effort to restrict the feedback of structurally incongruent image information. Second, it employs fixed-polarity feedback of the saturation data.

The first drawback is of consequence because the luminance and saturation components do not always exhibit the same local image structure. This has been borne out in a recent study [7]. The feedback of saturation information is generally not appropriate at locations where the component images do not have the same basic image structure. Such feedback can lead to noise artifacts.

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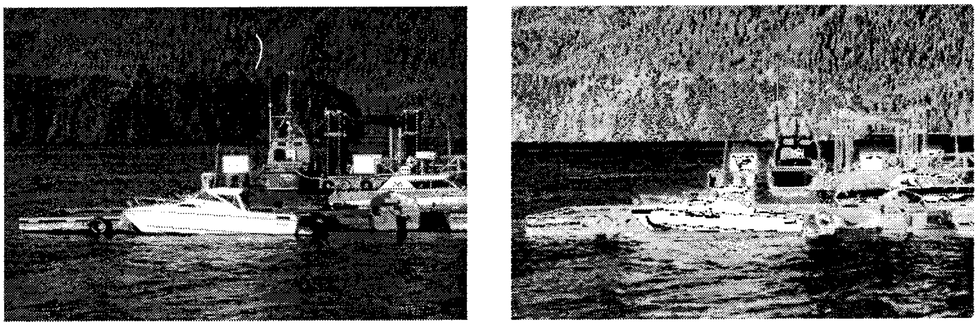

Figure 1: The luminance (left) and the negative image of the saturation (right) of a color image.

The second drawback is independent of the first and can affect those image regions where saturation feedback is structurally well-founded. At issue is the fixed, negative polarity of the saturation feedback term in (1). This can lead to destructive feedback if the luminance and saturation components are positively correlated. This is of concern because local correlation of luminance and saturation data (as computed using a 5×5 pixel window) has been shown to exhibit spatially-varying polarity [7]. The feedback of saturation information having improper polarity leads to contrast reversals and the loss of luminance information.

4. NEW ALGORITHM

The preceding discussion has described two issues associated with the original saturation feedback formulation of (1). Similar issues have arisen in the image fusion literature. Efforts headed by Burt [1] and Li [3] describe image fusion strategies capable of dealing with such issues. Both of these techniques employ a local measure of "salience" which serves to identify key regions of image data. This concept motivates a new approach to saturation feedback.

A recent study [7] of the luminance and saturation components of color images has introduced various measures of structural correspondence. Among the measures used was a local correlation coefficient operator. This was found to be a particularly useful metric, one capable of gauging the polarity and strength of luminance-saturation correlation at each location in a color image. When employed as a measure of salience, this operator provides a succinct way of overcoming the shortcomings of the original saturation feedback formulation of (1).

This leads to a new, spatially adaptive method of saturation feedback which takes the form,

$$\begin{aligned} L_{enh}(x,y) = L(x,y) + k_1\left[L(x,y) - \bar{L}(x,y)\right] \\ + k_2\left[S(x,y) - \bar{S}(x,y)\right]\rho(x,y) \end{aligned} \quad (2)$$

where the saturation feedback is now additive and includes a new factor, $\rho(x,y)$. This added scaling factor produces a locally varying measure of salience which is computed using

$$\rho(x,y) = \frac{\sum_{(x',y')\in W}\left[L(x',y') - \bar{L}_W\right]\left[S(x',y') - \bar{S}_W\right]}{\left[\sigma_L^2(x,y)\,\sigma_S^2(x,y)\right]^{\frac{1}{2}}}. \quad (3)$$

The set W identifies a 5×5 pixel window which is centered about pixel (x,y) in both the luminance and saturation component images. The local means and scaled local variances of the component images are also computed using the same window:

$$\sigma_L^2(x,y) = \sum_{(x',y')\in W}\left[L(x',y') - \bar{L}_W\right]^2 \quad (4)$$

$$\bar{L}_W = \frac{1}{25}\sum_{(x',y')\in W} L(x',y'). \quad (5)$$

The local correlation product of (3) is well-suited to the saturation feedback problem. It delivers values lying in the interval $[-1,1]$. The magnitude of $\rho(x,y)$ determines how appropriate the saturation data is at a given location. Uncorrelated regions are considered to be inappropriate and are scaled back accordingly. The sign of $\rho(x,y)$ sets the polarity of the saturation feedback, thus enabling it to adapt to the local data. These characteristics help prevent noise artifacts and opposite polarity problems. The computation of $\rho(x,y)$ is also scale invariant. This means that (2) can deliver the same benefits to image contrast in regions of low luminance contrast as the original saturation feedback algorithm of (1).

5. RESULTS

The key refinements offered by the new saturation feedback algorithm can be readily observed. Fig. 2 demonstrates how the spatially adaptive nature of (2) serves to reduce noise artifacts produced by the original algorithm. The improvements are particularly noticeable in the background and along the nose and shoulder portions of the image. Fig. 4a is a visualization of the salience map used.

Fig. 3 demonstrates the increased contrast and improved spatial detail that is achieved by the spatially adaptive algorithm. The airborne balloon illustrates this quite well. Contrast reversal artifacts have also been prevented. This can be seen in the central portion of the tall balloon. Fig. 4b is a visualization of the salience map used.

In order to assess the impact of the new algorithm on color image quality, 28 observers with normal color vision were asked to rate color images processed using (1) and (2). Six different color images were tested. Enhanced versions of these color images were created by using an $RGB \rightarrow LHS$ color transform (the $w_1 = w_2 = w_3 = \frac{1}{3}$ subcase presented in [2]), computing $L_{enh}(x, y)$ using (1) and (2), and then computing the inverse color transform $L_{enh}HS \rightarrow R'G'B'$. The observers were asked to comparatively rate the enhanced color images with respect to "sharpness and overall appearance." This resulted in the tally of preference votes listed in Table 1.

	Preference Tallies	
	# votes	% of total
new algorithm is preferred over old	97	56%
old algorithm is preferred over new	23	13%
both are equally preferred	53	31%

Table 1: Results of Preference Rating Experiment.

The experimentally measured result that 56% of the population of ordinary observers explicitly prefer the new algorithm is statistically significant. In fact, based on the number of samples collected, this value can be established to within ± 7 percentage points with a 95% degree of confidence.

The performance of the new algorithm depended upon the type of color image being processed. Two of the test images contained natural scenes. These produced a significant proportion of equal preference votes. This coincides with the observation that the original algorithm tends to work well on images of natural scenes. Experience has shown that images containing natural foliage tend to yield strong, negative luminance-saturation correlation. Hence, the performance of the old algorithm is expected to closely match the performance of the new algorithm for such images.

6. CONCLUSIONS

The saturation feedback approach to color image enhancement offers a unique way of introducing additional high-pass spatial information into the luminance component of color images. Several issues arise when performing color image enhancements under such a scheme. The use of a local correlation coefficient as a spatially adaptive measure of salience provides an effective way of overcoming these issues. The resulting algorithm produces fewer artifacts, better contrast and improved sharpness enhancement than the original approach. Good results have been achieved for a wide variety of color images. The new algorithm also provides a general framework for "cross-component USM", a color enhancement strategy that may be applied to components from any color space.

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Figure 2: Luminance component of a color image processed using $k_1 = k_2 = 2$: (a) unprocessed, (b) processed using original algorithm, (c) processed using new algorithm.

Figure 3: Luminance component of a color image processed using $k_1 = k_2 = 2$: (a) unprocessed, (b) processed using original algorithm, (c) processed using new algorithm.

Figure 4: $\rho(x, y)$ images corresponding to (a) the image shown in Fig. 2 and (b) the image shown in Fig. 3. The white regions have $\rho(x, y) > 0.8$, the gray regions have $\rho(x, y) < -0.8$, and the black regions have $|\rho(x, y)| \leq 0.8$. The new algorithm provides strong amounts of saturation feedback in the white and gray regions.