Adaptive filtering for noise reduction in hue saturation intensity color space

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Abstract. Even though the hue saturation intensity (HSI) color model has been widely used in color image processing and analysis, the conversion formulas from the RGB color model to HSI are nonlinear and complicated in comparison with the conversion formulas of other color models. When an RGB image is degraded by random Gaussian noise, this nonlinearity leads to a nonuniform noise distribution in HSI, making accurate image analysis more difficult. We have analyzed the noise characteristics of the HSI color model and developed an adaptive spatial filtering method to reduce the magnitude of noise and the nonuniformity of noise variance in the HSI color space. With this adaptive filtering method, the minimum error rate in edge detection improves by approximately 15%. © 2002 Society of Photo-Optical Instrumentation Engineers.

1 Introduction

Many different color models have been developed for hardware or for image representation and manipulation. For example, the hardware-oriented models are red, green, and blue (RGB) for color monitors, cyan, magenta, and yellow (CMY) for color printers, and YIQ for NTSC color TV broadcasting. Color models such as the hue, saturation, and intensity (HSI) are well suited for image analysis.1,2 Among several color models, the HSI model is based more on the color sensing properties of human vision. The intensity is related to the luminance component that is decoupled from color, and the hue and saturation components are related to the way in which human beings perceive color. Compared to other color models, the HSI is therefore more suitable for color image processing, segmentation, and analysis.3–7

Unfortunately, conversions from RGB to HSI and from HSI to RGB are very nonlinear. One of the main problems associated with this nonlinear conversion is that in the presence of random Gaussian noise in an RGB image, the noise in the HSI color space (after conversion) is not uniformly distributed and depends on the intensity and saturation values. For example, when the intensity value is small, the noise in the saturation and hue components is large. This nonuniform noise in the saturation and hue components produces false edges that are not present in the original image when an edge enhancement operation is performed using the HSI color model. To reduce the noise in HSI, several different HSI color models have been proposed. In one variation used by Carron and Lambert,8 the saturation component is made to be less sensitive to the nonlinear effects than in the conventional HSI model. However, the model still has nonuniform noise characteristics in the hue component.

We have experimentally analyzed the noise characteristics of the hue and saturation components in the HSI model. Based on the analysis, we propose a spatial filtering procedure for the hue and saturation components in a HSI image. Unlike traditional spatial filtering, our method uses a filter kernel size that varies throughout the image. The kernel size is determined based on our noise analysis results. We have shown quantitatively that the performance of an image analysis operator, like an edge detector, is better after filtering with an adaptive spatial filter rather than a fixed kernel (nonadaptive) filter.

Section 2 briefly describes the HSI color model and conversion formulas from the RGB color space. The noise in the HSI color space is analyzed in Sec. 3. Based on the noise analysis, an adaptive spatial filtering method to facilitate more reliable image analysis is proposed in Sec. 4. Section 5 shows several examples and quantitative analysis results with adaptive spatial filtering.

2 HSI Color Model

Many people use the classical HSI color model in electronic image processing.1,2 Most color sensors, including color cameras, utilize a RGB format to acquire color images. Therefore, it is reasonable to assume that the analysis of most HSI images starts from the RGB images. The HSI color values are obtained from the RGB values using the following conversion equations:
The mean and the variance for a Cauchy distribution cannot be determined analytically due to the unbounded nature of the integral in the expression for the mean and variance. Thus, the noise characteristics of hue and saturation were analyzed experimentally.

To measure the noise variance of hue and saturation and to analyze the noise dependency on the signal, a $256 \times 256$-pixel test image was created in the HSI color space, where it was divided into $256$ blocks with each block having the following constant values for $16 \times 16$ pixels:

$$H(i,j) = 64 \quad \text{for} \quad 1 \leq i \leq 16, 1 \leq j \leq 16$$

$$S(i,j) = 9 + 7j \quad \text{for} \quad 1 \leq i \leq 16, 1 \leq j \leq 16$$

$$I(i,j) = 9 + 7i \quad \text{for} \quad 1 \leq i \leq 16, 1 \leq j \leq 16,$$

where $i$ and $j$ are the block numbers in horizontal and vertical directions, respectively. This test image has the intensity value increasing horizontally, while the saturation value increases vertically. The experiment was repeated with several different hue values.

The test image in the HSI color space was converted to the RGB color space, and random noise that was normally distributed with zero mean and $\sigma^2$ variance was added to each RGB color component. The noise-contaminated image in the RGB color space was reconverted to the HSI color space, where the noise characteristics were analyzed. Noise in the HSI color space was computed as follows:

$$n_h = \text{RGBtoHSI}[R+n_r, G+n_g, B+n_b] - \text{RGBtoHSI}[R, G, B],$$

where $\text{RGBtoHSI}[]$ is the conversion function from RGB to HSI given in Eqs. (1)–(3), and $(n_r, n_g, n_b)$ and $(n_h, n_i, n_j)$ are the noises in RGB and HSI color components, respectively. Figure 2 shows $(n_r, n_g, n_h)$ after applying Eq. (7) to the test image when $H$ was 64. The noise that was added to the RGB image $(n_r, n_g, n_h)$ had a variance of 9. As shown in Fig. 2, the noise in the saturation component $(n_s)$ depends on the intensity value, i.e., it is large when the intensity is small, as shown in the left side of Fig. 2(b). The noise in the hue component $(n_h)$ depends on the intensity and saturation values, i.e., it is large when the intensity and saturation values are small, as shown in the upper-left corner of Fig. 2(a).

To show the relationship between noise and signal, the noise variances in saturation and hue were analyzed with respect to the intensity and saturation values. In Fig. 3, the variance of $n_s$ is plotted with respect to the intensity value, which is approximately proportional to $1/\text{Intensity}^2$. It also depends on the hue and saturation values, but their effects are negligible in comparison with that from the intensity value. Figure 4(a) shows the variance of $n_h$ with respect to the intensity and saturation values. Figure 4(a) can be simplified to a 2-D plot shown in Fig. 4(b), where the variance of $n_h$ is plotted with respect to the product of intensity and saturation values. The variance of $n_h$ also depends on the

$$H = \cos^{-1}\left\{ \frac{\frac{1}{2}[\sqrt{(R-G)^2+(R-B)(G-B)}]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}} \right\}$$

$$S = 1 - \frac{3}{R+G+B} \left[ \min(R,G,B) \right]$$

$$I = \frac{1}{3}(R+G+B),$$

where $\min()$ denotes a minimum function. In these equations, the ranges of $S, I, R, G,$ and $B$ are in $[0, 1]$, whereas $H$ is in degrees with the range of $[0, 360]$. The hue value in Eq. (1) is given in the interval $0 < H < 180$ deg, but $H$ has to be greater than 180 deg when $B > G$. So, the correct $H$ value is 360 deg $-H$ if $B > G$.

Figure 1 shows the coordinate system of the HSI color model. As shown in Fig. 1 and Eqs. (1)–(3), the hue $H$ is an angle in a counterclockwise direction with respect to the red radial line. The saturation $S$ is proportional to the distance from the color point to the center of the circle, which indicates the color purity or the degree by which the color is undiluted by white.

3 Noise Analysis in the HSI Color Space

Since color images are usually acquired in RGB format, let us assume that the noise is introduced in the RGB color space. The common noise that is found in images is Gaussian noise as the result of electronic noise present in cameras and sensors. Thus, we modeled that random Gaussian noise with zero mean and $\sigma^2$ variance was added to RGB images. In addition, the noise in each RGB color component was assumed to be independent from one another and also from the signal. As shown in Eqs. (1)–(3), the RGB-to-HSI conversion equations are nonlinear. We can easily see from Eq. (3) that the intensity has a noise variance of $\sigma^2/3$. However, the noise variances in hue and saturation cannot be easily defined. From a probability theory, it is known that a function, which involves a ratio of random variables with Gaussian probability distributions, has itself a Cauchy distribution. The noise in the hue and saturation components therefore has a kind of Cauchy distribution.
hue value itself, but this dependency is minimal compared with those on the intensity and saturation values.

4 Adaptive Spatial Filtering

To better control the noise, especially when the intensity value is small, we have developed a new adaptive spatial filtering method. It uses an averaging filter, whose kernel size is adaptive, to try to make the noise distribution in the HSI color space more uniform while preserving the image edge information. The overall flow diagram of this adaptive spatial filtering method is shown in Fig. 5.

In adaptive spatial filtering, various sets of filter kernels can be used. One example kernel set is shown in Fig. 6. The filter kernel to be used is selected for each pixel according to the intensity and saturation values. For example, the threshold values for switching to a different kernel in filter-

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Fig. 2 The noise in the HSI test image according to Eq. (7): (a) $n_h$, (b) $n_s$, and (c) $n_i$.

Fig. 3 Variance of $n_s$ with respect to the intensity value.

Fig. 4 Variance of $n_h$ with respect to the intensity and saturation values.
ing the saturation component can be defined based on the noise analysis results in Fig. 3 as follows: The filter kernel \( K_1 \) is applied when the variance of \( n_s \) is between 3 and \( 7\sigma^2 \). With this \( K_1 \) kernel, the noise variance after filtering would be between \( 3\sigma^2/5 \) and \( 7\sigma^2/5 \). Also, the smoothing filters with the \( K_2, K_3, \) and \( K_4 \) kernels can reduce the noise variance by \( 1/9, 1/25, \) and \( 1/49 \), where the \( K_2, K_3, \) and \( K_4 \) kernels are used when the variance range of \( n_i \) is \([7\sigma^2,18\sigma^2]\), \([18\sigma^2,35\sigma^2]\), and \([35\sigma^2,\infty]\), respectively. These variance ranges of \( n_i \) and a set of filter kernels were selected to make the noise variance of the filtered signal as uniform as possible and be around \( \sigma^2 \). The threshold values of \( A_s \), \( B_s \), \( C_s \), and \( D_s \) were determined along the intensity axis to correspond to \( 3\sigma^2, 7\sigma^2, 18\sigma^2, \) and \( 35\sigma^2 \) in the \( n_s \) variance axis, respectively, as shown in Fig. 7. The threshold values \( (A_h, B_h, C_h, \) and \( D_h) \) in the intensity \( \times \) saturation axis for switching to a different kernel in filtering the hue component can be determined similarly from Fig. 4(b) by using \( 3\sigma^2, 7\sigma^2, 18\sigma^2, \) and \( 35\sigma^2 \) as transition points in the \( n_h \) variance axis.

Once the threshold values \( (A_s, B_s, C_s, \) and \( D_s) \) are established, the saturation component of the HSI image can be filtered adaptively by the filter kernel selected for each pixel based on its intensity value:

\[
\begin{align*}
\text{filter kernel for } S(x,y) &= \begin{cases} 
\text{no filter, for } A_s < I(x,y) \\
K_1, & \text{for } B_s < I(x,y) \leq A_s \\
K_2, & \text{for } C_s < I(x,y) \leq B_s \\
K_3, & \text{for } D_s < I(x,y) \leq C_s \\
K_4, & \text{for } I(x,y) \leq D_s
\end{cases} \\
\text{filter kernel for } H(x,y) &= \begin{cases} 
\text{no filter, for } A_h < S(x,y) \\
K_1, & \text{for } B_h < S(x,y) \leq A_h \\
K_2, & \text{for } C_h < S(x,y) \leq B_h \\
K_3, & \text{for } D_h < S(x,y) \leq C_h \\
K_4, & \text{for } S(x,y) \leq D_h
\end{cases}
\end{align*}
\]

where \((x,y)\) is the horizontal and vertical coordinates in an image. After the saturation component is filtered, the hue component can be filtered in a similar way. However, the filter kernel for each hue pixel is selected based on the product of intensity and saturation values as follows:

\[
\text{filter coefficient at } (u,v) = \begin{cases} 
0, & \text{if } |I(x,y)-I(x,y)| > 2\sigma \\
1, & \text{if } |I(x,y)-I(x,y)| \leq 2\sigma
\end{cases}
\]

where \((x,y)\) is the center pixel of the kernel, i.e., the pixel to be filtered, and \((u,v)\) are other pixels in the filter kernel. In Eq. (10), \( \sigma \) is the standard deviation of noise in the RGB color space. If the threshold value in Eq. (10) is too large, the image edges would be smoothed by our adaptive spatial filtering, whereas the noise cannot be reduced much if the threshold value is too small. We have used the threshold value of \( 2\sigma \) to handle about 90% of noise in intensity, since the variance of \( n_i \) is \( \sigma^2/3 \). In practice, the noise variance \( \sigma^2 \)
in an RGB image can be estimated as follows. First, we identify a region in the RGB image where the color does not vary much, e.g., constant background. Then, the mean and variance of this color region are measured. To ensure the accuracy in this measurement, this procedure can be repeated for several different regions.

To validate the adaptive spatial filtering method, it was applied to the same noise-added test image used in Sec. 3. Figure 8 shows the variance of $n_s$ with respect to the intensity value and the variance of $n_h$ with respect to the intensity and saturation values after the adaptive spatial filters have been applied. The variance of $n_s$ in Fig. 3 and $n_h$ in Fig. 4 has been significantly reduced (please note the different vertical scales) by our adaptive spatial filtering. The sawtooth pattern can be found in the variance plots in both Figs. 8(a) and 8(b), since each filter kernel is used only in a certain range of intensity [Fig. 8(a)] or the product of intensity and saturation [Fig. 8(b)]. Since the size of the largest smoothing filter is currently $7 \times 7$, the noise variance after filtering is still relatively high when the intensity and/or saturation values are extremely small.

Our experiment was performed with four different filter kernels, as shown in Fig. 6. If the number of filter kernels increases, the noise distribution could be made more uniform, and also the noise variance can be further reduced for extremely small intensity and/or saturation values. Our adaptive spatial filtering method can use more filter kernels, different filter shapes, and kernel coefficients. For example, instead of the box-car type filters shown in our design, one can use Gaussian filters with different values of $\sigma$, depending on the noise variance. This method, while avoiding the abrupt changes in the filter kernel, significantly increases the computation time (due to the multiplication operations) for the filtering operation. Our choice of kernels, on the other hand, does not require any multiplications.

### 5 Application to Color Gradients

Even though image segmentation has been researched for a long time and is a prerequisite for image analysis and computer vision, image segmentation tightly coupled with video object tracking has become a very active research area due to its wide potential applications in future multi-media systems, particularly MPEG-4 and MPEG-7. Most image segmentation methods are currently based on the edge information of an object. A number of edge extraction techniques have been developed. Since abrupt gray-level changes occur at the edge points, most edge detection algorithms use image gradient information. Furthermore, by utilizing the additional edge information present in the hue and saturation components, stronger and better edges than using the intensity component alone can be generated. Figures 9(b), 9(c), and 9(d) show the edge-enhanced images, i.e., color gradients, with and without our adaptive spatial filtering, and with a fixed kernel filter for the same
test image used in Sec. 3, where the noise variance in the RGB image was nine. The color gradient image was obtained by applying the horizontal and vertical gradient operators to each HSI component as follows:

\[
\nabla C(x,y) = \left[ \frac{\nabla H(x,y)^2 + \nabla S(x,y)^2 + \nabla I(x,y)^2}{3} \right]^{1/2},
\]

where \( \nabla H(x,y)^2 = [H(x,y)^*G_h(x,y)]^2 \)
\[+ [H(x,y)^*G_v(x,y)]^2, \]
\[
\nabla S(x,y)^2 = [S(x,y)^*G_h(x,y)]^2 + [S(x,y)^*G_v(x,y)]^2, \]
\[
\nabla I(x,y)^2 = [I(x,y)^*G_h(x,y)]^2 + [I(x,y)^*G_v(x,y)]^2, \]

where \( G_h(x,y) \) and \( G_v(x,y) \) are the gradient operators in the horizontal and vertical directions, respectively, and * denotes the convolution operation. In this experiment, the derivative of Gaussian (DOG) gradient operator was used:

\[
G_h(x,y) = -\frac{x}{2\pi \sigma^2} \exp \left( \frac{x^2+y^2}{2\sigma^2} \right)
\]
\[ G_\varepsilon(x,y) = -\frac{y}{2\pi\sigma^5} \exp\left(\frac{x^2+y^2}{2\sigma^2}\right), \]  

(12)

with \( \sigma \) of 1.5 and the kernel size of \( 5 \times 5 \).

To evaluate the effect of our adaptive filtering, we quantified the gradient images in Figs. 9(b), 9(c), and 9(d). Each gradient value was converted into a binary value with a given threshold \( T \). If it is 1, it is considered an edge point. Otherwise, it is a nonedge point. As a measure of edge detection accuracy, the edge detection error rate defined by Nikolaidis and Pitas\(^{13}\) was used:

\[ R(T) = \frac{P_F(T) + P_{ND}(T)}{P_D(T)}, \]  

(13)

where \( P_F(T) \) is the probability of a nonedge point to be classified as an edge for a given threshold \( T \), \( P_{ND}(T) \) is the probability of an edge point not to be detected as such, and \( P_D(T) \) is the probability that an edge point is detected as such. The edge detection error rate \( R(T) \) is a parabolic-shape function of \( T \) with a single minimum value. The threshold value for the minimum \( R(T) \) for each image is automatically determined. This minimum value of \( R(T) \) was used in quantitatively assessing our adaptive filtering algorithm. The minimum edge detection error rates were 0.77, 0.73, and 0.69 for Figs. 9(b), 9(c), and 9(d), respectively. Figure 10 shows the minimum \( R(T) \) with respect to the variance of noise added to the RGB image for four different cases: without any type of filtering, with adaptive spatial filtering, and nonadaptive filtering with kernels \( K2 \) and \( K3 \). It is clear from Fig. 10 that our adaptive filtering can significantly reduce the noise effect in the hue and saturation component images [as shown by the low \( R(T) \) values]. It is also interesting to note that the error rate for nonadaptive filtering with kernel \( K2 \) increases over the error rate for the case without any filtering when the noise variance is relatively small. This is due to the fact that using a \( K2 \) filter for areas in the image with noise variances less than three would blur the normal edges resulting in loss of true edges. A similar effect can be seen when using only the \( K3 \) kernel.

Figure 11 shows the hue, saturation, and intensity images, and the color gradient image with and without the adaptive spatial filtering, and with a \( K2 \) nonadaptive filtering. As evidenced in Figs. 9 and 11, the noise is definitely reduced in the color gradients with our adaptive spatial filtering, while the image edges are preserved. For example, the color gradients in Fig. 11 show a marked improvement in both localization and continuity of the edges of the woman’s legs. Many image processing tasks, e.g., segmentation and object tracking, which depend to a large degree on good edge detection, can benefit from such an improvement as offered by this adaptive filtering algorithm.

6 Conclusions

We have attempted to address the problems caused by the nonlinear property of the RGB-to-HSI conversion, i.e., the noise amplification and nonuniform noise distribution. The noise characteristics of the HSI image have been analyzed. The adaptive spatial filtering technique utilized the results of this noise analysis to filter the saturation and hue components, using a smoothing filter kernel adaptively determined for each pixel based on its intensity and saturation component values. To avoid degradation of essential image information, the edge-preserving procedure was used in conjunction with the adaptive filtering method. The experimental results with the adaptive filtering applied to color gradients showed a significant improvement in reducing the edge detection error rate. We believe that the adaptive filtering method can alleviate the noise problem and make the HSI color model more suitable for color image processing, segmentation, and object tracking.

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References


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