Perceptually Uniform Color Spaces for Color Texture Analysis: An Empirical Evaluation

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***Abstract*—RGB, a nonuniform color space, is almost universally accepted by the image processing community as the means for representing color. On the other hand, perceptually uniform spaces, such as $L^*a^*b^*$, as well as approximately-uniform color spaces, such as HSV, exist, in which measured color differences are proportional to the human perception of such differences.**

This paper compares RGB with $L^*a^*b^*$ and HSV in terms of their effectiveness in color texture analysis. There has been a limited but increasing amount of work on the color aspects of textured images recently. The results have shown that incorporating color into a texture analysis and recognition scheme can be very important and beneficial.

The presented methodology uses a family of Gabor filters specially tuned to measure specific orientations and sizes within each color texture. Effectiveness is measured by classification performance of each color space, as well as by classifier-independent measures. Experimental results are obtained with a variety of color texture images. Percuptually uniform spaces are shown to outperform RGB in many cases.

***Index Terms*—Classification, color spaces, color texture analysis, evaluation, Gabor filtering.**

I. INTRODUCTION

THE USE of the RGB space for representing image data is very common in image processing research, dictated primarily by the availability of such data as produced by the camera apparatus. RGB, however, is not a perceptually uniform space in the sense that differences between colors (i.e., Euclidean distances) in the three-dimensional (3-D) RGB space do not correspond to color differences as perceived by humans [1].

For this reason, the international committee on colorimetry (CIE: Commission Internationale de l'Eclairage) has defined two perceptually uniform color spaces, namely, $L^*a^*b^*$ and $L^*u^*v^*$ [1]. Further, the $L^*C^*H^*$ (Lightness, Chroma, Hue) and HVC (Hue, Value, Chroma) color spaces have been formed as derivatives of $L^*u^*v^*$ [22], [23]. Another, approximately-uniform color space is HSV (Hue, Saturation, Value) [8]. One of the reasons inhibiting these spaces from being widely used in image processing tasks is their noise-sensitivity due to the nonlinear transformations involved [5]. In addition, their nonlinearity poses a computational complexity problem [8]. Perceptually uniform spaces have been used in some instances for image processing [5], [22], [23] with the main justifications for their use being their intuitive appeal to humans and their provision for isolating the luminance component [22]. However, there has not been a study that justifies the use of such color spaces in terms of their effectiveness compared to using RGB.

In this work, we present an evaluation study that compares two of these color spaces, $L^*a^*b^*$ and HVS, against RGB, in terms of their effectiveness in color texture analysis (classification/segmentation). A color texture is a spatio-chromatic pattern, which may be defined as "the distribution of colors over a surface," as opposed to gray scale textures where only luminance is considered. There has been a limited but increasing amount of work on the color aspects of textured images recently [2]–[5], [15]–[20], [22], [24]. The results have shown that incorporating color into a texture analysis and recognition scheme can be very important and beneficial. Our scheme uses a set of Gabor filters that extract local orientation and scale information from different color bands. Gabor filters have been shown to parallel early stages of the human visual system in the detection of features of this type [14], [21]. The evaluation is based on classification performance, as well as on classifier-independent measures. Classification is performed using a minimum-distance/nearest-centroid scheme, i.e., pixels are classified to the nearest class based on distance from the pre-computed class feature centroids. Non-classification-based evaluation is also performed using the Bhattacharyya distance figure of merit. Results on a variety of color texture images are presented showing superior performance of the perceptually uniform spaces over RGB in many cases.

The rest of the paper is organized as follows. Section II presents the three color spaces. Section III provides the theoretical motivation. Section IV describes the evaluation approach, while Section V presents the results obtained along with observations. Finally, conclusions are presented in Section VI.

II. COLOR SPACES

Typically, the raw image data are given in the RGB space. The definition of $L^*a^*b^*$ is based on an intermediate system, known as the CIE XYZ space (ITU-Rec. 709), which is derived from RGB as follows [1]:

$$
\begin{aligned}
X &= 0.412\,453R + 0.357\,580G + 0.180\,423B \\
Y &= 0.212\,671R + 0.715\,160G + 0.072\,169B \\
Z &= 0.019\,334R + 0.119\,193G + 0.950\,227B. \qquad (1)
\end{aligned}
$$

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Based on this definition, $L^*a^*b^*$ is defined as follows [1]:

$$\begin{aligned} L^* &= 116 f(Y/Y_n) - 16 \\ a^* &= 500\,[f(X/X_n) - f(Y/Y_n)] \\ b^* &= 200\,[f(Y/Y_n) - f(Z/Z_n)] \end{aligned} \tag{2}$$

where

$$f(q) = \begin{cases} q^{1/3}, & \text{if } q > 0.008\,856 \\ 7.787q + 16/116, & \text{otherwise.} \end{cases} \tag{3}$$

X_n, Y_n, and Z_n represent a reference white as defined by a CIE standard illuminant, D_{65} in this case, and are obtained by setting $R = G = B = 100$ in (1) $\left(q \in \left\{\frac{X}{X_n}, \frac{Y}{Y_n}, \frac{Z}{Z_n}\right\}\right)$.

HVS, an approximately-uniform space, is defined directly on RGB. Given a triplet $R, G, B \in [0, 1]$, the corresponding $H, S, V \in [0, 1]$ triplet is determined by the algorithm shown in Table I [8].

III. Theoretical Motivation

The first and fundamental processing stage in our color texture analysis methodology is based on the mechanism of filtering. Filtering in the discrete domain is essentially defined as the sum of products (of a certain image property measured within part or the whole of an image). For an image window of size $W \times W$, the filter output is defined as follows:

$$F = \sum_{i=1}^{W^2} f_i C_i \tag{4}$$

where f_i is the filter coefficient corresponding to, and C_i is the value of, pixel i. To characterize textural properties, a set of Gabor filters is used [6], [12], [13]. Gabor filters have been shown to parallel the mechanisms employed in the early stages of human visual perception [14], [21]. A Gabor filter is a modulated Gaussian and is defined at image coordinates (m, n) as follows:

$$g(m, n) = e^{-(m^2+n^2/2\sigma^2)} e^{-2j\pi\phi(m\,\cos\,\theta + n\,\sin\,\theta)}. \tag{5}$$

The coefficients of a typical Gabor filter are divided into positive and negative ones. Separating the negative from the positive terms, F can be put in the following form:

$$F = \sum_{f_i>0} f_i C_i - \sum_{f_i<0} (-f_i) C_i. \tag{6}$$

Let us consider the $L^*a^*b^*$ color space and assume that the pixel values are color values [e.g., $C_k = (L_k^*, a_k^*, b_k^*)$]. Filtering the three color components separately yields

$$\begin{aligned} F_{L^*} &= \sum_{f_i>0} f_i L_i^* - \sum_{f_i<0} (-f_i) L_i^* \\ F_{a^*} &= \sum_{f_i>0} f_i a_i^* - \sum_{f_i<0} (-f_i) a_i^* \\ F_{b^*} &= \sum_{f_i>0} f_i b_i^* - \sum_{f_i<0} (-f_i) b_i^*. \end{aligned} \tag{7}$$

By using a more simplified notation, (7) may be written as

$$\begin{aligned} F_{L^*} &= F_{L^*}^+ - F_{L^*}^- \\ F_{a^*} &= F_{a^*}^+ - F_{a^*}^- \\ F_{b^*} &= F_{b^*}^+ - F_{b^*}^-. \end{aligned} \tag{8}$$

Taking absolute values and summing yields

$$F = |F_{L^*}^+ - F_{L^*}^-| + |F_{a^*}^+ - F_{a^*}^-| + |F_{b^*}^+ - F_{b^*}^-|. \tag{9}$$

On the other hand, let us consider the two color sets corresponding to pixel sets A and B as two extended points in color space, i.e., $C_A = (L_A^*, a_A^*, b_A^*)$ and $C_B = (L_B^*, a_B^*, b_B^*)$. Their distance is defined as follows:

$$CD = |L_A^* - L_B^*| + |a_A^* - a_B^*| + |b_A^* - b_B^*|. \tag{10}$$

(An extended point C_A representing a set of pixels A may be thought of as the line that connects the individual color points in color space, where each individual color point represents a pixel of the set. Thus, the distance between two extended color points is the set of distances between the corresponding individual color points.)

Thus, the filter output F for a window is a weighted color difference. Since color differences in a perceptually uniform color space are proportional to humanly perceived differences, we expect that a uniform color space will provide a better and more accurate characterization of color textures compared to a nonuniform space.

It should be noted that the use of L_1 distances instead of L_2 is made for the purposes of illustrating the analogy between filter outputs and color differences. Typically, in color science L_2 distances are used when measuring color differences. However, in this study (i.e., in the experimental evaluation) color differences are not utilized explicitly. Thus, the "perceptual uniform" property of these color spaces is expected to factor into the processing and final results.

IV. Evaluation Methodology

The evaluation methodology is based on the general idea of pixel-level classification. A set of color texture features is extracted at each pixel in a given image. The set of features (feature vector) thus defines a multidimensional space in which points corresponding to feature vectors extracted from pixels of the same image are expected to be in the same vicinity, thus forming a multidimensional cluster. Ideally, there will be a 1–1 mapping between color texture images and feature clusters.

The color texture features are extracted through a Gabor filtering scheme with three scales and four orientations [recall (5)]. Following [2], the scale parameter is determined by the following recursion:

$$\begin{aligned} \phi_{q+1} &= 0.5\phi_q, \quad q = 0, 1, 2 \\ \phi_0 &= \frac{0.5}{1 + \tan(B_\theta/2)} \end{aligned} \tag{11}$$

where B_θ is the half-peak orientation bandwidth (set to 40°). The orientations (θ) we use are 0°, 45°, 90°, and 135°, for a total

TABLE I
RGB-TO-HSV CONVERSION ALGORITHM

```
max←max(R, G, B)
V←max
if(V<>0.0) S←(V-min)/V
else S←0
if(max=min) H←-1
else {
    r←(max-R)/(max-min)
    g←(max-G)/(max-min)
    b←(max-B)/(max-min)

    if(R=max and G=min) H←5+b
    else if(R=max and G<>min) H←1-g
    else if(G=max and B=min) H←1+r
    else if(G=max and B<>min) H←3-b
    else if(B=max and R=min) H←3+g
    else H←5-r

    H←H/6.0
  }
```

of 12 different filters. The width of the modulating Gaussian σ is dependent on the scale of each filter as follows:

$$\sigma = \frac{\sqrt{2\ln 2}}{2\pi\phi\tan(B_\theta/2)}. \tag{12}$$

The evaluation procedure is divided into two parts. The first part applies the method from the previous section, which consists of computing Gabor measurements for each of the three color components (that is, 12 filters $\times$ 3 components $=$ 36 filter outputs per pixel) and taking absolute values and adding corresponding triads of filter outputs (yielding 12 filter measurements per pixel [see (9)]). Since our aim is to compare the effectiveness of the color space, and not particularly that of any given classifier, we use the Bhattacharyya distance figure of merit [10], [11], for a classifier-independent comparison. For two classes i, j with means μ_i and μ_j, and covariance matrices Σ_i and Σ_j, as measured in a color space S, the Bhattacharyya distance is defined as follows [9]:

$$B_S(i, j) = \frac{1}{4}(\mu_j - \mu_i)^T[\Sigma_i + \Sigma_j]^{-1}(\mu_j - \mu_i) + \frac{1}{2}\ln\left[\frac{\left|\frac{1}{2}(\Sigma_i + \Sigma_j)\right|}{\sqrt{|\Sigma_i||\Sigma_j|}}\right] \tag{13}$$

where $|\cdot|$ signifies matrix determinant. B measures the pairwise separability achieved by a certain set of features without the need to perform costly classification. In addition, given two

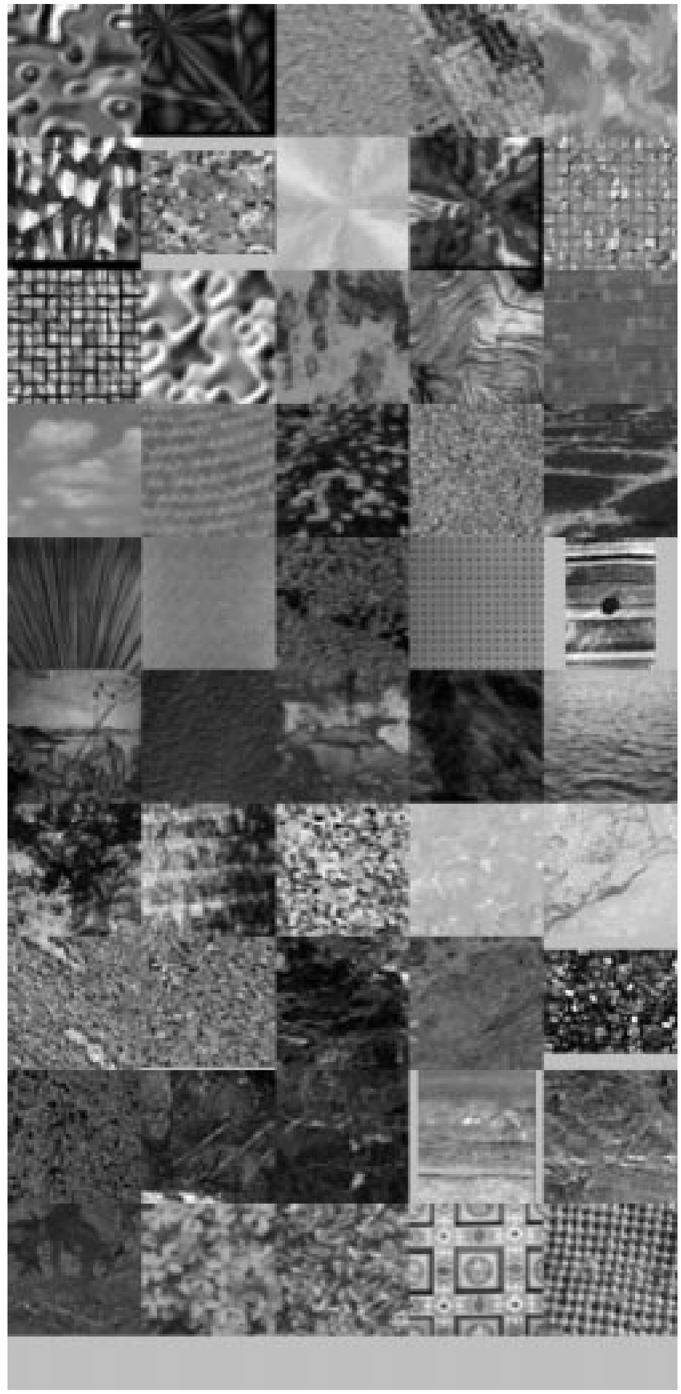

Fig. 1. Test color textures (the original color version can be obtained from the author at gpaschos@usa.net).

color spaces S_1 and S_2, their average B-difference over all possible color texture class pairs is used as an overall indicator of effectiveness, and it is defined as:

$$B_{avg} = \frac{1}{K(K-1)/2}\sum_{i=1}^{K-1}\sum_{j=i+1}^{K}(B_{S_1}(i, j) - B_{S_2}(i, j)) \tag{14}$$

where K is the number of color texture classes considered.

In the second part of the evaluation, classification is performed based on the complete set of Gabor filter outputs, i.e., using each of the three color component filter outputs separately

TABLE II
PAIR-WISE BHATTACHARYYA COLOR TEXTURE CLASS DISTANCES FOR THE TEN-CLASS CASE. B-INDEX SHOWS THE CLASSES BEING COMPARED. THE TEN CLASSES BEING COMPARED ARE THE FIRST TEN COLOR TEXTURES IN FIG. 1, NUMBERED 0–9

B-index	RGB	L*a*b*	HSV
B(0,1)	0.44	1.95	2.07
B(0,2)	-0.22	0.02	-0.43
B(0,3)	-0.45	-0.19	-0.17
B(0,4)	0.41	0.54	3.44
B(0,5)	-0.31	-0.16	-0.02
B(0,6)	-0.59	-0.26	0.09
B(0,7)	1.46	-0.08	-0.63
B(0,8)	-0.76	-0.44	0.19
B(0,9)	0.09	0.02	0.71
B(1,2)	3.03	1.29	2.07
B(1,3)	1.78	1.39	-0.11
B(1,4)	6.60	20.99	13.83
B(1,5)	-0.06	0.16	-0.15
B(1,6)	0.43	0.32	-0.51
B(1,7)	10.40	10.24	2.96
B(1,8)	-0.37	0.56	0.77
B(1,9)	2.10	2.90	1.92
B(2,3)	-0.32	0.19	0.40
B(2,4)	-0.40	35.26	13.56
B(2,5)	-0.13	0.10	0.43
B(2,6)	0.05	0.07	1.14
B(2,7)	1.10	4.85	0.59
B(2,8)	0.46	0.06	0.88
B(2,9)	0.23	1.51	1.76
B(3,4)	-0.27	3.78	1.78
B(3,5)	-0.72	-1.30	-1.27
B(3,6)	-0.63	-0.93	-0.73
B(3,7)	0.17	0.93	-0.50
B(3,8)	-0.46	-0.86	-0.63
B(3,9)	-0.46	-0.36	0.05
B(4,5)	0.57	2.71	3.11
B(4,6)	0.13	4.07	10.62
B(4,7)	-0.02	0.05	6.27
B(4,8)	1.55	2.77	0.92
B(4,9)	0.49	2.21	1.17
B(5,6)	-0.74	-0.95	-0.31
B(5,7)	-0.12	0.68	-0.15
B(5,8)	-0.78	-1.25	-1.12
B(5,9)	-0.33	-0.09	0.33
B(6,7)	-0.41	1.36	1.05
B(6,8)	-0.95	-0.72	-0.10
B(6,9)	-0.45	0.25	1.24
B(7,8)	2.59	1.28	0.25
B(7,9)	0.81	0.88	0.79
B(8,9)	0.39	-0.20	-0.53

TABLE III
AVERAGE DIFFERENCES OF THE PAIR WISE B-DISTANCES BETWEEN THE COMPARED COLOR SPACES FOR THE TEN-, 20-, AND 50-CLASS CASES. A POSITIVE AVERAGE DIFFERENCE INDICATES HIGHER SEPARABILITY BY THE FIRST SPACE

# Classes	L*a*b* vs. RGB	HSV vs. RGB
10	1.562	0.926
20	0.790	0.737
50	0.225	0.485

[(7)]. This yields a feature vector of 36 elements (3 scales $\times$ 4 orientations $\times$ 3 color components). Once such a feature vector per pixel has been formed and the average feature vector over the entire image (centroid) has been computed for each color texture class, nearest-centroid classification is performed. The Euclidean distance is used, normalized by the per-class feature standard deviations. For a pixel p with feature vector f_p, and a class k with centroid vector μ_k and standard deviation vector sdv_k, the normalized Euclidean distance of the feature vector from the class is

$$D_k = \sqrt{\sum_{i=1}^{36} \left(\frac{f_p(i) - \mu_k(i)}{sdv_k(i)} \right)^2}. \tag{15}$$

TABLE IV
CORRECT CLASSIFICATION RATES (%) FOR THE TEN-CLASS CASE

Class	RGB	L*a*b*	HSV
1	93.75	93.75	93.75
2	100.0	93.75	100.0
3	100.0	100.0	100.0
4	31.25	81.25	75.0
5	100.0	93.75	93.75
6	93.75	87.5	93.75
7	72.55	37.59	86.84
8	93.75	93.75	93.75
9	81.25	81.25	87.5
10	100.0	100.0	100.0
Average	86.3	85.8	92.0

TABLE V
CORRECT CLASSIFICATION RATES (%) FOR THE 20-CLASS CASE

Class	RGB	L*a*b*	HSV
1	93.75	93.75	93.75
2	93.75	93.75	100.0
3	100.0	100.0	100.0
4	31.25	81.25	75.0
5	100.0	93.75	93.75
6	75.0	68.75	93.75
7	33.08	22.18	62.03
8	56.25	87.5	93.75
9	81.25	75.0	87.5
10	100.0	100.0	100.0
11	100.0	93.75	100.0
12	75.0	37.5	75.0
13	93.75	75.0	93.75
14	75.0	56.25	81.25
15	75.0	68.75	75.0
16	12.5	62.5	50.0
17	93.75	100.0	93.75
18	100.0	93.75	100.0
19	100.0	100.0	100.0
20	100.0	87.5	100.0
Average	74.6	79.15	88.15

V. RESULTS

Several tests have been performed with the set of 50 color textures shown in Fig. 1, where each of these images represents a color texture class. The various tests have been applied on three sets of classes, namely, the first ten, the first 20, and all 50 classes (note: the numbering of images in Fig. 1 starts at the upper left corner and continues in a left-to-right, top-to-bottom fashion).

In the first part of the evaluation, comparative results based on the Bhattacharyya distance figure of merit (B-distance) have been obtained. The set of B-distances for the ten-class case is shown in Table II. It may be seen that in most cases the two perceptually uniform spaces achieve larger distances. Further, the average per class-pair difference of B-distances, as defined in (14), between RGB and each of the other two spaces has been measured. The B_{avg} measurements for the ($S_1 = L^*a^*b^*$, $S_2 = RGB$) and ($S_1 = HSV$, $S_2 = RGB$) cases

TABLE VI
CORRECT CLASSIFICATION RATES (%) FOR THE 50-CLASS CASE. ALSO SHOWN ARE THE CORRESPONDING RATES WHEN ONLY THE LUMINANCE COMPONENTS OF THE TWO UNIFORM SPACES ARE USED, i.e., L^* AND V, RESPECTIVELY

Class	RGB	L*a*b*	HSV	L*-only	V-only
1	3.75	75.00	93.75	62.50	31.25
2	62.50	93.75	93.75	25.00	37.50
3	100.00	100.00	100.00	75.00	68.75
4	31.25	50.00	68.75	12.50	12.50
5	100.00	93.75	93.75	6.25	100.00
6	75.00	68.75	93.75	37.50	50.00
7	28.20	20.30	24.06	18.42	17.67
8	56.25	75.00	75.00	18.75	50.00
9	75.00	75.00	87.50	6.25	37.50
10	100.00	100.00	100.00	68.75	100.00
11	100.00	93.75	100.00	87.50	87.50
12	75.00	37.50	50.00	43.75	25.00
13	93.75	56.25	93.75	6.25	12.50
14	31.25	37.50	62.50	12.50	25.00
15	75.00	56.25	75.00	56.25	56.25
16	12.50	43.75	50.00	12.50	0.00
17	87.50	100.00	93.75	37.50	31.25
18	100.00	75.00	93.75	43.75	43.75
19	100.00	100.00	100.00	12.50	75.00
20	75.00	75.00	87.50	31.25	25.00
21	68.75	31.25	62.50	0.00	25.00
22	25.00	0.00	12.50	12.50	25.00
23	75.00	93.75	87.50	25.00	56.25
24	25.00	75.00	75.00	12.50	31.25
25	41.07	62.86	33.21	14.29	14.64
26	12.50	18.75	25.00	6.25	0.00
27	37.50	31.25	0.00	37.50	31.25
28	31.25	12.50	37.50	25.00	18.75
29	68.75	31.25	62.50	50.00	6.25
30	18.75	25.00	56.25	6.25	12.50
31	25.00	87.50	81.25	12.50	12.50
32	18.75	18.75	37.50	0.00	0.00
33	53.72	78.51	72.73	38.84	25.62
34	57.02	80.17	69.42	43.80	61.98
35	80.99	74.38	72.73	74.38	47.11
36	62.81	76.86	81.82	41.32	37.19
37	64.46	73.55	89.26	24.79	27.27
38	59.50	83.47	73.55	37.19	61.16
39	45.45	47.93	56.20	14.05	15.70
40	76.98	85.32	75.00	23.02	13.10
41	70.25	53.72	91.74	28.10	24.79
42	40.50	80.99	86.78	15.70	23.97
43	67.77	54.55	76.86	13.22	14.88
44	27.08	27.08	37.50	12.50	12.15
45	19.01	21.49	69.42	8.26	9.09
46	79.34	12.40	82.64	22.31	23.14
47	56.25	62.50	93.75	31.25	18.75
48	75.00	93.75	100.00	18.75	31.25
49	93.75	93.75	87.50	93.75	31.25
50	100.00	93.75	81.25	68.75	68.75
Average	59.18	62.16	72.1	29.72	33.32

TABLE VII
CORRECT CLASSIFICATION RATES (%) FOR THE TEN-CLASS CASE WHERE 10% NOISE HAS BEEN INDUCED IN EACH OF THE IMAGES BEFORE CLASSIFICATION

Class	RGB	L*a*b*	HSV
1	93.75	93.75	93.75
2	100.0	100.0	100.0
3	100.0	100.0	100.0
4	37.5	56.25	75.0
5	100.0	87.5	100.0
6	68.75	81.25	75.0
7	50.37	40.97	79.69
8	100.0	100.0	100.0
9	81.25	75.0	81.25
10	93.75	100.0	100.0
Average	82.2	83.2	90.3

are shown in Table III. The positive differences indicate larger B-distances for the color space listed first. $L^*a^*b^*$ and HVS achieve higher average pair-wise class separability than RGB.

TABLE VIII
CORRECT CLASSIFICATION RATES (%) FOR THE TEN-CLASS CASE WHERE 20% NOISE HAS BEEN INDUCED IN EACH OF THE IMAGES BEFORE CLASSIFICATION

Class	RGB	L*a*b*	HSV
1	93.75	93.75	93.75
2	93.75	100.0	100.0
3	100.0	87.5	0.0
4	43.75	62.5	87.5
5	100.0	87.5	100.0
6	62.5	75.0	75.0
7	50.75	48.49	77.06
8	100.0	75.0	100.0
9	81.25	75.0	81.25
10	93.75	93.75	100.0
Average	81.5	79.5	81.3

TABLE IX
CORRECT CLASSIFICATION RATES (%) FOR THE TEN-CLASS CASE WHERE 50% NOISE HAS BEEN INDUCED IN EACH OF THE IMAGES BEFORE CLASSIFICATION

Class	RGB	L*a*b*	HSV
1	50.0	6.25	93.75
2	0.0	37.5	0.0
3	100.0	6.25	0.0
4	43.75	62.5	62.5
5	81.25	31.25	100.0
6	43.75	56.25	50.0
7	55.26	60.90	56.76
8	62.5	43.75	93.75
9	62.5	56.25	81.25
10	68.75	100.0	100.0
Average	56.4	45.7	63.5

Between the two, HVS appears to be more effective in this respect, particularly as the number of classes increases.

In the second part of the evaluation, actual classification tests have been performed as outlined in the previous section (it should be noted that our aim is not to achieve the highest possible rates of correct classification but rather to compare the relative rates achieved by different color spaces). As initial experiments indicated, pure pixel-wise classification is bound to yield rather low correct classification rates due to inevitable overlaps in the feature space. Thus, block-based classification has been used instead, where the block (i.e., image window) used is 25×25 pixels. The results for the different class cases are shown in Tables IV–VI. Average rates are also shown at the bottom row in each case.

In addition, Table VI includes results for the case when only the luminance component is used in each of the two perceptually uniform spaces, i.e., L^* and V. The rates achieved in these two cases are rather low and do not support the claim that texture can be characterized mainly by luminance. Inclusion of the full chromatic content amounts to a doubling (if not more) of the correct classification rates. Comparing the performance of the three color spaces, HVS achieves the highest rates, overall, followed by $L^*a^*b^*$, with RGB coming in third. The only exception in this ranking order is observed in the ten-class case, where $L^*a^*b^*$ is by a small margin inferior to RGB. In general, HVS is superior to RGB by at least a 10% margin, overall, while $L^*a^*b^*$'s superiority to RGB is merely by 3–4%.

Finally, classification has been performed in the presence of noise, at three different levels. For each of the first ten color textures, 10%, 20%, and 50% of its pixels have been randomly perturbed by uniform noise before performing classification. The corresponding results for these three cases are shown in Tables VII–IX, respectively. HVS appears to be more resilient to noise, not only compared to $L^*a^*b^*$, but also compared to RGB.

VI. Conclusions

An experimental evaluation study has been presented that measures the impact of the use of different color spaces on the performance of typical color texture analysis methods such as segmentation/classification. In particular, two perceptually uniform/approximately-uniform color spaces ($L^*a^*b^*$, HVS) have been compared against the more traditionally used RGB space. It has been shown that perceptually uniform color spaces have an overall performance advantage over RGB.

In particular, it has been found that HVS performs better than both $L^*a^*b^*$ and RGB in normal (i.e., no-noise) as well as noisy conditions. $L^*a^*b^*$ performs better than RGB overall, but only when noise does not exist (verifying in this way its theoretically expected noise-susceptibility).

Thus, the evidence presented in this paper suggests that HVS could be a superior color space compared to RGB for color texture analysis. In addition, and specifically in noise-free conditions, $L^*a^*b^*$ may also be so.

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