

# A Color Space Performance Comparison in the Processing of Color Textured Images: RGB vs. L\*a\*b\*

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## Abstract

The RGB color space is almost universally accepted by the image processing research community for representing images, the main reason being that RGB information is readily available as the raw data produced by the camera. There are, however, perceptually more uniform spaces, such as L\*a\*b\* and L\*u\*v\*, where measured color differences are proportional to the human perception of such differences. Whether the use of such a color space would provide better results in image processing tasks (segmentation/classification) is an issue that has not been adequately addressed.

This paper compares RGB and L\*a\*b\* in terms of their effectiveness in a typical image processing task, namely, image segmentation. Particularly important to this line of research is the segmentation of color textures. There has been only limited work on the color aspects of textured images. However, recent results have shown that incorporating color into a texture analysis and recognition scheme can be very important.

The presented methodology uses a set of gabor filters specially tuned to measure specific orientations and sizes within a color texture. The vector of filter measurements thus obtained is then used in a minimum-distance classification scheme to segment the image. Images composed of two or more different color texture patterns are processed. The goal is to separate (i.e., segment) the image into its constituent color texture patterns. Segmentation results are presented.

## 1. 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 a camera. RGB, however is not a perceptually uniform space in that differences between colors (i.e., Euclidean

distances) in the 3-dimensional RGB space do not correspond to color differences as perceived by humans.

For this reason, the international committee on colorimetry (CIE:Commission Internationale de l'Eclairage) has defined two perceptually uniform color space, namely, L\*a\*b\* and L\*u\*v\* [1].

Very limited work, however, exists in the image processing literature that utilizes these two spaces. One of the reasons is the noise-sensitivity of these spaces due to the non-linear transformations involved.

In this work, we perform a comparison between RGB and L\*a\*b\* in a typical image processing task, namely image segmentation. In addition to performing segmentation based purely on color information only, we are also interested in measuring the performance of these three color spaces when combining color and texture information.

Specifically, our color texture segmentation scheme uses a set of gabor filters that extract orientation and scale information from different color bands. A set of feature vectors are, thus, computed, one per pixel. Segmentation is performed following a minimum-distance, nearest centroid clustering technique. Results from various granite and marble images are presented.

Section 2 presents the three color spaces. Section 3 describes the processing steps followed for segmentation. In section 4 results are presented, while conclusions are included in section 5.

## 2. Color Spaces

Typically, the image raw data are given in the RGB space. The definition of the perceptually uniform color spaces is based on an intermediate system, known as the XYZ space, which is derived from RGB as follows:[1]

$$\begin{aligned} X &= 0.607 * R + 0.174 * G + 0.200 * B \\ Y &= 0.299 * R + 0.587 * G + 0.114 * B \\ Z &= 0.066 * G + 1.111 * B \end{aligned} \quad (1)$$

Based on this set of equations, L\*a\*b\* is defined as follows:

$$\begin{aligned} L &= 116f(Y/Y_n)^{1/3} - 16 \\ a &= 500[f(X/X_n) - f(Y/Y_n)] \\ b &= 200[f(Y/Y_n) - f(Z/Z_n)] \end{aligned} \quad (2)$$

where

$$f(q) = \begin{cases} q^{1/3} & \text{if } q > 0.008856 \\ 7.787q + 16/116 & \text{otherwise} \end{cases} \quad (3)$$

$X_n, Y_n, Z_n$  represent a reference white as defined by a standard illuminant (98.1, 100, 1nd 118.2 are the values used here [2]).

### 3. Image Segmentation

A given image in general contains several different regions of interest (e.g., in an image taken from an outdoors scene, a tree, a house, and the sky are three such regions). Segmentation is the task of identifying different regions in an image based on certain visual attributes. In the following, a segmentation method combining color and texture attributes is described. The underlying algorithm is based on feature space clustering and is as follows:

#### Algorithm:

initialize cluster centroids

foreach(pixel  $p$ ) {

1. Extract a set of features and form a feature vector  $f_p$ .
2. Assign  $f_p$  to a cluster  $c$  based on minimum distance from centroid.
3. Label  $p$  as belonging to cluster  $c$ .

}

#### 3.1. Color and Texture Segmentation

In order to characterize and capture textural properties, a set of Gabor filters is used. A Gabor filter is a modulated Gaussian and is defined as follows [3]:

$$g(x, y) = e^{-\frac{(x^2+y^2)}{2\sigma^2}} e^{-2j\pi\phi(x\cos\theta+y\sin\theta)} \quad (4)$$

where  $\phi$  is the scale, and  $\theta$  is the orientation parameter of the filter. The real part is used in this method (see also [5]), i.e.,

$$g(x, y) = e^{-\frac{(x^2+y^2)}{2\sigma^2}} \cos 2\pi\phi(x\cos\theta + y\sin\theta) \quad (5)$$

with three scales and four orientations, following [4].

One may view a given image as a set of three component images. For instance, in the L\*a\*b\* space one has



Figure 1: The test images.

an L-image, an a-image, and a b-image. Filtering is, thus, performed on each of the three image components separately, and gives rise to a 36-dimensional feature vector for each pixel (3 scales  $\times$  4 orientations  $\times$  3 components).

### 4. Results

The original set of images is shown in Figure 1. The corresponding segmentation results are shown in Figure 2.

Another set of results is shown in Figure 3. In this case, 10% random noise has been induced to the original images and segmentation was carried out in the same manner as before.

### 5. Conclusion

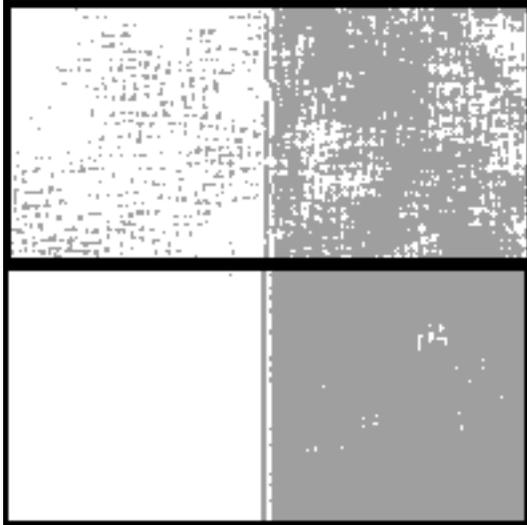
Looking at Figure 2, one can observe that L\*a\*b\* outperforms RGB.

However, RGB seems to be more robust in terms of noise-sensitivity as it degrades more gracefully than L\*a\*b\* (Figure 3). These observations eventually coincide with theory (i.e., noise-sensitivity of perceptually uniform spaces).

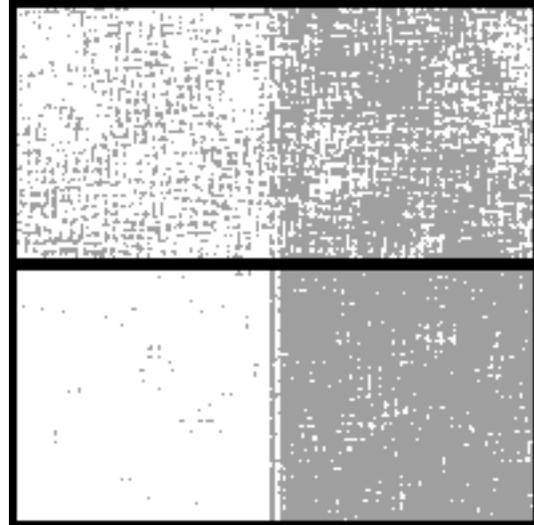
In conclusion, L\*a\*b\* appears to provide a better space than RGB for image processing tasks such as color texture segmentation. Further experimental analysis will be performed in order to validate this hypothesis.

### 6. References

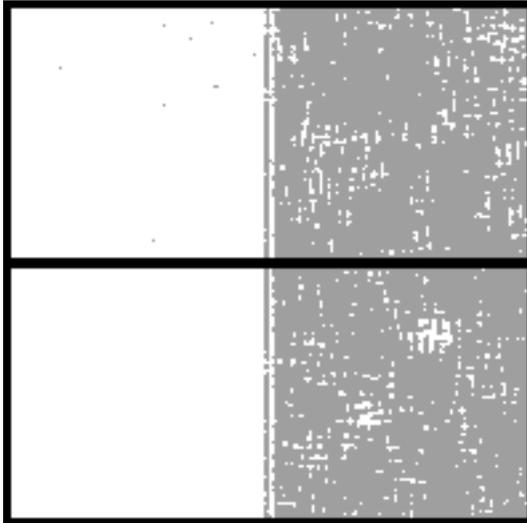
1. G. W. Wyszecki and S. W. Stiles, Color Science: Concepts and Methods, Quantitative Data and Formulas, John



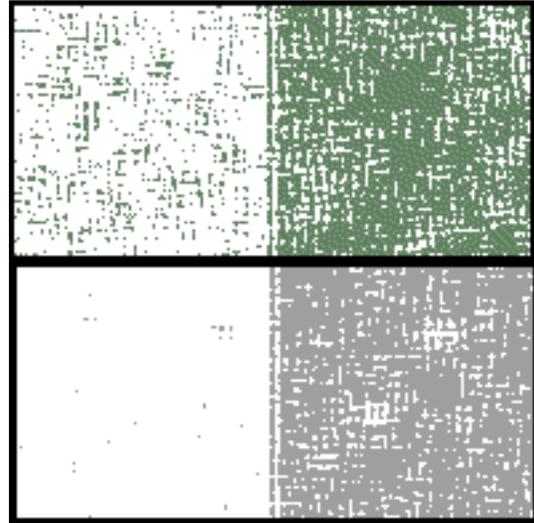
(a)



(a)



(b)



(b)

Figure 2: The color and texture-based segmentation results: (a) RGB, (b)  $L^*a^*b^*$ .

Figure 3: The color-based segmentation results where 10% noise has been induced in the image: (a) RGB, (b)  $L^*a^*b^*$ .

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