# The number of discernible colors in natural scenes 

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#### Abstract

The number of colors discernible by normal trichromats has been estimated for the idealized object-color solid. How well these estimates apply to natural scenes is an open question, as it is unknown how much their colors approach the theoretical limits. The aim of this work was to estimate the number of discernible colors based on a database of hyperspectral images of 50 natural scenes. The color volume of each scene was computed in the CIELAB color space and was analyzed using the CIEDE2000 color-difference formula. It was found that the color volume of the set of natural scenes was about $30 \%$ of the theoretical maximum for the full object-color solid, and it corresponded to a number of about 2.3 million discernible colors. Moreover, when the lightness dimension was ignored, only about $26,000(1 \%)$ could be perceived as different colors. These results suggest that natural stimuli may be more constrained than expected from the analysis of the theoretical limits. © 2008 Optical Society of America OCIS codes: $330.1690,330.1720,330.6180$.


## 1. INTRODUCTION

The chromatic richness experienced by observers with normal color vision suggests the perception of an enormously large number of color nuances, a notion that seems to be supported by some textbooks that often quote the number of 10 million [1,2], a figure with an unclear origin [3]. Yet there are two main constraints limiting the number of colors that can be perceived in natural scenes: the light reflected by natural surfaces is not arbitrary in its spectral composition, and our ability to discriminate similar light stimuli is limited. In spite of significant research addressing this classical issue [4-9], the question of how many colors can be discriminated by the human eye in natural scenes still has no definitive answers.

Estimates of the number of discernible colors perceived in complex scenes or, more generally, in natural environments provide information about the diversity of the physical stimuli and about the visual processing producing distinguishable perceptions. In particular, comparing the maximum theoretical chromatic diversity with that actually experienced in natural scenes provides a measure of how much the real world approaches the theoretical limits. In practice, it may be useful to measure the color rendering properties of illuminants [8,10-12], to access the visual effects of a colored lens [13], to compare normal color vision with defective color vision [14], and to evaluate the color gamut of display devices [3,15,16].

The set of all possible colors normal trichromats can see is represented by a volume in color space limited by the colors of monochromatic lights and embodies color sensations resulting from a variety of stimuli [17]: direct observation of light sources, highlights, fluorescence, diffuse reflection (or transmittion), and other physical processes producing colors, e.g., Rayleigh or Mie scattering responsible for the blue of sky and the white of clouds, respectively $[18,19]$, and amazing optical effects produced
by natural photonic structures, such as the brightly colored birds and insects [20]. The subset of colors arising only by reflection (or transmittion) are the object colors [21] and form a subvolume of the color space, the objectcolor solid, delimited by the optimal colors. The theory underlining the spectral properties of optimal colors was developed early in the 20th century [9], and the corresponding loci were computed in a color diagram [22,23] and were recalculated later in the I.C.I. 1931 coordinate system by D. L. MacAdam [4,5] to obtain the MacAdam limits. The full characterization of these limits is still a matter of interest, for example, in lighting where they can be useful in the characterization of the color rendering properties of light sources $[8,10]$.

The number of colors perceived by normal trichromats was initially estimated using chromatic discrimination data [6,7]; recent estimates [3,8,10,24] take advantage of the advances in specification of color differences and are based on representations of the theoretical object-color solid in approximate uniform color spaces, e.g., CIELAB [25], DIN99 [26], and CIECAM [27]. The estimates for the theoretical limit vary over a considerable range depending on the assumptions made, but a number close to 2 million for the entire theoretical object-color solid is common to several reports [3,8]. This number was obtained by computing the volume of the object-color solid in CIELAB with the implicit assumption of just noticeable cubic subvolumes, which corresponds to a coarse approximation.

How realistic are these estimates? The reflectance spectra corresponding to the optimal colors do not actually occur in nature: they are spectral reflectance functions having only values of either zero or unity [9]; how much real colors approach this idealized limit is still uncertain.

The color gamut of real colors has been investigated using large sets of colored samples containing colors of paints, flowers, plastics, and inks, among others [28], and


Fig. 1. (Color online) Thumbnails of the 50 scenes analyzed in this study.
in spite of the limitations of the sampling methodology [29], the results suggest that the gamut of real colors is much smaller than that of the optimal colors. Measurements taken directly from natural scenes $[30,31]$ overcome some limitations but were limited by the sampling size.

The purpose of this work was to estimate the number of discernible colors that can be perceived in natural scenes based on a database of hyperspectral images of 50 natural scenes from rural and urban environments. Hyperspectral images have been used in the characterization of the spectral and chromatic properties of natural scenes [31-35], artistic paintings [11,12], and other valuable objects [36], and given their unique property of combining spectral information with spatial information at a resolution comparable to that of the human eye, they are the ideal data source for the problem addressed here. The present study took into account a large sample of colors measured in natural conditions and therefore represents a novel contribution to the analysis of the chromatic diversity of the natural world. However, like other studies on discernible colors, the estimations are constrained by the limitations of the color vision models applied and by the natural samples analyzed. At present, there are no accepted models predicting color vision and color discrimination in natural scenes, where the illumination has a complex spatial distribution and the background and size of the objects vary considerably. Thus, this study applied the models available, which are optimized for samples viewed in ideal laboratory conditions, that is, in specific backgrounds and under uniform illumination. On the other hand, it is not possible to sample the natural word with generality, and the study was based on a limited, although large, sample of natural scenes.

## 2. METHODS

A database with hyperspectral data from 50 natural scenes acquired in the Minho region of Portugal was ana-
lyzed. Scenes were of rural and urban environments and contained both close-ups and distant views. Rural scenes contained natural elements such as dark terrain, trees, grass, ferns, flowers, rocks, and stones, and urban scenes contained buildings and painted or treated surfaces. For a more detailed description of the database, see Foster et al. [33] and Foster et al. [37]. Figure 1 represents the thumbnails of the complete set of 50 scenes analyzed in this study.

The hyperspectral images were obtained with a hyperspectral imaging system with a low-noise Peltier-cooled digital camera capable of a spatial resolution of 1344 $\times 1024$ pixels (Hamamatsu, Model C4742-95-12ER, Hamamatsu Photonics K. K., Japan) and with a fast tunable liquid-crystal filter (Varispec, Model VS-VIS2-10-HC-35-SQ, Cambridge Research \& Instrumentation, Inc., Massachusetts) mounted in front of a lens, with an infrared blocking filter. Each image was acquired from 400 nm to 720 nm in 10 nm steps. The lens had a 75 mm focal length, the angle of view was about 6 deg , and in these conditions the system delivered a spatial resolution close to that of the human eye.

Hyperspectral data were calibrated using the spectrum of the light reflected from a gray surface present in the scene measure with a telespectroradimeter (SpectraColorimeter, PR-650, PhotoResearch Inc., Chatsworth, California) just after image acquisition. The spectral radiance from each pixel of the image was then obtained after corrections for dark noise, spatial nonuniformities, stray light, and chromatic aberrations (for more details on these corrections see Foster et al. [33]). Notice that in the calibration procedure, to obtain the spectral radiance, no assumptions about the illuminant on the scene were made, and therefore the data reflect the spatial variations of the illumination across the scene.

Spectral radiances were converted into tristimulus values for the CIE 1931 standard colorimetric observer and then converted into the CIELAB color coordinates


Fig. 2. (Color online) Examples of three scenes of the database. On the left are represented the color images, and on the right the CIELAB representation of each of the scenes. For clarity, only a fraction of the data points are represented in each of the graphs. The numbers indicate the number of discernible colors estimated for each scene using the CIEDE2000 color-difference formula, and the numbers in parentheses indicate the number of colors estimated ignoring the lightness dimension. The top picture represents a scene with a number of discernible colors less than the average, the picture in the middle a scene with a number of discernible colors close to the average, and the picture in the bottom a scene with a number of discernible colors larger than the average.
( $L^{*}, a^{*}, b^{*}$ ). The reference illuminant for these computations was obtained from the gray reference surface present in the scene, and the white object was assumed the perfect reflecting diffuser. Figure 2 shows, as illustration, the CIELAB representation of three scenes of the database. For clarity, only a fraction of the data points are represented in the graphs. In the figure some points show values of $L^{*}$ larger than 100 and corresponded to highlights; these points represented about $3 \%$ of all data and were excluded from further analysis.

The general principle to estimate the number of discernible colors was to segment the color space in just noticeable subvolumes and to count the number of these containing the color representation of at least one pixel $[3,8]$. Because the CIELAB color-difference formula is
known to represent only approximately perceived differences [27,38-41], the estimations were carried out using the CIEDE2000 color-difference formula [42,43] with the parametric factors $k_{\mathrm{L}}, k_{\mathrm{C}}$, and $k_{\mathrm{H}}$ of the CIEDE2000 formula set to one [25], the default values [44]. Specifically, a color was first selected at random from the image. Then all colors with a color difference equal to or less than 0.3 CIEDE2000 units in relation to this reference color were counted as one discernible color; this procedure was repeated until all colors of the image were considered. To avoid double counting, in each iteration the corresponding colors were removed from the sample. This procedure assumes that the discriminable difference is 0.6 CIEDE2000 units [26,45] and is robust against the random selection of the initial color: estimates based on dif-
ferent starting points have a standard error of less than $0.1 \%$ of the average value. Notice that the procedure does not segment the space into a regular array of spheres with equal empty spaces in between, but rather an irregular packing of spheres is obtained where all colors are within a sphere.

To obtain an estimate of the number of colors discernible on the basis of nuances in hue and chroma, the computations described in the preceding paragraph were repeated ignoring the lightness component $L^{*}$, and therefore spheres were replaced with circles.

The color volume of natural scenes was obtained by segmenting the corresponding color space in unitary cubic subvolumes and by counting the number of these containing the color representation of at least one pixel [3,8]. For comparison with natural scenes, the total volume of the object-color solid was also estimated as follows. First, the optimal colors were computed for $L^{*}$ in the range 99-1, with spectral sampling of 0.1 nm in the range $380 \mathrm{~nm}-780 \mathrm{~nm}$, using the CIE 1931 XYZ color matching functions linearly interpolated for 0.1 nm and assuming that the rendering illuminant was CIE standard illuminant C. This illuminant was selected for comparison with previous studies. The volume enclosed by the optimal colors was then estimated using linear interpolation.

## 3. RESULTS

Figure 3 shows on the left the color gamut for the 50 scenes represented in the CIELAB ( $a^{*}, b^{*}$ ) diagram for $L^{*}=50$; on the right it shows the color volume for $L^{*}$ $<100$ projected into the same diagram. For comparison, optimal colors and the gamut obtained with the 4089 samples tabulated by M. Pointer [28] are also represented assuming that the rendering illuminant was CIE standard illuminant C. These samples comprise the Matte Munsell Atlas, The Royal Horticiltural Society Colour Chart, pigments from paints, printing nks, colored paper,
plastics, and textiles. The data for the optimal colors represented on the right were obtained by superimposing the areas corresponding to all lightness levels and by selecting the limiting points of the resulting region.

For $L^{*}=50$ the gamut of colors from natural scenes is considerable smaller than for optimal colors, and it is similar, although not coincident, to that determined by M . Pointer. For other lightness levels (not represented) the patterns of results present similar features.

The projection of the color volume in the CIELAB $\left(a^{*}, b^{*}\right)$ diagram produces an extended color gamut, but similar properties are observed; that is, the gamut of natural colors is smaller than for optimal colors and similar to that determined by M. Pointer. Notice that a couple of data points lay slightly outside the limits of the optimal colors; these points corresponded to colors produced by processes other than reflection (or transmission) and therefore are not object colors.

The total volume of the object-color solid in CIELAB was found to be 2.22 million, that is, close to the 2.28 million estimates by M. Pointer and G. G. Attridge [3] and the 2.05 million by Martínez-Verdú et al. [8]. On the other hand, the color volume occupied by the natural scenes was only 689,734 , that is, about $31 \%$ of the limiting theoretical volume.

Figure 4 shows on the left the distribution of the number of discernible colors for the set of 50 scenes. The solid curve represents a Gaussian fit to the data. Table 1 shows the average number of discernible colors across the 50 scenes obtained for the two conditions analyzed. As illustration, the top scene shown in Fig. 2 represents an example of a scene with a number of discernible colors below the average, the middle scene an example with a number of discernible colors about the average, and the bottom scene an example of a scene with a number of discernible colors above the average. The number of colors is represented in each case, and in parenthesis is represented the number of colors obtained when ignoring $L^{*}$.


Fig. 3. Color gamut represented in the CIELAB $\left(a^{*}, b^{*}\right)$ diagram corresponding to the colors of the 50 scenes of the database for lightness level $L^{*}=50$ (left) and the projection on that diagram of the colors corresponding to $L^{*}<100$ (right). For comparison, the optimal colors and the gamut obtained with 4089 samples tabulated by M. Pointer [28] are also represented assuming samples illuminated by CIE standard illuminant C.


Fig. 4. (Left) Distribution of the number of discernible colors for the set of 50 scenes analyzed. Estimates based on the CIEDE2000 formula. The solid curve represents a Gaussian fit to the data. (Right) Total number of discernible colors as a function of the number of scenes considered in the analysis. Data also based on the CIEDE2000 formula. The smooth curve represents an exponential fit to the data.

## Table 1. Estimates Obtained Using the ColorDifference Formula CIEDE2000: Average Number of Discernible Colors for the Set of 50 Scenes Analyzed and Asymptotic Values Obtained from the Exponential Fits

| Parameter | $\left(L^{*}, a^{*}, b^{*}\right)$ | $\left(a^{*}, b^{*}\right)$ |
| :---: | :---: | :---: |
| Average number <br> of discernible colors | $274,736(92,976)$ | $11,276(3,232)$ |
| Asymptotic values | $2,275,698$ | 26,256 |

${ }^{a}$ Data based on the three dimensions $\left(L^{*}, a^{*}, b^{*}\right)$ and just on $\left(a^{*}, b^{*}\right)$. Values in parenthesis indicate the sample standard deviation.

An average value of 274,736 discernible colors was obtained, that is, roughly 1 color for every 5 pixels of the images. The values obtained when ignoring $L^{*}$ were about $4 \%$ of the total number. Thus, the number of different colors that can be perceived are largely due to lightness variations and only a small fraction differ in hue and chroma.

Figure 4 shows on the right the total number of discernible colors expressed as a function of the total number of scenes considered in the analysis. The smooth curve represents an exponential fit to the data of the form $N \times\left(1-\mathrm{e}^{-k n}\right)$, where $n$ represents the number of scenes in the analysis and $N$ and $k$ were adjustable parameters. Table 1 shows the asymptotic values $N$ obtained for the two conditions analyzed.

The number of colors seems to converge to an asymptotic value, suggesting that the sample of scenes is representative of the population. The number of colors obtained when ignoring $L^{*}$ was about $1.1 \%$ of the total number of colors, which is a smaller fraction than that obtained for individual scenes and may indicate that there is more redundancy in hue and chroma than in lightness.

## 4. DISCUSSION

The main contribution of this work was to estimate for what we believe to be the first time the number of discern-
ible colors based on hyperspectral data of natural scenes and to compare the corresponding color volume with that of the theoretical limit of object colors. It was estimated that the total number of colors that can be discriminated in natural scenes is about 2.3 million and that this number corresponds to a volume of about $30 \%$ of the theoretical maximum. A number close to 2 million was reported previously for cubic just noticeable volumes [3,8] but was based on the idealized object-color solid and should not be confounded with the estimate obtained here.

Why is the gamut of the natural colors much smaller than for object colors? A possible interpretation is that natural spectral reflectances are considerably different from the idealized ones and, as a result, colors obtained in nature are more constrained than the idealized objectcolor solid, suggesting that a significant number of possible colors do not actually occur or are very rare.

If discrimination was assumed to be based only on the attributes of hue and chroma, the estimate obtained was about $1.1 \%$ of the total number. For individual scenes, however, this relationship was higher, about 4\%, suggesting that there is more redundancy in the hue and chroma than in lightness.

How representative is our database of the chromatic properties of the natural world? Clearly, there are limitations in the colors represented in the database. For example, it is well know that flowers with very saturated colors can be encountered in tropical environments [46], and these are unlikely to be well represented in databases of Mediterranean or Atlantic regions. Nevertheless, the fact that the number of colors obtained is practically stable as the number of scenes considered increased above 30 suggests that the 50 scenes selected may contain a good sample of all natural colors of that region.

The hyperspectral data were collected under a range of natural illuminants and, strictly, cannot be compared with data for the object-color solid illuminated by a single illuminant. Yet studies investigating the variation of the number of colors for the object-color solid as a function of the spectral composition of the illuminant [8] show that
the variations for daylights are small, and therefore the effect is unlikely to be large. The spectral composition of the illuminant in natural scenes also varies across the scene, and the application of the color-difference formulas in these nonideal conditions will produce only approximate results, but it is unlikely to influence the results critically.

Strictly, CIEDE2000 formulas apply only for uniform stimuli under well-defined adaptation conditions and do not describe with precision more complex conditions. Discrimination even with uniform samples depends on adaptation $[15,47]$ and, in images with complex chromatic structures, chromatic discrimination is determined by several parameters such as the color distribution in the images, the adaptation state of the observers, memory color, and chromatic textures, among others [30,48-50]. The spatial structure of the images also influences discrimination [51], and the S-CIELAB [44,52] metric is an attempt to extend the CIELAB to colored images; however, it only quantifies how accurate the reproduction of a color image is against the original and cannot be used here. Unfortunately, there are no available models taking all these effects into account, and our method is the one possible approach at present. Nevertheless, because the main effects are already considered, it seems unlikely that more complete models will change dramatically the order of magnitude of the figures obtained.

The results of this work imply that the visual system has to deal with less variety of colors than predicted from the analysis of the theoretical limits. Therefore, natural stimuli may, in some tasks, be thought as less demanding to the visual system than expected, for example, in color constancy, which is known to be less efficient with saturated colors [53]. On the other hand, the results suggest that the visual system may not use fully the available range for chromatic discrimination, which may represent a limitation in other tasks.

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