A METHOD FOR COLOR NAMING AND DESCRIPTION OF COLOR COMPOSITION IN IMAGES

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ABSTRACT

Color is one of the main visual cues and has been frequently used in image processing, analysis and retrieval. The extraction of high-level color descriptors is an increasingly important problem, as these descriptions often provide link to image content. When combined with image segmentation color naming can be used to select objects by color, describe the appearance of the image and even generate semantic annotations. For example, regions labeled as *light blue* and *strong green* may represent sky and grass, *vivid* colors are typically found in man-made objects, and modifiers such as *brownish*, *grayish* and *dark* convey the impression of the atmosphere in the scene. This paper presents a computational model for color categorization, naming and extraction of color composition. In this work we start from the *National Bureau of Standards'* recommendation for color names [4], and through subjective experiments develop our color vocabulary and syntax. Next, to attach the color name to an arbitrary input color, we design a perceptually based color naming metric. Finally, we extend the method and develop a scheme for extracting the color composition of a complex image. The algorithm follows the relevant neurophysiological findings and studies on human color categorization. In testing the method the known color regions in different color spaces were identified accurately, the color names assigned to randomly selected colors agreed with human judgments, and the color composition extracted from natural images was consistent with human observations.

1. COLOR PERCEPTION AND CATEGORIZATION

Color is a perceptual phenomenon related in a complex way to the spectral characteristics of electro-magnetic radiation that strikes the retina [1]. According to the theories postulated to explain human perception, color vision is initiated in retina where the three types of *cones* receive the light stimulus. The cone responses are then coded into one achromatic and two antagonistic chromatic signals. These signals are interpreted in the cortex, in the context of other visual information received at the same time and the previously accumulated visual experience. Once the intrinsic character of colored surface has been represented internally, one may think that the color processing is complete. However, humans go beyond the purely perceptual experience to categorize things and attach linguistic labels to them and color is no exception. A breakthrough in the current understanding of color categorization came from a study conducted by Berlin and Kay [2] who discovered remarkable regularities in the shape of the basic color vocabulary across different languages. Berlin and Kay introduced a concept of *basic color terms* and identified 11 basic terms in English (*black*, *white*, *red*, *green*, *yellow*, *blue*, *brown*, *pink*, *orange*, *purple* and *gray*). They also established the definitions of the *focal colors* as the centers of color categories and *graded*/*fuzzy membership*. Many later studies have proven this hypothesis, indicating that prototypical colors play a crucial role in internal representation of color categories, and the membership in categories is judged relative to the prototype. Unfortunately, the mechanism of color naming is still not completely understood: The existing theories of color naming have important drawbacks and are not implemented as full-fledged computational models [3].

Although color spaces allow us to specify or describe colors in unambiguous manner, in everyday life we mainly identify colors by their names. Hence, there were several attempts towards designing a vocabulary, syntax and standard method for choosing color names. Following the recommendation of the Inter-Society Council the National Bureau of Standards developed the *ISCC-NBS lexicon* of color names for 267 regions in color space [4]. This lexicon employs English terms to describe colors along the dimensions of **hue** (28 names constructed from a basic set *red*, *orange*, *yellow*, *green*, *blue*, *violet*, *purple*, *pink*, *brown*, *olive*, *black*, *white* and *gray*), **lightness** (*very dark*, *dark*, *medium*, *light* and *very light*), **saturation** (*grayish*, *moderate*, *strong* and *vivid*), and **lightness/saturation** (*brilliant*, *pale* and *deep*). One problem with this model is the lack of systematic syntax, which was addressed during the design of a new *Color-Naming System* (CNS) [5]. Both methods are based on the *Munsell system* [1], and thus provide explanation on how to locate each name within the Munsell color space. However, a notable disadvantage of the Munsell system for color-based processing is the lack of the exact transform from other color spaces. Furthermore, it is not obvious how to use the ISCC-NBS lexicon or CNS syntax to automatically attach names to sample colors, describe the color regions in a scene, and ultimately, communicate the color composition of an image. The only computational model that provides the solution to these problems is proposed in [3]. This work starts from the Berlin and Kay's color naming data and applies the normal distribution as a category model. However, the method is constrained to the fundamental level of color naming, as it was fitted to the basic color names, and does not account for commonly used saturation or luminance modifiers. Since it depends on the intricate fitting procedure, there is no straightforward extension of the model to include these attributes. The goal of our work is to develop a perceptually based color naming method that allows for higher level of color communication. The method should satisfy the following properties. Color naming operation should be performed in a perceptually controlled way so that the names attached to different colors reflect perceived color differences among them. Segmenting the color space into the color categories should produce smooth regions. The method should account for the basic color terms and use systematic syntax to combine them. It should respect the graded nature of category membership, the universality of color foci, and produce results in agreement with human judgments. The first step in our work (Section 2) involves a development of balanced and well-represented set of color prototypes, i.e. *vocabulary*, and the corresponding *syntax*. In the next step we design a *color naming metric*, which, for an arbitrary input color, determines the category membership (Section 3). Finally, we extend this approach to name color regions and develop descriptors of color composition in complex scenes (Section 4).

2. THE COLOR NAMING VOCABULARY AND SYNTAX

As a starting point for our vocabulary we adopted the ISCC-NBS lexicon, since it provides a model developed using controlled perceptual experiments and includes the basic color terms. Each category is represented with its centroid color, thus preserving the notion of color foci. Yet, due to the strict naming convention the dictionary includes several names that are not well understood by the general public (*blackish red* for example) and lacks a systematic syntax. As the centroid colors span the color space in uniform fashion and allow grading between the categories, we decided to use these points as the prototypes in our color naming algorithm, yet we had to devise our own name structure that follows few simple systematic rules. To determine a reliable color vocabulary, we have performed a set of subjective experiments aimed at testing the agreement between the names from the ISCC-NBS lexicon and human judgments, adjusting the lexicon for the use in automatic color naming applications, and, most importantly, gain better understanding of human color categorization and naming.

We conducted four experiments: *color listing experiment* aimed at testing eleven basic color categories established in Berlin and Kay study [2], *color composition experiment* aimed at determining color vocabulary used in describing complex scenes, and two *color naming experiments* aimed at understanding human behavior in color naming and adjusting the differences between the human judgments and the semantics of the ISCC-NBS vocabulary. Ten subjects participated in the experiments. All subjects had normal color vision and normal or corrected-to-normal vision.

Color listing experiment In addition to the 11 basic color terms in English, some studies indicated few marginal cases such as *beige*/*tan* or *olive* and *violet*. To test the relevance of these terms we asked each of our subjects to write on a sheet of paper names of at least twelve "most important" colors.

Color composition experiment Here the subjects were presented with 40 photographic images in a sequence and asked to name all the colors in the image. The images were selected to include different color compositions, spatial frequencies and arrangements among the colors, and provided broad content. Each image was displayed on the computer monitor, against light gray background. The order of presentation was randomly generated for each subject.

Color naming experiments In these experiments, the subjects were presented with the 267 centroid colors and asked to name each one of them. The color patches were displayed on the computer monitor, in a room that received daylight illumination. The monitor was calibrated so that there was no difference between the colors on the monitor and corresponding chips form the Munsell Book of Colors [1]. In the first experiment, 64×64 pixel patches were arranged into 9×6 matrix and displayed against the light gray background. The names were assigned by typing into a text box below each patch. After naming all the colors, the display was updated with the new set of patches, until all 267 centroid colors have been named. In the second color naming experiments, only one 200×200 pixels color patch was displayed on the screen. In all experiments subjects were advised to use common color names and common modifiers for brightness or saturation, to avoid names derived from objects/materials, and derive new names by combining the basic hues with the modifier *–ish* (*greenish blue*).

Here is the brief summary of the most important findings. As expected, in the Color listing experiment 11 basic colors were found on the list of every subject. Nine subjects included *beige*, four included *violet*, and two included *cyan* and *magenta*. Modifiers for hue, saturation and luminance were not used. None of the subjects listed more than 14 color names. Surprisingly, the subjects maintained the same limited vocabulary when describing images in the Color composition experiment, and added only *beige* to the basic colors. In attempt to distinguish between the different types of the same hue, the subjects often used modifiers for saturation and luminance. The modifiers for hue were not frequently used. Although most of the images had rich color histograms, the subjects were not able to perceive more than ten colors at once. Dark colors, which typically exist in natural images due to shadows and edges, or light colors due to highlights and specularities, were never included in the description, and were named only when referring to well-defined objects/regions. The subjects showed the highest level of precision in the Color naming experiments. Most of them (9/10) frequently used modifiers for hue, saturation or brightness. Seven subjects used *olive*, although they had not used this term in the previous experiments. On the other hand, although it had been listed in the Color listing experiment, *violet* was seldom used and was most of the time described as *bluish purple*. Modifiers *brilliant* and *deep*, as in the ISCC-NBS vocabulary, were not used - they were replaced with the descriptors *strong light* and *strong dark*. There was a very good degree of concordance between the subjects; In the first Color naming experiment, 223 samples were assigned the same hue by all subjects (with variations in the use of modifiers), 15 were assigned into one of two related hue categories (such as *greenish blue* and *blue*), 19 were assigned into one of three related hue categories. The remaining 10 color samples were not reliably assigned into any category. Out of 223 hues that were assigned into the same category by all subjects, 195 were the same as in the ISCC-NBS vocabulary, 22 were assigned to a related hue, and 8 were assigned entirely different color name. Similar results were obtained in the second Color naming experiment. The major difference between the subjective results and the color names from the ISCC-NBS vocabulary involved the use of the saturation modifiers - colors appeared less saturated to our subjects and they generally applied higher thresholds when attaching modifiers like *vivid* or *grayish*. There was also a very good agreement between the two experiments - 79 samples were assigned the same color name in both experiments, 121 were assigned the same hue, 42 were assigned one of two related hues, 20 were assigned one of three related hues, and 5 samples were assigned into non-related categories. The difference between the two experiments was in the use of modifiers, since the same color was often perceived lighter and more chromatic when displayed in the smaller window. For the final vocabulary we have selected the names from the first Color naming experiment, as they were generated in interactions with multiple colors and seem to provide a better representative of the real-world applications. Based on our findings we have devised the final vocabulary and generalized it in the following syntax (note that : denotes "is defined as", | denotes meta-or, and [] is the optional occurrence of the enclosed construct):

color name : achromatic name | chromatic name
achromatic name : lightness *gray* | *black* | *white*
chromatic name : lightness saturation hue | saturation lightness hue
lightness : *blackish* | *very dark* | *dark* | *medium* | *light* | *very light* | *whitish*
saturation : *grayish* | *moderate* | *medium* | *strong* | *vivid*
hue : generic hue | -ish form generic hue
generic hue : *red* | *orange* | *brown* | *yellow* | *green* | *blue* | *purple* | *pink* | *beige* | *olive*
ish form : *reddish* | *brownish* | *yellowish* | *greenish* | *bluish* | *purplish* | *pinkish*

3. THE COLOR NAMING METRIC

Since the color naming process should address the graded nature of category membership and take into account the universality of color foci, we will perform color categorization through the *color naming metric*. Assuming a well-represented set of prototypes (foci), the metric computes the distance between the input color and all the prototypes, thus providing a membership value for each categorical judgment. Although commonly used as measure of color similarity, Euclidean distance in the *CIE Lab* color space has several serious drawbacks for the application in our method. The first problem is related to the sparse sampling of the color space. It is well known that the uniformity of the *Lab* suffers from defects, so that "nice" perceptual properties remain in effect only within a radius of few *just-noticeable differences* [1]. Since there are only 267 points in our vocabulary, the distances between the colors may be large and the metric only partially reflects the degree of color similarity. For example, when the vocabulary was used with the *Lab* distance to name the points on the gray line ($0<L<100$, $a = b = 0$), some regions were named *pinkish white* and *dark greenish gray*, instead of *white* and *dark gray*. The other, more serious problem is related to our perception of color names and their similarity. Let us assume an arbitrary color represented by a point c_p in the *Lab* space, and a set of neighboring colors $\{c_{ni}\}$, on a circle with the radius L in that space. Although all the pairs (c_p, c_{ni}) are equally distant, we do not perceive them as equally similar. This is illustrated in Fig. 1, where the color c_p is compared to the colors c_{x1} - c_{x5}, all with $D_{Lab}(c_p, c_{xi}) = 10$, demonstrating that the perceptual differences between these colors are not equal.

Testing the hypothesis: Color similarity experiment

To test the relationship between the perceptual similarity, color distances and angles in the *Lab* and *HSL* color spaces, we conducted a subjective experiment. Four subjects participated in the experiment. The subjects were given ten sets of color samples. Each set consisted of a "prototype" color c_p, and five colors, $\{c_{xi}\}_{i=1,..5}$, so that $D_{Lab}(c_p, c_{xi}) = const$. The distances between the prototype and the rest of the colors ranged from 6 to 25. For each set the subjects were asked to order the samples according to the perceived similarity to the set prototype. The sets were displayed in sequence on a computer monitor with light gray background under the daylight illumination. The first thing we observed is that for $D_{Lab} < 7$ all the colors were perceived as equally similar to the prototype. In all other cases subjects identified the best and worst match unanimously, frequently leaving other samples unranked. Typically, the colors our subjects failed to rank were close in all three values. For the ranked colors, the correlation between the rankings and θ_{HSL} was 97%, the correlation with D_{HSL} was 95%, and the correlation with θ_{Lab} was only 77%. These results indicate that θ_{HSL} and D_{HSL} (alone or combined) are much better predictors of perceptual similarity between the equidistant colors than θ_{Lab}, although none of these two values alone represents an accurate color naming metric.

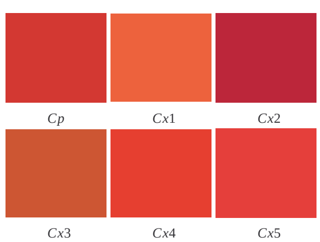

Fig. 1: Example of the equidistant pairs of colors. The color data is given in Table I.

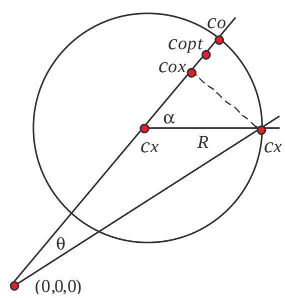

Fig. 2: Developing the color naming metric.

TABLE I	c_p: $(L,a,b) = (47,70,55)$ $(h,s,l) = (0,90,85)$					
	(L,a,b)	(h,s,l)	D_{Lab}	D_{HLS}	θ_{Lab}	θ_{HLS}
c_{x1}	(57,70,55)	(5,82,98)	10.0	17.0	4.8	7.5
c_{x2}	(37,70,55)	(349,100,73)	10.0	24.0	5.3	11.1
c_{x3}	(47,60,55)	(11,91,81)	10.0	17.8	4.4	8.3
c_{x4}	(53,76,60)	(0,89,96)	9.9	11.0	0.90	3.8
c_{x5}	(53,76,50)	(354,89,95)	9.9	13.7	4.8	5.5

Designing and testing the color naming metric

The color naming metric we designed captures the findings from the experiment. Let us assume a prototype c_p and arbitrary input color c_x. As discussed previously, for a given $D_{Lab}(c_p, c_x)$, the combination between $D_{HSL}(c_p, c_x)$ and $\theta_{HSL}(c_p, c_x)$ reflects the "reliability" of the *Lab* distance as the measure of similarity in the colorname domain. Thus, we will use this relationship to modify D_{Lab} in the following manner. We first compute the distances between c_p and c_x in the *Lab* and *HSL* spaces:

$$D_{Lab}(c_p, c_x) = L = \sqrt{(l_p - l_x)^2 + (a_p - a_x)^2 + (b_p - b_x)^2}\ ,$$

$$D_{HLS}(c_p, c_x) = R = \sqrt{s_p^2 + s_x^2 - 2 s_p s_x \cos(h_p - h_x) + (l_p - l_x)^2}\ .$$

Given the radius R, we then find the color $c_o : (h_o, s_o, l_o)$, so that:

$$D_{HLS}(c_p, c_o) = R\ ,\ \theta_{HSL}(c_p, c_o) = \frac{s_p s_o + l_p l_o}{\sqrt{(s_p^2 + l_p^2)(s_o^2 + l_o^2)}} = 0\ . \quad (1)$$

Solving (1) results in: $h_o = h_p$, $s_{o1,2} = s_p(1 \pm R/(s_p^2 + l_p^2)^{1/2})$, $l_{o1,2} = l_p(1 \pm R/(s_p^2 + l_p^2)^{1/2})$, and we chose the point that satisfies $\theta_{HSL}(c_x, c_o) < \pi$. This is illustrated in Fig. 2. According to our hypothesis, given the distance L, the optimal perceptual match corresponds to the direction $\theta_{HSL}(c_p, c_o) = 0$. Assuming a small increment ΔR, we then update the initial solution c_o in the following manner: $R_o = D_{HSL}(c_p, c_o)$, $s_o = s_o(1 \pm \Delta R/R_o)$, and $l_o = l_o(1 \pm \Delta R/R_o)$, until $D_{Lab}(c_p, c_o) \approx D$. At this point, c_o represents an optimal perceptual match to c_p, for the given *Lab* distance. We denote this solution c_{opt}. As an estimate of perceptual dissimilarity between c_x and c_{opt}, we compute the relative difference between c_{opt}, and the projection $c_x \perp c_{opt}$:

$$\begin{aligned}\Delta d(c_p, c_x) &= \frac{d(c_p, c_{opt}) - d(c_p, c_{ox})}{d(c_p, c_{opt})} = \frac{R_o - R\cos\beta}{R_o} \\ &= 1 - \frac{s_p s_x \cos(h_p - h_x) + l_p l_x - s_p^2 - l_p^2}{R_o \sqrt{s_p^2 + l_p{}^2}}\end{aligned} \quad (2)$$

As required by our model, in predicting the amount of perceptual similarity this formula takes into account both the distance and the angle in the *HSL* space. Therefore, we use this value to modify the *Lab* distance between the colors c_p and c_x as follows:

$$D(c_p, c_x) = D_{Lab}(c_p, c_x)[1 + k(D_{Lab}(c_p, c_x))\Delta d(c_p, c_x)] \quad (3)$$

i.e. the *Lab* distance is increased proportionally to the amount of dissimilarity Δd. The factor $k(L)$ is introduced to avoid modifying distances between very close points, $k(L) = 0$ if $L < 7$, and limit the amount of increase for large L, $k(L) = const$ if $L > 30$.

To test the stability of the method we applied the metric to name different color regions in the *RGB* and *HSV* color spaces. Fig. 3 shows the transition of color names along the black-red and purple-white lines in the *RGB* space, and along the "color circle" in the *HSL* space defined with $s = 83$ and $l = 135$. As it can be seen in both color spaces color names change smoothly and the know color regions are identified accurately. To test the agreement with human observers we asked four subjects to review the color names assigned by our method to 100 randomly selected colors. Each subject received a different set of colors. The experimental setup was the same as in the first color naming experiment. The subjects agreed with the assigned color name in 91% of cases (362/400). For the remaining 38 colors the subjects felt that the second-best color name provided more accurate description.

4. EXTRACTING THE COLOR COMPOSITION

The human observation of a scene is very different from the recorded image. Thus, the histogram of color names, computed from the image pixels directly, without taking into account their spatial interactions does not provide an accurate description of color content. To address the issue of color composition we need to resolve, at least to a certain extent, the issues of color constancy, segmentation and scene understanding. In this section we present an algorithm that takes into account these problems and provides a description consistent with human observation. The algorithm has two parts. The first one deals with color constancy, while the second part performs image smoothing and segmentation suitable for the extraction of perceived colors.

Color constancy The approach we adopt here is similar to the one described in [3], as it seems to be fairly robust with respect to different lightning conditions, and to some extent, different sensing devices. As we need to compensate for the differences in illumination conditions, we will rely on the Von Kries *law of coefficients* as the most accepted hypothesis. Although the properties of the light source cannot be completely recovered from the image, as long as the spectrum of the light source is not too distorted, this model provides reasonable results [1,3]. We therefore search the image for the "best representatives" of white w, and black b, and use them to apply the modified Von Kries adaptation

$$c'(x,y) = \frac{c(x,y) - b}{w - b}$$

where $c(x,y)$ is the original color in the linear color space at the position (x,y), $c'(x,y)$ is the transformed value, and b and w are found as follows. The original image is first median filtered to refine the well-defined color regions and remove "noisy" pixels that do not contribute to the perceived colors. Next, each pixel is represented as: $c(x,y) = (d_b(x,y), d_w(x,y))$, where $d_b(x,y)$ and $d_w(x,y)$ are the color name distances (3) between the given pixel and the black and white prototypes from the vocabulary, respectively. Then the black and white prototypes are chosen as: $b = c(x_p, y_p)$, $(x_p, y_p) = \arg\min(d_b(x,y))$, and $w = c(x_p, y_p)$, $(x_p, y_p) = \arg\min(d_w(x,y))$. This procedure can be understood as stretching the gray axis of the original image and realigning it with the theoretical gray axis for perfectly homogeneous flat-spectrum illumination. The color constancy algorithm is illustrated in Fig. 4b.

Spatial averaging and segmentation In the early stages human visual system performs significant amount of spatial averaging, which accounts for the way we interpret color information. However, the amount of averaging depends on the spatial frequencies, color interactions, size of the observed objects and the global context. For example, the capability of human visual system to distinguish different colors drops rapidly for high spatial frequencies. As only averages of the microvariations are perceived we describe textures with very few colors. Still, we do not average isolated edges, since they represent object/region boundaries. Therefore, we model human perception as an adaptive low-pass filtering operation. We start by reducing the number of colors in the image to 5 bits/pixel, via the *LBG* vector quantization algorithm. For each pixel we then compute its local color contrast, *con*(x,y)

$$con(x,y) = \frac{\| c(x,y) - \bar{c}(x,y) \|}{\| \bar{c}(x,y) \|}$$

where $\bar{c}(x,y)$ is the average color in a small neighborhood around $c(x,y)$ (we used the radius of D/50, where D is larger between the image height and width) and $\|\cdot\|$ is the norm of the vector. The pixel (x,y) is considered an edge if its contrast exceeds a predefined threshold con_{min}. To separate contour, uniform and texture pixels we use a sliding window to estimate the mean m, and variance v, of edge density for each pixel. Depending on these estimates we label pixels as: TYPE 1) uniform, $m = 0$, TYPE 2) noise, $m < t_{m1}$, TYPE 3) contour, i.e. edge between two uniform regions, $t_{m1} < m < t_{m2}$, TYPE 4) texture edge, i.e. transition between uniform and textured region, $t_{m2} < m < t_{m3}$, TYPE 5) coarse texture $t_{m3} < m$, $t_v < v$, or TYPE 6) fine texture $t_{m3} < m$, $t_v > v$. This operation produces *edge maps* (Fig. 4 c,d), which control the smoothing process and computation of dominant colors in the following way. The noise pixels are removed. Since human eye creates a perception of single color within uniform regions, the amount of smoothing is largest for the uniform pixels. To allow for the highest amount of smoothing, the radius of the smoothing kernel is chosen adaptively at each point, depending on the distance to the closest contour or transition pixel. Contour and transition pixels are not smoothed. Also, they are not used in computing the color composition, since edges do not contribute to the way humans describe color content. The amount of averaging performed in textured areas depends on the edge density, and is higher for fine textures and lower for coarse textures. Thus, for each pixel the perceived color $pc(x,y)$ is computed as:

$$pc(x,y) = (c * g_{N(x,y)})(x,y), \quad g_{N(x_c,y_c)}(x,y) = k\exp(-\frac{x^2+y^2}{\sigma^2})$$

where the radius of the support of the Gaussian kernel g_N, $N(x,y)$, depends on the type of pixel in the center of the kernel (x_c, y_c) as:

$$N(x,y) = \begin{cases} \|(x,y) - (x_e,y_e)\|, & \text{uniform region, } (x_c,y_c) \text{ is Type 1} \\ D, & \text{coarse texture, } (x_c,y_c) \text{ is Type 5} \\ 2D, & \text{fine texture, } (x_c,y_c) \text{ is Type 6} \end{cases}$$

and (x_e, y_e) is the edge pixel closest to (x,y). The resulting image is then subjected to the mean-shift color segmentation [6]. To generate the color composition, we then use the color segmented image, and via (3) attach the color name to all significant regions. Fig. 4 shows the most important steps in the algorithm, resulting in the following color composition: *strong purplish red* 29%, *vivid yellow* 21%, *strong light yellowish green* 4%, *moderate purplish pink* 22%, and *moderate dark purplish pink* 9%. In the Color naming experiment the same image was described as: *bright purple*, *yellow*, *light green*, *pink* and *dark pink*. In conclusion, we have tested the procedure on the images used in the Color composition experiment, and obtained descriptions in excellent agreement with human observations.

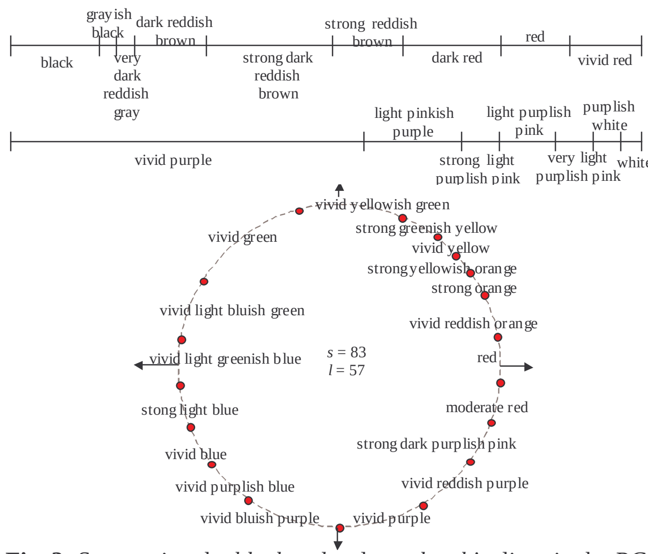

Fig. 3: Segmenting the *black-red* and *purple-white* lines in the *RGB* space, and the color circle in the *HSL* space.

Fig. 4: a) Original image, b) color-constancy processed image, c) edges and transition regions (white), d) textured regions (white), e) smoothed image, and f) color segmented image.

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