

Research Article

A Discrete Model for Color Naming

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The ability to associate *labels* to *colors* is very natural for human beings. Though, this apparently simple task hides very complex and still unsolved problems, spreading over many different disciplines ranging from neurophysiology to psychology and imaging. In this paper, we propose a discrete model for computational color categorization and naming. Starting from the 424 color specimens of the OSA-UCS set, we propose a fuzzy partitioning of the color space. Each of the 11 basic color categories identified by Berlin and Kay is modeled as a fuzzy set whose membership function is implicitly defined by fitting the model to the results of an ad hoc psychophysical experiment (Experiment 1). Each OSA-UCS sample is represented by a feature vector whose components are the memberships to the different categories. The discrete model consists of a three-dimensional Delaunay triangulation of the CIELAB color space which associates each OSA-UCS sample to a vertex of a 3D tetrahedron. Linear interpolation is used to estimate the membership values of any other point in the color space. Model validation is performed both directly, through the comparison of the predicted membership values to the subjective counterparts, as evaluated via another psychophysical test (Experiment 2), and indirectly, through the investigation of its exploitability for image segmentation. The model has proved to be successful in both cases, providing an estimation of the membership values in good agreement with the subjective measures as well as a semantically meaningful color-based segmentation map.

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1. INTRODUCTION

Color is a complex issue. Color research is intrinsically interdisciplinary, and as such gathers the efforts of many different research communities, ranging from the medical and psychological fields (neurophysiology, cognitive sciences) to the engineering fields (image and signal processing, robotics). Color naming implies a further level of abstraction, going beyond the field of vision-related sciences. The strong dependency on the development of the language implies a progressive *evolution* of the mechanisms responsible for color categorization and naming [1–3]. Accordingly, the definition of a computational model must account for the *dynamics* of the phenomenon, in the form of an *updating* of the *labels* used to describe a given color as well as of the *location* of the corresponding colors in the considered color space.

Color categorization is intrinsically related to *color naming*, which lies at the boundary between different fields of cognitive sciences: visual perception and linguistics. Color naming is about the labelling of a given set of color stimuli according to their *appearance* in a given observation condition. Pioneering this field, the work of Berlin and Kay [4] traces back to the early 1970's, and has settled the ground for

the proliferation of the next wave of cognitive studies, like those of Sturges and Whitfield [5, 6] and Lammens [7]. In particular, Berlin and Kay found that there are *semantic universals* in the domain of color naming, especially in the extension of what they call *basic color terms*.

The cornerstones of such a vast investigation can be summarized as follows:

- (i) the *best examples* of basic color categories are the same within small tolerances of speakers, in any language, that has the equivalent of the basic color terms in question;
- (ii) there is a hierarchy of languages with respect to *how many* and *which* basic color terms they possess (i.e., a language that has $i + 1$ basic color terms features all the basic terms of any language with i color terms, and any language with i basic color terms has the same ones);
- (iii) basic color categories are characterized by *graded membership functions*.

A corollary of such findings is that a set of *color foci* can be identified and, what is most important for image processing, *measured*, as being the *best representative* of the naming category they pertain according to psychophysical scaling. In

other terms, *color foci* represent the *best examples* of a named color out of a set of color samples.

As very well pointed out in [7], the *color naming* process consists in a mapping \mathcal{N} from the color representation domain to a multidimensional naming space which associates to a given color stimulus (i) a *color name*; (ii) a *confidence* measure, and (iii) a *goodness* or *typicality* measure.

The set of color terms that can be considered as universal constants (among the languages that have at least the necessary number of color terms) are the following: *white, black, red, green, yellow, blue, brown, pink, purple, orange, gray*.

Based on this, it is possible to derive the same number of equivalent classes, while keeping into account the fuzzyness of the categorical membership.

The interest of color categorization in the image processing framework is that it enables the identification of “color naming fuzzy clusters” in any color space, establishing a direct link between the *name* given to a color and its *location* in the color space. This goes beyond the classical partitioning of the color space by clustering techniques based on color appearance models, because the color descriptors are no more uniquely dependent on the (suitably defined) tristimulus values and colorimetric model.

Linking *semantic features* with numerical descriptors is one of challenges of the multimedia technology. Computational models of color naming naturally lead to the design of automatic agents able to predict and reproduce the performance of human observers in *sensing* (through cameras or other kind of equipments), *identifying*, and *classifying* colors, as pertaining to one out of a set of predefined classes with a certain degree of confidence and in a reproducible manner.

The potential of color naming models has triggered a considerable amount of research in recent years following the way opened by Lammens [7]. Among the more recent contributions are those of Belpaeme [1, 2], Bleys [8], and Mojsilović [9]. Designing a color naming system hides very difficult problems. The many possible choices for the set of control parameters (color naming system, reference color space, standard illuminant, model features) make it difficult to gather all this knowledge into a unified framework. Different color naming systems often refer to different uniform color spaces, for which a closed form or exact transformation to a “usable” color space (like XYZ, Lab, LMS) is usually not available. Roughly speaking, there is a great deal of uncertainty in managing colors, which makes it difficult to gain a clear and unified perspective.

The extraction of high-level color descriptors is gaining an increasing interest in the image processing field due to its intrinsic link to the representation of the image content. Semantic annotations for indexing, image segmentation, object recognition, and tracking are only few of the many examples of applications that would take advantage of an automatic color naming engine. When the exploitability of the model for image processing is an issue, the outcomes of the model must be some *measurable* quantities suitable for feature extraction and analysis, and, as such, eligible as image descriptors.

In this paper, we propose a discrete computational model for color categorization. Given the tristimulus value of a color randomly picked in the CIELAB space, the so-defined ideal observer provides the estimation of the probability of that color being classified as pertaining to each of the 11 predefined categories. This corresponds to a smooth partitioning of the color space, where the membership functions of each category are shaped on the data collected by an ad hoc psychophysical experiment (Experiment 1). The model is subsequently validated by comparing the estimated membership values of a color sample with the corresponding relative frequencies measured via another subjective test (Experiment 2). The model exploitability for image processing is assessed by the characterization of its performance for semantic color-based segmentation.

This paper is organized as follows. Section 2 describes the subjective experiments; Section 3 illustrates the discrete model. The performance is discussed in Section 4, and Section 5 derives conclusions.

2. METHODS

2.1. Color system

In this study, we used the OSA-UCS color system as in Boynton and Olson [10]. The data obtained by Boynton and Olson cannot be directly applied to our purpose because of two reasons. First, only the *centroids* and *foci* are provided for each color category and for each subject, while the whole set of subjective data is needed for fitting our model. Second, in that study the samples were observed in completely different conditions, namely, they were mounted on 5-inch squares of acid free Bristol board seen by the subject through a 3.8 cm-square aperture in a table slanted 20° upwards from horizontal. The source of illumination was a 200 Watts photoflood lamp at 3200 K mounted above the subject’s head [10].

The OSA-UCS is a color appearance system that has been developed by the Optical Society of America (OSA) [11]. Color samples are arranged in a regular rhombohedral lattice in which each color is surrounded by twelve neighboring colors, all *perceptually* equidistant from the considered one. Figure 1 shows the solid centered at a point in the L, g, j space.

The color chips illustrated in the atlas closely reproduce the appearance of a set of colors of given CIE 1964 coordinates when viewed under the daylight (D65) illumination on a middle gray surround (30% reflectance). The CIE 1964 and OSA-UCS L, g, j coordinates are related by a nonlinear transformation [11].

The OSA-UCS system has the unique advantage of equal perceptual spacing among the color samples. Such a supra-threshold uniform perceptual spacing is the main reason behind the choice of using the OSA-UCS space instead of another color dataset more suitable for the applications to be used as reference. The main inconvenience of this choice is that the volume of the color space corresponding to the OSA samples fails to extend to highly saturated regions. In consequence, this constrains the applicability of the model only to

the region of the color space that is represented by the OSA samples, of course limiting its exploitability from the image processing perspective. Accordingly, after having verified the potential of the proposed approach in the current prototyping phase, the next step of our work will be to extend the set of color samples to adequately represent the entire region of the color space that is concerned with the foreseen applications by designing a suitable color sampling scheme.

2.2. Color naming model

After choosing the color system, the color naming model must be specified. Attributing a label to a color requires a color vocabulary that is expression of both the cultural background (implicitly) of the speakers and the application framework. For instance, the Munsell color order system [11] is extensively used in the production of textiles and paintings, allowing a highly detailed specification of colors. The ISCC-NBS [12] dictionary was developed by the NBS following a recommendation of the Inter-Society Council. It consists of 267 terms obtained by combining five descriptors for lightness (*very dark, dark, medium, light, very light*), four for saturation (*grayish, moderate, strong, vivid*), three for brightness and saturation (*brilliant, pale, deep*), and twenty-eight for hues constructed from a basic set (*red, orange, yellow, green, blue, violet, purple, pink, brown, olive, black, white, gray*).

However, as pointed out in [9], such dictionaries often suffer from many disadvantages like the lack of both a well-defined color vocabulary and an exact transform to a different color space. This is the case for the Munsell system for instance, and to a certain extent also of the ISCC-NBS one. As it is usually the case, colors are *described* in terms of *hue, lightness, and saturation*. Noteworthy, since the language evolves in time, many terms of the dictionary become obsolete and as such are not adequate for color description.

In our work, we constrain the choice of the color names to the 11 basic terms of Berlin and Kay. The reasons is twofold. First, we want to set up a framework as simple as possible in order to design and characterize a prototype system and check its usefulness in a given set of applications (like image segmentation and indexing). It is worth mentioning that the more names are allowed, the more subjective data are needed for both model fitting and validation, in order to have an acceptable estimation of the categorization probabilities of each data sample. Second, we foresee to follow a *multiresolution* approach, allowing for a progressively refinable description of the color features generating a nested partitioning of the color volume. Accordingly, the color space will be initially split into a set of 11 regions corresponding to the 11 basic colors. Such regions will overlap due to the intrinsic *fuzziness* of the categorization process and will serve for the automatic naming of color samples at the first *coarser* level. Next step will be the definition of a set of descriptors for each color attribute (as exemplified above referring to the ISCC-NBS color naming system) jointly with a syntax allowing to combine them in a structured way, as in [9]. Again, we will follow the multiscale approach and

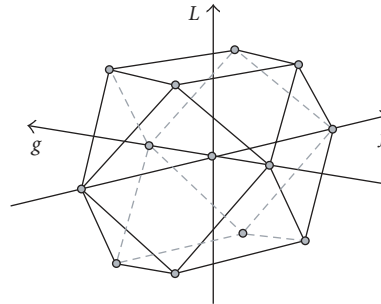


FIGURE 1: In the OSA color system, color samples are arranged in a regular rhombohedral lattice in which each point is surrounded by twelve neighboring colors, all perceptually equidistant from the central one.

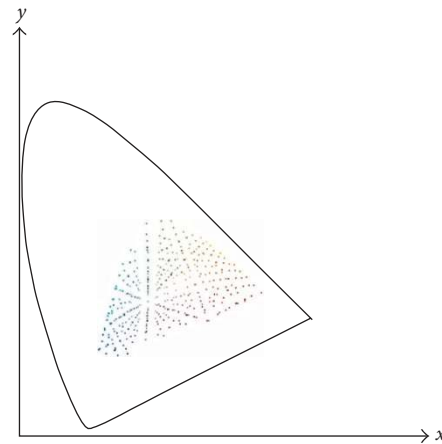


FIGURE 2: The 424 OSA-UCS samples represented in the xy space.

allow for a progressive refinement of the granularity in the description of the color features. This will end up with a sequence of nested subvolumes that will result in the description of a color in the form *80% light bluish green and 20% light blue*.

Though, this is left for future work and goes beyond the scope of this paper.

2.3. Experiment 1

As mentioned above, the first experiment aimed at the categorization of the 424 OSA-UCS color samples. Figures 2 and 3 illustrate the positions of the OSA samples in the xy and CIELAB spaces, respectively.

2.3.1. Subjects

Six subjects aged between 25 and 35 years participated in this experiment (5 males and 1 female). Two of them were familiar with color imaging and the others were naives. All of them were volunteers. They were screened for normal color vision

through the Ishihara test. Each subject repeated the test three times.

2.3.2. Procedure

The 424 OSA samples were displayed on a CRT calibrated monitor in a completely dark room. Each color sample was shown in a square window of size $2 \times 2 \text{ cm}^2$ in a mid luminance gray background. The visual angle subtended by the stimulus was about 2 degrees in order to avoid the interference of rod mechanisms. The viewing distance was of 57 cm. The OSA samples were presented one at a time in random order. The order was different for each block of trials (three for each subject) and within trials for the same subject. Standard instructions were provided in written form in the center of the screen using white characters on the same gray background used for the experiment. The task consisted in naming each color sample using one of the 11 basic terms. To this purpose, the labels were shown using the corresponding string of characters enclosed in a square of the same size of the sample. Both the characters and the square sides were light-gray. The squares were arranged along a circle centered on the sample location. The ray of the circle was such that the average distance of the squares resulted in about 2 cm. The location of the squares along the circle was randomized, in order to avoid bias effects on the judgement related to the relative distance of the squares from the starting gaze direction. No time constraints were given. When ready, the subject made her/his choice by clicking on the corresponding square with the mouse. Figure 4 shows an example of the test stimulus.

2.4. Experiment 2

The second experiment was aimed at the model validation. The same experimental setting as in Experiment 1 was used, the difference being in the set of color samples the subject was asked to classify.

2.4.1. Subjects

The same six subjects that participated in Experiment 1 also took part to Experiment 2. This allows limiting the fluctuations in color categorization due to intersubject variability. A larger number of subjects would be needed for a more precise fitting, or, equivalently, model training.

2.4.2. Procedure

A total of $N_c = 100$ colors were randomly sampled from the volume enclosed by the OSA outer (more saturated) samples at each luminance level following a uniform probability distribution. Figure 5 illustrates the resulting color set. The same paradigm as in Experiment 1 was followed: the subjects were shown each color sample and asked to name it by clicking on the corresponding square. The same set of colors was shown three times to each observer in random order to

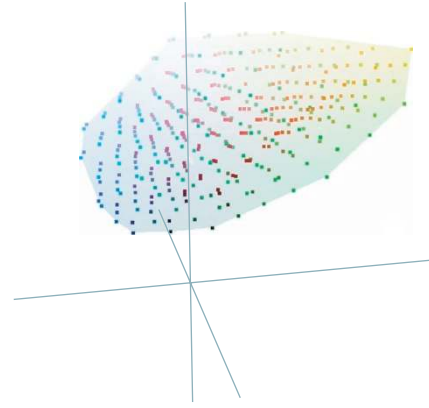


FIGURE 3: The 424 OSA-UCS samples represented in the CIELAB space.

estimate its probability of classification within each of the 11 categories.

The outcome of this experiment is the estimation of the category membership of each color sample.

3. THE DISCRETE MODEL

In our model, each point in the color space is represented by an 11-component feature vector. Each component represents the estimated membership value of the sample to one category. For points corresponding an OSA-UCS sample such values coincide with the measured relative frequencies of classification of the point in the different categories. The membership values for the rest of the colors are estimated by linear interpolation. The discrete model consists of a three-dimensional Delaunay triangulation [13] of the color space which associates each OSA sample to a vertex of a 3D tetrahedron. The Delaunay triangulation is particularly suitable for our purpose because it provides a well-balanced partitioning of the space, according to a predefined criterion.

The membership value of any color lying inside of the tetrahedron is estimated as a linearly weighted sum of the analogous values of the four vertexes of the enclosing tetrahedron.

Let $f_C(\vec{x})$ be the feature vector associated to color C at position \vec{x} , $\vec{x} = \{L, a, b\}$ in the CIELAB space. For the points corresponding to the OSA samples, the i th component of the feature vector represents the relative frequency of classification of color C in the category i :

$$f_C^i(\vec{x}) = \frac{N_C^i}{N}, \quad (1)$$

where N_C^i is the number of times C has been classified as pertaining to class i evaluated over the whole set of subjects and blocks, and N is the total number of times that the color was displayed (number of subjects $\times 3$). Setting such membership values amounts to fitting the model to the actual data gathered by the subjective experiment.

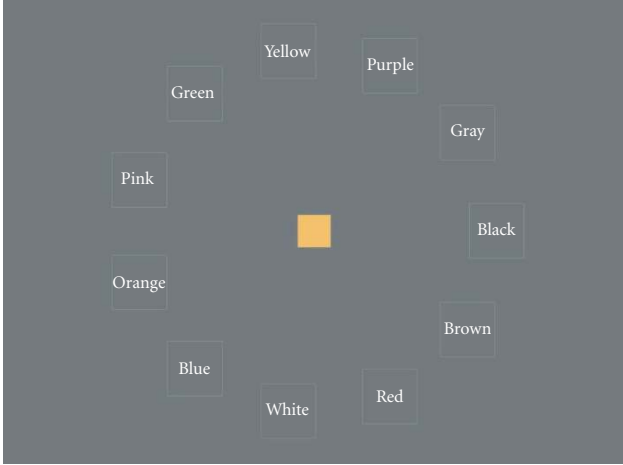


FIGURE 4: Stimulus example. The test color is pasted at the center of the image, on a gray background.

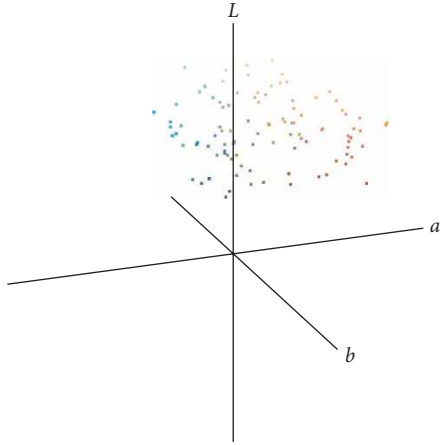


FIGURE 5: Set of color samples used for model validation.

For any color c inside the tetrahedron, the components of the feature vector are estimated as follows:

$$f_c^i = \sum_{j=1}^4 \lambda_j f_{C_j}^i, \quad (2)$$

where $\lambda_j, j = 1, \dots, 4$, are the centroidal coordinates of the point within the tetrahedron and $f_{C_j}^i$ is the i th component of the feature vector of the OSA color C_j located at the j th vertex of the tetrahedron. The λ_j coordinates satisfy the following equations by construction:

$$\lambda_j \geq 0 \quad \forall j, \quad \sum_j \lambda_j = 1. \quad (3)$$

The resulting model provides a prediction for the feature vector associated to any point in the space, at a very low computational cost. Furthermore, the normalization of the feature

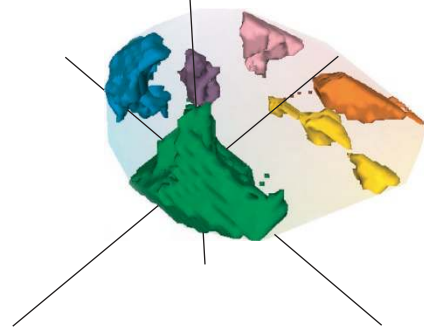


FIGURE 6: Surfaces delimiting the 11 color categories corresponding to a membership value $\bar{p} = 1$.

vectors is preserved by construction

$$\sum_{i \in N_c} \sum_{j=1}^4 \lambda_j f_{C_j}^i = \sum_{j=1}^4 \lambda_j \sum_{i \in N_c} f_{C_j}^i = \sum_{j=1}^4 \lambda_j = 1, \quad (4)$$

where $N_c = 11$ is the number of color categories.

4. RESULTS AND DISCUSSION

4.1. Model fitting

The proposed model provides a very effective mean for the visualization of the color categorization data in any 3D space. In this paper, we have chosen the CIELAB space, whose perceptual uniformity makes it exploitable for image processing. The first goal of this study was the estimation of the probability of choosing a color name given the color sample, irrespectively of the observer, for each color of the OSA system. The model performance was characterized by measuring the number of times each OSA sample was given the label i , as in (1). This implicitly qualifies as *consistent* and *consensus* colors [10] those samples for which there exists a $\bar{i}, \bar{i} \in \{1, 11\}$ such that

$$f_{C_j}^i = \begin{cases} 1 & \text{for } i = \bar{i}, \\ 0 & \forall i \neq \bar{i}. \end{cases} \quad (5)$$

It might be useful to recall here the definitions of *consistency* and *consensus*, the two parameters used by Boynton and Olson to analyze their data. They regard the agreement on color naming by a single subject for two presentations of the same color as *consistency*, while *consensus* is reached when all subjects name a color sample consistently using the same basic color term. Such colors are those that have been attributed the same name by all the subjects in all the trials.

The surface representing the consensus colors can be effectively rendered by the *marching cube* algorithm [14].

Figure 6 illustrates the result of the rendering. Each surface inscribes the volume of the CIELAB space which encloses all the OSA samples that were given the name of the basic color represented by the surface color, consistently and with consensus. The solids in general are not convex, and

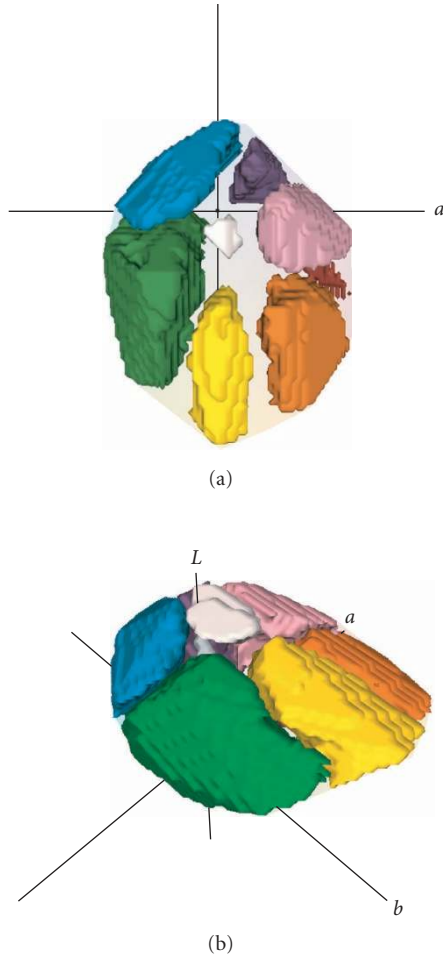


FIGURE 7: Surfaces delimiting the 11 color categories corresponding to a membership value (a) $\bar{p} = 0.8$; (b) $\bar{p} = 0.5$.

some isolated points appear to be located outside the surfaces. Such a topology is due to the fact that the surfaces enclose all and only the color samples featuring both consistency and consensus by construction. Points in-between color samples of this kind, which do not hold the same property, unavoidably produce a discontinuity in the surface, and may result in the presence of isolated points. This is emphasized by rendering the surfaces enclosing all the samples whose membership value is above a certain threshold \bar{p} for each category. Figure 7 illustrates the cases $\bar{p} = 0.8$ and $\bar{p} = 0.5$, respectively. For membership values smaller than one, the fuzzy nature of the categories generates an overlapping of the surfaces. This is illustrated in Figure 8, which shows the level sets for the membership values in an equi-luminance plan for the green and blue categories.

4.2. Model validation

The model validation was performed by the comparison of the membership values as predicted by the model, by linear interpolation, with those estimated on the basis of Ex-

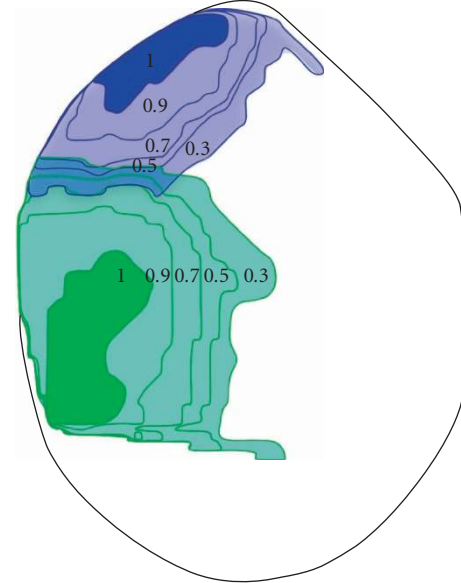


FIGURE 8: Level sets of the membership function in an equi-luminance plan for the green and blue categories.

periment 2. Using 100 random samples, each displayed three times to all the 6 observers, bounds the accuracy of the estimation to about 0.056. The accuracy of the model-based estimation of the membership values is only subject to the precision bounds set by the fitting. Accordingly, the characterization of the performance of the model must account for such an intrinsic limitation. In order to overcome it, an extended set of color samples will be used for both fitting and validation in the future developments of this work.

Even though the number of samples used is not large enough to completely characterize the model performance, and the simple linear interpolation is not expected to be the best choice in general, the results are quite satisfying. This emphasizes the potential of the proposed model. The CIELAB space was designed such that equal perceptual differences among color stimuli (in specified observation conditions) would correspond to equal intersample distances according to the Euclidean metric. Though, the uniformity property does not hold exactly, such that equidistant color samples, in general, do not correspond to equidistant percepts. Accordingly, an interpolation scheme aiming at mapping geometrical positions in the CIELAB space to perceptual differences should account for such nonuniformity through the definition of an ad hoc nonlinear metric. The reason why we believe the linear interpolation scheme is nevertheless a good starting point is twofold. First, the OSA-UCS color system consists of a relatively large number of perceptually equidistant samples. Therefore, their spatial distribution in the CIELAB space corresponds to a *fine* sampling of the color space, with a relatively small intersample distance (see Figure 3). Jointly with the uniformity properties of CIELAB, this justifies the assumption of the OSA-UCS samples being evenly distributed in the color space within small variations. Within the limits of such an approximation, it is then



FIGURE 9: The nine OSA-UCS samples that were not correctly named by the model.

reasonable to assume that the linear interpolation scheme is able to provide a good prediction of the appearance of the samples lying in-between the OSA-UCS ones. Second, the Euclidean distance between a test sample and each of the OSA-OCS samples located at the vertexes of the tetrahedron it belongs to is smaller than the distance between the vertexes. Overall, the fine granularity of the sampling grid and the locality of the model led us to consider linear interpolation as a good first-order estimator of the values of the membership function of the test samples in the color naming space. The analysis of the limitations of such an assumption requires the investigation of the distribution of the intersample distances among the OSA samples leading to the definition of a new metric, or, equivalently, a local deformation of the space allowing to recover the uniformity properties.

On top of this, it is worth mentioning that how color *appearance* differences map to color *naming* differences is still an open issue. Such information is of the first importance for the design of the *ideal* interpolation scheme. This implies the investigation of the (fuzzy) boundaries among color categories and subcategories, as well as the modeling of their relations with color descriptors. We leave both of these subjects for future investigation.

As mentioned above, the precision bound is the same for both the fitting and the validation. In both cases, each color sample was shown to each of the six subjects three times. In consequence, all the observed values of the membership functions are multiples of $1/18$. For the validation, the membership values estimated by the model are issued from the linear interpolation (2) thus can take any possible real value. Nevertheless, the precision bound is set by the fitting. The variability of the categorization data (i.e., quantified here through the membership functions) is due partly to the intrinsic fuzzyness of the categorization process, and partly to intersubject variability. The detailed investigation of this very interesting issue is beyond the scope of this contribution, and it is left for future research.

However, an indication of the goodness of the model in predicting the values of the membership function is given by the fact that the absolute value of the estimation error (i.e., the \mathbb{L}^1 difference between the predicted and the observed values of the membership function) is above the accuracy of the estimation only in 16.5% of the cases. An extended set of results would lead to a more robust and accurate estimation as well as to a more precise characterization of the system.

The performance was also evaluated in terms of the ability of the model to predict the human behavior in the naming task. Automatic naming was obtained by assigning a given test color the label corresponding to the maximum among the associated membership values. Agreement with the average observer (i.e., the subjective data) was reached in 91%

of the cases. Figure 9 shows the color samples that were not correctly labelled by the model. Importantly, five out of nine of these test colors have a very weak chromaticity, and were named as *gray*. This is most probably due to the fact that the gray category was not adequately represented in the training set, such that we expect this shortcoming to be overcome by an extended training color set.

Overall, these first results show that the basic color components of the test samples are almost always correctly identified. The model is thus able to provide a good estimation of the *perceived amount* of basic color in the test color samples, allowing the definition of the corresponding color naming label.

Before concluding this section, it is important to mention that the proposed model also holds a great potential as an imaging tool for vision research. The availability of a discrete model allows a very effective visualization of the match between color names and chromaticity coordinates, in any color space. As pointed out by Cao et al. [15], the possibility to map color appearance with the coordinates of the stimulus in the cone chromaticity space and the inclusion of color appearance boundaries in such space allow to link the physical and perceptual characterization of a chromaticity shift. In their work, they take a first step in this direction and provide an illustration of the regions covered by OSA color samples corresponding to the set of nondark appearing colors *blue, purple, white, pink, green, yellow, orange, red*. Though, a two-dimensional representation is chosen, where all the samples are represented irrespectively of the L value. The proposed model allows overcoming such a limitation, providing a very effective representation of the OSA named samples in any 3D color space that can be reached through a numerical transformation.

4.3. Image segmentation

An indirect way to validate the model consists in evaluating its exploitability for image processing. Here we have chosen to characterize its performance for image segmentation. The fact that the model was shaped on the OSA samples constrains its usability for images whose color content is bounded by the corresponding enclosing surface in the color space. Accordingly, the chosen images were preprocessed in order to satisfy such a condition.

The segmentation algorithm requires the definition of the color of the different regions of interest by the user. In the current implementation, an interface allows defining the color of a given object (or, equivalently, image region) through its naming attributes: the basic color components and the lower bounds of the corresponding membership

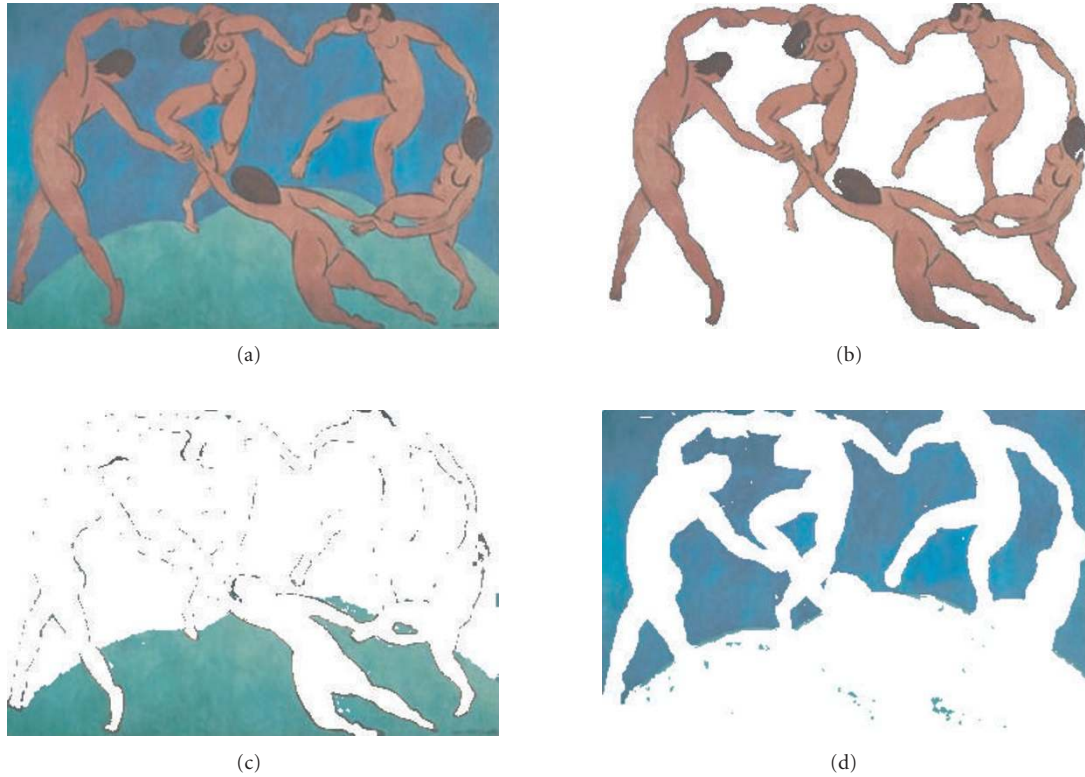


FIGURE 10: Matisse, *Les danseurs*. (a) Preprocessed image; (b) brown-orange-rose region; (c) green region; (d) blue region.

values. This allows a fuzzy definition of the color attributes, that provides a very natural way of identifying and segmenting the different objects. To illustrate the concept, the color attributes of a region are specified as *30% green and 40% blue*. Only basic colors are allowed in the current version, but the model can be very naturally generalized to a multiscale hierarchical framework in the color naming space.

From an implementation point of view, the segmentation algorithm selects the concerned tetrahedron for each image pixel and estimates the membership values. The segmentation map results from the aggregation of all the pixels sharing the same naming attributes, namely whose membership values are above the predefined threshold.

Figure 10 shows the segmentation map of the painting *Dance (1910)* by Henry Matisse. The dancers are correctly identified by setting the membership values as follows: $\bar{p}_{\text{brown}} \geq 0.1$, $\bar{p}_{\text{pink}} \geq 0.1$, and $\bar{p}_{\text{orange}} \geq 0.3$, as illustrated in Figure 10(b). Similarly, Figures 10(c) and 10(d) show the green and blue regions, that were obtained by setting $\bar{p}_{\text{green}} \geq 0.3$ and $\bar{p}_{\text{blue}} \geq 0.6$, respectively. The level of detail in the color description is not constrained by the application. The user can choose to describe the object of interest by either all or only one of its basic color components. Once the color of interest has been described at a satisfying level of detail (as indicated by the corresponding segmentation map), such a description can be used for image indexing. Among the many applications that could take advantage of such a semantic definition of the image content, of particular

interest are those in the fields of medical imaging and cultural heritage. As for the first, it could for instance be exploited for characterizing the color content of particular lesions, like melanomas, as well as to pick up the set of images sharing a common feature within a database to support diagnosis as well as epidemiological studies. Concerning cultural heritage, the model could be used to characterize the pigments used by a given painter, such that a *color signature* could be derived and used for both data mining in arts databases and to identify counterfeits.

The segmentation algorithm was also tested on sport images (see Figure 11). The grass color of the football field is spread over many different luminance levels, as illustrated in Figure 12. Setting the membership value $\bar{p}_{\text{green}} \geq 0.9$ leads to the results shown in Figure 11. Even though in the current implementation the algorithm is not able to deal with highlights, changes in illumination and shadows, the results are quite satisfying, the field is correctly segmented and the players are not merged with the background. It is worth outlining that this algorithm provides a pixelwise resolution, since it does not use any statistical information about the neighborhood. Further improvements can be reached with the integration of color appearance models. We leave this issue for future investigation.

5. CONCLUSIONS

We presented a novel discrete model for color naming. The model was trained by fitting the parameters to the data



FIGURE 11: Football. (a) Original image; (b) green region $\bar{p}_{\text{green}} \geq 0.9$.

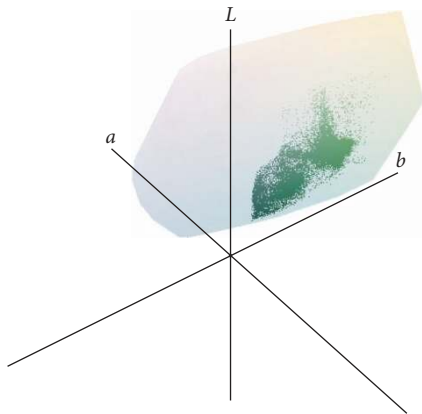


FIGURE 12: CIELAB illustration of the pixels featuring a green component whose membership value is above 0.9.

gathered by an ad hoc psychophysical experiment (Experiment 1) and validated by comparing the estimated membership values of a color sample with the corresponding relative frequencies measured via another subjective test (Experiment 2). First results show that the resulting ideal observer is able to provide an accurate estimation of the probability of a given color to be classified as pertaining to each of the 11 predefined categories. Due to the close match of the predicted and measured membership values, the model has proven to be effective in mimicking the average human observer, and thus to be suitable for the definition of an automatic color naming system. The model performance for color-based semantic segmentation was evaluated on both a painting and a sport image. The good performance and the high computational efficiency qualify it as a powerful tool for color-based computer vision applications. Among the many open issues that deserve further investigation are the definition of a new sampling criterion for a more complete set of color samples for both training and validation, the investigation of different

interpolation techniques accounting for the nonuniformity of the color space, and an extended set of subjective tests for improving the accuracy of the estimations. On top of this, the generalization to a multiscale formulation will enable a finer granularity in the labelling increasing its potential for multimedia applications.

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