Computing Color Categories from Statistics of Natural Images

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This article presents a framework for understanding, modeling, and computing color categories on the basis of knowledge from the color imaging science. One of the main assumptions advocated in this article is that the structure of color categories originates from the statistical structure of the perceived color environment that was observed throughout an individual's life. The perceived color environment can be modeled as color statistics of natural images in some perceptual and approximately uniform color space (e.g., the *CIELUV* color space). The process of color categorization can be modeled as the grouping of the color statistics by clustering algorithms (e.g., *K*–means). The proposed computational model enables one to predict the location, rank, and number of color categories. The model is examined on the basis of *K*–means clustering analysis of statistics of 630 natural images in the *CIELUV* color space. In general, the model predictions are consistent with data from psycholinguistic studies. The model might be applied in different areas of imaging science such as color quantization, image quality, and gamut mapping.

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Introduction

What is color categorization? What is the function of color categorization? What is the origin of color categories? Recently, these questions were widely discussed from philosophical, linguistic, cognitive, perceptual, and neurological perspectives.[1] During the last 30 years, significant progress has been made in theoretical understanding of the process of color categorization[2–5] and empirical measurement of locations, borders, and numbers of color categories.[1,6,7] Achievements in computational modeling of the color categorization process are less profound. The following research considers both theoretical and computational aspects of color categorization by the use of the knowledge from the color imaging science. The aim of the research is to develop a coherent framework for 1) understanding the fundamentals of the color categorization process, 2) modeling its essential components, and 3) computing color categories.

Understanding Color Categorization

Definition of Color Categorization

Color categorization can be defined as the grouping of color sensations into classes "by means of which nonidentical stimuli can be treated as equivalent".[4] In general, this grouping can be performed at different levels of visuo-cognitive processing. A computational model presented in this article focuses on the linguistic color categorization (i.e., color naming), which takes place between perceptual level (e.g., 'apparent color of a banana') and semantic level (e.g., 'yellow color'). More specifically, the model considers single-word color names, so-called "basic color terms", originally defined by Berlin and Kay,[2] and extensively studied by Boynton and Olson.[6] However, the model can be extended beyond the single-word color names. For example, the model can be applied to compute nonverbal color categories exposed by children or animals.

Function of Color Categorization

The obvious advantage of color categorization is the reduction of vast differences among perceived color stimuli to cognitively usable proportions. The magnitude of this reduction is enormous: from more than 2 million perceptually distinguishable colors[8] to approximately 30 colors that can be internally represented in cognitive space[9] and to approximately 11 color terms that can be easily identified in English language.[6]

Shepard,[5] referring to the general principle of shareability advocated by Freyd,[10] noted that categories make the sharing of knowledge between species easy. From this perspective, color categories help to consistently assign words to object colors and, therefore, facilitate communication *between* individuals. In addition, a categorical organization of color might make easy communication *within* an individual, e.g., from one information-processing module to another. Overall, it can be assumed that the primary function of color categorization is to facilitate the successful interaction of an individual with the surrounding world and with other individuals. This interaction can be performed much easier and faster using categorical (reduced) object description rather than detailed (complete) object description.

Origin of Color Categorization

The idea about external (ecological) origin of color categorization was discussed at great length by Shepard,[5]

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Color Plate 1 is printed in the color plate section of this issue, p. 481.

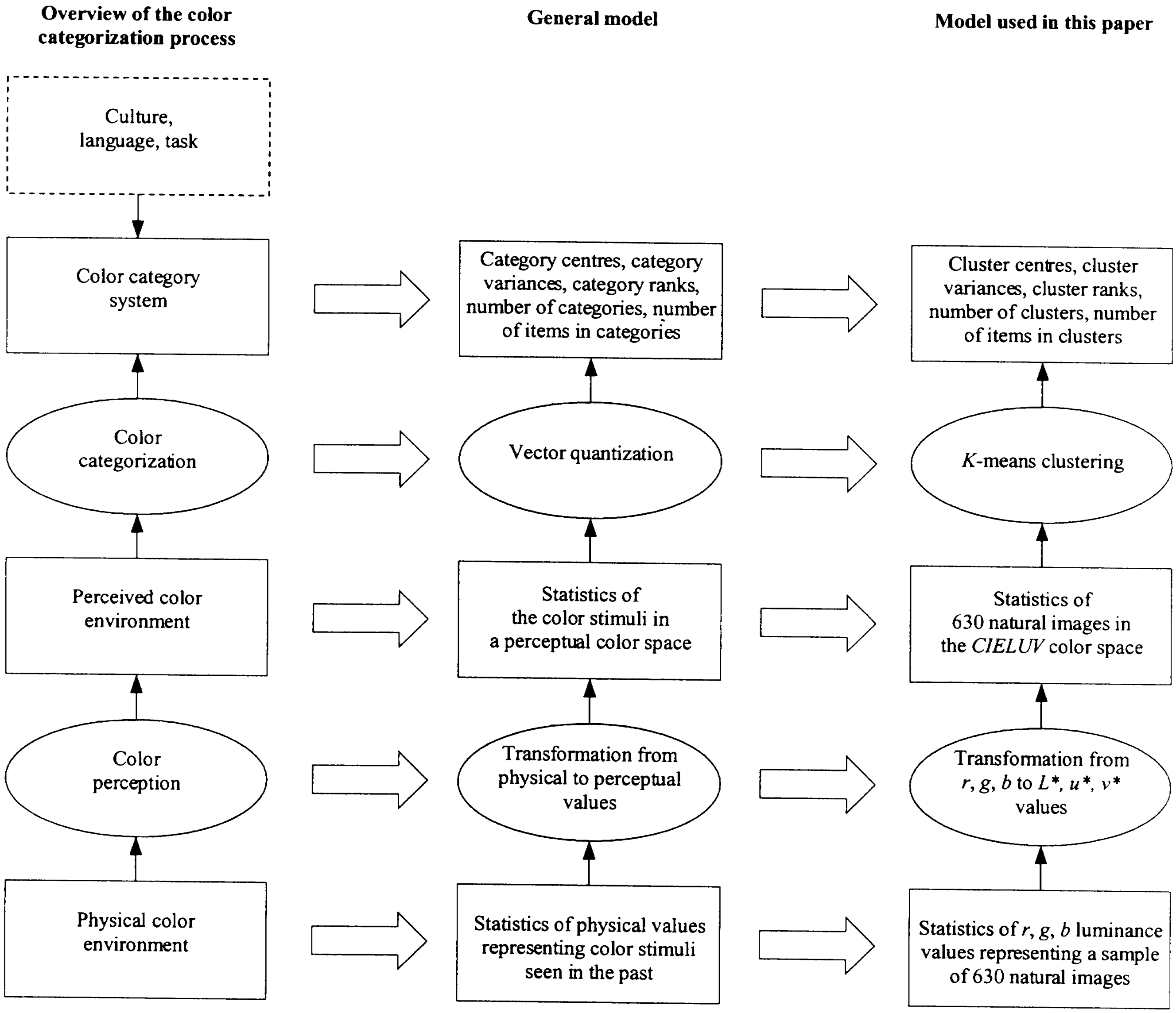

Figure 1. A computational model of color categorization.

who proposed that this organization most likely reflects something about natural groupings of the surface reflection distributions of biologically significant objects or something about the way in which terrestrial lighting has typically varied during evolutionary history. The information about surface reflections and terrestrial lighting is available to observers only through the process of color perception. As a result, the categorical color organization was argued to have an internal (physiological) basis and originate from metrical properties (e.g., interpoint distances) of the perceptual color space.[7]

One of the main assumptions advocated in this article is that the structure of color categories originates from the statistical structure of the perceived color environment that was observed throughout individual's life. By the use of words (1) 'perceived' and (2) 'environment' this assumption recognizes that color categorization is determined both by (1) the internal properties of the sensorial system and (2) the external properties of the outside world. From this perspective, color categories of an individual *A*, for example, might be different from ones of an individual *B* due to differences in their visual receptors (e.g., the individual *A* is a normal trichromate; the individual *B* is a dichromate) or/and due to differences in their environments (e.g., the individual *A* lives in jungle; the individual *B* lives in desert).

It should be noted that the example with the individuals *A* and *B* takes into account only 'bottom-up' factors involved in color categorization. However, there is evidence that the process of color categorization is also influenced by 'top-down' factors, such as culture,[11] language[12] and task.[13] For that reason, the color categories of the individuals *A* and *B* might still be different even if they have the same types of receptors and live in the same types of environments.

The computational model described in this article considers only 'bottom-up' aspects of color categorization. The model consists of five major components: physical color environment, color perception, perceived color environment, color categorization, and color categories (Fig. 1).

A Computational Model of Color Categorization

Physical Color Environment

Physical color environment corresponds to physical characteristics of visual stimuli seen by an individual in the past. A visual stimulus defines a momentary pattern of light reflected/radiated by observed objects (e.g., people, trees, fruits, lights, etc.). Generally, the physical color environment can be modeled by a representative sample of color stimuli entered individual's eyes throughout his/her life. Because such modeling is problematic one has to find plausible alternatives. In this article, the physical color environment is modeled by a representative sample of natural (photographic) images.

In line with this idea, a set of 630 natural images was collected. The images were taken from TV net (110 pictures), Photo CDs (170 pictures), and scanned from books about color in nature (350 pictures). They represented typical categories of scenes: portraits, landscapes, flowers, animals, etc. The whole set of natural images contained 5 424 000 pixels. A random sample of 10 000 pixels was chosen for further processing and analysis.

Color Perception

Color perception is a complex process of transforming visual stimulus into apparent object color. Generally, color perception can be modeled by a transformation from physical to perceptual color values. Here, the process of color perception is modeled by the *CIE 1976 L*u*v** (*CIELUV* for short) transformation, which is one of the standard transformations recommended by the *CIE* (Commission Internationale de l'Eclairage). Other transformations (e.g., *CIELAB*, *CIECAM97*) can be used as well (see Ref. 14 for a review).

The R, G, B gray values representing the sample of 10 000 pixels from the natural images were transformed to r, g, b luminance values, then to the X, Y, Z tristimulus values, and eventually, to the L^*, u^*, v^* color coordinates. The transformation from R, G, B to X, Y, Z values was made using a CRT characterization procedure based on the assumption that the images were to be shown on a CRT display with typical PAL (European color television) characteristics: $\gamma = 2.5$; $Y_{\min} = 0.001$ cd/m^2 ; $Y_{\max} = 70.0$ cd/m^2 ; $(x_r, y_r) = (0.64, 0.33)$, $(x_g, y_g) = (0.30, 0.60)$, $(x_b, y_b) = (0.15, 0.06)$, $(x_w, y_w) = (0.313, 0.329)$. The transformation from X, Y, Z to L^*, u^*, v^* was made using standard formulae.[15]

Perceived Color Environment

Perceived color environment corresponds to perceptual color characteristics of visual stimuli seen by an individual in the past. Generally, the perceptual color environment can be modeled by statistics of a representative sample of these stimuli in a perceptual color space. In this article, perceived color environment is modeled by statistics of the representative sample of the natural images in the *CIELUV* color space.

The sample of 10 000 randomly chosen pixels representing the natural images in the *CIELUV* color space is shown in Fig. 2 (left). The normalized histograms of the *CIE* lightness L^*, hue H and chroma C^* values are presented in Fig. 2 (right). For comparison, Fig. 2 (right) also shows L^*, H and C^* histograms of 10 000 pixels from an image with uniformly distributed R, G, B gray values. Apparently, the color statistics of the natural images is not spread uniformly in the *CIELUV* color space, especially in the chroma (Fig. 2d) and hue (Fig. 2f) dimensions. Most of the points are concentrated around the lightness L^* axis of the *CIELUV* color space. This area represents achromatic colors, i.e., colors with small chroma C^* values. Two other areas with a high frequency of occurrence can be identified. These two areas correspond to red–yellow–green, and blue parts of the *CIELUV* color space (Fig. 2f). There are very little colors in the green–blue and red–blue parts of the *CIELUV* color space.

The data agrees well with the measurements reported by Howard and Burnidge,[16] Hendley and Hecht,[17] and by Burton and Moorhead.[18] They showed that naturally occurring colors are distributed within a very restricted area of the chromaticity diagram, and that there are three important groups of colors in nature. Water, sky, and distant objects fall within a blue region; green plants fall within a yellow–green region; earth and dried vegetation are yellow to orange–red. The last group also includes the average color of human complexions, which have a dominant wavelength close to 590 *nm*.[19]

It should be noted that the color statistics of the natural images shown in Fig. 2 does not match the actual colors in the original scenes. The natural images were obtained from various image sources and they were assumed to be shown on the CRT display with PAL characteristics. Therefore, the color statistics of the natural images is affected by color gamut of the image sources and, in particular, by the color gamut of the PAL display. Further research is needed to obtain a better colorimetrical representation of the perceived color environment. This can be achieved, for example, through collection of a large database of natural scenes using the multi-spectral imaging technique.[20]

Color Categorization

Color categorization can be considered as the grouping of color sensations into classes. Generally, the process of color categorization can be modeled using the concept of vector quantization from information theory. Vector quantization is a data compression method where a set of data points is encoded by a reduced set of reference vectors, the codebook.[21] One can assume that the color categorization is based on the minimum distance criterion. This implies that points with minimum distance to each other in the color space are likely to belong to the same color category. Therefore, the process of color categorization can be modeled by a clustering algorithm such as the *K*–means or *ISODATA* clustering algorithms.

In this research, the process of color categorization was modeled by *K*–means clustering of the *CIE L*u*v** color coordinates of the statistics of the natural images in the *CIELUV* color space. Modeling was performed using a *K*–means clustering routine of CANTATA visual programming environment for the Khoros system.[22] This routine converts an input image into vectors of equal size and performs the *K*–means clustering algorithm on the vectors using randomly chosen K initial cluster centers. After K initial cluster centers are chosen, the image vectors are iteratively distributed among the K cluster domains. New cluster centers are computed from these results, such that the sum of the squared distances from all points in a cluster to the new cluster center is minimized.

Color Category System

The color category system can be described by few basic parameters (location, border, order, number, and weight) of color categories. Generally, these parameters can be modeled by the corresponding parameters (location, border, rank, number, and weight) of clusters derived by the clustering algorithm. This article focuses

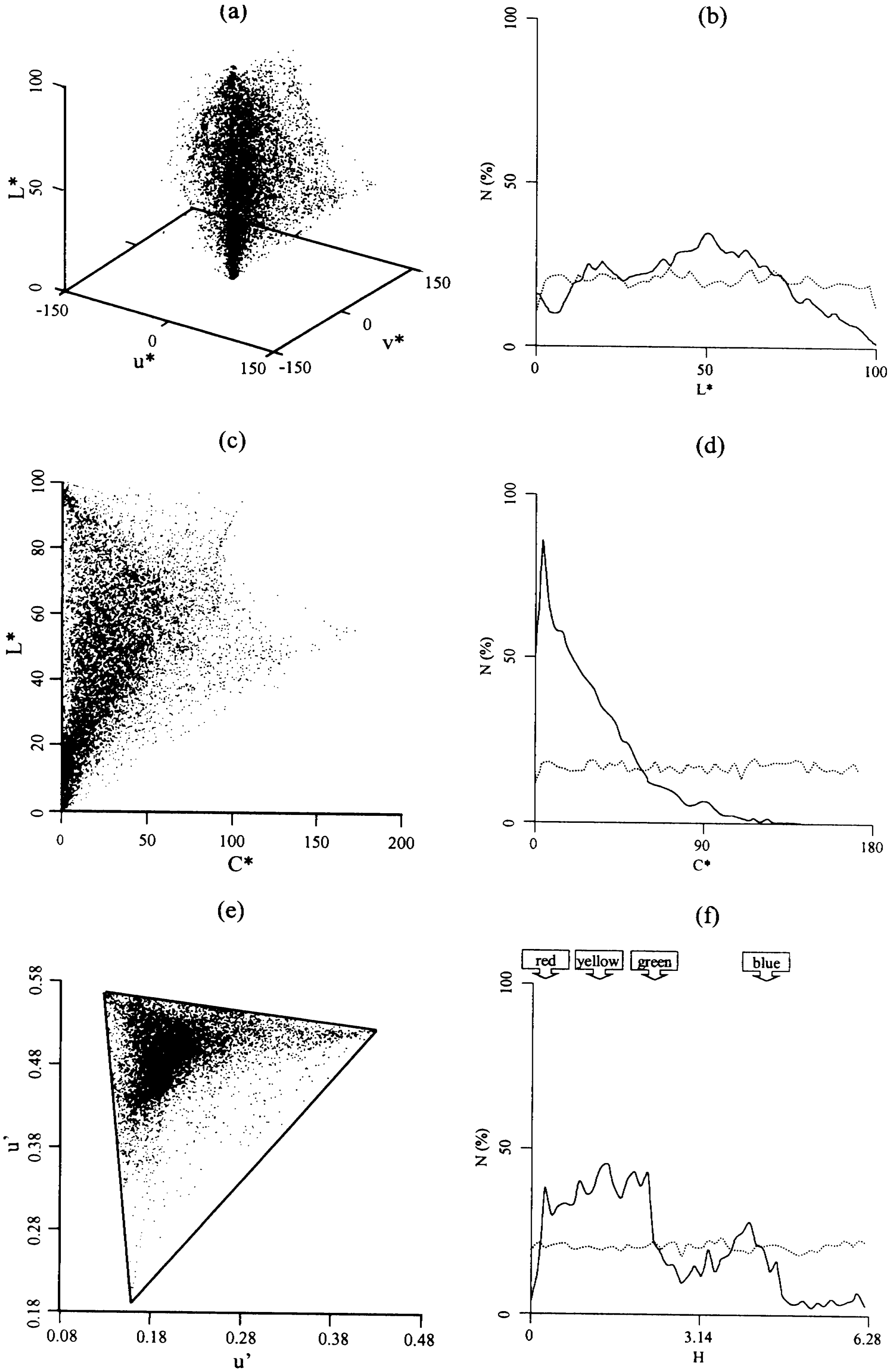

Figure 2. (left) A random sample of the color statistics of 630 natural images in the *CIE* (a) $L^*u^*v^*$ color space, (c) L^*C^* diagram, and (e) $u'v'$ diagram. The solid line indicates the PAL TV color gamut. (right) Normalized histograms of the (b) lightness L^*, (d) chroma C^* and (f) hue H values for (solid lines) the natural images and (dashed lines) the image with uniformly distributed *R, G, B* gray values.

on modeling the location, rank and number of color categories, because these parameters have been extensively studied in psychology and linguistic. The model of color categorization proposed here enables to compute these parameters and compare them with the empirical data. The following section describes the result of this comparison.

Computing Color Categories

Location of Color Categories

The location of color categories can be computed from coordinates of cluster centers derived by the K–means clustering algorithm from the color statistics of the natural images in the *CIELUV* color space. Figure 3 (top) illustrates eleven cluster centers derived by the CANTATA K–means clustering algorithm from the sample of 10 000 pixels representing the natural images. The cluster centers are plotted in the *CIE* u^*v^* (Fig. 3a) and *CIE* $u'v'$ (Fig. 3b) chromaticity diagram together with the eleven focal colors found by Boynton and Olson.[6] The original focal colors were derived by Boynton and Olson on the basis of single-word color naming of 424 color samples from the *OSA* space. The coordinates of focal colors shown in Fig. 3 were obtained through the sequential transformation of the *OSA* $L, j, g,$ values to the *CIE* Y, x, y values, and, eventually, to the *CIE* L^*, u^*, v^* values by using standard table and formulae.[15]

The location of the cluster centers in the *CIELUV* space was close to the location of the focal colors with one exception. Among the cluster centers there was a 'green–yellow' cluster, which did not belong to the eleven focal colors described by Boynton and Olson. On the other hand, the analogue of the focal color 'purple' was not derived by the K–means clustering algorithm.

A linear regression analysis demonstrates that the coordinates of 10 focal colors and 10 corresponding cluster centers are similar: the correlation between their lightness L^* values is $r = 0.762$ (Fig. 3c); the correlation between their hue H values is $r = 0.999$ (Fig. 3d); the correlation between their chroma C^* values is $r = 0.876$ (Fig. 3e); the correlation between their saturation (s) values is $r = 0.900$ (Fig. 3f). These results support the idea that the structure of color categories originates from the statistical structure of the perceived environment.

Rank of Color Categories

Berlin and Kay[2] have suggested that if languages are ranked according to number of color category terms, the evolutionary sequence of these terms (in reference to English names) is generally as follows: 1) black and white; 2) red; 3) green/yellow; 4) yellow/green; 5) blue; 6) brown; 7) pink, purple, orange, and gray. In other words, if a language has only three color terms, they are most likely to correspond to English white, black, and red, and not, for example, to pink, orange, and brown. The exact evolutionary order of color words varies across different languages, but in general shows a remarkable consistency [see Ref. 1 for a recent review]. The same order was found in the rate of usage of color words within the English language by McManus[23] who studied the frequency of the color terms in literature and science databases.

Overall, the rank (order of emergence) of the cluster centers resulting from the K–means algorithm is similar to the rank of color terms described by Berlin and Kay. For example, the cluster centers obtained by the K–means algorithm with $K = 3$ roughly correspond to English terms 'black', 'white', and 'red' (Fig. 4a); the cluster centers obtained by the K–means algorithm with $K = 7$ roughly correspond to English terms 'black', 'white', 'red' 'green', 'yellow', 'blue' and 'brown' (Fig. 4b); the cluster centers obtained by the K–means algorithm with $K = 11$ roughly correspond to English terms 'black', 'white', 'red' 'green', 'yellow', 'blue', 'brown', 'grey', 'orange', 'pink' and 'green–yellow' (Fig. 4c). Interestingly, the proposed computational model enables to predict the future development of English language with 15 color terms (Fig. 4d).

Figure 5 shows a moderately high correlation ($r = 0.710$) between rank of 10 color-terms derived from Berlin and Kay's data and the sum of the two parameters: (1) normalized numbers of items in the clusters and (2) normalized *CIELUV* distance between the cluster center and the average center of all clusters. The results suggest that the development of a color term across languages might be determined by two constraints: (1) frequency at which colors represented by this term occur in environment, and (2) perceived remoteness of these colors from colors represented by already existing terms.

In general, the obtained results support the idea that the evolutionary order of color terms depends on both the external properties of the outside world (frequency of color occurrence) and the internal properties of the perceptual system (metrics of color space). This idea might explain the old mysteries of why the color term 'red' has a particular salience in different cultures and why it evolves before other color terms in many languages. The possible explanation is that the color term 'red' corresponds to colors that are *both* frequently occurred in the perceived environment of people speaking these languages and substantially distant from other colors in their perceptual spaces. On the one hand, the term 'red' evolves before, for example, the term 'pink' because pink colors are relatively rare in nature (Fig. 2). On the other hand, the term 'red' evolves before, for example, the term 'green' because green colors are relatively close to the average center of the all colors in the *CIELUV* color space and, especially, in the *CIE* $u'v'$ chromaticity diagram (Fig. 2).

Number of Color Categories

Rosch[4] has argued that the primary task of category systems is to "provide maximum information with the least cognitive effort". This can be achieved if categories represent the perceived world with minimum distortions and minimum complexity. One can assume that the simultaneous minimization of the distortion and complexity costs (values) yields an optimal number of color categories. This is similar to the strategy to jointly optimize distortion errors and a codebook complexity function for the design of an optimal vector quantizer proposed by Buhmann and Kuehnel.[21] Considering the color categorization process within the framework of optimal vector quantization is a promising direction for future research. The following discussion is a first step in this direction.

In order to compute the optimal number of color categories, we need to specify distortion measure and complexity measure. A widely used distortion measure is the Euclidean distance:

$$D_{i\alpha}(\mathbf{x}_i, \mathbf{y}_\alpha) = \left|\mathbf{x}_i - \mathbf{y}_\alpha\right|^2, \tag{1}$$

where $D_{i\alpha}(\mathbf{x}_i,\mathbf{y}_\alpha)$ is a difference between a given set of data vectors $\mathbf{x}_i$ and a smaller set of codebook vectors $\mathbf{y}_\alpha$. In our case, data vectors $\mathbf{x}_i$ correspond to the *CIE* L^*, u^*, v^* color coordinates of 10 000 randomly chosen pixels

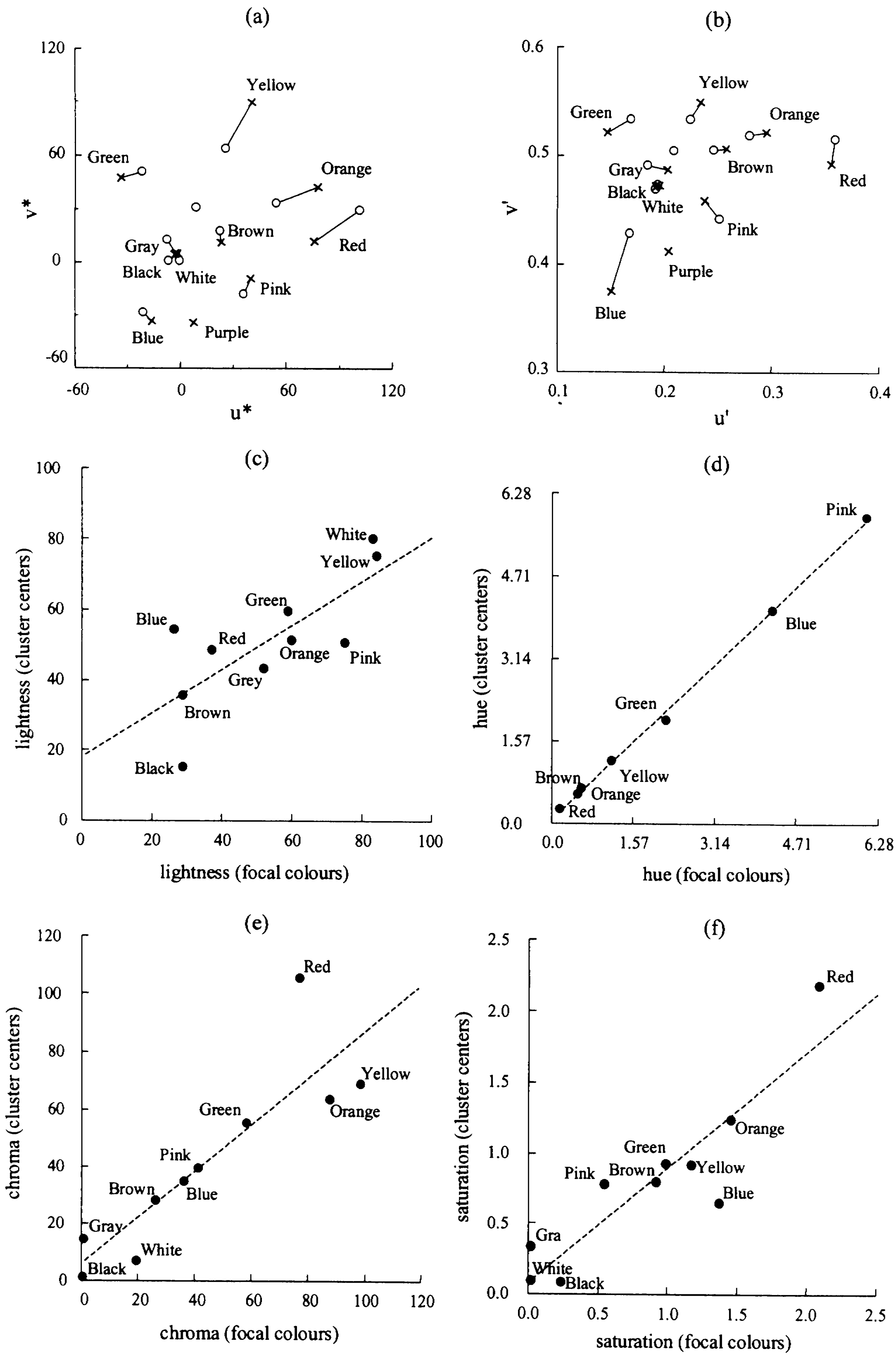

Figure 3. Eleven (circles) cluster centers derived from the color statistics of natural images and (crosses) focal colors found by Boynton and Olson[6] in the *CIE* (a) u^*v^* and (b) $u'v'$ chromaticity diagram. The relationship between (c) lightness L^*, (d) hue H, (e) chroma C^*, and (f) saturation s values of the cluster centers and the focal colors.

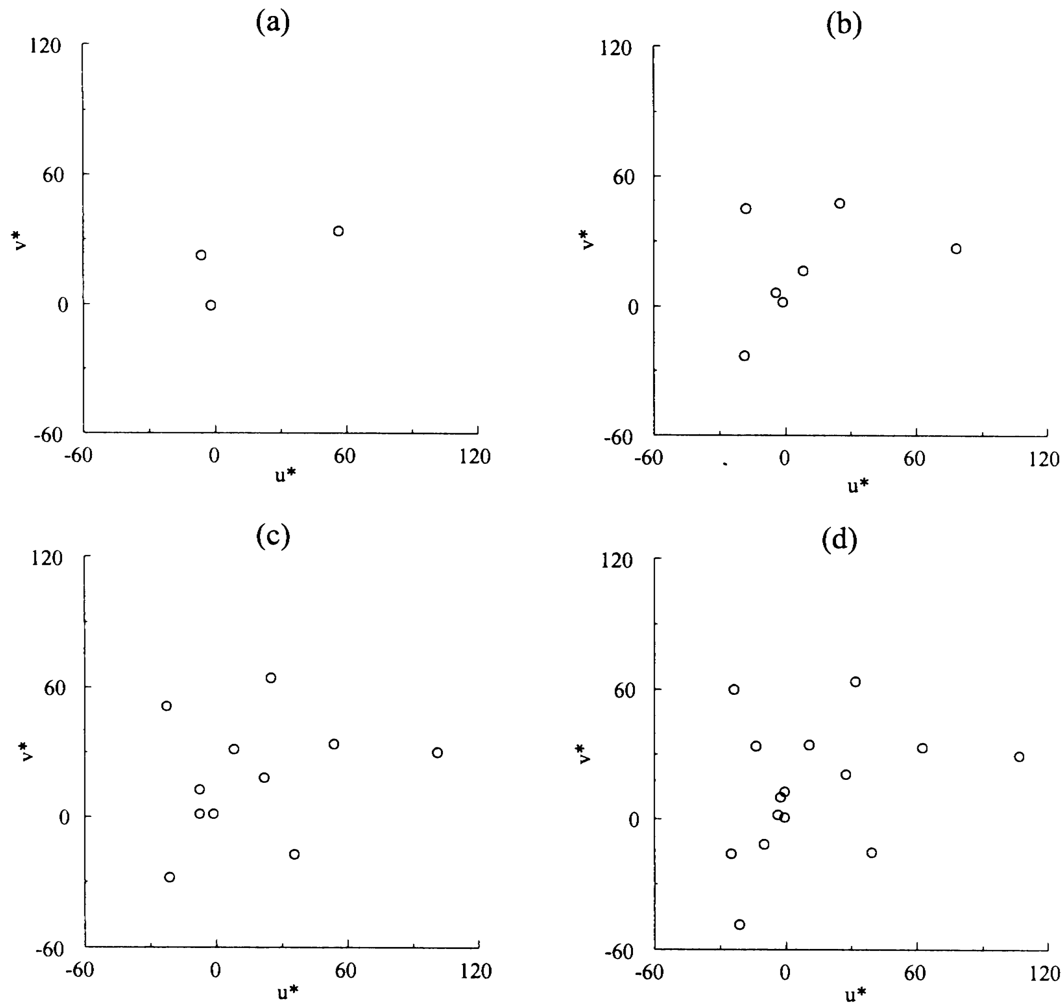

Figure 4. Cluster centers derived by the K–means clustering algorithm from the color statistics of natural images for (a) K = 3, (b) K = 7, (c) K = 11, and (d) K = 15.

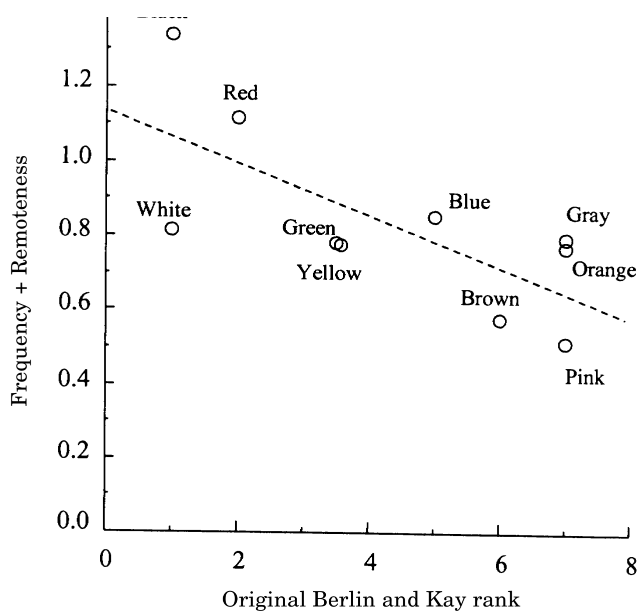

Figure 5. Relationship between the color-terms rank obtained from Berlin and Kay's data[2] and the sum of the normalized frequency (i.e., numbers of items in the clusters) and the normalized remoteness (i.e., *CIELUV* distance between the cluster center and the average center of all clusters) obtained from the statistics of the natural images.

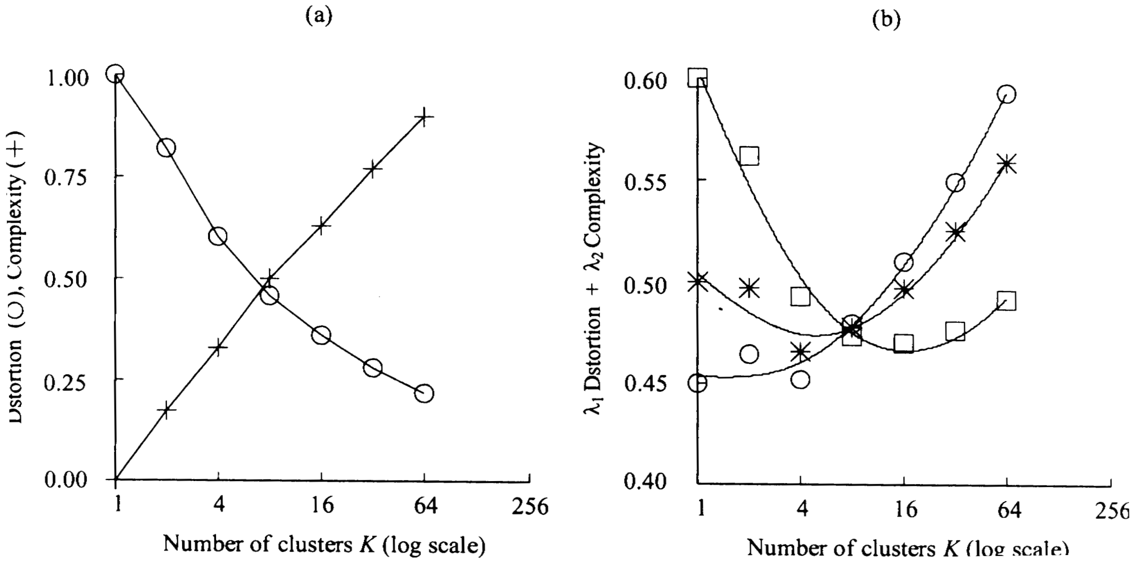

Figure 6. (a) The normalized (circles) distortion and (crosses) complexity costs for number of clusters K = 1, 2, 4, 8, 16, 32, and 64. (b) The sum the distortion and complexity costs for (circles) $\lambda_1 = 0.4$, $\lambda_2 = 0.6$; (stars) $\lambda_1 = 0.5$, $\lambda_2 = 0.5$; and (squares) $\lambda_1 = 0.4$, $\lambda_2 = 0.6$. See text for details.

representing the color statistics of the natural images before applying the K–means clustering algorithm; codebook vectors $\mathbf{y}_\alpha$ correspond to the *CIE L*, u*, v** color coordinates of the cluster centers representing the color statistics of the natural images after applying the K–means clustering algorithm; $D_{i\alpha}(\mathbf{x}_i,\mathbf{y}_\alpha)$ corresponds to the *CIELUV* color difference ΔE^*_{uv} between vectors $\mathbf{x}_i$ and $\mathbf{y}_\alpha$. Figure 6a shows normalized $D_{i\alpha}(\mathbf{x}_i,\mathbf{y}_\alpha)$ for number of clusters K = 1, 2, 4, 8, 16, 32, and 64. Apparently, the bigger is the number of clusters the smaller is $D_{i\alpha}(\mathbf{x}_i,\mathbf{y}_\alpha)$.

A detailed analysis of different complexity measures is given by Buhmann and Kuehnel.[21] In general, complexity can be defined by means of entropy from information theory:

$$C(p_\alpha) = -\sum p_\alpha \log p_\alpha, \qquad (2)$$

where $C(p_\alpha)$ is the codebook complexity and p_α is the probability of occurrence of the α^{th} value. Figure 6a shows normalized $C(p_\alpha)$ values, which were calculated by a statistical program of the Khoros system for number of clusters K = 1, 2, 4, 8, 16, 32, and 64. Evidently, the bigger is the number of clusters the bigger is $C(p_\alpha)$. To minimize the distortion costs the number of cluster centers should be increased, whereas to minimize the complexity costs the number of clusters should be decreased. Because the two constraints conflict with each other, the optimal number of color categories K can be determined by a compromise between the distortion and complexity costs:

$$K = \min\{\lambda_1 D_{i\alpha}(\mathbf{x}_i,\mathbf{y}_\alpha) + \lambda_2 C(p_\alpha)\} \qquad (3)$$

where λ_1 and λ_2 are weighting parameters. Figure 6b shows an example of how the weighting parameter might influence the optimal number of clusters representing the color statistics of the natural images. When the complexity costs have a stronger weight than the distortion costs ($\lambda_1 = 0.4$; $\lambda_2 = 0.6$) the optimal number of clusters is about 2. This situation can be associated with a 'primitive' language distinguishing very few color terms. When the distortion and complexity costs have equal weights ($\lambda_1 = 0.5$; $\lambda_2 = 0.5$), the optimal number of clusters is about 8. This situation approximately corresponds to the number of color words frequently used in everyday English. When the distortion costs have a stronger weight than the complexity costs ($\lambda_1 = 0.4$; $\lambda_2 = 0.6$) the optimal number of clusters is about 16. Such a situation relates to an 'advanced' terminology exhibited by, for example, professional painters and color designers.

Possible Applications and Future Research

The result of this research can be applied in different areas of imaging science such as color quantization, image quality, and gamut mapping. For example, the analysis of the color statistics representing the natural images in the *CIELUV* color space (Fig. 2) revealed that the obtained distribution was more uniform (less redundant) in the lightness L^* dimension than in the hue H dimension, and, especially, in the chroma C^* dimension. Therefore, one can hypothesize that distortions of the lightness L^* values would probably be more visible than distortions of the hue H and chroma C^* values.

Color Plate 1 (p. 481) provides an initial support of this hypothesis. Plate 1 contains the original image (top, left) from a Kodak Photo CD and three processed images. The processed images were obtained using a program that spatially scrambled pixels independently for the hue H (top, right), chroma C^* (bottom, left), and lightness L^* (bottom, right) values of the original image. It can be seen from the Plate 1 that the distortion of the lightness values is, indeed, more visible than the distortion of the hue and chroma values. Based on these observations, one can suggest that color quantization would probably require more levels for lightness L^* dimension than for hue H, and, especially, chroma C^* dimension. Our preliminary investigation has shown that the quantization with 128 levels of lightness L^*, 32 levels of hue H, and 16 levels of chroma C^* produced a fairly good results for many natural images.

The data described in this article support the assumption that the structure of color categories originates from the statistical structure of the perceived color environment observed throughout individual's life. Consequently, this implies that the location of prototypical colors in a perceptual space might be different for different individuals. In principle, it is possible to determine the exact coordinates of the prototypical colors in the perceptual space for an individual or a group of people (e.g., based on their age, geography, genotype, etc.). This can be achieved, for example, using the method described by Boynton and Olson.[6] If the exact coordinates of the prototypical colors are known, one can create a "prototypical color profile" that is specific for the individual or the group of people. The "prototypical color profile" can be used to customize the process of color reproduction through the transformation of chromaticity coordinates of all colors in an image towards the chromaticity coordinates of the corresponding color prototypes. This transformation can be total, i.e., all colors are replaced by the corresponding color prototypes, or partial, i.e., all colors are shifted towards the corresponding color prototypes. One can hypothesize that an image with colors shifted towards individually specific color prototypes might have a higher subjective image quality than the original image. In general, the concept of the "prototypical color profile" might be used to develop new types of adaptive algorithms that optimize image quality based on individual and cultural differences. This idea needs to be investigated further.

The prototypical colors could also be used to optimize the process of color gamut mapping. In this case, it would be necessary to define a set of prototypical colors produced by a source device (e.g., a CRT monitor) and a set of prototypical colors produced by a destination device (e.g., an inkjet printer). This can be done experimentally by asking observers to estimate prototypicality of colors produced by both devices. When the prototypical colors of the devices are known, they can be used to convert any image from the source device into the destination device in such a way that the prototypical colors of the source device are mapped into the prototypical colors of the destination device. Interestingly, an algorithm that utilizes the notion of categorical colors for gamut mapping has been already proposed.[24]

The possible applications of the concepts of color categorization and color prototypes for color quantization, image quality and gamut mapping might be considered as a first step towards incorporating cognitive aspects of color in imaging science. One can even hypothesize that some image processing techniques (e.g., color quantization, color enhancement, gamut mapping, etc.) might be more appropriate to perform in a cognitively uniform color space rather than in a perceptually uniform color space. The equality of distances between centers of color categories (color prototypes) can be the criterion of uniformity for such a space. The development of a cognitively uniform color space for color imaging science is a subject of future research.

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