Representation of Memory
Prototype for an Object Color*

S. N. Yendrikhovskij,1† F. J. J. Blommaert, 1
H. de Ridder2

1 IPO, Center for Research on User-System Interaction, Eindhoven, The Netherlands
2 Delft University of Technology, Department of Industrial Design Engineering, Delft, The Netherlands

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Abstract: This article presents a general framework for modeling memory colors and provides experimental evidence supporting this model for one particular object, i.e., a banana. We propose to characterize memory colors from experimentally determined similarity judgments of apparent object colors with the prototypical color of that object category. The aim of the first experiment was to analyze the memory representation of banana color in the CIELUV color space. To this end, we prepared images imitating different colors of a banana and asked subjects to scale the similarity in color of a banana shown on a CRT display and a typical ripe banana as it is remembered from their past experience. The relationships between the similarity judgments and chromaticity coordinates representing the manipulated banana samples can be well described by a bivariate normal distribution. Another experiment was carried out to gain more insight into the perception process leading to an appearance of the banana stimuli. Additionally, a sample of banana colors from a fruit market was measured and compared with the similarity judgments.

Key words: memory colors; apparent colors; prototypes; similarity; categorization

INTRODUCTION

The first unification of the terms object, color, and memory was elaborated by Hering,1 who claimed that all objects known to us from past experience are seen through the “spectacles of memory colors.” Memory colors define the colors that are recalled in association with familiar objects in long-term memory.2 They should be distinguished from the term color memory, which refers to the ability to remember color in general. The notion of memory colors has long been of interest in different areas of color research. Several studies have discussed the concept of memory colors in reference to color appearance,3–5 color recognition,6 color matching,7 color focality,8 and color reproduction.9,10 However, only a few experimental investigations2,11 have aimed at characterizing the nature of memory colors per se.

The following research is an attempt to fill the gap in explicit characteristics of memory colors by adopting the computational notion of representation. Following Marr,12 representation defines “a formal system for making explicit certain entities … together with a specification of how the system does this.” In general, a computational model is based on the precise specification of the input and output of the process under investigation (semantic specification), and algorithms for the mathematical transformation of the input to the output (algorithmic specification). This article presents a computational model of memory colors and provides experimental evidence supporting this model for one particular object, i.e., a banana.

COMPUTATIONAL MODEL OF MEMORY COLORS

Semantic Specification

Let us consider a specific example of using memory colors in everyday life. Imagine a person searching for his favorite ripe banana in a supermarket. We assume that the process of choosing the desired banana is based on five major subprocesses: sensation, perception, generalization, comparison, and decision (see Fig. 1).
Sensation starts with a light incident in a person's eyes from an object surface in a certain viewing context. The viewing context includes the color of a light source, an object surrounding, and accounts for such perceptual phenomena as color constancy, adaptation, induction, etc. An important question is whether the perceptual phenomena influence the observer's choice. If so, then from the same set of fruits the person might pick out different bananas in the supermarket compared to outdoors, due to the fact that the fruits appear to be different (e.g., due to incomplete color
Perception is considered as a separate process to highlight the importance of assigning a meaning to complex color patterns. This assigning is based on the top-down input from the internalized object knowledge including memory colors and object names. The influence of the object knowledge on color appearance was demonstrated for example in experiments of Bonaiuto, where figures with incongruous object tonality such as blue bread were perceived by observers to be more saturated than figures with the same but congruous object tonality such as as a blue sea. Although the influence of memory colors on object color appearance is not our focus here (see Beck for a review), the postulated coupling leads to an interesting prediction examined in the present research: an unusual, or unnatural, depiction of an object complicates its interpretation. Presumably, the choice of the “right” color for the banana would be more difficult to make using color patches (i.e., unnatural depiction) than using real fruit (i.e., natural depiction). The difficulty may be caused by an obstacle in interpreting the color patches as object colors.

Generalization is argued to be an essential process in the formation of memory colors. According to Shepard, it is very unlikely for an object to reappear in exactly the same viewing context and, thus, it is useful for the organism to establish general regularity in object appearance. The generalization process is assumed to result in construction of a particular group, what is called a natural kind or category. Rosch argued that categories can be viewed in terms of prototypes or the “clearest cases of category membership.” The term prototype can be used at least in two senses. First, the prototype can be considered as an abstract model containing the most representative attributes of the category or corresponding to its central value. There is evidence that observers have a tendency to recognize the central value of a category, even when this central value or prototype has never been seen (e.g., see recent experiments with face recognition in Cabeza et al.). Second, the prototype can be considered as a particular exemplar resembling the abstract model best. It was shown that the most prototypical members of categories are learned and identified more rapidly than members with a lesser degree of prototypicality. In particular, prototypical colors tend to be more consistently perceived and remembered than nonprototypical colors. Therefore, we propose to represent memory color by prototypical color, i.e., the most typical color of an object category. In other words, we suggest that memory colors do not define all colors that are recalled in association with familiar objects but mainly the prototypical ones.

Comparison, or similarity judgment, is performed between an apparent object color and a prototypical color of the corresponding object category. It should be noted that the representation of an object category by its prototype in the similarity judgments is not without controversy. For example, according to Exemplar Models of Categorization (e.g., Nosofsky), the similarity is computed between the stimulus representation and the memory representation of all category members. Although the Exemplar Models have successfully accounted for different categorization phenomena (especially for categories with a small number of items), it seems unlikely in our example that the global matching operation includes all category members: to conclude that a green banana is not a ripe banana, it is not necessary to compute its similarity to every banana we have ever seen. The question “What is exactly stored and compared in memory?” has been one of the major points of discussion between different models of categorization (see Ashby for a review). In this article, this question has been reformulated into a computational question: “How many parameters are needed to sufficiently describe the similarity judgments?”

Decision is based on the degree of similarity between apparent and prototypical object colors. All green and brown bananas from our example would be judged unacceptable dissimilar with an observer’s desired banana, and, therefore, would be rejected. Apparently, an observer establishes a decision bound for the degree of similarity to be acceptable or not; there is no unique typical ripe banana in nature, but there are a lot of objects admitted to be within the bounds of “ripe banana.”

Algorithmic Specification

The basic representation assumptions of our study, following the multidimensional models of categorization, are that (1) any psychological representation is probabilistic, and (2) any perceptual and cognitive effect of a given stimulus can be represented as a point in a multidimensional psychological space. In general, any perceptual or cognitive representation can be described by a multivariate probability function. This assumption can be viewed as a multidimensional generalization of Signal Detection Theory. The exact way object colors and memory colors are represented is no trivial matter. For the present, we consider plausible alternatives and make the following assumptions.

Color can be represented as a point in some perceptually uniform color space. As a suitable approximation, we choose the CIE 1976 L*u*v* (CIELUV) color space. The CIELUV color space is one of the two approximately uniform color spaces recommended by the Commission Internationale de l’Eclairage (CIE) for industrial application. The CIELUV color space is widely used in practice for cathode ray tube (CRT) color television. Although this space has some shortcomings, we decided to use the CIE-
the induction effect of the background.

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represent the surface color of image i and its background color, respectively. Vector ai is shifted with respect to si due to the induction effect of the background. \( \eta_{Bi} \) is the distance between apparent object color ai and prototype \( \mu_B \) of category B with variance \( \sigma_u \) and \( \sigma_v \) on \( u^* \) and \( v^* \) dimensions.

LUV color space, because it has an associated chromaticity diagram.

Object color of any natural category is not a single point. Even homogeneously colored objects like bananas contain spots of different colors. To represent object color, i.e., colorimetric color of object surface, we propose a statistical description and assume that all colors belonging to an object surface are distributed around a centroid with a density function. There are at least three ways to specify the centroid: (1) the mean or the arithmetic average of the distribution, (2) the mode or the most probable value, and (3) the median or the point exactly midway between the top and bottom halves of the distribution (for more details on the mean, mode, and median definitions in statistics see, e.g., Hays24). As a first choice, we represent object color by the mean of its distribution in the CIELUV color space. Denote the coordinates of the apparent object color on the CIELUV color space with relation to the color of its background. The background color can be specified in the same way as the object color, i.e., by the mean of its distribution in the CIELUV color space. Denote the coordinates of the apparent object color ai and that of the background color gi in Fig. 2 by the vectors ai and gi, respectively. Then

\[ a_i = s_i + k g_i, \]

where \( k \) is a constant that accounts for the magnitude and direction of the induction effect.

The color of an object category is modeled as a probability density function around its prototypical color, which plays the role of a centroid. The variability of the distribution describes the spread, or the extent of differences, among the category members. The degree of variability can be represented by the variance of the distribution \( \sigma_c^2 \), i.e., the average of the squared deviations from the mean. The category distribution is proposed to have three sources of variability:

\[ \sigma_c^2 = \sigma_s^2 + \sigma_i^2 + \sigma_p^2. \]

The first source is the variability in surface reflectance of objects distribution \( \sigma_s^2 \). One can assume that the variance of the probability density function for the category “apple color” might be bigger than for the category “banana color” because of a greater variability of apple surface colors in nature. The second source is the variability in light illuminating the objects distribution \( \sigma_i^2 \). This variability is most likely to be similar for various objects. The third source is the variability caused by perceptual phenomena distribution \( \sigma_p^2 \), e.g., the variation in appearance of object colors due to object surroundings, adaptation, etc. This variation is determined by the properties of the visual system and also assumed to be approximately equal for different object categories. In general, the statistical properties of the density function representing an object category can be derived from the frequency distribution of the apparent object colors seen in the past. Note that, if \( \sigma_c^2 \approx (\sigma_s^2 + \sigma_i^2) \), the total spread of the category distribution \( \sigma_c^2 \) should be independent of object category.

The probability density function can be described more accurately by increasing the number of parameters. As a first approximation, we adopt the assumption from General Recognition Theory22 that the structure of natural categories can be effectively modeled by a multivariate normal (Gaussian) distribution. This model assumes (1) a very large number of exemplars within categories, (2) the dimensions of categories are continuous-valued, (3) a category contains a few extremely atypical members, (4) the distribution of exemplars within a category tends to be unimodal and symmetrical. Apparently, these assumptions are disputable: there are some categories that do not completely possess all these properties.

For example, in our preliminary experiments we have found that the category “banana color” actually is not uni-
modular but has two maxima: “yellow banana” and “green banana.” Categories “apple color” and “pepper color” are clearer instances of multimodality. One of the obvious solutions is to consider an object as a member of a hierarchy of categories. For example, it is possible to describe the category of “banana color” as the conjunction of two subcategories, namely “ripe banana color” and “unripe banana color,” which are both unimodal. Let the category $B$ represent the category of “ripe banana color” and its centroid be denoted by $\mu_B$. In a normal distribution, the mean, median, and mode are all equal, so $\mu_B$ is a good candidate for the prototype. Let the prototype $\mu_B$ of the ripe banana be represented by a point in the $u^*v^*$ plane (see Fig. 2).

Similarity is modeled as the likelihood that an apparent object sample belongs to the category and, therefore, is proportional to the function value of the category distribution. If the category is described by a Gaussian probability density function, then the similarity is also assumed to be consistent with a Gaussian distribution. The particular similarity between the apparent object color $A_i$ and prototypical color $\mu_B$ from Fig. 2 can be characterized by a bivariate Gaussian distribution:

$$
\eta_{bi} = \exp \left( -\frac{1}{2(1-\rho^2)} \left( \frac{u_{A_i} - \mu_B}{\sigma_u} \right)^2 - 2\rho \left( \frac{u_{A_i} - \mu_B}{\sigma_u} \right) \left( \frac{v_{A_i} - \mu_B}{\sigma_v} \right) + \left( \frac{v_{A_i} - \mu_B}{\sigma_v} \right)^2 \right),
$$

where $\eta_{bi}$ is the similarity between apparent object color $A_i$ and prototypical $\mu_B$; $u_{A_i}$ and $v_{A_i}$ are corresponding $u^*$ and $v^*$ coordinates of apparent object color $A_i$ in the CIELUV chromaticity plane; $\mu_B$ and $\mu_B$ are corresponding $u^*$ and $v^*$ color coordinates of prototype $\mu_B$ in the CIELUV chromaticity plane; $\sigma^2_B$ and $\sigma^2_B$ are the variances of the category distribution on $u^*$ and $v^*$ dimensions; and $\rho$ is the correlation coefficient of $u^*$ and $v^*$ values of the category distribution in the CIELUV chromaticity plane. If the strength of the viewing context is not significant, then Eq. (3) is equivalent to

$$
\eta_{bi} = \exp \left( -\frac{1}{2(1-\rho^2)} \left( \frac{u_{Si} - \mu_B}{\sigma_u} \right)^2 - 2\rho \left( \frac{u_{Si} - \mu_B}{\sigma_u} \right) \left( \frac{v_{Si} - \mu_B}{\sigma_v} \right) + \left( \frac{v_{Si} - \mu_B}{\sigma_v} \right)^2 \right),
$$

where $u_{Si}$ and $v_{Si}$ are corresponding $u^*$ and $v^*$ coordinates of object color $S_i$ in the CIELUV chromaticity plane.

Another way of presenting the category distribution is via the contours of equal likelihood. All points of the same contour are associated with the same likelihood. Specifically, the contours of equal likelihood are the set of all $u^*$ and $v^*$ that satisfy

$$
\eta_B(u^*,v^*) = e^{-d^2} = \text{constant}
$$

for some arbitrary constant $d$. It follows from Eq. (4) that

$$
d^2 = \frac{1}{2(1-\rho^2)} \left( \frac{u_{Si} - \mu_B}{\sigma_u} \right)^2 - 2\rho \left( \frac{u_{Si} - \mu_B}{\sigma_u} \right) \left( \frac{v_{Si} - \mu_B}{\sigma_v} \right) + \left( \frac{v_{Si} - \mu_B}{\sigma_v} \right)^2.
$$

The constant $d$ can be regarded as the distance in the CIELUV chromaticity plane between the prototype $\mu_B$ and points of the same likelihood. To represent the decision bound for the degree of similarity acceptable to an observer, we propose to use $d^2 = 1/2$. The distance $d^2 = 1/2$ from the prototype to any given point of the category distribution can be used to represent a “just-acceptable” chromaticity difference.

The notion of “just-acceptable” chromaticity differences is comparable to the notion of “just-noticeable” chromaticity differences studied by MacAdam.26

If values $\eta_{bi}$, $u_{Si}$, and $v_{Si}$ are known, we can derive the general characteristics of the category distribution. However, it is hardly possible to determine $\eta_{bi}$ directly. One of the alternatives is to use scaling methods and estimate the perceived similarity $\eta_{perceived}$ from the scaled similarity $\eta_{scaled}$ that is determined experimentally. As a first choice, let $\eta_{scaled}$ increase approximately as a linear function of $\eta_{perceived}$. That is,

$$
\eta_{scaled} = a \eta_{perceived} + b,
$$

where $a$ and $b$ are scaling coefficients of the mapping from the perceptual scale to the response scale. It is important to note that the response scale might be biased by stimulus set and experimental procedure.27-29

To summarize, we propose to (1) represent memory color of an object by prototypical color of the corresponding object category; (2) characterize the prototypical color by its similarity with apparent colors of object samples of that category; (3) describe the perceived similarity by a multivariate probability density function (e.g., Gaussian) in a perceptually uniform color space (e.g., CIELUV); (4) derive the parameters of the probability density function from experimental research.

EXPERIMENTAL RESEARCH OF MEMORY COLORS

Aim of the Experimental Study

The following research was designed to provide experimental support for some of the main assumptions made in the computational model of memory colors as discussed above (see Fig. 1).

The first part of the research focuses on the comparison stage of the model and specifies the representation of prototypical color of the category “ripe banana” in the CIELUV color space. The second part of the research focuses on the perception stage of the model and specifies the representation of apparent colors of few banana samples in an appearance space. The third part of the research focuses on the generalization stage of the model and determines a sampling of surface colors of ripe bananas from a Dutch fruit market.
In Experiment 1, subjects scaled the similarity in color of a banana shown on a CRT display and a typical ripe banana as remembered from their past experience. In Experiment 2, observers scaled the differences in colors of two banana samples displayed on the screen. In both experiments, three types of object depictions were used: (1) fruit, i.e., a banana among other fruits; (2) banana, i.e., the same banana against a homogenous grayish background; and (3) contour, i.e., a silhouette of a banana with its average color against the grayish background (see Plate 1). Note, that from types (1)–(3) the amount of texture information and the naturalness of the object depiction are decreased.

Three questions have been formulated for the first part of the research:

- Does the naturalness of object depiction influence the similarity judgments?
- How many parameters are needed to sufficiently describe the representation of prototypical color in the CIELUV color space?

PLATE 1. Examples of images used in Experiment 1 and Experiment 2. The CIELUV hue-angle values of each pixel representing banana was rotated over (first column) – 15 degrees, (second column) 0 degrees, (third column) 15 degrees for the (upper row) “fruit,” (middle row) “banana,” and (lower row) “contour” images.
• Does the type of object depiction influence the representation of prototypical color in the CIELUV color space?

Three questions have been formulated for the second part of the research:

• Does the type of object depiction influence the representation of apparent colors in the appearance space?
• How many parameters are needed to sufficiently describe the representation of prototypical color in the appearance space?
• Does the type of object depiction influence the representation of prototypical color in the appearance space?

One question has been formulated for the third part of the research:

• How large is the variability of the surface colors in comparison with the variability of prototypical color?

Experiment 1: Prototypical Object Color

The aim of Experiment 1 is to specify the representation of prototypical color of the category “ripe banana” in the CIELUV color space.

Method

Subjects. Eight subjects, 4 females and 4 males, with normal or corrected-to-normal vision took part in the experiment. All were checked with the H-R-R Pseudoisochromatic Plates30 and had no deficiencies in color vision. Their ages varied between 20–30.

Stimuli. A set of common food items from a supermarket was used to make a picture composition. The items (banana, potato, carrot, lime, orange, kiwi, tomato, plum, peas, green and blue grapes, green and red apples, and green, red and yellow pepper) were arranged together with a set of Kodak color control patches on a fairly neutral cloth under natural daylight (correlated color temperature 5400 K) and were photographed using a Pentax P30 Professional Photocamera. The slide used in the experiment was selected from several originals on the basis of object distance, exposure range, and overall quality impression. Red, green, and blue gray-values for video signals were obtained by scanning the slide and digitizing it with 8 bits per pixel on a grid of 512 × 512 pixels using a Leaf System Leafscan 35-SCSI. A region of interest of 448 × 450 pixels was selected for further image processing.

The digitized image was described by its color point distribution in the CIELUV color space through the sequential transformation of \( r, g, b \) gray values to absolute \( R, G, B \) luminance values, then to the \( X, Y, Z \) tristimulus values, and, eventually, to the \( L^*, u^*, v^* \) color coordinates. The transformation into the CIELUV space was made by using standard formulae.31 Each color point corresponded to one pixel. Reference white was D55 with the CIE 1931 chromaticity coordinates \( (x_w, y_w) = (0.332, 0.347) \). The CIE 1931 \((x, y)\) chromaticity coordinates of the green, red, and blue phosphors of our monitor, measured by the Spectraspectrophotometer SpectraScan PR-650, were: \( (x, y) = (0.619, 0.349) \), \( (x_p, y_p) = (0.308, 0.594) \), \( (x_p, y_p) = (0.148, 0.073) \).

The two types of banana depiction, namely “fruit” and “banana,” were distinguished only by the characteristics of their backgrounds. The image of the original scene was used as the “fruit” depiction. The “banana” depiction was constructed by cutting out the banana from the other fruits and by filling in a homogenous background in the rest of the image. To produce the background, the colors of all the pixels belonging to the table cloth were determined and averaged in terms of the \( L^*, u^*, v^* \) color coordinates. Thus, the background had the average lightness, chroma, and hue of the original surroundings with the exception of the fruits. For the third type of depiction, namely “contour”, the silhouette of the banana with its average color against the same background as in the “banana” stimuli was used. Photographs of these three scenes are further called master images. The color point distributions of the master images in the CIELUV chromaticity plane are presented in Fig. 3.

For each master image, a set of new images was prepared by changing the CIELUV chroma and hue-angle values for each pixel of the banana, while its lightness and the rest of the images were kept constant. For the chroma changes, the chroma value of each pixel in the master images was multiplied by the constants 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3. For the hue changes, the hue-angle values were rotated by \(-15, -10, -5, 0, 5, 10, 15\) degrees. This image processing was aimed to imitate the different colors of a banana and cover the main part of its variation in nature. If, during the processing of the images, calculated values were out of the possible range for the gray values of the monitor, the nearest possible value of the chroma was used without changing the hue (clipping). Plate 1 presents a few examples of the processed images. Averaged color coordinates of the whole 7*7 set of the “fruit” and “banana” stimuli together with two corresponding backgrounds in the CIELUV color space are shown in Fig. 4.

The images were displayed by an Image Sequence Processor ISP500 of a Digital Video System. A high-resolution 50 Hz noninterlaced BARCO CCD7351B color monitor driven by a SUN-3/260 workstation was used to present the stimuli. The monitor was colorimetrically characterized and calibrated by using a Look-Up-Table technique in such a way that the total gamma, i.e., the luminance transfer, equals one for the whole chain reality-slide-scanner-monitor. Screen luminance measured by the Luminance meter LMT L1003 ranged from 0.01–70 cd/m².

Because of unavoidable inaccuracies in all stages of an image preparation process, it is not possible to produce a perfect match in chromaticity coordinates between real and displayed objects. The magnitude of the mismatches in the color reproduction was evaluated by comparing the original CIE 1931 \((x, y)\) chromaticity coordinates of the Kodak color control patches at the moment of taking the picture with those reproduced by the monitor. The absolute values of the
The experiments were run in a dark room with a white dimly lit 2.5 cd/m\(^2\) background behind the monitor. The subjects were seated approximately 1.5 m from the screen. The images were displayed with flexible timing until the subjects gave a response. The interval between two image exposures was 4 s, during which a 6.7 cd/m\(^2\) (i.e., approximately the mean luminance of the whole set of images) gray adaptation field appeared on the screen. During a 5-min period of adaptation to the room illumination and screen luminance, the subjects studied instructions and then performed a training series of 10 stimuli to familiarize themselves with the experimental procedure and to establish an internal scale sensitivity.

The instructions stated that the purpose of the experiments was to investigate memory colors, namely, “colors that are recalled in association with familiar objects.” The subjects’ task was to judge the similarity in colors between the banana samples displayed on the screen and a typical ripe banana as they remembered it from their experience, using an 11-point numerical category scale: from 0 (no similarity between perceived and remembered colors) to 10 (complete similarity between perceived and remembered colors). The experiments were divided into six sessions (two sessions per presentation) with a random intra/inter-subject order. For each presentation, all 49 images were randomly shown 2 times in 2 separate sessions. Each experimental session lasted approximately 25 min.

Results
To minimize the effect of different scaling constants for different subjects, the data obtained for each observer were standardized via \(z\)-score transformations\(^24\) by subtracting the mean and dividing by the standard deviation of the individual scales. The comparison of intra-subject scores (among 4 replications per subject) with inter-subject scores from the screen. The images were displayed with flexible timing until the subjects gave a response. The interval between two image exposures was 4 s, during which a 6.7 cd/m\(^2\) (i.e., approximately the mean luminance of the whole set of images) gray adaptation field appeared on the screen. During a 5-min period of adaptation to the room illumination and screen luminance, the subjects studied instructions and then performed a training series of 10 stimuli to familiarize themselves with the experimental procedure and to establish an internal scale sensitivity.

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**FIG. 3.** Color point distribution in the CIELUV color space for the master (a) “fruit,” (b) “banana,” and (c) “contour” images, projected on the \(u^* v^*\)-plane (every 16th point plotted).

**FIG. 4.** Averaged \(u^*\) and \(v^*\) color coordinates of the (square) “banana” and (circle) “fruit” stimuli used in (small open symbols) Experiment 1, (small black symbols) Experiment 2, and (large gray symbols) the two backgrounds.
(among 8 observers per three object depictions) did not reveal systematic differences. Therefore, we combined the individual z-scores of 32 trials and converted them to a common scale by adding the mean and multiplying by the standard deviation of the averaged scales.

Figure 5 presents the averaged similarity-to-prototypical-banana-color judgments vs. the CIELUV hue and chroma differences with the master image for (top) “fruit,” (middle) “banana,” and (bottom) “contour” images. The data are least-squares fitted by Gaussian curves. The vertical bars indicate the standard error of the mean. Five parameters were determined by least-squares fitting: $\mu_{Bu}$ and $\mu_{Bv}$, i.e., corresponding $u^*$ and $v^*$ coordinates of prototypical color $\mu_B$ in the CIELUV chromaticity plane; $\sigma_u^2$ and $\sigma_v^2$, i.e., the variances of the category distribution on $u^*$ and $v^*$ dimensions; $\rho$, i.e., the correlation coefficient of the $u^*$ and $v^*$ values in the category distribution (see Fig. 7). The values $\mu_{Bu}$ and $\mu_{Bv}$ specify the location of the mean of the distribution, $\sigma_u^2$ and $\sigma_v^2$ specify the spread of the distribution, the ratio $\sigma_u/\sigma_v$ specifies the shape the distribution, the value $\rho$ specifies the orientation of the distribution. Figure 8 shows the best-fit of a Gaussian surface and the contours of equal likelihood $d^2 = 1/2$ (further referred to as d-ellipses) on the grid of stimuli in the CIELUV chromaticity plane.

An analysis of the distribution parameters reveals the following effects. As can be seen in Fig. 9, the three distributions have similar orientation, which corresponds to the angle of inclination of the major ellipse axis to the axis of the $u^*$-coordinates. The major ellipse axes approximately agree with the chroma direction, and the minor ellipse axes with the hue direction.

The shape, which corresponds to the ratio of the major and minor axes, is also similar for the three distributions. Apparently, the variances of the distributions representing the similarity judgments in the CIELUV color space are bigger in the chroma dimension than in the hue dimension. This implies that subjects were more tolerant to the variation in the banana colors along the chroma direction than to the variation along the hue direction.

The spread, which corresponds to the total area within the ellipses, of the “banana” and “fruit” distributions is slightly smaller than that of the “contour” distribution (see also Fig. 7). The d-ellipses are proposed to represent the decision...
bounds for the degree of similarity between perceived and prototypical object colors that is acceptable to an observer. Given this model, the decision bound varies for the three object depiction. Although these differences are not big, they are in agreement with the observer’s remarks that the similarity judgments were more difficult to make with the “contour” images than with the “fruit” and “banana” images. The difficulty is caused by an obstacle in interpreting the “contour” colors as object colors. The same obstacle might produce the differences in the total variance of inter-subject scores (see Fig. 10). In conformity with the prediction postulated above, the more natural the objects look, the more easily and consistently they are compared with the prototypical color.

The location, which corresponds to the center of the ellipses, of all three distributions in Fig. 9 is close to the master stimuli, but moved towards a slightly more saturated point. Evidently, there also is a significant shift in location among the three distributions. The center of the “banana” distribution is slightly more saturated than that of the “fruit” distribution, and slightly more reddish than that of the “contour” distribution.

To summarize the main results of the experiment, (1) the naturalness of the banana depiction facilitates the similarity judgments between the apparent and prototypical colors; (2) the similarity judgments representing the prototypical banana color in the CIELUV space can be sufficiently described by five parameters of a bivariate normal distribution; (3) the location and spread of the distribution representing the prototypical banana color in the CIELUV space vary for the three types of object depiction.

Discussion
It should be noted that the spread and location of the distribution representing the prototypical banana color
might be biased by the range and centroid of the stimulus set used in the experiment. We studied the impact of the stimulus range on the basic parameters of the distribution in a preliminary experiment and found that the orientation, shape, and location of the distributions were not influenced by the stimulus range. The spread of the distribution grows monotonically with the stimulus range up to a certain degree. When the stimulus range (represented by the variance of the $u^*$ and $v^*$ values of the stimuli) is sufficiently large, as it is in Experiment 1, its impact on the spread of the distribution is negligible. For published data of a similar research and justification of assumption of ratio scale see Yendrikhovskij et al.\textsuperscript{10}

The impact of the centroid of the stimulus set could be revealed by a tendency of the subjects to scale the similarity with the mean of the stimulus set rather than the prototypical color held in their memory. We calculated the centroids for the three stimulus sets used in Experiment 1 and found that they were slightly less saturated than the originals, i.e., master images. This was due to the partial clipping of highly saturated values of the banana stimuli. Figure 9 shows that the centroids of the distributions representing the similarity judgments for the “fruit”, “banana,” and “contour” stimuli are more saturated than the master images. Therefore, even if the centroid-effect influenced the subjects’ response, this influence was probably not large. The precise impact of the centroid-effect requires comparison of the similarity judgments of stimulus sets with different centroids, which is a subject for future research.

Experiment 2: Apparent Object Colors

The aim of Experiment 2 is to specify the representation of apparent colors of 15 stimuli used in Experiment 1.

Method

Subjects. Eight subjects took part in the experiment, only 4 of them participated in Experiment 1. Other subject characteristics were similar to those in Experiment 1.

Stimuli. From the same set of stimuli as in the previous experiment, 15 images (5 for each banana depiction) were chosen to run the study (see Fig. 4). To present two stimuli simultaneously, we deleted an area of 89*450 pixels (i.e., 20%) from the left side of each image.

Procedure. The viewing conditions were identical to those in Experiment 1. The instructions stated the purpose of the experiment “to investigate the differences in color appearance of objects.” The subjects’ task was to judge the difference in apparent color between two bananas presented simultaneously on the right- and left-hand side of the monitor screen. They were allowed to use the integer numbers from 0 (no difference in apparent colors) to 10 (maximum difference in apparent colors). Before the actual experiment, the subjects estimated a training series of 10 stimuli to familiarize themselves with the experimental procedure and to establish an internal scale sensitivity. The stimuli were combined to form 225 stimulus pairs. These pairs were presented once in a random order in two sessions, yielding four repetitions per pair ignoring the presentation position on the monitor.

Results: Obtained-Appearance Space

Two 15*15 matrices of color differences between the images were obtained for each observer. These matrices were combined in one averaged lower-half matrix per subject before they were processed by the Symmetrical INDSCAL (SINDSCAL) program (e.g., Schiffman et al.\textsuperscript{32}; Green et
al.\textsuperscript{33}). This program represents data by points in a multidimensional Euclidean space, such that the distances between the points are linearly related to the corresponding difference judgments. The advantage of this program is the possibility of finding a common space that holds for all the subjects as well as individual spaces for each subject. With an iterative least-squares procedure, the program determines the stimulus coordinates and the dimension weights that account for the maximum variances in matrices of scalar products derived from the experimental data. The correlation \( r \) between the scalar product and the computed scores indicates the goodness-of-fit.

An analysis of individual spaces did not reveal considerable differences and only the common two-dimensional space \( (r = 0.90) \) obtained for all subjects is discussed here. This space (further referred to as obtained-appearance space) is shown in Fig. 11(a). The data demonstrate small but systematic differences between locations of the apparent colors for the three object depiction. The “fruit” stimuli are slightly shifted in the unsaturated-greenish (U-G) direction, and the “contour” stimuli in the unsaturated-reddish (U-R) direction relative to the “banana” stimuli. The differences between the locations of the apparent colors might be caused by two effects: (1) mode-effect in representing object colors, and (2) induction-effect in representing apparent object colors, which are discussed in the following section.

**Results: Predicted-Appearance Space**

The differences between the apparent “banana” and “contour” stimuli can be explained by the mode-effect. Before starting the experiments, we assumed that the object color could be represented by the mean of all colors belonging to an object surface. Consequently, the “contour” master image was produced with the same average chromaticity as the “banana” master image. However, the object color can also be represented by the mode, i.e., the most frequent value. If the internal-apparent representation of the banana color is determined by the mode, then the external-stimulus representation of the banana color of the “contour” image should also have been chosen as the mode. The “banana” stimuli in Fig. 11(a) are shifted towards a slightly more greenish point compared with the “contour” stimuli. This shift is approximately in the same direction and has about the same magnitude as the one resulting from applying the mode instead of the mean as the representation of the banana color [see Fig. 11(b)]. The color coordinates of the mode were computed from histograms of the pixels representing “banana” stimuli in the CIELUV color space and corresponded to the value with the highest number of pixels on the \( u^* \) and \( v^* \) dimensions.

The differences between the apparent “banana” and “fruit” stimuli can be explained by the induction-effect. The backgrounds of the “banana” and “fruit” stimuli have slightly different average chromaticities and, therefore, the observers’ adaptation states in the two conditions are not exactly the same. As a result, the “banana” and “fruit” stimuli might have different apparent colors due to the influence of chromatic adaptation on color appearance (e.g., Webster and Mollon\textsuperscript{34}). If this is true, the same induction-effect should also be observed in the previous experiment.

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**FIG. 11.** (a) Obtained-, (b) predicted-, and (c) calculated-appearance spaces of 15 apparent object colors for (circle) “fruit,” (square) “banana,” and (triangle) “contour” images. G, S, R, and U denote greenish, saturated, reddish, and unsaturated directions from the master image, respectively.
In fact, by means of Eq. (1), it is possible to derive the coordinates of the apparent “banana” and “fruit” colors from the results of Experiment 1. The only unknown parameter in this equation is a constant $k$ describing the magnitude of the induction effect. This constant was calculated from the distance between coordinates of the centers of the two distributions representing similarity estimates of the “banana” and “fruit” stimuli (see Fig. 9). Figure 11(b) shows the location of 5 apparent colors of the “fruit” stimuli obtained by the shift $k$ from the “banana” stimuli.

In general, Fig. 11(b) can be interpreted as a space showing the location of 15 apparent object colors predicted from Experiment 1 on the basis of the mean-mode and induction effects. This space (further referred to as predicted-appearance space) is largely in agreement with the obtained-appearance space from Experiment 2 [Fig. 11(a)]. Both spaces demonstrate a small but systematic shift of the “fruit” stimuli in the unsaturated-greenish (U-G) direction, and the “contour” stimuli in the unsaturated-reddish (U-R) direction relative to the “banana” stimuli. The only disagreement between the predicted-appearance space and the obtained-appearance space is with the chroma values of a few “contour” stimuli.

It is interesting to note that, although the metrical properties of both spaces are very similar, there are two small differences that can be seen in Fig. 11. First, the distance between points in the chroma direction (S-U) of the obtained-appearance space is slightly smaller than in the hue direction (R-G), while in the predicted-appearance space these distances are almost identical. It seems that the subjects underestimated the apparent chroma differences in comparison with the apparent hue differences of the displayed banana stimuli. Second, the distance between saturated (S) and reddish (R) points of the obtained-appearance space is slightly larger than the distance between unsaturated (U) and reddish (R) points, while again in the predicted-appearance space these distances are almost identical. It indicates that there is some small correlation between the chroma and hue values in the obtained-appearance space.

**Results: Calculated-Appearance Space**

The metrical differences between the obtained-appearance space and predicted-appearance space can be reduced by means of a matrix transformation procedure called MATFIT.\textsuperscript{5} Let us consider the $x$, $y$ coordinates of the stimuli in the obtained-appearance space as a 2-dimensional orthogonal matrix $O$, and the $u^*$, $v^*$ coordinates of stimuli in the predicted-appearance space as 2-dimensional orthogonal matrix $P$. The MATFIT algorithm finds an optimal transformation matrix $T$, such that the correlation between $O$ and $TP$ for the given stimulus configuration is maximal. Since we do not know the characteristic of the mapping function from the CIELUV to the SINDSCAL metrics, both linear and nonlinear transformations on the $u^*$ and $v^*$ axes were applied. The matrix $T$ derived by the MATFIT procedure was used to transform the coordinates of the stimuli in the predicted-appearance space to new coordinates in a calculated-appearance space [see Fig. 11(c)]. On the one hand, the calculated-appearance space has the advantage over the predicted-appearance space that it more closely resembles the actual appearance of object colors determined in the experiment. On the other hand, the calculated-appearance space has the advantage over the obtained-appearance space that it can represent not only the 15 stimuli, but the whole set of images used in Experiment 1.

The averaged similarity judgments of Experiment 1 were characterized by a bivariate normal distribution in the calculated-appearance space. The agreement between the similarity judgments derived experimentally and those calculated on the assumption of a normal distribution is good: correlation between the model and experimental data is $r = 0.957$ for the “fruit”, $r = 0.917$ for the “banana,” and $r = 0.955$ for the “contour” stimuli (see Fig. 12). The statistical parameters of the density functions are shown in Fig. 13. The differences between the parameters for the three object depictions are smaller than the ones obtained in Experiment 1 for the CIELUV color space (compare Fig. 13 with Fig. 7). The result that the average correlation coefficient $r$ of the $u^*$ and $v^*$ values in the category distribution is close to 0 implies that the number of parameters needed to sufficiently describe the similarity judgments in the calculated-appearance space is reduced to four: two chromaticity coordinates of the prototype and two variances of the category distribution. Using the fact that there are only small differences between $\sigma_u$ and $\sigma_v$, the number of parameters could be decreased down to three.

Figure 14 shows the best-fit of Gaussian $d$-ellipses representing the similarity judgments in the calculated-appearance space.
ance space. One of the remarkable results seen from this figure is that the distributions are less elongated and more overlapping in comparison with the ones shown in Fig. 9. This implies that the shift between the distributions representing the prototypical color, the tolerance to the chroma differences, and the correlation between the hue and chroma values found in Experiment 1 have approximately the same direction and magnitude as the shift between the apparent colors, the underestimation of the chroma differences, and the correlation between the hue and chroma values found in Experiment 2.

To summarize the main findings of the experiment, (1) the location of apparent colors in the obtained-appearance space vary for the three object depictions, probably due to the mode-effect and the induction-effect; (2) the similarity judgments representing the prototypical banana color in the

FIG. 13. The statistical parameters of the bivariate normal distribution representing the similarity judgments of Experiment 1 in the calculated-appearance space. The vertical bars indicate 95% confidence intervals of the fit. The dashed lines indicate the average values.
calculated-appearance space can be sufficiently described by three parameters of a bivariate normal distribution; (3) the distribution representing the prototypical banana color in the calculated-appearance space does not vary much for the three types of object depiction.

Discussion
The results of Experiment 2 suggest that the differences in location between the distributions representing similarity judgments for the three object depiction found in Experiment 1 can be explained by the difference in appearance of the object colors. Siple and Springer\textsuperscript{11} argued that access to memory for object color is independent of the object context. They compared memory colors of food items with and without shape and texture cues, and concluded that these cues did not produce any differences in location of memory color selection. We found small differences in location of the prototypical object colors in the CIELUV color space, but come to the same conclusion. The results of Experiment 2 demonstrate that these differences might be due to the mode-effect and the induction-effect.

The outcomes of the experimental research with the three object depictions lead to the discussion whether apparent and prototypical colors are invariant. The location of the prototypical color, derived from the similarity judgments of Experiment 1, seems to be independent of the object depictions in the calculated-appearance space, but not in the CIELUV color space. Therefore, the prototypical colors might be invariant on the level of apparent object colors, but not on the level of colorimetric object colors. The location of the apparent colors, derived from the difference judgments of Experiment 2, vary for the three object depictions in the obtained-appearance space. In particular, apparent colors of exactly the same objects in the “fruit” and “banana” depictions were perceived differently due to the effect of the object surroundings. Although the differences found in our experiments are rather small, the surroundings effect can be more impressive (e.g., see Fairchild\textsuperscript{25} for a recent review) and affect not only appearance but color name as well. For example, McFadden \textit{et al.}\textsuperscript{36} shown that some chromaticities were labeled purple with a red surround, whereas with a blue surround they were labeled pink. It seems that the visual system incorporates the object in a context-dependent appearance. The context-dependent appearance is also expressed in the phenomenon known as color constancy, i.e., the perceived invariance of object colors under different illuminants.

One of the main problems of color constancy is that human color vision exhibits only approximate color constancy (see Thompson \textit{et al.}\textsuperscript{37} for ecological reasoning) and its degree depends on the experimental task,\textsuperscript{36,39} learning and illuminant familiarity,\textsuperscript{40} and complexity of the scene in view.\textsuperscript{41} For example, Jin and Shevell\textsuperscript{41} studied the relationship between color memory and color constancy for two experimental conditions. In their experiments, a test color was surrounded by either a complex pattern composed of several color patches or a simple pattern composed of a uniform gray field. They reported that results with the complex surround were consistent with a surface-reflectance hypothesis, which states that the color recalled from memory is based on an inferred spectral reflectance of a surface independent of the spectral distribution of the illuminant; while the results with the simple surround primarily support the photoreceptor hypothesis, which states that the color recalled from memory is determined by the light absorbed by each type of cone. These findings are in agreement with computational models implying that color constancy increases with the number of distinct chromaticities in view.\textsuperscript{42}

Returning to our example of the person searching for his favorite ripe banana, we can conclude that perceptual phenomena might influence the observer’s choice. From the same set of fruits, the person might pick out different bananas in the supermarket compared to outdoors simply due to the fact that the fruits might appear to be different under different illuminating conditions or surroundings. This chance is even bigger, if he participates in an experiment with an artificial stimuli when banana colors are represented by color patches and the complexity of the scene in view is limited. However, the inconsistency of the observer’s choice does not necessarily imply the inconsistency of memory color, which might be invariant in the observer’s appearance space.

Population of Object Colors in Nature
The aim of this investigation was to determine the sampling of ripe banana colors in the CIE $u'v'$ chromaticity

FIG. 14. The (solid curves) best-fitting Gaussian $\sigma$-ellipses and (dash curves) 95% confidence intervals representing the similarity judgments of Experiment 1 in the calculated-appearance space. Symbols are the same as in Fig. 9.
diagram and compare it with the similarity-to-prototypical-banana judgments derived from Experiment 1.

The sampling was obtained by 100 measurements of bananas from a Dutch fruit market. The measurements were carried out using a Spectroradiometer SpectraScan PR-650 from eye level. The choice of location, object, and measurement areas was random, i.e., the Spectroradiometer was “blindly” pointed towards a branch of bananas. Before taking the measurement, we checked whether it was really pointed towards a banana surface. If not, it was directed towards the closest surface. For every 10 different locations (10 samples per location), a reference white was also measured.

Figure 15 shows the CIE $\Delta_u$ and $\Delta_v$ coordinates of the measured samples together with the best-fit of 2 $d$- and 3 $d$-ellipses of the Gaussian distribution representing these samples, and the $d$-ellipse of Gaussian distribution representing the similarity judgments of Experiment 1 for the “fruit” stimuli. Both distributions are similar in their shape and orientation, but not in location and size. The mean of the distribution representing the similarity judgments is slightly shifted towards more saturated points than the mean of the object sample distribution. The effect, however, is not large, and considerably smaller than the shift in the hue direction. The size of the $d$-ellipse of the similarity judgments is approximately 2.5 times bigger than the $d$-ellipse for the measured samples.

The presented measurements of the surface samples is just a first step in investigating the complex relationships between memory colors and statistics of the outside world. However, even these preliminary and rather arbitrary measurements lead to the following important conclusions. First, the measurements show that the shape and orientation of the distribution representing the prototypical banana color correspond well with the shape and orientation of the distribution representing the population of the banana surface colors. As far as we know, this is one of the first comparison of these attributes (most of the previous research on memory colors was limited by comparison of the mean values only). It provides a direct evidence that the formation of memory colors might indeed be determined by the statistics of object colors seen in the past. Second, the measurements show that the variability of the surface colors is approximately 2.5 times smaller than the variability of the distribution representing the prototypical color. Therefore, the size of the surface variability is most likely to be small, but not negligible. This conclusion indicates that the total spread of the category distribution probably is dependent on object’s category [see our discussion with respect to Eq. (2)].

General Discussion and Future Research

This article gives an insight into the phenomenon of memory colors and provides the framework for their formal specification. We present a computational model of memory colors and propose to characterize them from similarity judgments, i.e., experimentally determined similarity judgments of apparent object colors with the prototypical color of the corresponding object category. The similarity judgments can be described by a multivariate probability density function (e.g., Gaussian) in a perceptually uniform color space (e.g., CIE Leon UV). Two aspects have to be emphasized here. First, we have considered memory colors within a framework of categorization, which is one of the fundamentally important processes for perception and cognition in general (e.g., Ashby22; Rosch 17) and for color vision in particular (e.g., Boynton and Olson43; Uchikawa and Shinoda44; see Saunders and Brakel45 for discussion). The categorical aspect is essential to understand memory colors and refers to the semantic level of their specification. Second, we have represented memory colors by a Gaussian probability density function in the CIE UV color space. The type of the function and the space is not essential to understand memory colors and refers to the algorithmic level of their specification. The Gaussian function and the CIE UV space were chosen as a first approximation, but other functions and spaces can also be used. For example, color categories can be modeled employing fuzzy set theory,46,47 and the recently proposed CIECAM97’s space48 might be a better choice to model the appearance space.

The results of Experiment 2 for the “fruit” and “banana” stimuli show that apparent colors of exactly the same objects were perceived differently due to the effect of the object’s surroundings. It seems that the visual system does not correct for this effect and incorporates the object in a context-dependent appearance. Roughly speaking, this leads
to the fact that a banana on a very blue background might
look slightly more yellow than exactly the same banana on
a very yellow background. What are the biological or eco-
logical reasons that the visual system works in this manner?
What are the advantages and disadvantages of such a pro-
cess? So far one can only speculate that despite the obvious
disadvantage in establishing dissimilarity in color appear-
ance of identical objects due to their context, the visual
system apparently gains something from processing infor-
mation globally, i.e., over the whole field of view (see
Thompson et al.37; Thompson39 for discussion). The advan-
tage of global processing might be related to another in-
triguing phenomenon known as approximate color con-
stancy, i.e., the relatively stable appearance of object colors
under various illuminants. It would be interesting to inves-
tigate an effect of color categories on color constancy. Some
experiments have already been started in these impor-
tant directions, but more research is needed.

For the present, the relation between outside world sta-
tistics and memory representations is also an issue for open
discussion. We have measured samples of banana colors
and compared the parameters of the distributions describing
these samples with those describing the similarity judg-
ments. The closeness of both types of distributions in their
shape and orientation indicates that the formation of mem-
ory prototypes for object colors might be determined by the
population of object colors seen in the past. But the differ-
ences in location and spread of these distributions suggest
that the determination should not be considered straightfor-
ward. For example, the fact that the variability of the dis-
tribution representing the prototypical color is approxi-
ately 2.5 times bigger than the variability of the measured
samples might be caused by a number of factors. In general,
the spread of the category’s distribution can be influenced
by (1) variability in the surface reflectance statistic, (2)
variability in the illuminant statistic, (3) variability in the
perceptual domain [see Eq. (2)]. It would be interesting to
investigate the impact of these variables on the formation of
prototypical colors in more detail. For example, one can
analyze the representation of memory color of a well-known
object exhibiting very limited variation in surface reflect-
tance, e.g., cash bank-notes. This would give an approxi-
mate estimate of variability in the illuminant and perceptual
domain only.

CONCLUSIONS

We introduce a computational model of memory colors,
which (1) represents memory color of an object by proto-
typical color of the corresponding object category; (2) char-
acterizes the prototypical color by its similarity with appar-
rent colors of object samples of that category; (3) describes
the perceived similarity by a multivariate probability den-
sity function in a perceptually uniform color space.

Experiment 1 specifies the representation of prototypical
color of the category "ripe banana" in the CIELUV color
space for the three object depictions and shows that (1) the
naturalness of the banana depiction facilitates the similarity
judgments between the apparent and prototypical colors; (2)
the similarity judgments representing the prototypical ba-
nana color in the CIELUV space can be sufficiently de-
scribed by five parameters of a bivariate normal distribu-
tion; (3) the distributions for the three object depictions in
the CIELUV space have similar shape, orientation, but not
the same spread and location.

Experiment 2 specifies the representation of apparent
colors of 15 stimuli used in Experiment 1 and shows that (1)
the location of apparent colors in the obtained-appearance
space vary for the three object depictions; (2) the similarity
judgments representing the prototypical banana color in the
calculated-appearance space can be sufficiently described
by three parameters of a bivariate normal distribution; (3)
the distributions for the three object depictions in the cal-
culated-appearance space have similar shape, orientation,
spread, and location.

We also determined the sampling of 100 ripe banana
colors in the CIE \(u'v'\) chromaticity diagram and showed that
(1) the shape and orientation of the distribution representing
the prototypical banana color were consistent with the shape
and orientation of the distribution representing the popula-
tion of the banana surface colors; (2) the variability of the
surface colors is approximately 2.5 times smaller than the
variability of the distribution representing the prototypical
color.

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