38 Color Constancy

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Vision is useful because it informs us about the physical environment. In the case of color, two distinct functions are generally emphasized (e.g., Jacobs, 1981; Mollon, 1989). First, color helps to segment objects from each other and the background. A canonical task for this function is locating fruit in foliage (Regan et al., 2001; Sumner & Mollon, 2000). Second, color provides information about object properties (e.g., fresh fish versus old fish; figure 38.1). Using color for this second function is enabled to the extent that perceived object color correlates well with object reflectance properties. Achieving such correlation is a nontrivial requirement, however, because the spectrum of the light reflected from an object confounds variation in object surface reflectance with variation in the illumination (figure 38.2; Brainard, Wandell, & Chichilnisky, 1993; Hurlbert, 1998; Maloney, 1999). In particular, the spectrum of the reflected light is the wavelength-by-wavelength product of the spectrum of the illumination and the object's surface reflectance function (figure 38.2B). The dependence of the reflected light on illumination leads to ambiguity about object reflectance because changes in the spectrum of the reflected light can arise from changes in object reflectance, changes in illumination, or both. Despite this ambiguity, color appearance is often quite stable across illumination changes (e.g., Helmholtz, 1896/2000; Katz, 1935; Brainard, 2004). The approximate invariance of object color appearance is called color constancy. When color constancy fails, as in the case of Uluru (figure 38.2A), it is a phenomenon to remark on.

Ambiguity occurs pervasively in perception (e.g., Gregory, 1978; Helmholtz, 1896/2000; Wolfe et al., 2006) and at higher levels of processing (for example, language) (Foder, Bever, & Garrett, 1974; Miller, 1973). Characterizing how biological information processing resolves informational ambiguity is a priority for vision science (e.g., Brainard, 2009; Knill & Richards, 1996; Purves & Lotto, 2003; Rust & Stocker, 2010). Object color perception provides a model system for moving such characterization forward.

This chapter provides an update on the treatment of color constancy that appeared in the first edition of this volume (Brainard, 2004). Our emphasis here is to provide a self-contained introduction, to highlight some more recent results, and to outline what we see as important challenges for the field. We focus on key concepts and avoid much in the way of technical development. Other recent treatments complement the one provided here and provide a level of technical detail beyond that introduced in this chapter (Brainard, 2009; Brainard & Maloney, 2011; Foster, 2011; Gilchrist, 2006; Kingdom, 2008; Shevell & Kingdom, 2008; Smithson, 2005; Stockman & Brainard, 2010).

MEASURING CONSTANCY

The study of constancy requires methods for measuring it. The classic approach to such measurement is to assess the extent to which the color appearance of objects varies as they are viewed under different illuminations. Helson (1938; Helson & Jeffers, 1940), for example, trained observers to use a color-naming system (Munsell notation) and then had them name the colors of surfaces viewed under different illuminants. He found very good constancy as long as the illumination was not too close to monochromatic.

More recent work has focused on continuous measures. For example, in a cross-illumination *asymmetric matching* experiment, the observer adjusts the color of a matching stimulus seen under one illuminant so that it appears to have the same color as a reference stimulus presented under another illuminant (e.g., Arend & Reeves, 1986; Brainard, Brunt, & Speigle, 1997; Burnham, Evans, & Newhall, 1957). The conceptual idea is illustrated in figure 38.3. The top of the figure illustrates two contexts, shown as two collections of flat colored rectangles (so-called *mondrians*), each uniformly illuminated. One context is defined as the standard context, and the other is defined as the test context. In the figure the two contexts differ because the collection of surfaces in each is seen under a different illuminant. In parallel with our nomenclature for the contexts, we refer to these as the standard and test illuminants. A reference surface is presented in the standard context, and the observer's task is to adjust a matching surface, presented in the test context, so that its color appearance matches that of the reference.

FIGURE 38.1 Color tells us about object properties: The sushi on the left plate looks more appetizing than the sushi on the right plate. (Image on left courtesy of Michael Eisenstein. Image on right manipulated by hand in Photoshop to simulate aging of the fish. After a demonstration by Bei Xiao.)

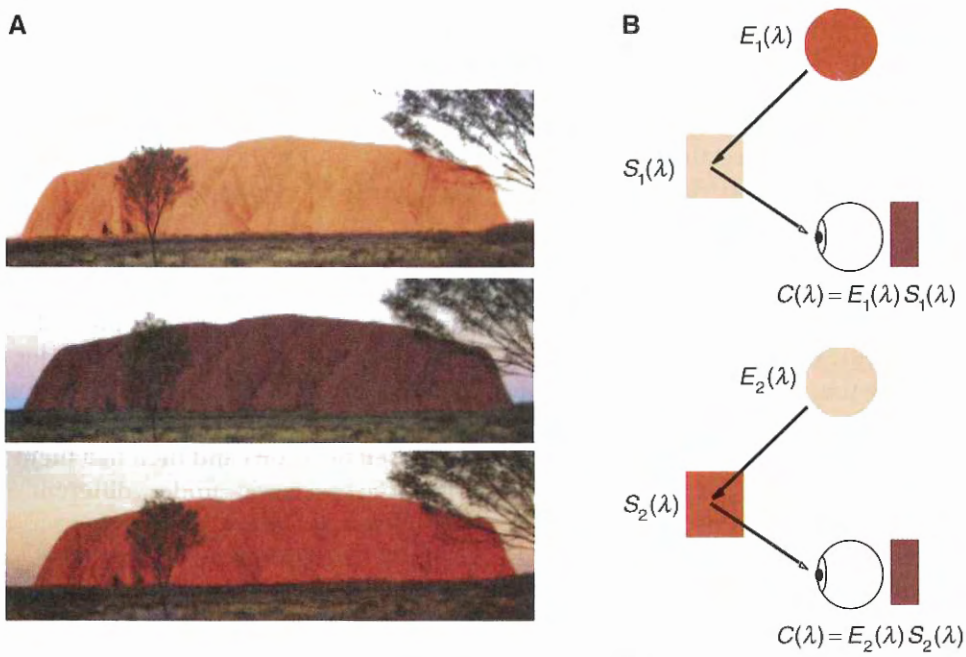

FIGURE 38.2 (A) Uluru, a sandstone formation in the Australian outback famous for its large changes in color appearance. These changes occur because of variation in the spectrum of the light impinging on the rock, which in turn affects the reflected spectrum. What is unusual about Uluru is not the illumination changes—these are pervasive in natural viewing—but that they are perceived as large changes in object color. Photographs copyright © Anya Hurlbert and reproduced with permission. (B) The spectrum of the light reflected from an object, $C(\lambda)$, is the wavelength-by-wavelength product of the illuminant spectrum $E(\lambda)$ and the object's surface reflectance $S(\lambda)$. The same spectrum reaching the eye can arise from many different combinations of illuminant and surface. The figure illustrates two such combinations.

Various techniques may be used to produce and manipulate the stimuli for this type of experiment (for examples, see Arend & Reeves, 1986; Brainard, Brunt, & Speigle, 1997; Delahunt & Brainard, 2004; Xiao et al., 2012).

To connect asymmetric matches to color constancy, consider possible experimental outcomes. One possibility is that the observer will set the matching surface to have the same reflectance as the reference surface despite the change in illuminant. This surface will reflect different light to the observer under the test illuminant than under the standard illuminant. An observer who sets such a match would be considered perfectly color constant (100% constant, figure 38.3) because for such an observer we can infer that the reference surface retains its appearance across the change in illuminant.

A second possibility is that the observer will set the matching surface so that it reflects the same spectrum to the eye under the test illuminant as does the

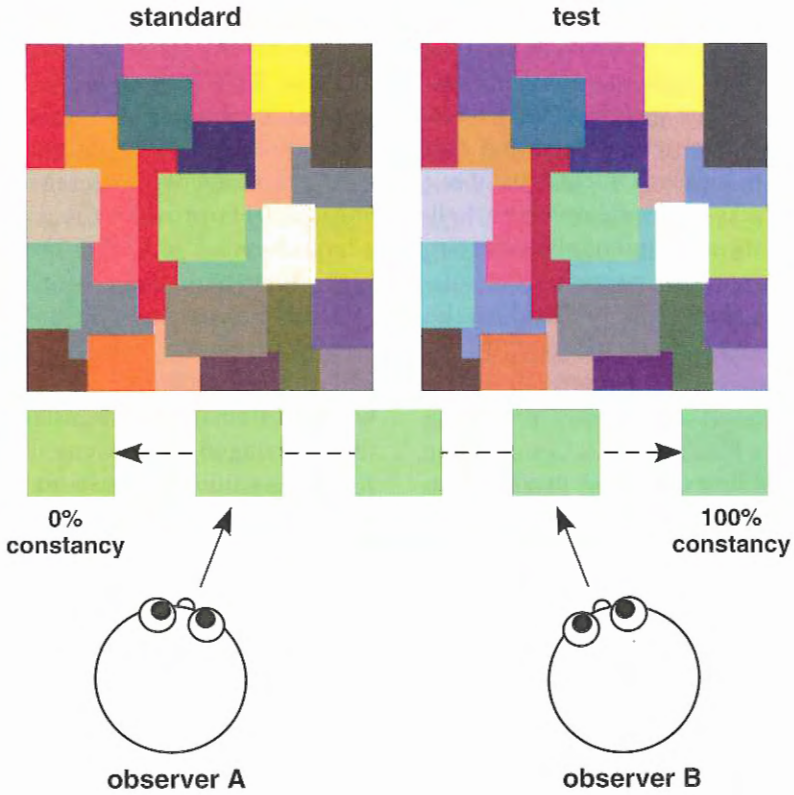

FIGURE 38.3 In a cross-illumination asymmetric matching task, an observer is presented with two contexts. In the figure these are shown as two collections of colored rectangles (so-called mondrians). One context is the standard, and the other is the test, with the illumination differing between the two. The experimenter presents a reference surface in the standard context, and the subject adjusts a matching surface presented in the test context until its color matches that of the reference. In the figure the reference and matching surfaces are at the center of their corresponding mondrians. Below the mondrians are shown five example matches that might be set by an observer. One possibility is that the observer will set a match that has the same surface reflectance as the reference surface. This is illustrated on the right and labeled 100% constancy. Another possibility is that the observer will set a match that corresponds to a different surface reflectance, but that reflects the same spectrum as the reference. This is shown schematically on the left and labeled 0% constancy. Observer matches typically fall between these two theoretical endpoints, and a constancy index may be assigned according to where between the endpoints the match lies. For example, if observer A sets the match indicated by the leftmost arrow, then A's constancy index would be approximately 25%. Similarly, observer B's constancy index would be approximately 75%.

reference surface under the standard illuminant. This possibility is depicted at the left-hand side of the set of sample squares in the figure. Note that the matches set by an observer of this type are the same as those that would be set on the basis of physical measurements of the reflected spectrum. Thus, we say that an observer who sets this type of match has no constancy (0% constant).

In actual experiments observers' matches tend to lie between the two possibilities described above: The matches are neither 0% constant nor 100% constant. Based on this it is common to use asymmetric matching data to assign a constancy index value, typically ranging between 0% and 100%, that characterizes how close the observer's matches are to the idealized endpoint matches. Such indices summarize performance and allow consideration of what factors influence the degree of constancy exhibited by observers. A number of sources discuss the quantitative analysis used to compute constancy indices from asymmetric matches (Arend et al., 1991; Brainard, Brunt, & Speigle, 1997; Brainard & Wandell, 1991; Troost & de Weert, 1991).

A second method that has been used to assess constancy is achromatic adjustment. This method is conceptually similar to asymmetric matching except that instead of adjusting a test surface to match a physical reference, the observer adjusts the chromaticity of a test so that it appears achromatic and then repeats this adjustment with the test embedded in a variety of contexts. The resulting achromatic chromaticities obtained

in different contexts are then considered to be matched in appearance, and the data can be analyzed to produce constancy indices in much the same way as achromatic matching data (Brainard, 1998). Speigle and Brainard (1999) established that asymmetric matching and achromatic adjustment lead to similar conclusions about constancy when the two tasks are compared with well-matched stimuli. Achromatic adjustment allows one to study performance across contexts presented in isolation without introducing a heavy memory load on the observer.

BASIC OBSERVATIONS

Given an understanding of how constancy may be measured, we can turn to making some basic empirical generalizations from over 100 years of experimental literature. Much of the experimental literature has considered a simplified laboratory model in which a spatially diffuse light source homogeneously illuminates a set of flat matte surfaces (*flat-matte-diffuse conditions*; for reviews see Brainard, 2004; Brainard & Maloney, 2011; Maloney, 1999; for a selection of experiments see Arend & Reeves, 1986; Brainard, 1998; Brainard, Brunt, & Speigle, 1997; Delahunt & Brainard, 2004; Granzier et al., 2005; Helson & Jeffers, 1940; Kraft & Brainard, 1999; McCann, McKee, & Taylor, 1976; Olkkonen, Hansen, & Gegenfurtner, 2009). Such simplification is reasonable. Although one might view a characterization of constancy for the richer conditions of natural viewing as the ultimate end goal, it is also true that natural scenes are very complicated. To make experimental progress some degree of simplification is necessary, and actual experiments represent a compromise between an attempt to capture key aspects of natural viewing and an attempt to provide enough experimental control that the data are interpretable.

For flat-matte-diffuse conditions constancy across illuminant changes can be very good. Brainard (1998), for example, used real illuminated surfaces and the method of achromatic adjustment and found constancy indices of about 85%. High degrees of constancy can also be observed with stimuli that consist of graphics simulations of illuminated objects (Delahunt & Brainard, 2004, experiment 1, average constancy index 73%). Foster (2011) provides the constancy indices found in a large number of studies many of which are similarly high. Such high degrees of constancy are consistent with the intuition that the color appearance of objects does not change much from one situation to another, and data of this type lead to the empirical generalization that human color constancy is very good when all that is changed is the scene illumination.

In most studies of constancy the experimental manipulation is as described above—the illuminant is changed while the surfaces surrounding the test and reference are held fixed. This is the manipulation that is illustrated by the comparison between figure 38.4A and figure 38.4B. Although the motivation for studying this type of manipulation is obvious, note that for a collection of scenes where most of the surfaces never change, constancy is not a challenging computational problem. Indeed, changing only the illuminant is not the only way to vary the context in which an object is seen. The comparison between figure 38.4A and figure 38.4C illustrates a case in which the illuminant changes and the reflectance of the surface that forms the immediate background of the test also changes. In this example the change in background reflectance was chosen to exactly cancel the effect of the illuminant change for that background surface so that the light reflected from the background remained the same. The effect of this manipulation is to silence local contrast as a cue to constancy. For stimulus manipulations of this type constancy is reduced but not eliminated (Delahunt & Brainard, 2004; Kraft & Brainard, 1999; Kraft, Maloney, & Brainard, 2002; McCann, 1992; McCann, Hall, & Land, 1977; Werner, 2006). For example, Delahunt and

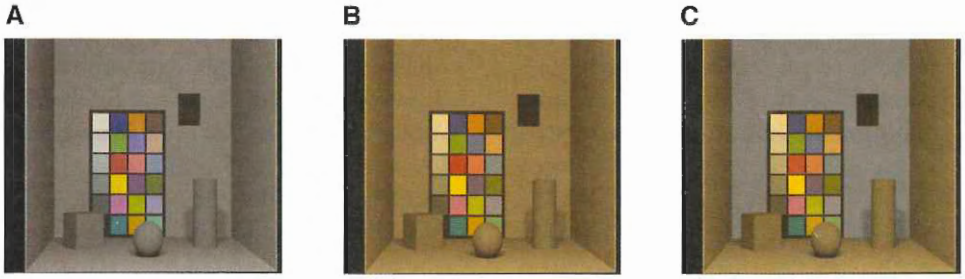

FIGURE 38.4 Experimental manipulations used in studying constancy. Between A and B the illuminant has changed. Between B and C the illuminant is held constant, but the reflectance of the background surface has been changed so that the light reflected from the background is the same as in A. Images depict stimuli used by Delahunt and Brainard (2004). (Reprinted with permission from Brainard & Maloney, 2011.)

Brainard (2004, experiment 2) found an average constancy index of 22% across context changes of this type. Kraft and Brainard (1999) showed similarly that manipulations that silence the change in the most luminous surface in the contextual image or the change in the spatial average of the reflected light have a similar effect: Constancy is reduced but not completely eliminated.

The results outlined above highlight the point that blanket statements about the degree of human constancy are not useful because the measured degree is highly dependent on the stimulus manipulation chosen for study. Any successful model of constancy must account not only for the fact that constancy is sometimes very good but also for the systematic failures of constancy that can be observed. This point appears underappreciated in the literature and is critical to bear in mind when one is comparing the degree of constancy reported across studies.

MODELING CONSTANCY

One approach to understanding how constancy varies with different stimulus manipulations is to connect human performance to a model of how an ideal visual system would estimate and correct for illuminant changes so as to stabilize object color appearance. Early efforts along these lines focused on the information carried by the spatial mean of the reflected light or on the information carried from the most luminous surface in the scene (Judd, 1940; Land, 1964; von Kries, 1902, 1905). Models of this sort capture a number of regularities in the data for experiments when only the illuminant is changed (McCann, McKee, & Taylor, 1976), but their predictions deviate from the data when the cues they rely on are silenced experimentally (Kraft & Brainard, 1999).

A more general approach is to employ a Bayesian algorithm to estimate the illuminant (Brainard & Freeman, 1997; D'Zmura, Iverson, & Singer, 1995; Gehler et al., 2008) and to use this to predict performance. The Bayesian approach has the advantage that it is sensitive to all the information about the illuminant carried by the initial visual representation of color. This information is provided by the isomerization rates of photopigment in three classes of cone photoreceptors (e.g., Brainard & Stockman, 2010). Indeed, there is useful information not only in the spatial average of the cone isomerization rates but also in their covariance and higher-order moments. Note that the observation that the covariance of the isomerization rates carries information about the illuminant precedes Bayesian treatments of color constancy (MacLeod & Golz, 2003; Maloney & Wandell, 1986; Webster & Mollon, 1995; Zaidi, 1998).

Brainard and colleagues (Brainard et al., 2006) used the Bayesian approach to model the data of Delahunt and Brainard (2004) and showed that it provided a good account of performance. The essence of their model was to assume that observers, in effect, use a specific Bayesian algorithm to estimate the illuminant and then discount the effect of this estimated illuminant (see also Brainard, Brunt, & Speigle, 1997; Brainard & Wandell, 1991; Speigle & Brainard, 1996). Brainard (2009) and Brainard and Maloney (2011) provide a conceptual review of this approach and how it may be generalized to more complex viewing situations.

A key feature of Brainard et al.'s (2006) Bayesian model is that it correctly predicts variation in the degree of measured constancy across different stimulus manipulations and connects this variation to the information about the illuminant available in natural images. Although the efficacy of this model has not been tested extensively even within the restricted flat-matte-diffuse stimulus ensemble, it provides both a framework for thinking about constancy at Marr's (1982) computational level of analysis and theory that links the computations to measurements of human performance. In addition, a successful computational model is important for understanding the neural mechanisms that subserve constancy in that such a model characterizes the phenomena a neural theory must account for. That said, an important challenge for theories of color constancy remains elucidation of the mechanisms that implement it in the human visual pathways. In this regard the Bayesian analysis does not provide any direct insight about the mechanisms that accomplish constancy.

The earlier version of this chapter (Brainard, 2004; see also Stockman & Brainard, 2010) provides an overview of mechanistic ideas as they relate to color constancy, and we briefly review these ideas here. At a general level, mechanistic accounts of constancy focus on the notion of adaptation. This is the idea that the transformation between the initial representation of the stimulus and responses later in the visual pathways depends on context. As noted above, the initial representation of a color stimulus is given by the isomerization rates of photopigment in three classes of cone photoreceptors (e.g., Brainard & Stockman, 2010). These are referred to as the L (long-wavelength-sensitive), M (middle-wavelength-sensitive), and S (short-wavelength-sensitive) cones. Subsequent retinal and cortical processing then transforms the LMS cone representation into one that consists of sums and

differences of signals from the different cone classes. At various sites along the pathways that implement this transformation, the signals are subject to multiplicative gain control as well as a subtractive form of adaptation (e.g., Blakeslee & McCourt, 2004; Chen, Foley, & Brainard, 2000; Engel & Furmanski, 2001; Jameson & Hurvich, 1964; Poirson & Wandell, 1993; Shevell, 1978; Stiles, 1967; Valeton, 1983; von Kries, 1902; Wade & Wandell, 2002; Walraven, 1976; Webster & Mollon, 1994; for reviews see Smithson, 2005; Stockman & Brainard, 2010; Walraven & Werner, 1982; Webster, 1996). Key is that the exact values of the multiplicative and subtractive transformations depend on the viewing context, so the representation corresponding to any triplet of LMS cone isomerization rates varies with context. Adaptation of this sort supports constancy to the extent that its overall effect is to stabilize the post-receptoral representation of the light reflected from objects across changes of illumination (as well as other contextual changes).

A challenge for connecting our mechanistic understanding of color adaptation to color constancy is that the stimuli that have been used to study constancy are generally more complex than those that have been used to study adaptation. For example, we know that constancy as measured under flat-matte-diffuse conditions is well described by changes in multiplicative gain (e.g., Bauml, 1995; Brainard, Brunt, & Speigle, 1997; Brainard & Wandell, 1992; McCann, McKee, & Taylor, 1976). What we do not know is how to independently derive the values of the multiplicative gain from a specification of a spatially rich stimulus. Two lines of research that aim to close this gap are worth note. First, Webster and Mollon (1994, 1995) analyzed how illuminant variation changes the mean and covariance of cone isomerization rates and showed that measured adaptation to such changes could support color constancy with respect to illumination changes. Second, Blakeslee and McCourt (2004; Blakeslee, Reetz, & McCourt, 2009) developed a model of lightness based on an abstracted model of mechanistic processing from retina to early visual cortex and showed that such a model can account for a variety of constancy-related lightness effects. Pushing the connections between mechanistic models, computational models, and the empirical data represents an important research frontier.

FUTURE DIRECTIONS

It is now possible to imagine a fairly complete account of color constancy for flat-matte-diffuse stimuli, although there is still much to be done. Even within the flat-matte-diffuse stimulus ensemble, we can go further toward incorporating a growing knowledge about the statistical structure of natural scenes as it pertains to color (surface reflectance functions: Jaaskelainen, Parkkinen & Toyooka, 1990; Krinov, 1947; Nickerson, 1957; Parkkinen, Hallikainen, & Jaaskelainen, 1989; Vrhel, Gershon, & Iwan, 1994; illuminant spectral power distributions: DiCarlo & Wandell, 2000; Judd, MacAdam, & Wyszecki, 1964; calibrated color images: Burge & Geisler, 2011; Ciurea & Funt, 2003; Gehler et al., 2008; Geisler & Perry, 2011; Olmos & Kingdom, 2004; Tkacik et al., 2011; hyperspectral image datasets: Chakrabarti & Zickler, 2011; Foster, Nascimento, & Amano, 2004; Longère & Brainard, 2001; Parraga et al., 1998; Ruderman, Cronin, & Chiao, 1998). Nonetheless, one can envision how a focused research program could bring together the computational and mechanistic ideas outlined above and test these with experiments that are within current technical reach.

Thus, it is worth asking, suppose that enterprise of understanding color constancy for flat-matte-diffuse conditions is brought to a successful conclusion, what would remain to be done within the field of color constancy? Below we outline what we see as some important directions.

Real-World Scenes

Real scenes do not consist of flat matte surfaces under diffuse illumination. First, real scenes exist in three-dimensional space so that objects differ in their depth as well as their position on the retinal projection. Second, real objects have three-dimensional shape and are made of nonmatte materials. Third, real objects often have texture of some sort, so that surface reflectance can vary across an object. Finally, real illumination has geometric structure.

Figure 38.5 illustrates richness that is introduced when we depart from flat-matte-diffuse. Figure 38.5A shows the effect of varying the three-dimensional pose of a flat matte surface when the light is directional rather than diffuse. As illustrated by the figure, the amount of light reflected to an observer depends strongly on the pose. Although the figure illustrates the effect for a change in intensity, similar effects occur in color (Bloj, Kersten, & Hurlbert, 1999; Boyaci, Doerschner, & Maloney, 2004). If the visual system did not compensate for such effects, objects would change their appearance as a function of their pose in the three-dimensional environment.

Constancy with respect to surface pose has received attention in the literature, although primarily in the domain of lightness (Bloj & Hurlbert, 2002; Bloj, Kersten, & Hurlbert, 1999; Boyaci, Doerschner, &

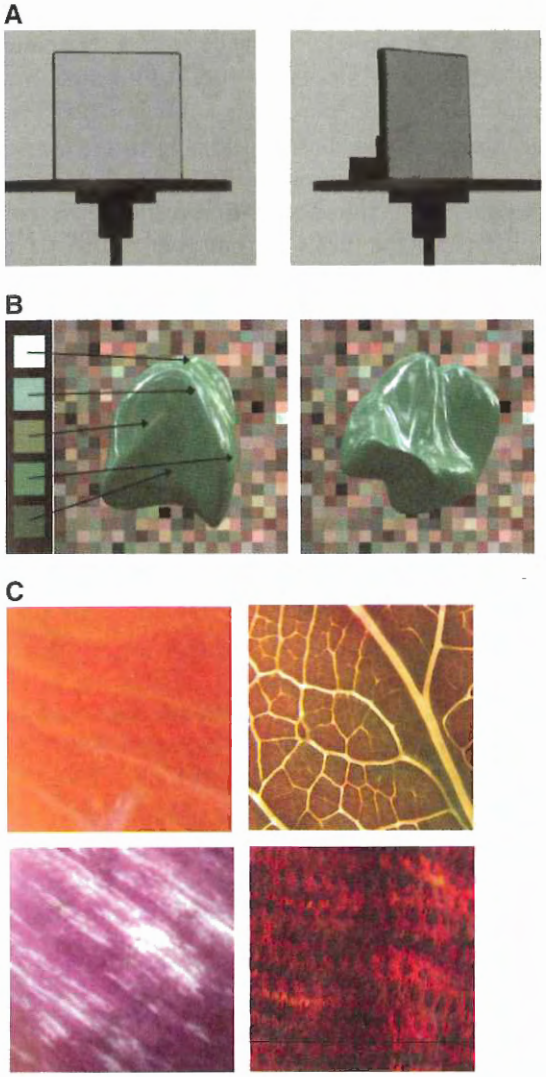

FIGURE 38.5 (A) Photograph of the same surface in two different poses with respect to a directional light source. The intensity of the light reflected from the surface varies with pose. (Reprinted with permission from Ripamonti et al., 2004.) (B) Two objects ("blob" and "pepper") made from the same material and rendered under the same spatially complex illumination field. The pattern of light reflected to the eye across the object varies with object shape. This variation is shown explicitly by the colored squares (left), which are drawn from individual pixels on the "blob." (Figure courtesy of Maria Olkkonen.) (C) Illustrative image patches from polychromatic objects. Clockwise from upper left: salmon (original photograph copyright © James Bowe); leaf (original photograph copyright © Peter Shanks); sweater (original photograph copyright © "orchidgalore"); eggplant (original photograph copyright © Liz West). Image patches obtained from photographs posted at flickr.com; all were posted under the creative commons attribution 2.0 generic license (http://creativecommons.org/licenses/by/2.0/deed.en).

Maloney, 2004; Boyaci, Maloney, & Hersh, 2003; Doerschner, Boyaci, & Maloney, 2004; Epstein, 1961; Gilchrist, 1980; Hochberg & Beck, 1954; Radonjić, Todorović, & Gilchrist, 2010; Ripamonti et al., 2004). The bulk of this work indicates that the human visual system indeed compensates for changes in reflected light that arise from changes of surface pose within three-dimensional scenes, although the exact stimulus conditions that support such compensation are less well understood. Outlines of theories that could be deployed to understand these effects are also available. One line of thought seeks to connect the result of three-dimensional manipulations of surface pose to results for flat-matte-diffuse conditions by invoking grouping principles that segment the three-dimensional scene into separate frameworks and applying principles derived from studies of simplified stimuli to understand what happens within each framework (Gilchrist, 2006; Gilchrist et al., 1999; see also Adelson, 2000; Anderson & Winawer, 2005). A second approach is to extend the computational approach described above to include geometric aspects of the illumination (Bloj et al., 2004; Boyaci, Doerschner, & Maloney, 2004; Boyaci, Maloney, & Hersh, 2003; Doerschner, Boyaci, & Maloney, 2004; reviewed in Brainard & Maloney, 2011).

Figure 38.5B shows how the light reflected from a three-dimensional object can vary across the surface of the object. For a fixed surface reflectance the pattern of reflected light can depend strongly on object shape. Variation in the pose of a three-dimensional object, the geometry of the illumination, and the material out of which the object is made affects the pattern of reflected light. A challenge is thus to measure and understand how we judge the color of objects in the face of these effects. The challenge arises because once variations in object shape, pose, illumination geometry, and object material are introduced into the experimental paradigm, the number of stimulus dimensions available for exploration grows to a point where systematic study via fully crossed designs is not feasible. Therefore, some type of simplifying theory becomes critical for guiding experiments. At present, such a theory is not available.

One theoretical suggestion, explored primarily in the lightness literature, is that simple summary statistics extracted from the luminance histogram of light reflected from an object might provide direct predictors of its lightness (and also of its perceived glossiness). Although initial results were promising (Motoyoshi et al., 2007; Nishida & Shinya, 1998; Sharan et al., 2008), this approach has not generalized well (Anderson & Kim, 2009; Kim & Anderson, 2010; Kim, Marlow, & Anderson, 2011; Olkkonen & Brainard, 2010, 2011). It remains possible, however, that theories that combine

such statistics with other information, such as object shape, will be useful. Another theoretical approach has been to test for simplifying empirical regularities (e.g., separability of effects of shape and illumination geometry/spectra), but these efforts have not to date led to successful accounts of the empirical data (Olkkonen & Brainard, 2010, 2011; Xiao et al., 2012). Work aimed at generalizing our understanding toward the full richness of three-dimensional objects and scenes thus remains exploratory.

Many objects (e.g., leaves, skin, rock, fabric) exhibit reflectance variation with varying degrees of spatial regularity. This is a form of texture, although the variation often does not have the quasi-periodic spatial structure of stimuli typically studied in the texture literature. Introspection suggests that reflectance variation need not prevent us from perceiving objects as having a characteristic color appearance (figure 38.5C). We currently know little about color constancy for such polychromatic objects, or indeed about how their overall color is extracted even under a single illuminant, although interest in this question is growing (Beeckmans, 2004; Hurlbert, Ling, & Vurro, 2008; Hurlbert et al., 2009; Hurlbert, Vurro, & Ling, 2008; Ling, Pietta, & Hurlbert, 2009; Olkkonen, Hansen, & Gegenfurtner, 2008; Vurro, Ling, & Hurlbert, 2009; Yoonessi & Zaidi, 2010). As with the geometric effects considered above, progress toward understanding color appearance and color constancy for polychromatic objects will require identification and confirmation of simplifying regularities.

Real-World Tasks

The discussion of constancy above focused on color appearance as the key dependent measure, and indeed, most of what we know about constancy is based on measurements of color appearance. These measurements, however, do not directly characterize performance in real-life tasks that require the use of color to choose among objects. As Zaidi (1998; see also Abrams, Hillis, & Brainard, 2007) has emphasized, an object could look different across a change in illumination, but it still might be possible to use color effectively for object selection or identification. This would, for example, be the case if a person perceived that the illumination had changed and used this fact to reason about object identity. Only a few papers report studies of how well subjects can use lightness or color to identify objects across changes in illumination (Robilotto & Zaidi, 2004, 2006; Zaidi & Bostic, 2008). Related work has considered the extent to which subjects can discriminate between image changes that result from changes in illumination and those that result from changes in surface reflectance (Craven & Foster, 1992; D'Zmura & Mangalick, 1994; Foster & Nascimento, 1994; Gerhard & Maloney, 2010). Additional study of the relation between perceived color appearance and performance on color-based tasks is a priority for understanding how color is used in the real world.

A second challenge for understanding the role of color in real-world tasks is that the results of color appearance experiments can depend on the instructions given to subjects (Arend & Reeves, 1986; Arend et al., 1991; Bauml, 1999; Reeves, Amano, & Foster, 2008; Troost & de Weert, 1991). In an influential asymmetric matching study Arend and Reeves (1986) found that when subjects are asked to "match the hue, saturation, and brightness of the [target color], while disregarding as much as possible other areas in the screen," the data show very little constancy across changes in illuminant. On the other hand, when they are asked to "to make the [match] look as if were cut from the same piece of paper [as the target]," constancy is considerably better.

There is no agreement about the fundamental nature of such instructional effects. Some authors (Arend & Spehar, 1993; Logvinenko & Maloney, 2006; Rock, 1975) posit that subjects have available multiple perceptual modes of color appearance and that instructions modulate which mode is used when making a match. Other authors are of the view that there is a single perceptual representation and that instructional effects modulate the degree to which subjects use explicit reasoning (Blakeslee, Reetz, & McCourt, 2008; MacLeod, 2011; see also Gibson, 1966; Koffka, 1935). Distinguishing between these and other related accounts has been difficult (see Wagner, 2012, for a recent review of the broad issues in the context of size judgments). This is in part because the varying views do not make discernibly different predictions for the outcome of most of the relevant experiments (but see Logvinenko & Maloney, 2006, for an interesting exception) and in part because delineating the precise experimental conditions (method, class of stimuli, and instructional wording) that lead to instructional effects has proved elusive (Cornelissen & Brenner, 1995; Delahunt & Brainard, 2004; Logvinenko & Tokunaga, 2011; Ripamonti et al., 2004). Independent of the theoretical position one adopts, understanding the relation between laboratory experiments and how color is used in real life clearly requires better control and characterization of instructional (as well as related individual difference) effects. Our sense is that these issues will become more acute as we continue to extend our experiments and thinking to richer and more naturalistic stimuli.

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