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Chapter 1

ON THE COMPUTATIONAL MODELING OF HUMAN VISION

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1. INTRODUCTION

The computational approach to human vision had its origin in the nineteenth-century algebraic formulas for predicting perceived hue from the spectral energy distribution [53], perceived sizes and shapes from retinal sizes and shapes [53], perceived depth from the disparity of the images in the left and right eyes [111], and perceived brightness from simple luminance distributions [34, 55, 76]. Visual problems involving image structure such as the perceived lightness of an unevenly illuminated wall that curves in space, the recognition of shapes and patterns, and the perceived spatial layout of objects were not easily solved mathematically. Algorithms for these more complex problems have evolved with the use of the computer for visual modeling. These models, however, often assume restricted and ecologically unrealistic conditions.

The remarkable flexibility and effectiveness of human vision poses a challenge to machine vision. A motivation for research on neural networks is the belief that the power of human vision can be achieved by using an architecture and processes that functionally mimic those utilized in biological vision. Though recognizing that the characteristics of biological vision and their efficient implementation are interdependent, this chapter focuses on three characteristics of human vision that I believe underlie its unusual effectiveness, rather than on how these characteristics can best be implemented. Rosenfeld [100] posed the question: Why is the effectiveness of machine vision so limited in comparison to the remarkable success of biological vision? He conjectured that one reason for the success of biological vision is its application of multiple processes to the information extracted from images. A second reason that he suggested is the generation of multiple representations designed for specific tasks. A third factor that I believe to be important is that perception is a function of multiple information sources. I examine the role of these factors in human vision in the perception of lightness, visual segregation, and the perception of transparency.

2. ONE-STAGE THEORIES

Multiple processing stages and interactions are a striking characteristic of higher biological vision. Neurophysiological studies indicate that there are many visual areas that encode properties of visual stimuli over varying-size areas of the visual field [68]. Psychophysical studies reveal interactions between the perceptions of color, shape, space and motion [88]. Despite the neurophysiological and psychophysical evidence that perception involves interactions among multiple processes, there has been a consistent attempt to simplify the problem by formulating one-stage computational theories. Helmholtz [53], Koffka [72], and Gibson [41] represent three differing theoretical approaches but are alike in formalizing vision as a one-stage process. For Helmholtz [53], percepts result from inferential-like processes based on the information provided by cues. Cues are the meanings attached to stimuli acquired in the course of phylogenetic or ontogenetic development. Bayesian vision algorithms are contemporary formulations of the Helmholtzian computational point of view [39]. Koffka [72] hypothesized that perception is to be explained in terms of an "energy field" which takes into account the total stimulus situation and tends toward a global minimum. Algorithms in which vision problems are mathematically formulated as minimization problems are representative of this computational point of view [91]. For Gibson [41], as with Helmholtz, perception is a function of information. Information, however, is conveyed by what he called higher-order variables: Spatial and temporal patterns of stimulation that specify information about the environment. Gibson [42] wrote: "For every aspect or property of the phenomenal world ...there is a variable of the energy flux at [the] receptors, however complex, with which the phenomenal property would correspond ...". Perception involves either innate or learned responses to stimulus invariants. The computational vision problem reduces to a lookup table.

Aloimonos and Rosenfeld [4] describe progress in the computational modeling of human vision since 1970. In the early 1970's, machine vision systems employed a Helmholtz-like one-stage computational approach using "high-level" knowledge about a scene in conjunction with "low-level" cues to account for perception. These systems quickly proved inadequate. Researchers then turned to a multistage approach, modeling low-level, mid-level and high-level visual modules. However, this too did not lead to the development of a successful machine vision system. Aloimonos and Rosenfeld suggest that an active rather than a passive observer must be modeled. For an active observer, many mathematically ill-posed vision problems (e.g., shape from shading) become well-posed and allow for a unique solution (see Table 1 in [4]). Though motion-produced stimulation provides many more stimulus invariants [43], it is doubtful whether the difficulties in modeling human vision are solely due to not adequately taking into account available stimulus information [56]. An alternative possibility is that human vision evolved representations and processes designed to accomplish particular tasks [3]. Vision, for example, may create several representations of space, which may range from pure 2D representations to pure 3D representations. Space may further be coded for catching or picking up objects (e.g., far space, near space, and space near limbs) as well as in terms of spatial layout [52, 83]. Multiple processes, data representations, and sources of information may be the bases for the highly adaptive nature of perception and the reasons for the difficulties in formulating mathematical or computer algorithms.

3. MULTIPLE PROCESSES: PERCEPTION OF LIGHTNESS

The perception of lightness illustrates the multiple processes involved in the perception of even relatively simple visual attributes. Lightness is the attribute of a surface that varies from black to gray to white. Lightness constancy is the tendency for the lightness of a surface to remain constant with changes in illumination and the juxtaposition of surfaces. The perception of lightness depends on the effects of adaptation, contrast, assimilation, contours, figure-ground, grouping, depth and illumination. The perception of lightness is a function of both stimulus energy (luminance) and stimulus information (figural unity, figure-ground, illumination, etc.).

3.1 SENSORY, ORGANIZATIONAL, AND COGNITIVE PROCESSES

Beck [13] categorized the processes relevant to lightness perception under the general rubrics of "sensory", "organizational", and "inferential". There is no accepted terminology. Roughly the same hierarchy of processes has been described as "low-level", "mid-level", and "high-level" and as "sensory", "perceptual" and "cognitive". These terms will be used here interchangeably.

Sensory processes or low-level processes transform the pattern of retinal luminances into a neural pattern that encodes important intensity changes. Neighboring intensities facilitate and suppress the neural activity through excitation and inhibition. Light adaptation and simultaneous contrast describe psychophysically the effects of these interactions. Light adaptation adjusts visual sensitivity to the overall light level. Contrast computes a measure of relative luminance. Since relative luminance remains constant with overall changes in illumination, contrast may yield approximate lightness constancy with global changes in illumination [36, 64]. Adaptation and contrast have been studied extensively psychophysically, physiologically, and by computational modeling [31, 46, 60, 109].

The processes of adaptation and contrast that yield lightness constancy with global changes in illumination oppose constancy of lightness with local changes in illumination, and changes in background or juxtaposition to other surfaces [13]. Under ordinary circumstances, however, lightness constancy is not greatly impaired. Perceptual or mid-level processes that recover surface attributes maintain lightness constancy. Factors such as form [66], grouping [105] and depth [81] modify lightness perception in the direction of constancy. For example, they equalize contrast within a contoured area and within a figure-ground organization such as in the Benussi ring [87], the Wertheimer-Benary cross [13], and the White effect [112].

The Benussi ring nicely illustrates the existence of processes that equalize contrast effects within contours. When a gray ring is placed on a half-black and half-white background, the lightness difference resulting from contrast is slight. If a border divides the ring, however, a marked contrast difference appears. The part of the ring on the white background appears darker than the part of the ring on the black background. The lightness difference between the two half-rings is a function of the properties of the boundary dividing the ring. Berman and Leibowitz [28] found that the difference in the lightness of the two half-rings increased as the width of the boundary separating the two halves increased. Anderson, Pine and Rosenfeld [5] found that the perceived lightness difference is affected not only by the actual separation of the two half rings but by the apparent separation between the parts of the ring. The appearance of separation between parts of the figure enhances contrast.

The Benussi effect shows the importance of borders for the perception of lightness. The decreased or enhanced lightness induced at luminance discontinuities spreads out to the shape outlined by the contours. Constant luminance or hue is redundant information and is not encoded by the visual system [73]. By eliminating the redundancy in intensity and hue information, the visual system provides an economical description of a scene. Grossberg and colleagues have developed the idea that lightness and hue are specified only at contours into a general computational theory of how lightness and shape are encoded by the visual system [49, 50, 51].

Cognitive or high-level processes refer to the effects of expectation, meaning and inference. Two common examples are the effect of illumination cues and the effect of memory color. The Gelb experiment illustrates the effect of illumination cues on perceived lightness. In Gelb's experiment, the beam of a projection lantern was focused on a black disk. Observers reported seeing a dim white disk in the general illumination of the room. When a small piece of white paper was held in front of the disk to intercept the beam of the projection lantern, the percept dramatically changed. The disk was now seen as black and the paper as white. Both were seen as bright in strong illumination. Gelb argued that the disk changed from a weakly illuminated white to a strongly illuminated black because the white paper visually indicated that the disk was strongly and not weakly illuminated. There is, however, a confounding between information that the disk is under a strong special illumination and the presence of a new high intensity in the Gelb experiment. Changes in perceived lightness may therefore have resulted from contrast effects rather from information about the illumination. Beck [12] conducted an experiment in which a shadow was used to give the impression that a surface was strongly illuminated. Observers saw the illuminated portion of the black surface in the shadow condition as darker. The fact that a shadow gave rise to the perception of a darker color cannot be explained by lightness contrast.

The perception of lightness is the result of the combined effects of sensory, perceptual and cognitive processes. Low-level sensory processes encode relative and absolute luminances. Mid-level organizational processes involve the effects of the geometric aspects of a visual scene such as figure-ground, depth, and contour and surface completion. They may also involve processes of disambiguation. Perceptual information is often ambiguous and disambiguation is necessary. Rosenfeld [94] proposed an approach he called "relaxation" for disambiguating percepts. Relaxation eliminates possible interpretations by applying constraints to neighboring parts of an image. Disambiguation may also involve a Praegnanz principle or a tendency for the visual system to encode the simplest possibility consistent with the stimulus conditions. Attneave [6] suggested that the visual system fails to follow an overall principle of Praegnanz but seeks uniformity of specific properties such as length, orientation, coplanarity and so forth. The visual system may also seek uniformity of lightness consistent with the stimulus information. Beck [13] proposed that organizational and inferential processes determine whether a change in the neural correlates of luminance represents a change in lightness or a change in illumination. Knill and Kersten [71] report that a luminance gradient is seen as a difference in the lightness of the two halves of a surface when the bounding contours of the surface lead to the perception of the surface as planar. However, the difference in the perceived lightness of the two halves of the surface disappears when the bounding contours make the surface appear curved. A change in luminance is seen as a change in lightness when the surface is seen as planar because this is the simplest or most likely interpretation. The perception of a constant surface lightness and a varying illumination when the surface is seen as curved is either because of a tendency to minimize lightness changes or because this is the most likely cause of the intensity change. It is important to point out that there is no obligatory or precise coupling between the perceptions of illumination and lightness. Beck [13] has shown that in many instances the perceptions of illumination and lightness are not coupled in a one-to-one relation, as implied by theories in which the visual system calculates surface reflectance.

3.2 RECOVERING REFLECTANCE

The hierarchy of processes affecting the perception of lightness keeps surface lightness approximately constant with changes in global and local illumination and changes in the luminances of neighboring surfaces. But these processes do not explicitly compute reflectance and do not necessarily lead to a veridical perception of lightness. For example, as mentioned above, contrast computes a measure of relative luminance rather than reflectance and may yield constancy in what Beck [13] called darkroom settings. The visual surface with the highest luminance is seen as white with the lightnesses of other surfaces determined by their relative luminances. When the reflectances of the surfaces do not cover the complete range of reflectances from white to black, the correspondence between the perception of lightness and reflectance is not in accordance with that in daylight vision. An alternative view is that computational algorithms for the perception of lightness are based on recovering surface reflectance [53, 58, 59, 74]. The computational problem of lightness constancy is formulated in terms of how the visual system is able to decompose the product of illuminance $\times$ reflectance and recover the reflectance of a surface (e.g., the albedo hypothesis of Helmholtz [53]). To perceive lightness, the visual system determines a lightness transfer function that discounts illumination, overlying transparent layers, and other viewing conditions [1].

3.3 ONE-STAGE THEORIES OF LIGHTNESS

As mentioned above, there have been attempts to simplify the computational problem in perception by formulating single-stage theories. For the perception of lightness, the attempt to do so has been based on the basic idea that perceived lightness correlates with the luminance ratio of a target relative to a reference level [54, 72, 108]. Helson [54] proposed that perceived lightness correlates with the luminance of a surface and a weighted average of luminances in the entire field that he called the adaptation level. A problem is that not all luminances in a field enter equally into determining the adaptation level. The weights are not specified and remain parameters to be determined. How successfully the adaptation formula is able to effectively summarize the differing effects of contrast and adaptation remains unclear [36, 64]. However, it is clear that it does not take into account the non-uniform illumination of a field. The adaptation level formula for lightness holds only if a scene is perceived to be uniformly illuminated. When a surface is perceived as shadowed, the perceived lightness is not determined by the luminance of the surface relative to the adaptation level luminance [63].

A single-stage theory taking into account the effects of perceptual organization and unequal illumination has been formulated by Gilchrist and coworkers [44]. They proposed a one-stage theory to account for the perception of lightness and have applied it ingeniously to a large number of lightness induction, assimilation and constancy phenomena. As proposed by Koffka [72] and Wallach [108], the theory makes the perception of the lightness of a surface a function of its luminance ratio relative to an anchor that is perceived as white. The anchor is usually the maximum luminance in the framework although it can also be a function of surface area. An important novel idea of the theory is that a surface may belong to more than one framework. A second novel aspect of the theory is that area is treated like luminance and affects the surface chosen as the anchor. The perceived lightness of a surface is a weighted average of its lightnesses determined by the different frameworks to which it belongs. A key problem is giving a precise definition to the concept of "belongingness". How the different perceptual frameworks are established is critical for explaining the many complex interactions between the perceptions of lightness, depth, orientation, and transparency. The concept had previously been introduced by Koffka [72], Kardos [67] and Flock and Nusinowitz [37]. They too used the concept to specify the relevant luminance ratios for calculating perceived lightness. Koffka and Kardos took the ratios of surfaces perceived to lie in the same plane and Flock and Nusinowitz took the ratios of surfaces perceived to be illuminated commonly.

Gilchrist also suggests that lightness effects can be accounted for without invoking perceived illumination except as it affects the framework to which a surface belongs. However, illumination cues appear to affect lightness perception when they do not obviously change the framework to which a surface belongs [11, 13]. Gilchrist is aware that his model does not adequately account for the relationship between lightness and perceived illumination. One-stage theories are also incomplete in that they are one-dimensional and do not account for the perception of brightness. There is experimental evidence that an achromatic surface color is bidimensional [14, 37, 55]. An achromatic surface color varies in lightness, i.e., from white to gray to black, and varies in brightness, i.e., from bright to dim. In the experiment of Gelb [40] the introduction of the small bit of white paper changed the appearance of the disk not only from white to black but also from a dim surface to a bright surface. Beck [9] found that the apparent illumination of the disk in the Gelb effect is greatly influenced by the brightness of the area seen as white. The perceived illumination of a surface is strongly influenced by the intensity of the area seen as white and by the intensity of highlights [7, 8, 37]. Schirillo and Shevell [101] report that apparent illumination affects perceived brightness. Whether the brightness of a surface and the apparent intensity of the illumination are separate phenomena or the same, as suggested by Koffka [72], is unclear.

4. MULTIPLE REPRESENTATIONS: VISUAL SEGREGATION

The representation of information for rapid spontaneous visual segregation has been extensively studied [26]. Beck [15] proposed that rapid spontaneous visual segregation is based on the computation of stimulus differences. These differences are computed on three different stimulus representations: (1) the point (pixel) intensities in a pattern, (2) the properties of pattern elements, and (3) the preattentive grouping of pattern elements [17].

4.1 SPATIAL FILTERING

Rosenfeld [93] proposed that the spontaneous and immediate segregation of a visual field into regions occurs independently of higher-order cognitive processes. Beck, Sutter and Ivry [25] hypothesized that differences in the outputs of relatively early spatial filtering mechanisms operating on pixel intensities provide information for region segregation.

Such mechanisms encode differences in spatial-frequency content prior to the specification of element shapes and their properties. Thus the perceived similarity of element shapes [10] and of lightness [20] fails to predict perceived segregation. Perceived segregation is also not predicted by the perceived similarity of the hues in chromatic texture patterns. Opponent channel differences computed from cone contrasts predict the perceived segregation of texture patterns that differ in hue [86].

MacLeod and Rosenfeld [77] proposed a model of vision in which the spectral analyzers were bar detecting units having a spatial extent of two or three cycles. They suggested such bar detecting units in place of a Fourier spectral representation of an image. A similar model of early visual detectors involving Gabor filters was proposed by Watson [110]. The precise shape of the kernel turns out to be unimportant. For the segregation of texture regions, numerous investigators have shown that differences in two-dimensional spatial-frequency content or, equivalently, differences in the way textures stimulate unoriented (e.g. Difference of Gaussian, DOG) or oriented (e.g., Gabor) filters, account for how well texture regions perceptually segregate (e.g., [25, 27, 38, 45, 47, 78, 104, 106]). Region segregation cannot be explained solely in terms of linear operations, and the application of spatial-frequency analysis to texture segregation involves at least compression and rectification nonlinearities [45, 47].

4.2 PATTERN FEATURES

Visual segregation may be based on pattern features as well as on spatial-frequency content. Region segregation, for example, is based on feature differences when there are no differences in the spatial content of two regions [19]. Beck [13] studied the segregation of two randomly interspersed elements into two groups. The segregation of a display into two groups is an example of pure similarity grouping. The displays are representative of an important type of segregation in which there are no boundaries between regions. Beck [15] reported that segregation occurred strongly on the basis of differences in simple properties of the pattern elements such as brightness, color, size, and the orientations of lines of figures. More complex differences such as differences in the arrangement of lines of a figure or in the orientation of a figure that leaves the slopes of the component lines the same did not produce strong segregation. Beck, Graham, and Sutter [20] showed that the segregation of a randomly interspersed population of light and dark squares into two groups is not explainable by the differential stimulation of spatial-frequency analyzers. They showed that the relevant variable for visual segregation based on pattern features is perceived lightness, while the relevant variable for the segregation of patterns based on spatial-frequency content is contrast. Since the two element types in a population pattern are randomly distributed, filtering can only determine that two types of elements are present, without assuring the perception of two coherent groups of elements. Rosenfeld [97] suggests that the perception of two groups depends on the detection of bimodality. He describes a pyramid-based technique that directly detects bimodality rapidly without computing a histogram.

Bimodality is a global property. The detection of global properties is an incompletely understood aspect of the biological visual system. The Gestalt psychologists proposed a field model to explain local-global interactions. Rosenfeld and colleagues [95] have introduced a class of techniques for computing global properties known as pyramid algorithms. Algorithms are implemented on a pyramid of processors in which each higher level of the pyramid looks at the level below it. The first level looks at its immediate neighbors, the second level looks at its immediate neighbors at the first level, and so on. Thus, the interactions are always local but encompass larger and larger areas of the image. The pyramid architecture mimics the finding in biological visual systems that receptive fields become larger at higher levels of the visual system. Pyramid image representations provide the capability of rapidly detecting and extracting global structures such as smooth curves from a background of short curves [98] and groupings based on similarity, proximity, good continuation, and closure [95]. A familiar but unexpected object can be recognized in a fraction of a second using pyramids [96]. A pyramid model also accounts for the effects of size, relative precision and eccentricity on the recognition of whether shapes are the same or differ [90].

4.3 PREATTENTIVE GROUPING

Visual segregation may also be based on stimulus differences resulting from the grouping of pattern elements. Grouping involves a diversity of mechanisms that operate at many levels of representation [17, 113]. Rapid spontaneous segregation occurs from the preattentive grouping of oriented elements like lines and bars. Beck, Prazdny, and Rosenfeld [23] found that the segregation of upright and inverted U's depends on the grouping of the bases of the U figures and is not explainable by dipole statistics or differences in spatial-frequency content [16]. Beck, Rosenfeld, and Ivry [24] showed that the segregation of a line-like pattern composed of discrete elements in a background of distractors cannot be explained by differences in the outputs of Gabor filters. Line segregation is based on element grouping that is affected by stimulus features such as edge alignment, edge length, and principal axis orientation. The results indicate that line segregation is a function of edge grouping. Field, Hayes, and Hess [35] have also shown that the perception of "curved paths" in their experiments cannot be ascribed to filtering; instead, they suggest that a grouping process is responsible for "path determination". Their "association field" hypothesis bears close similarities to the cooperative bipole mechanism of Grossberg and Mingolla [49, 50] and to the criteria for grouping edges according to "relatability" advanced by Kellman and Shipley [69]. The immediate segregation of aligned lines and contours has also been studied in [30, 102]. A model that suggests how the visual system groups image contrasts has been presented by Grossberg and Mingolla [49, 50] as part of a general model of how the visual system groups edges, textures, and shading.

5. MULTIPLE SOURCES OF INFORMATION: PERCEPTION OF TRANSPARENCY

Biological vision combines in a flexible way multiple sources of information that are not always consistent. The perceptual system deals with conflicting information in three ways. First, a group of cues can simply overrule a conflicting cue. If you reverse the left and right images of a face in a stereogram, the nose is still seen to protrude. Familiarity overrides the information provided by binocular disparity that the nose is receding. Second, the perceptual system can alternate between the conflicting cues. This results in multistability in which two percepts alternate, as in the perception of ambiguous figures that give rise to alternate percepts. Third, the visual system compromises. In looking at a picture of a receding road, the perspective cues indicate that the road is parallel to the line of sight. Motion parallax and disparity indicate that the road is perpendicular to the line of sight. One generally sees a compromise in which the road is seen receding at an intermediate angle, e.g., 45 degrees to the line of sight. The integrative nature of the perceptual process is illustrated by the perception of transparency with moving and stationary images.

5.1 PLAID PATTERNS

When two moving gratings are superimposed to form a plaid pattern, the perceived motion of the plaid pattern can be coherent or incoherent. In coherent motion, the component gratings move together as a single object. In incoherent motion, the component gratings move independently. Transparency is then perceived; one grating is seen through the other. For plaid patterns seen through an aperture, the intersection of the two gratings comprising a plaid pattern form intersections that act as features whose motions can be tracked. When features are salient, feature-tracking signals capture the motions of the lines to which they belong [75]. When features are not salient, perceived global motion may be biased toward the vector average or toward the intersection of the constraints. In vector averaging, the plaid pattern is seen to move in the direction of the vector average of the normal components of the plaid pattern [84]. In intersection of constraints, the plaid pattern is seen to move in the direction of the intersection in velocity space of the constraint lines of the plaid components [2].

Jasinschi, Rosenfeld and Sumi [61] proposed a model that combines a feature tracking scheme with intersection of constraints to explain motion transparency and coherence. The model uses a velocity histogram that combines votes from the velocities of features such as corners and line endings with those from the intersections of all possible constraint lines due to the motion of image contours. The perception of motion transparency or coherence depends on the total number of prominent peaks in the velocity histogram and on their relative heights. For two superimposed patterns in relative translational motion one perceives motion coherence, transparency, or mixed motion depending on whether the velocity histogram is unimodal, bimodal, or trimodal. The model succeeds in explaining motion transparency as well as the bistability of motion transparency and coherence in plaid displays. Viswanathan [107] presents an alternative model of how the visual system integrates multiple sources of information in perceiving global motion.

5.2 ACHROMATIC PATTERNS

The integration of multiple information sources also occurs in the perception of transparency in stationary images. Metelli [82] proposed two constraints to account for the perception of transparency in achromatic patterns. These constraints were derived from a physical model of transparency using physical or psychophysical variables such as reflectance or luminance. In Figure 1.1a, let A and B be opaque surfaces and D a transparent surface. (Lowercase letters in Figure 1.1a indicate regions of differing intensity.) Constraint (i) is a restriction on the order of the intensities: if $a > b$, then $d > c$, and if $a < b$, then $c < d$. Constraint (ii) is a restriction on the magnitudes of the intensities: the absolute difference $|a - b|$ must be greater than the absolute difference $|c - d|$. According to Metelli's constraint (i), transparency is seen only if

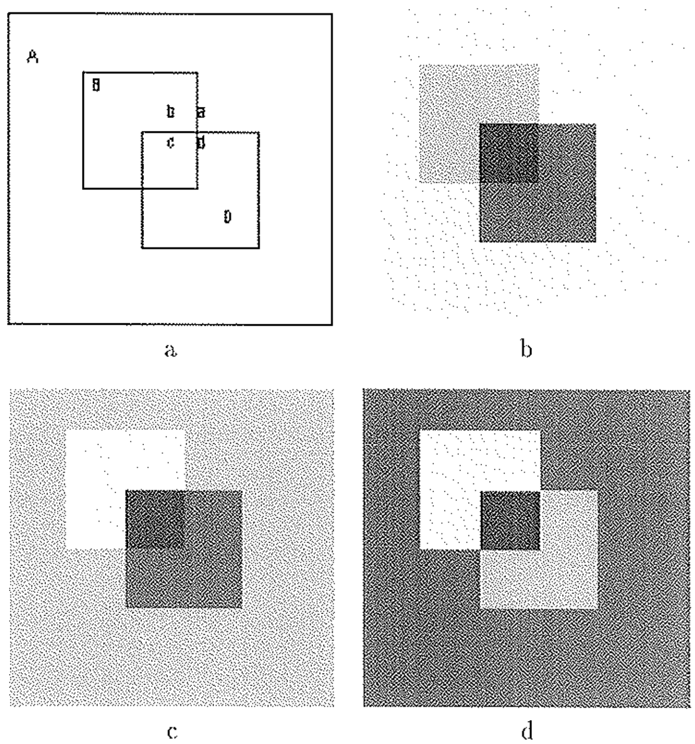

Figure 1.1 (a) Upper-case letters are surfaces and lower-case letters are regions. (b) Stimulus *cdba* satisfies Metelli's order restriction for seeing surface D as a transparent surface overlying surfaces B and A or surface B as a transparent surface overlying surfaces D and A. (c) Stimulus *cdab* satisfies Metelli's order restriction for seeing surface B as a transparent surface overlying surfaces D and A but violates the restriction for seeing surface D as a transparent surface overlying surfaces B and A. (d) Stimulus *cadb* violates Metelli's order restriction for seeing either surface D or surface B as a transparent surface.

the polarity of contrast changes is consistent across a surface boundary. Thus, in Figure 1.1a, if the bottom surface (D) is seen as transparent, the direction of contrast between regions a and b has to be consistent with the direction of contrast between regions d and c. If in Figure 1.1a A and D are opaque surfaces and B a transparent surface, then the direction of contrast between regions a and d has to be consistent with the direction of contrast between regions b and c. The lower-case letters in Figure 1.1a designating regions are used in referring to the patterns in Figures 1.1b–d. In Figure 1.1b, *cdba*, the pattern of polarities of contrasts is consistent with seeing either the top (B) or the bottom (D) surface as transparent. The order of the letters indicates increasing lightness values from lowest to highest. In Figure 1.1c, *cdab*, the polarities of contrasts are consistent with seeing the top surface (B) as transparent but not the bottom surface (D). In Figure 1.1d, *cadb*, the polarities of contrasts are inconsistent with seeing either the bottom or top surface as transparent.

Beck, Prazdny, and Ivry [22] distinguished between what they called "weak" and "strong" violations of the order and magnitude restrictions. In a strong violation of the order restriction, the polarities of contrasts are inconsistent across both contours of an x-junction (Figure 1.1d). For strong violations, the perception of transparency does not occur. In a weak violation of the order restriction the polarities of contrasts are inconsistent across one of the boundaries of an x-junction but not across the other boundary (Figure 1.1c). For weak violations, although they are inconsistent with physical instances of transparency, perception of transparency still occurs, though it is markedly reduced. Stimulus patterns *cadb* (Figure 1.1d) and *cdab* (Figure 1.1c) both violate the Metelli order constraint (i). Beck, Prazdny, and Ivry [22] found that no subjects saw surface D as transparent in stimulus *cadb* (a strong violation) but that 13 of 21 saw surface D as transparent in stimulus *cdab* (a weak violation). Masin and Fukuda [79] also found that the perception of transparency occurs for weak violations of the order constraint. That is, the perception of transparency is reduced, but still occurs, when the polarities of contrasts are inconsistent across a surface boundary but are consistent across the boundary between the transparent surface and the opaque surfaces.

The perception of transparency with the pattern *cdab* illustrates the problem of integrating conflicting information. The global configuration in Figures 1.1a–d suggests overlapping surfaces. For some subjects, the strong figural cues prevail over the inconsistency in local contrast and they see surface D in Figure 1.1c as transparent. The inconsistency in the contrast changes across the x-junction is reinterpreted as a change in the lightness of the underlying opaque surface or in the density of the transparent layer, or is ignored. For other subjects, the conflicting contrast cues cause the pattern to be seen as not transparent. There are limits to the visual system's ability to ignore contradictions. No observers saw pattern *cadb* as transparent. To do so would require seeing an overlapping transparent filter differing in density and an underlying opaque surface differing in lightness. This does not appear possible.

5.3 CHROMATIC PATTERNS

The perception of transparency with chromatic colors indicates that transparency perception can involve different mechanisms. Metelli [82] proposed that scissioning of the overlapping color is the basis of transparency and is a consequence of processes that decompose an image into causal contributors. For example, the mechanism underlying the scissioning of an orange hue into red and yellow hues may require the firing of cells that respond both to red and orange and yellow and orange. The perception of transparency may also occur, however, for hues that are not explainable in terms of a scissioning mechanism. For example, observers indicated that what was seen with a figure similar to Figure 1.1a with area a black, area b red, area c orange, and area d blue is an orange hue through a blue transparent layer (d plus c) or an orange hue through a red transparent layer (b plus c) [70]. In this instance the hue of the overlapping region is not scissioned. An explanation of the perception of transparency is that region d or b is completed by the visual system when they are seen at differing depths from region c. The hue in region c does not disappear but may be seen veridically. When region d is seen as overlying region c one may see an orange surface through a blue veil. When region b is seen as overlying region c one may see an orange surface through a red veil. Thus, another possible mechanism for the perception of transparency is that the hue of the overlapping region is partially or totally inhibited and the hues of the adjacent non-overlapping regions flow into the two regions demarcated by the overlapping region boundaries at the different represented depths. Beck and Ivry [21] proposed that the perception of transparency could occur with and without scissioning of the lightness of the overlapping area. When scissioning occurs, the overlapping lightness is not seen and is split into the lightnesses of the non-overlapping areas [21, 22]. When the perception of transparency occurs without scissioning, the lightness of the overlapping region may not be altered. One sees the lightness of region d through the lightness of region c or vice versa.

6. IMPENETRABILITY

The view that cognitive processes can influence perception has been challenged. Kanizsa [65], for example, presents evidence that amodal completion occurs in terms of geometric regularities such as the good continuation of contours, despite the absurdity of the completion in terms of our past experience. He interprets his examples as showing that "autochthonous factors of perceptual organization" can override past experience. An alternative interpretation is that past experience with formal or general properties of objects such as the continuity of surface contours overrides past experience or familiarity with particular objects [13]. The Gestalt laws of grouping can be interpreted as expressing general properties of objects such as uniformity, compactness, and smoothness [93]. Pylyshyn [92] proposed that these regularities are embodied as constraints by the visual system and do not reflect the effect of cognitive processes on perception. He argues that cognitive information per se does not affect perception. Meanings and expectations do not affect perception unless they have been internalized as constraints by visual processes.

The modeling of perception would be simplified if cognitive factors could be ruled out. Low-level operations in human vision such as segmentation and the perception of edges, lines and angles appear to be largely independent of purposive factors [93]. Rosenfeld [99], however, suggests that cognitive information about individual objects affects recognition. Peterson and Gibson [89] have shown that figure-ground perception is influenced by whether the shape of a region is a familiar or meaningful object. Subjects perceived the meaningful regions for longer periods of time in displays in which one region was meaningful and the other was not. The dependence of the perception of shape on low-, mid- and high- level processes is easily demonstrated. Shape perception depends on the extraction of edges. In Figure 1.2a, one can see a shape when only some edges or lines are present. Edges in themselves, however, are not sufficient to define a shape. Figure 1.2b shows that shape also depends on figure-ground organization or on whether the contour is a bounding edge of the face or of the vase. Figure 1.2c shows that a particular figure-ground organization is not sufficient to define a figure. In all instances the lines make up the figure, but different shapes can be seen depending on how the lines are grouped. For example, one can see two adjacent hourglasses, upright and inverted overlapping triangles, or two overlapping parallelograms. Figure 1.2d shows that the perception of a shape depends not only on how the lines are grouped but on how they are interpreted. The figure can be seen as either a rabbit or a duck depending on whether the left or right parts of the drawing are seen as the front or the back of a head. Altering the interpretation leaves the figure-ground relations and the grouping of lines unchanged.

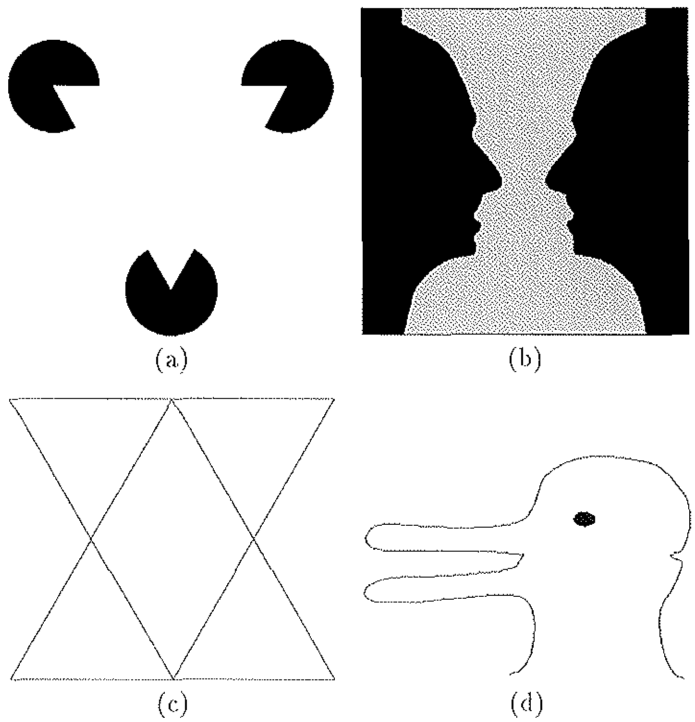

Figure 1.2 Illustrations showing the effects on the perception of shape of (a) subjective contours, (b) figure-ground, (c) alternative groupings, and (d) alternative interpretations.

The phenomenon of apparent motion illustrates the difficulty of specifying the conditions in which cognitive factors influence perception. Beck, Elsner, and Silverstein [18] studied the perception of apparent movement when the second of two successive stimuli always appeared in the same position and when it varied randomly between two positions. Foreknowledge of the position of the second stimulus does not facilitate the perception of apparent movement. The space-time relationship of Korte's third law of apparent movement was not affected by whether the position of the second stimulus was always the same or varied randomly. Manipulations of shape and apparent depth that make the motion more likely also failed to affect the direction of apparent motion [33]. In contrast, the quality of motion was affected by expectation. For example, the motion of a car was perceived to move more smoothly than an unfamiliar motion such as the motion of an oval [62]. Dawson and Piercey [32] suggest that the meaning of a stimulus affects the quality of perceived motion but fails to affect the perceived direction of motion. Under some conditions, however, knowledge does affect the direction of perceived motion. Shiffrar and Freyd [103] found that apparent motion does not always follow the shortest path. Observers tended to perceive the shortest path with short stimulus onset asynchronies despite violations of anatomical constraints. However, observers perceived the anatomically possible but longer paths with longer stimulus onset asynchronies. The influence of inferential processes under longer observation time was also found in amodal completion, which is accounted for by local cues when the exposure duration is short, and is influenced by global regularities when the exposure duration is longer [85]. As with short time separations, the perceived direction of apparent motion with small spatial separations (less than about 0.5 degrees) depended largely on stimulus geometry [29]. For larger spatial separations, however, cognitive expectations may influence the perceived direction of apparent motion. McBeath, Morikawa, and Kaiser [80], for example, found with larger spatial separations a bias to see motion in the direction that the shapes face when the shapes were faces and geometric figures like arrows, but not when the shapes were letters. It is not easy to precisely characterize cognitive influences on perception.

7. SUMMARY

This chapter described the multiple processes in the perception of lightness, the multiple representations in visual segregation, and the local-global interactions in integrating multiple sources of information in the perception of transparency in moving and stationary displays. The global character of perception derives from the hierarchical integration of sensory, perceptual and cognitive processes. Perception may also depend on meaning and familiarity as well as on stimulus and configurational factors [57]. These characteristics render human vision highly adaptive but also difficult to model computationally.

Perception is not based on a single global field-like process as suggested by Gestalt psychology. Instead, perception involves the interaction of multiple processes and representations. The perception of lightness is the result of multiple sensory, perceptual, and cognitive processes. Perceptual and cognitive processes determine whether a difference in luminance is seen as a difference in illumination, depth, or lightness.

The visual system has also evolved multiple representations for different purposes. Visual segregation can occur in terms of differences in spatial frequency content, feature differences, or differences resulting from the grouping of pattern elements. Grossberg [48] presents a theoretical framework for a model in terms of interacting processing streams. The model is based on the conflicting constraints of biological vision. Decomposition of vision into its component processes and how the visual system integrates information from different processes remains largely an unsolved problem.

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