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Human and Machine Vision II

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Human and Machine Vision II

Preface

The second Workshop on Human and Machine Vision was held in Montreal, Canada on August 1–3, 1984, in conjunction with the International Conference on Pattern Recognition. This book contains eleven of the papers presented at the Workshop, together with three other papers (by M. Leyton, B. Smith, and G. Sperling) on related themes.

The Proceedings of the First Workshop, held in Denver, Colorado in 1980, were published in book form by Academic Press in 1983 (J. Beck, B. Hope, and A. Rosenfeld, eds., *Human and Machine Vision*.) The papers in the present volume first appeared in the August, September, and October 1985 issues of the journal *Computer Vision, Graphics and Image Processing*; they are collected here in book form to make them more widely available to students and researchers in both fields — visual perception and computer vision.

The workshops, and the publications resulting from them, serve an important purpose in enhancing communications between the two fields. Both groups can benefit substantially from exchanges of ideas. It is planned to continue to hold such workshops on a regular basis.

Azriel Rosenfeld

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Contents

Perception of Transparency in Man and Machine*

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The different tactics employed by human and machine vision systems in judging transparency are compared. Instead of luminance or reflectance (relative luminance), the human visual system uses lightness, a nonlinear function of reflectance, to estimate transparency. The representation of intensity information in terms of lightness restricts the operations that can be applied, and does not permit solving the equations describing the occurrence of transparency. Instead, the human visual system uses algorithms based on simple order and magnitude relations. One consequence of the human visual system not using a mathematically correct procedure is the occurrence of nonveridical perceptions of transparency. A second consequence is that the human visual system is not able to make accurate judgments of the degree of transparency. Figural cues are also important in the human perception of transparency. The tendency for the human visual system to see a simple organization leads to the perception of transparency even when the intensity pattern indicates transparency to be physically impossible. In contrast, given the luminances or reflectances, a machine vision system can apply the relevant equations for additive and subtractive color mixture to give veridical and quantitatively correct judgments of transparency.

1. INTRODUCTION

This paper compares how a person judges transparency with how a machine judges transparency when programmed not to simulate human perception but to estimate transparency veridically. The case dealt with is of a diffusely reflecting achromatic object viewed in neutral illumination through a transparent medium that is nonselective for wavelength.

Transparency arises physically in two ways. Transparency can occur in looking through a fine wire mesh screen. If a person is far enough so that his eyes fail to accommodate for the wire mesh, the light from the wire mesh and from the holes blur on the retina. The retinal stimulus is a weighted average of the light intensity reflected from the wire mesh of the screen and the light transmitted by the holes in the screen from the object. Transparency occurring in this way is described as occurring through additive color mixture. Transparency also occurs when one looks through a transparent medium, such as a filter. When an object is viewed through a filter, part of the light is absorbed by the filter, and part of the light is transmitted by the filter, reflected by the object, and retransmitted by the filter. There are multiple reflections between the object and the filter before a ray emerges. The retinal stimulus is the result of the light reflected by the object and transmitted by the filter plus the surface reflectance from the filter. Transparency occurring in this way is described as occurring through subtractive color mixture.

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2. ADDITIVE COLOR MIXTURE

Metelli [1, 2] has proposed a model for the perception of transparency based on additive color mixture. Additive color mixture occurs when a device with open and closed sectors, called an episcotister, rotates rapidly in front of surfaces. Figure 1 depicts the retinal stimulus resulting when an episcotister rotates in front of surfaces A and B. Rotating the episcotister rapidly produces the perception of a transparent color (regions d and c) lying in front of surfaces A and B. The apparent reflectances of regions d and c is a weighted average, sometimes called Talbot's Law, of the light reflected from the background surfaces A and B and from the blades of the episcotister e. The apparent reflectances of regions d and c are equal to

$$d = \alpha a + (1 - \alpha)e \tag{1}$$

$$c = \alpha b + (1 - \alpha)e \tag{2}$$

where α is the proportion of light reflected from surface A (corresponding to the areal fraction occupied by the open sectors of the episcotister), $1 - \alpha$ is the proportion of light reflected from the blades of the episcotister (corresponding to the areal fraction occupied by the blade of the episcotister), a is the reflectance of surface A, b is the reflectance of surface B, and e is the reflectance of the episcotister blades.

The values of a, b, c, and d are given by the retinal stimulus and the visual system needs to solve for α and e. Solving Eq. (1) and (2) for α and e yields

$$\alpha = (d - c)/(a - b) \tag{3}$$

$$e = (ac - bd)/(a + c) - (b + d). \tag{4}$$

Alpha is the proportion of the apparent reflectances of d and c determined by the reflectances a and b and is an index of transparency. When the apparent reflectance (or luminance) of region d equals the apparent reflectance (or luminance) of region c, $\alpha = 0$ and the overlying surface composed of regions d and c is opaque. When the difference in apparent reflectance (or luminance) $d - c$ equals the difference in apparent reflectance (luminance) $a - b$, the overlying surface composed of regions d

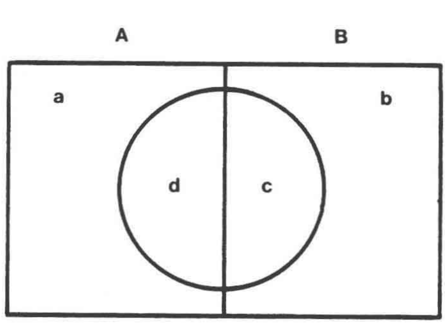


FIG. 1. The retinal stimulus resulting from an episcotister rotating in front of two surfaces differing in reflectance. Capital letters A and B indicate the background surfaces. Lowercase letters indicate regions of differing intensity.

and c is perfectly transparent. Certain constraints follow from the physics of the situation. Since α is restricted to values between 0 and 1, Eq. (3) implies (i) if $a > b$, then $d > c$ and vice versa if $a < b$, and (ii) the absolute difference $|a - b|$ must be greater than the absolute difference $|d - c|$. Constraint (i) is a restriction on the order of the intensities and ensures that α is positive. Constraint (ii) is a restriction on the magnitudes of the intensities and ensures that α is less than 1. Since e is also restricted to values greater than or equal to 0 and less than or equal to 1, order and magnitude constraints can also be derived from Eq. (4). Eq. (4) implies (iii) if $(a + c) > (b + d)$ then $ac > bd$ and vice versa if $(a + c) < (b + d)$, and (iv) the absolute difference $|(a + c) - (b + d)|$ must be greater than the absolute difference $|ac - bd|$. Constraint (iii) ensures that e is nonnegative, and constraint (iv) ensures that e is less than 1. The four constraints are independent. Numerical values can be assigned to the reflectances a, b, c, and d in Eqs. (3) and (4) that satisfy three of the constraints but not the fourth.

Beck *et al.* [3] investigated how violations of constraints (i) through (iv) affect the perception of transparency. Figure 2a depicts the stimuli used. Capital letters identify surfaces and lowercase letters regions of differing reflectance. The stimuli were computer generated pictures of two overlapping squares, a top and bottom square on a larger background surface. Figure 2b shows a stimulus satisfying constraints (i) through (iv). The bottom square can be seen as transparent and overlying the top square and the background.

Metelli [1, 2] showed that violations of either constraints (i) or (ii) adversely affect the perception of transparency. Beck *et al.* [3] found that the perception of transparency varied inversely with the salience with which constraints (i) or (ii) are violated. The perception of transparency did not occur when either constraint (i) or constraint (ii) were violated strongly. Figure 3a shows a stimulus which strongly violates the order relation of constraint (i). The reflectance of region a is less than

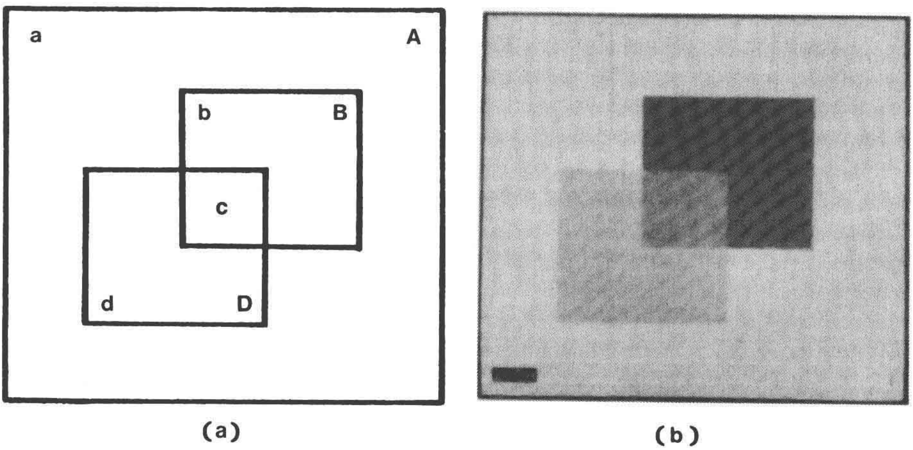
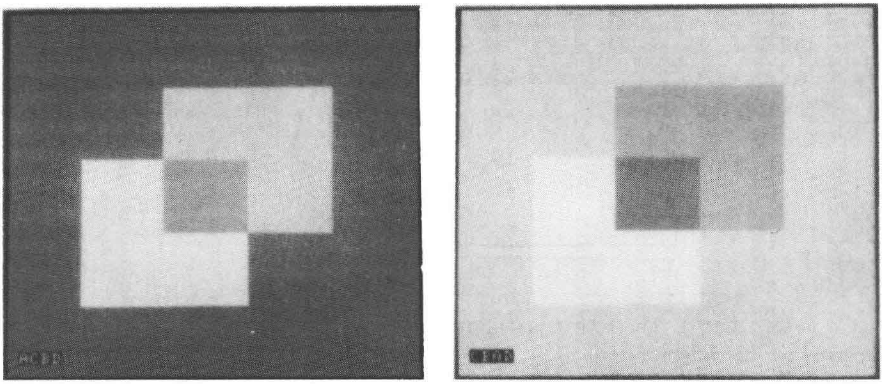


FIG. 2. (a) Stimulus configuration. Capital letters indicate the surfaces depicted. Lowercase letters indicate regions of differing intensity. (b) Stimulus satisfying constraints (i) through (iv).



(a) (b)

FIG. 3. (a) Stimulus strongly violating constraint (i); (b) stimulus strongly violating constraint (ii).

that of region b, but the reflectance of region d which overlies a is greater than that of region c which overlies b. Figure 3b shows a stimulus which strongly violates the magnitude relation of constraint (ii). The reflectance difference between a and b is contained within the reflectance difference between c and d. Metelli did not investigate the effect of violating constraints (iii) and (iv) on transparency. Beck *et al.* [3] have shown that violations of constraints (iii) and (iv) do not adversely affect the perception of transparency. This has important consequences for the perception of transparency. It makes possible the nonveridical perception of transparency. That is, a pattern of intensities which physically cannot occur in an actual case of transparency will be seen as transparent. Before pursuing this further, I will turn to another question first.

3. SUBTRACTIVE COLOR MIXTURE

The perception of transparency often occurs in terms of subtractive color mixture rather than in terms of additive color mixture. Constraints (i) and (ii) were derived from a model which assumes additive color mixture. The question can be raised: Why do constraints (i) and (ii) predict the perception of transparency as well as they do since they appear to be ecologically unrepresentative?

The physical situation is depicted in Fig. 4a. Figure 4b illustrates the multiple reflections and transmittances that occur. Light is in part reflected from the front surface of the filter, and in part transmitted by the filter and reflected from the opaque surface behind the filter; the reflected light is in part transmitted and in part reflected back and so on. In Fig. 4, a is the reflectance of surface A, b is the reflectance of surface B, f is the reflectance of the filter F, and t is the transmittance of the filter. The apparent reflectances of regions d and c are equal to

$$d = f + (t^2a)/(1 - fa) \tag{5}$$

$$c = f + (t^2b)/(1 - fb). \tag{6}$$

The values of a, b, c, and d are given by the retinal stimulus and the visual system needs to solve for t and f.

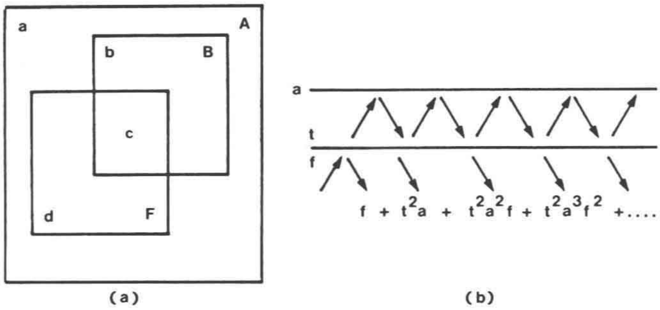


FIG. 4. (a) Illustration of subtractive color mixture occurring with a filter. Capital letters A, B, and F indicate the background surfaces and the filter. Lowercase letters indicate regions of differing reflectance. (b) Illustration of the pattern of reflectance—a is the reflectance of surface A, f is the reflectance, and t the transmittance of filter F.

Solving Eqs. (5) and (6) for t and f yields

$$t = \sqrt{\frac{(c - bcd + bd^2 - d)(b - a - abc + a^2c)}{(b - a + abd - abc)^2}} \tag{7}$$

$$f = \frac{(bd - ac)}{(b + abd) - (a + abc)}. \tag{8}$$

Order and magnitude constraints for the perception of transparency with subtractive color mixture can be derived from Eqs. (7) and (8). Since the perception of transparency occurs when t is restricted to values between 0 and 1, Eq. (7) implies: (v) $(c - bcd + bd^2 - d)(b - a - abc + a^2c) > 0$ and (vi) $(b - a + abd - abc)^2 > (c - bcd + bd^2 - d)(b - a - abc + a^2c)$. Constraint (v) ensures that t is positive and constraint (vi) that it is less than 1. Since the reflectance of the filter, f, is also restricted to values greater than or equal to 0 and less than 1, Eq. (8) implies: (vii) if $bd > ac$, then $b + abd > a + abc$ and vice versa if $bd < ac$, and (viii) the absolute difference $|b + abd - a + abc|$ must be greater than the absolute difference $|bd - ac|$. Constraint (vii) ensures that f is positive and constraint (viii) ensures that f is less than 1. An additional constraint is that $t + f$ must be less than or equal to 1.

What is the relationship between the equations derived from the episcotister and filter models? Equations (1) and (2) are clearly not equal to Eqs. (5) and (6). The order and magnitude constraints defining the boundary conditions for solutions of the two sets of equations, however, appear to be closely related. Equations (5) and (6) of the filter model imply constraints (i) and (ii) derived from Eq. (3) of the episcotister model, and Eqs. (1) and (2) of the episcotister model imply constraints (v) and (vi) derived from Eq. (7) of the filter model. Although we have not been able to demonstrate it mathematically, a computer search of the solutions to Eqs. (5) and (6) of the filter model has failed to find any solutions that violate constraints (iii) and (iv) derived from Eq. (4). Similarly, a computer search of the solutions to Eqs. (1) and (2) of the episcotister model has failed to find any solutions that violate constraints (vii) and (viii) derived from Eq. (8) of the filter model. The variables were incremented by 0.02 within the bounds for each set of equations, and the calculations were carried out to four decimal places. Thus, transparency with subtractive color mixture entails the computationally simpler constraints (i) through (iv) derived from the equations for additive color mixture. Judgments of the degree of transparency based on Eq. (3) will not be quantitatively correct with subtractive color mixture. However, this is not important since, as will be shown, humans are not generally able to make quantitatively accurate judgments of transparency.

Constraints (i) and (ii) are ecologically valid indicators of transparency because the order and difference relations embodied by them are true for both additive and subtractive color mixture. If we translate constraints (i) and (ii) into words, one can see intuitively why they hold. Constraint (i) says: No matter how transparency is produced, the overlaying of a transparent surface cannot change the order of the lightness values. If in Fig. 2a region a is lighter than region b, then the area overlying region a, region d, must be lighter than the area overlying region b, region c. Constraint (ii) says: When lightness values are reduced by overlaying a transparent surface, the lightness difference within the transparent area (regions d and c) must be less than the lightness difference outside of the transparent area (regions a and b). The brain has internalized constraints (i) and (ii) for inferring transparency on the basis of the physical causes of transparency. If constraints (i) or (ii) are violated, the change in intensities in a pattern are not ascribed to transparency. Constraints (iii) and (iv) do not have a simple interpretation in terms of lightness and the visual system does not use them in judging transparency.

4. NONVERIDICAL PERCEPTION OF TRANSPARENCY

What are the consequences of the visual system not being sensitive to violations of constraints (iii) and (iv)? Equation (3) gives the degree of transparency for additive color mixture when Eq. (4) is satisfied. That is, when the values a, b, c, and d are such that constraints (i) through (iv) are satisfied. Since α and e in a physical instance of transparency are less than or equal to 1, constraints (i) through (iv) are automatically satisfied. However, since the visual system is not sensitive to violations of constraints (iii) and (iv), it is possible to choose reflectance values which produce a perception of transparency but which physically is impossible. If in Fig. 2a the reflectance of region a is 0.57, of region b 0.47, of region c 0.24 and of region d 0.33, constraints (i) and (ii) are satisfied ($\alpha = 0.90$), while constraints (iii) and (iv) are not ($e = -1.83$). Though constraints (iii) and (iv) are not satisfied, the bottom square was readily seen as transparent [3]. Substituting the values for a, b, c, and d in Eq. (3) gives a predicted transparency of 0.90. The mean of subjects' judgments of transparency was 0.46. The reason for the discrepancy between subjects' estimates of transparency and the predicted transparency from Eq. (3) is easily seen. Though the difference between reflectances d and c (0.90) is close to the difference between reflectances a and b (0.10) giving a transparency estimate of (0.90), the reflectance of region d (0.33) is not similar to the reflectance of region a (0.57) and the reflectance of region c (0.24) is not similar to the reflectance of region b (0.47). This can occur because constraints (iii) and (iv) are not satisfied. In a real physical instance of transparency, where constraints (iii) and (iv) are not violated, this would not be possible. When the difference between the reflectances d and c $(d - c)$ approaches the difference between the reflectances a and b $(a - b)$, then the reflectance of region d approaches the reflectance of region a, and the reflectance of region c approaches the reflectance of region b. Physically, Eq. (3) both sets conditions through constraints (i) and (ii) for the occurrence of transparency and tells how transparent a surface is with additive color mixture. Psychologically, Eq. (3) sets conditions through constraints (i) and (ii) on *whether* the perception of transparency occurs, but does not always accurately indicate *how* transparent a surface is seen to be. As in the example just given, to suppose that the visual system always uses Eq. (3) without modification to determine the degree of transparency can lead to an absurdity. Two questions need to be answered: Why is the human visual system not sensitive to violations of constraints (iii) and (iv)? How does the human visual system judge the degree of transparency?

5. REFLECTANCE VS LIGHTNESS

To answer these questions, we have to deal first with another question. Metelli's Eq. (3) describing the conditions for the perception of transparency assumes that perceived transparency is determined by reflectance values. Reflectances are physical values and not psychological values. The psychological dimension corresponding to reflectance is lightness. Lightness is the dimension of sensory experience which may be described as going from white through gray to black as reflectance goes from 100 to 0%. Physical differences are not the same as psychological differences. Several equations have been proposed as approximate expressions of the relation between lightness and reflectance (or relative luminance). For example, lightness has been proposed to grow as a logarithmic function of reflectance, and as a linear function of the cube root of reflectance. A minimal condition is that lightness is a negatively accelerated monotonic function of reflectance. Figure 5 illustrates such a relationship. Lightness on the y axis is related by a negatively accelerated function to reflectance on the x axis. A monotonic transformation preserves order. Thus, constraint (i) is satisfied in terms of lightness if it is satisfied in terms of reflectance. The satisfaction of constraint (ii), which involves differences, depends on particular values. Constraint (ii) can be satisfied in terms of reflectance values, but not in terms of lightness values and vice versa. For example, consider the absolute differences $|a - b|$ and $|d - c|$ in Fig. 5. In terms of reflectance, the difference $|a - b|$ is greater than the difference $|d - c|$ satisfying constraint (ii). In terms of lightness, the difference $|a' - b'|$ is smaller than the difference $|d' - c'|$ violating constraint (ii).

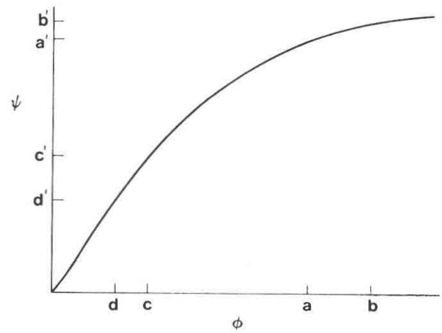


FIG. 5. Illustration of the relationship between lightness (ψ) and reflectance (ϕ).

The perception of transparency depends on checking whether constraints (i) and (ii) are satisfied. What is the nature of the representation on which this checking is done? Is it in terms of reflectance values or in terms of lightness values? Beck *et al.* [3] have shown that the stimulus representation for transparency judgments is, as might be expected, in terms of lightness values and not reflectance values. Why constraints (i) and (ii) and not (iii) and (iv) are psychologically relevant can now be understood. The constancy of lightness in a scene with an overall change in the illumination keeps the ratios of intensities in the scene the same. Thus it is important for the visual system to encode information about the ratios of intensities. If the sensory transformation is approximately logarithmic, this means that the visual system has to encode information about sensory differences. That is, in order to determine whether intensity ratios are the same, the visual system has evolved mechanisms for comparing lightness differences. The order of lightness values, their differences, and the relative sizes of lightness differences are encoded by the visual system because of their ecological importance. The visual system is thus equipped for determining whether constraints (i) and (ii) are satisfied. Constraints (iii) and (iv) involve operations of addition and multiplication. What is the sum of a light gray and a medium gray or the product of a light gray and a medium gray seems like a nonsensical question. It is an unnatural psychological thing to take sums and products of lightness values. They are not intuitively interpretable, I believe, because there is no adaptive need for the visual system to judge sums and products of lightnesses. Applying constraints (iii) and (iv) to lightness values is not possible because there has been no ecological reason for developing this ability.

6. PERCEPTION OF THE DEGREE OF TRANSPARENCY

What determines the perception of transparency? One possibility is that substituting lightness values for reflectances in Eq. (3) correctly predicts the perceived degree of transparency. The argument for this is that the estimate of transparency is based on the reduction of apparent contrast. The perception of the degree of transparency is assumed to be a function of the similarity of the lightnesses in regions d and c relative to the similarity of the lightnesses in regions a and b. If the lightnesses of regions d and c are equal, that is, if their contrast is zero, then the degree of perceived transparency is zero. As the lightness difference between regions d and c approaches the lightness difference between regions a and b, the perceived degree of transparency goes to 100%.[1] This equation, however, cannot be correct without further restriction. In Fig. 6b, the lightness difference between d and c is nearly equal to that between a and b. Substituting subjects' estimates of lightness values in Eq. (3) gives a predicted transparency of 0.96 when the rectangle is seen as transparent and overlying the square [3]. A transparency of 0.96 implies that the lightnesses of regions d and a should be similar, and the lightnesses of regions c and b should be similar. This is clearly not the case. The mean of subjects' transparency estimates was 0.38 [3]. Just as with reflectances, substituting lightness values in Eq. (3) can lead to an incorrect prediction of transparency.

Figure 6b does not correspond to a physically possible instance of transparency. In an actual physical instance of transparency, if the reflectance difference $d - c$ is

[1] Transparency judgments based on Eq. (3) and on lightness, of course, will not be quantitatively correct for either additive or subtractive color mixture.

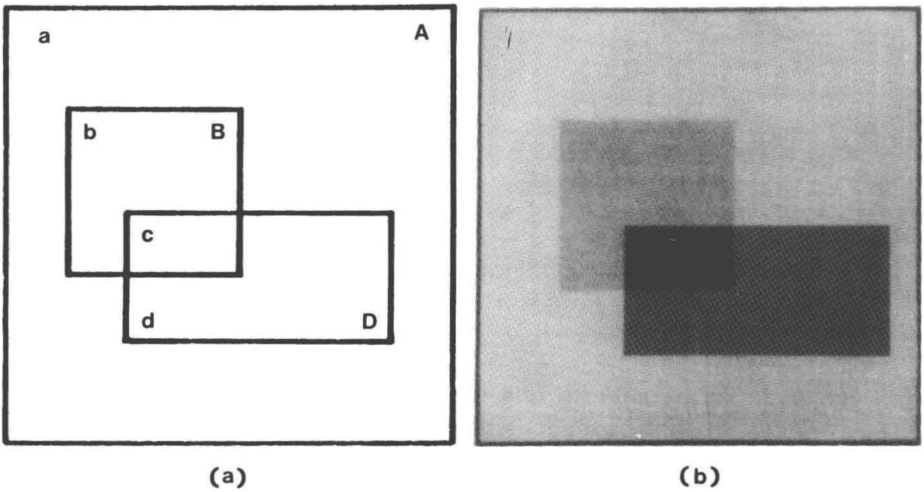


FIG. 6. (a) Stimulus configuration. Capital letters indicate the surfaces depicted. Lowercase letters indicate regions of differing intensity. (b) Stimulus violating constraint (iii).

close to the reflectance difference $a - b$ indicating high transparency, then the reflectance of region d would approach the reflectance of region a, and the reflectance of region c would approach the reflectance of region b. If the reflectances of regions d and a and of c and b approach each other, then the lightnesses of regions d and c would approach the lightnesses of regions a and b. The discrepancy between the predicted transparency of 0.96 and subjects' mean transparency judgment of 0.38 appears to be based on the fact that the lightness values of regions d and c differ from the lightness values of regions a and b. This occurs because the stimulus violates constraint (iii). One possibility is that in an actual instance of transparency where constraints (i) through (iv) are satisfied, perceived transparency is based on substituting lightness values in Eq. (3). That is, the perception of the degree of transparency is a function of the lightnesses of regions d and c relative to regions a and b. Only if application of Eq. (3) leads to contradiction, as it can in nonveridical instances of transparency, is the estimate modified. If Eq. (3) results in a high transparency (e.g., greater than 80 or 90%) and the lightnesses of regions d and a, and c and b are not similar (as they should be with high transparency), the estimate of transparency is adjusted downward. This is not a rational mathematical adjustment. The human visual system, when presented with conflicting information, produces a compromise. The estimated transparency is decreased by an arbitrary amount to resolve the contradiction. The adjustment is probably even nonlinear. A second possibility is that the perception of the degree of transparency is based on stimulus relations other than those that determine whether the perception of transparency occurs [3]. This is suggested by an initial study in which a correlation of only 0.55 was found between the means of 26 subjects' transparency estimates of 8 stimuli satisfying constraints (i) through (iv) and the transparency predicted by substituting lightness values in Eq. (3). There are 4 lightness contrasts in Fig. 6b. The