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Transparency and Translucency

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Related Concepts

- Transparent layers
- Dehazing
- Transmittance; opacity
- Layered surface representation
- Image decomposition
- Color and lightness
- Color scission

Definition

Transparency is the property of some materials that allows light to be partially transmitted through. The proportion of light a material transmits through determines its transmittance, α. The term translucency is generally used in cases where light is transmitted through diffusely.

Background

When a surface is viewed through a partially-transmissive material, the optical contributions of the two layers in a given viewing direction are collapsed onto a single intensity in the projected image. If a computer vision system is to recover the scene correctly, it must be able to decompose or *scission* the image intensity into the separate contributions of the two material layers (see Fig. 1A).

The inverse problem of recovering layered surface structure is generally divided into two sub-problems: (1) the qualitative problem of inferring the *presence* of an interposed partially-transmissive layer in parts of the image; and (2) the quantitative problem of assigning surface properties—reflectance and transmittance—to the separate layers.

Theory

Physical models

Metelli [15] used Talbot's equation for color mixing to model transparency: the "color" of the partially-transmissive surface or filter (r) and that of the underlying opaque surface (a) are mixed linearly, with the mixing proportions determined by the transmittance α of the transparent layer:

$$p = (1 - \alpha)r + \alpha a \tag{1}$$

Metelli noted that this equation is consistent with a simple physical model of transparency involving an *episcotister*—a rapidly rotating disk with an open

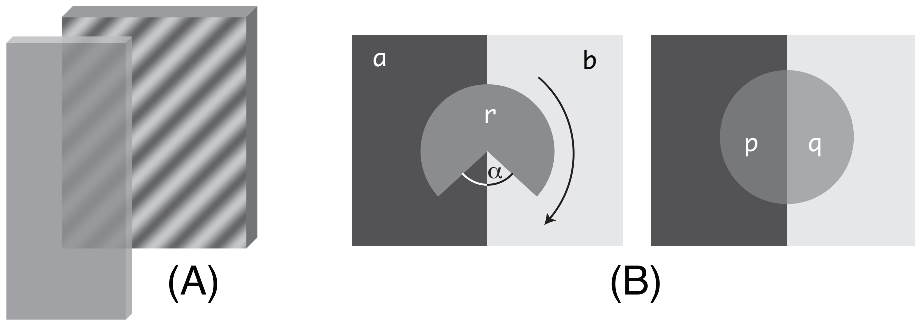

Fig. 1. (A) Illustration of the problem of transparency: In each visual direction, the contributions of two distinct layers are collapsed onto a single pixel intensity. These contributions must be disentangled if the scene structure is to be recovered. (B) Metelli's model of transparency based on a linear combination of the two contributions.

sector—placed in front of a background surface (see Fig. 1B-C). The same equation is also consistent with an opaque surface with a large number of holes that are too small to be resolved individually (e.g., a mesh). In the latter case, the "color mixing" takes place spatially, rather than over time. (Metelli himself considered only the achromatic case, so the colors he refers to are "achomatic colors," but his model has also been extended to the chromatic domain, e.g., [8,10]).

Physically more accurate models of transparency incorporate the pattern of light reflection and transmission between a transparent filter and the underlying opaque surface (see Fig. 2A)[22,7,6,11,10,17], leading to the following equation:

$$p = f + \frac{\alpha^2 a}{1 - fa} \tag{2}$$

In this equation, reflectance f plays the same role as the product $(1 - \alpha)r$ in Metelli's model. Moreover, f and α can be further expressed in terms of intrinsic physical parameters of the partially transmissive filter (see Fig. 2B)—its *reflectivity* β (at the air-filter interface) and *inner transmittance* θ (ratio of radiant flux that reaches the back surface of the transparent filter to the flux that enters the filter at its front surface) e.g., [22,10,17]. (For models of sub-surface scattering within volumetric translucent materials, see e.g., [14]. In such cases, background structure is often not visible through the translucent material, e.g., marble or cheese.)

It has been argued that, despite its simplicity, Metelli's linear equation provides a reasonable approximation to the more complete filter model [11], as well as to other more complex cases such as fog and haze [12]. Computer vision algorithms aimed at undoing the effects of fog and haze similarly employ a linear

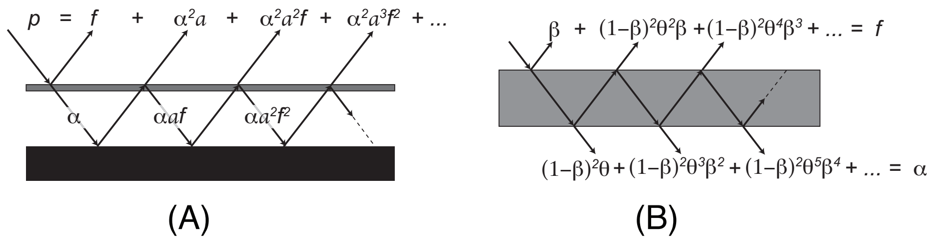

Fig. 2. (A) Model of a transparent filter that takes into account the pattern of transmission and reflection between the filter and the underlying opaque surface. (B) The overall transmittance and reflectance of the filter are functions of two intrinsic parameters: reflectivity β, and inner transmittance θ.

generative model, containing a multiplicative—attenuative—component due to absorption and scattering (a negative exponential of the fog extinction coefficient, generally taken to be a constant), plus an additive contribution of the airlight[18,16,9,21,13].

The Inverse Problem

Given a single equation such as (1) above, it is clearly impossible to determine transmittance α and reflectance r from knowledge of p and a alone. However, if the background surface contains *two* distinct 'colors' a and b—both partly visible through the same transparent filter—the two equations:

$$p = (1-\alpha)r + \alpha a \quad \text{and} \quad q = (1-\alpha)r + \alpha b \tag{3}$$

can be uniquely solved for α and r:

$$\alpha = \frac{p-q}{a-b}; \quad r = \frac{aq-bp}{a+q-b-p} \tag{4}$$

(Note that, more generally, with multiple colored patches visible through the transparent layer, a common solution may not exist and least-squares methods may be required; see, e.g., [8].)

Transparent overlap of surfaces generically leads to X-junctions in the image (see Fig. 3). However X-junctions differ greatly in the degree of local support they provide for interpretations of transparency. Compare, for instance, the interpretations of perceived transparency elicited by the three displays in Fig. 3. In addition to making quantitative predictions for transmittance and reflectance, the above solutions also yield qualitative predictions for interpretations of transparent overlap and depth layering [15,7,6]. In order to have valid transparency, α must be non-negative with magnitude no larger than 1. Hence, based on the expression for α above, it follows that:

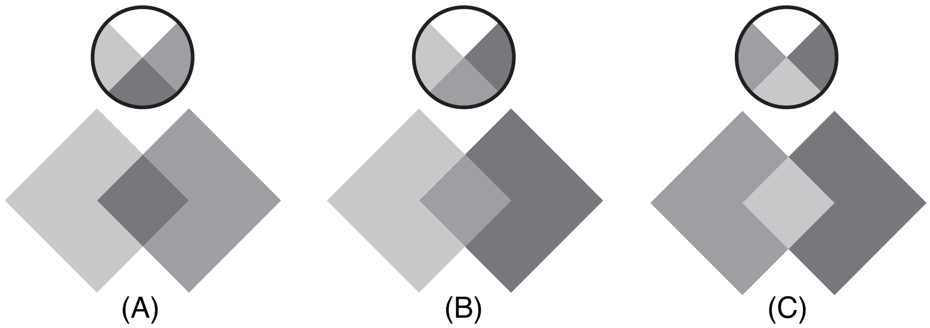

Fig. 3. Classification of X-junctions based on their support for the interpretation of transparent overlap. (A) Non-reversing junctions. (B) Single-reversing junctions. (C) Double-reversing junctions.

1. $sign(p - q) = sign(a - b)$. The contrast polarity must be the same inside and outside a putative transparency boundary.
2. $|p - q| \leq |a - b|$. The magnitude of the luminance difference must be no greater inside the transparency boundary than outside it.

Based on the polarity constraint above, researchers have classified X-junctions into three qualitative kinds [2,1]. In a *non-reversing* junction, contrast polarity is preserved across both edges of the "X", hence either edge could be the boundary of a transparent layer (Fig. 3A). In a *single-reversing* junction, contrast polarity is preserved across one edge only; hence there is only one possible interpretation of transparent overlap (Fig. 3B). Finally, in a *double-reversing* junction, neither edge preserves contrast polarity, so this junction type does not support an interpretation of transparency (Fig. 3C).

The above analysis provides local constraints for the interpretation of transparency. Local support can often be overruled by global context, however. Mechanisms are needed to integrate local evidence across the image. In the achromatic domain, an integration algorithm was proposed by Singh & Huang [20], which propagates local junction information by searching for chains of polarity-preserving X-junctions with consistent sidedness (i.e., side with lower contrast), and then propagating the transparency labeling to interior regions. Despite its simple, deterministic nature, the algorithm performs well on synthetic images and simple real images with well-defined X-junctions.

In the chromatic domain, D'Zmura et al. [8] developed an algorithm for separating transparent overlays that (i) searches for chains of X-junctions; and (ii) tests for a consistent chromatic convergence across this chain. This algorithm is based on the finding that a convergence (possibly accompanied by a translation) in color space across a boundary tends to generate the percept of an overlying color filter, whereas other transformations such as shears and rotations do not. (This result is largely consistent with Metelli's model extended to the color domain—although some transformations that cannot be achieved with Metelli's equations, such as equiluminous translations in color space, can also generate a percept of transparency [8].)

Going beyond junctions. The schemes reviewed above rely on the accurate extraction of junctions in images. A reliance on junctions may ultimately be too restricting, however, especially in images of natural scenes. For example, partially-transmissive media with varying opacity, such as fog and haze, generate gradual changes in contrast along an edge in the background, without well-defined junctions. In order to deal with such cases, Anderson [3] proposed the *transmittance-anchoring principle* which states that, as long as contrast polarity is preserved across a contour, the visual system anchors the highest-contrast regions to full transmittance (i.e., surfaces seen in plain view), whereas lower-contrast regions are perceived as containing an overlying transparent layer with varying degrees of transmittance. Perceptual experiments suggest that human observers do anchor transmittance in this way [4,5].

Application

Recent work in computer vision has focused on undoing the effects of fog and haze in images, and recovering versions of these images that are free of atmospheric disturbance. One class of methods relies on having multiple images of a scene, taken either under different levels of atmospheric disturbance [16], or with different degrees of polarization [18]. More recent methods, relying on a single image, have adopted a number of strategies, including maximizing local contrast in the restored image [21], the assumption that transmission and surface shading are uncorrelated [9], and the "dark-channel prior"—the assumption that in images of outdoor scenes taken under clear viewing conditions, most local patches tend to contain pixels with very low intensity in at least one of the color channels [13].

As noted above, another class of algorithms designed to separate transparent overlays from the background, relies on the explicit extraction of X-junctions [8,20]. These algorithms work well in simple images with well-defined junctions; it remains to be seen how well this approach scales up to complex natural images.

Physical versus perceptual models. One issue that computer-vision systems must consider is whether they are aimed at recovering physically accurate estimates of the transmittance of a transparent material, or obtaining estimates that are aligned with the way human observers perceive transmittance. One can readily imagine applications in which either may be more appropriate. Perceptual experiments have shown that the human perception of surface transmittance is not well-predicted by Metelli's equations, and can deviate significantly from physical predictions. Specifically, these studies have shown that the visual estimate of transmittance is based on the *perceived contrast* within the region of transparency (suitably normalized by the perceived contrast in surrounding regions); and perceived contrast is not well predicted by the luminance differences (or luminance range) that appear in Metelli's solution for transmittance α; see e.g., [19,17,4]. Consistent with a perceived-contrast model, a dark-colored surface can visually appear to be significantly more transmissive than a light-colored surface of the same physical transmittance.

Recommended Readings

[1] E. H. Adelson. Lightness perception and lightness illusions. In M. Gazzaniga, editor, *The New Cognitive Neurosciences*, pages 339–351. M.I.T. Press, Cambridge, M.A., 2000.

[2] E. H. Adelson and P. Anandan. Ordinal characteristics of transparency. *AAAI-90 Workshop on Qualitative vision, Boston, MA*, 1990.

[3] B. L. Anderson. The role of occlusion in the perception of depth, lightness, and opacity. *Psychological Review*, 110:762–784, 2003.

[4] B. L. Anderson, M. Singh, and J. Meng. The perceived transmittance of inhomogeneous surfaces and media. *Vision Research*, 46:1982–1995, 2006.

[5] B. L. Anderson and J. Winawer. Layered image representations and the computation of surface lightness. *Journal of Vision*, 8 (7):18, 2008.

[6] J. Beck. The perception of transparency in man and machine. *Computer Vision, Graphics, and Image Processing*, 31:127–138, 1985.

[7] M. H. Brill. Physical and informational constraints on the perception of transparency and translucency. *Computer Vision, Graphics, & Image Processing*, 28:356–362, 1984.

[8] M. D'Zmura, P. Colantoni, K. Knoblauch, and B. Laget. Color transparency. *Perception*, 26:471–492, 1997.

[9] R. Fattal. Single-image dehazing. *ACM Transactions on Graphics (proc. SIGGRAPH)*, 2008.

[10] F. Faul and V. Ekroll. Psychophysical model of chromatic perceptual transparency based on substractive color mixture. *Journal of the Optical Society of America, A*, 19:1084–1095, 2002.

[11] W. Gerbino. Achromatic transparency. In A. L. Gilchrist, editor, *Lightness, brightness, and transparency*, pages 215–255. Erlbaum, Hillsdale, NJ, 1994.

[12] J. Hagedorn and M. D'Zmura. Color appearance of surfaces viewed through fog. *Perception*, 29:1169–1184, 2000.

[13] K. He, J. Sun, and X. Tang. Single image haze removal using dark channel prior. *Computer Vision and Pattern Recognition*, 2009.

[14] H. W. Jensen, S. R. Marschner, M. Levoy, and P. Hanrahan. A practical model for subsurface light transport. *ACM Transactions on Graphics (proc. SIGGRAPH), 511–518*, 2001.

[15] F. Metelli. The perception of transparency. *Scientific American*, 230:90–98, 1974.

[16] S. G. Narasimhan and S. K. Nayar. Contrast restoration of weather-degraded images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25:713–724, 2003.

[17] R. Robillotto and Q. Zaidi. Perceived transparency of neutral density filters across dissimilar backgrounds. *Journal of Vision*, 4:183–195, 2004.

[18] Y. Y. Schechner, S. G. Narasimhan, and S. K. Nayar. Polarization-based vision through haze. *Applied Optics*, 42:511–525, 2003.

[19] M. Singh and B. L. Anderson. Toward a perceptual theory of transparency. *Psychological Review*, 109:492–519, 2002.

[20] M. Singh and X. Huang. Computing layered surface representations: an algorithm for detecting and separating transparent overlays. *Proceedings of Computer Vision and Pattern Recognition*, 2:11–18, 2003.

[21] R. T. Tan. Visibility in bad weather from a single image. *Computer Vision and Pattern Recognition*, 2008.

[22] G. Wyszecki and W. S. Stiles. *Color science: Concepts and methods, quantitative data and formulae.* John Wiley & Sons, New York, 1982.