The Plenoptic Function and
the Elements of Early Vision
Edward H. Adelson and
James R. Bergen

What are the elements of early vision? This question might be taken to mean, What are the fundamental atoms of vision?—and might be variously answered in terms of such candidate structures as edges, peaks, corners, and so on. In this chapter we adopt a rather different point of view and ask the question, What are the fundamental substrates of vision? This distinction is important because we wish to focus on the first steps in extraction of visual information. At this level it is premature to talk about discrete objects, even such simple ones as edges and corners.
Every body in light and shade fills the surrounding air with infinite images of itself, and these, by infinite pyramids diffused in the air, represent this body throughout space and on every side. Each pyramid that is composed of a long assemblage of rays includes within itself an infinite number of pyramids and each has the same power as all, and all as each.

— The Notebooks of Leonardo da Vinci (late 1400's)

Spectral nature of light

[Newton, 1665]
4.1 NEWTON’S SUMMARY DRAWING of his experiments with light. Using a point source of light and a prism, Newton separated sunlight into its fundamental components. By reconverging the rays, he also showed that the decomposition is reversible.

[from Wandell: Foundations of Vision, 1995]
The “Plenoptic” function

\[ I(x, y, \lambda, t, V_x, V_y, V_z) \]

(everything there is to see)

[Adelson & Bergen 91]

Imaging: capture of the plenoptic function on a 2D sensor surface
First production camera ("Daguerrotype"), 1839

$I(x, y, \lambda, t, V_x, V_y, V_z)$? Integrated over viewpoint and time, sampled in $(x,y)$ and wavelength
Perceptual color matching experiment

Arbitrary test light

Mixture of 3 primary lights

[Young, Helmholtz, Grassman, etc., 1800’s; slide c/o D. Brainard]
Grassmann’s Laws, 1853

1) Any light can be matched with a mixture of 3 primaries
2) Sum of 2 lights results in a sum of the corr. mixtures
3) Rescaling the light results in a rescaled mixture

- Matching can be described by an Nx3 linear system!
Theory: the visual system projects the wavelength spectra of light onto a 3-dimensional space

- Accurately predicts perceptual limitations
- Basis for color technology standards (CIE, 1931)
- Underlying mechanism (cones) verified 100+ years later

CIE “standard observer” color matching functions (1931)
CIE “standard observer” color matching functions (1931) used to define the standard “XYZ” color coordinate system

CIE-LUV color space (1976)

One (of many) attempts to create a perceptually-uniform color space.

\[ L' = \begin{cases} \left( \frac{20}{9} \right)^3 \frac{Y}{Y_n}, & \frac{Y}{Y_n} \leq \left( \frac{9}{4} \right)^3 \\ 116 \left( \frac{Y}{Y_n} \right)^{1/3} - 16, & \frac{Y}{Y_n} > \left( \frac{9}{4} \right)^3 \end{cases} \]

\[ u' = 13L' \cdot (u' - u'_n) \]

\[ v' = 13L' \cdot (v' - v'_n) \]

\[ w' = \frac{4X}{X + 15Y + 3Z} \]

\[ w' = \frac{9Y}{X + 15Y + 3Z} \]

\[ v' = \frac{9Y}{X + 15Y + 3Z} \]
ICC profiles

- Standard for specifying color coordinate system for displays and sensors (often embedded in digital photo files)
- 3x3 matrix [relative to XYZ coords]
- point nonlinearities [power, or lookup table]
Cone photoreceptor mosaic near fovea
- Roorda and Williams (1999)

$I(x, y, \lambda, t, V_x, V_y, V_z)$? Integrated over viewpoint and time, sampled in (x,y) and wavelength!
Light sources (illuminants)

[Graphs showing the spectral power distribution of two light sources: one with a peak around 500 nm and another with a linear increase across wavelengths.]

4.4 THE SPECTRAL POWER DISTRIBUTION of two important light sources are shown: (left) blue sunlight and (right) a tungsten bulb.

Reflectance functions

[Forzyth, 2002]
1) Graphics is easy, vision is hard/impossible :)

2) In fact, humans are quite good (but not perfect) at separating illumination from reflectance.


Even in grayscale, humans are pretty good at estimating reflectance, and local intensity changes, but are very poor at estimating absolute intensities.

[Adelson, 1995]
What's color perception for?

Perhaps humans try to estimate reflectance, regardless of lighting?

[c/o David Brainard]

Change of lighting, or change of paint?

[photo: Brainard 2003]
Why don’t colors look right in photographs? Sources of failure:
• viewing conditions
• multiple light sources
• sensor not matched to cone absorption space

Auto white balance? Sources of information:
• distribution of pixel colors in scene
• brightest point in scene (specularities)
• prior assumptions about illuminants, reflectances
• inter-reflections
red
rose
or
red
light?
red rose, white light:  \[ \int_{\lambda} c_i(\lambda) \, w(\lambda) \sum_{n=1} \alpha_n \, r(\lambda)^n \]

red light, white rose:  \[ \int_{\lambda} c_i(\lambda) \, r(\lambda) \sum_{n=1} \alpha_n \, w(\lambda)^n \]

c_i(\lambda): sensitivity of \(i\)th cone type
w(\lambda): white (either reflectance or spectral power rescaled to [0, 1])
r(\lambda): red(...)
\(\alpha_n\): proportion of light with \(n\) bounces
Bayesian color constancy

David H. Brainard
Department of Psychology, University of California, Santa Barbara, California 93106

William T. Freeman
MIT, a Massachusetts Electric Research Laboratory, Cambridge, Massachusetts 02139

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The problem of color constancy may be solved if we can recover the physical properties of illuminants and surfaces from knowable responses. We consider this problem within the framework of Bayes and decision theory. First, we model the relation among illuminants, surfaces, and photoreceptor responses. Second, we construct prior distributions that describe the probability that particular illuminants and surfaces exist in the world. Given a set of photoreceptor responses, we then use Bayes' rule to compute the posterior distribution for the illuminants and the surfaces in the scene. There are two widely used methods for obtaining a single best estimate from a posterior distribution. These are maximum a posteriori (MAP) and minimum mean-squared error (MMSE) estimation. We argue that neither is appropriate for perception problems. We describe a new estimator, which we call the maximum local mean (MLM) estimator, that integrates local probability density. The new method uses an optimization criterion that is appropriate for perception tasks. It finds the most probable approximately correct answer. For the case of two observation tasks, we provide an efficient approximation. We develop the MLM estimator for the color-constancy problem in which flat, matte surfaces are uniformly illuminated. In simulations we show that the MLM method performs better than the MAP estimator and better than a number of standard color-constancy algorithms. We note conditions under which even the optimal estimator produces poor estimates when the spectral properties of the surfaces in the scene are biased. © 1997 Optical Society of America
Reflectance Prior

\[ S(\lambda) = w_1 S_1(\lambda) + w_2 S_2(\lambda) + w_3 S_3(\lambda) \]

[Brainard & Freeman]

Illuminant Prior

\[ E(\lambda) = w [E'_1(\lambda) + u E'_2(\lambda) + v E'_3(\lambda)] \]

[Brainard & Freeman]