Introduction to Neural Networks

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Computing object properties: Surface Material

Initialize

- Spell check off

```mathematica
Off[General::spell1];
SetOptions[ArrayPlot, ColorFunction -> "GrayTones", DataReversed -> True, Frame -> False, AspectRatio -> Automatic, Mesh -> False, PixelConstrained -> True, ImageSize -> Small];
SetOptions[ListPlot, ImageSize -> Small];
SetOptions[Plot, ImageSize -> Small];
SetOptions[DensityPlot, ImageSize -> Small, ColorFunction -> GrayLevel];
nbinfo = NotebookInformation[EvaluationNotebook[]];
dir = "FileName" /. nbinfo /. FrontEnd`FileName[d_List, nam_, ___] :> ToFileName[d];
```

Introduction to material perception: *How does the brain enable us to see what things are made of?*

A basic assumption about the function of the ventral visual pathway of the brain is that the neural circuits are computing properties of objects that are invariant to changes in viewpoint and lighting. Another way of expressing the problem is to say that the visual system is discounting (or “integrating out” in Bayesian terms) unwanted variations in viewpoint and lighting. One aspect of this process is to compute representations of the form or shape of objects. Another is computing the intrinsic surface properties—the stuff, substance or material that an object is made of (cf. Cant et al., 2008).

We first start by understanding what we know about the physical generative process that produces the patterns of light as a function of material properties.

Material & Texture modeling
General categories of the "stuff" we see: surfaces (opaque and transparent), particle clouds (e.g. smoke, mist,...), liquids, hair, fur,...

Connection with count vs. mass nouns

**Uniform materials**

Surfaces with material properties or attributes:
- reflectance ("paint" or pigment or albedo)
  - matte and shiny
  - mirrors
- transparency
  - multiplicative, additive

- **Physics-based generative modeling: Bidirectional reflectance distribution functions**

Figure from: Image-Based BRDF Measurement Including Human Skin Stephen R. Marschner* Stephen H. Westin Eric P. F. Lafortune, Kenneth E. Torrance Donald P. Greenberg

The Bidirectional Reflectance Distribution Function (BRDF) describes directional dependence of the reflected light energy. The BRDF represents, for each incoming angle, the amount of light that is scattered in each outgoing angle.

For a given wavelength, it is the ratio of the reflected radiance in a particular direction to the incident irradiance:

\[
\rho(\theta_i, \phi_i, \theta_e, \phi_e) = \frac{dL_e(\theta_e, \phi_e)}{dE_i(\theta_i, \phi_i)}
\]
where $E$ is the irradiance, that is the incident flux per unit area (w-m-2), and $L$ is the reflected radiance, or the reflected flux per unit area per unit solid angle (w-m-2-sr-1). The units of BRDF are inverse steradians. Respects the physics: Reciprocity, energy conservation.

We've assumed isotropy, i.e. the BRDF is the same for all directions at a point, and spatially uniform material.

For a Lambertian (perfectly diffuse) surface, for example, the BRDF is constant. The Phong model described earlier in the context of shape-from-shading can approximate only a subset of surfaces characterized by BRDFs.

Figure from: http://graphics.stanford.EDU/~smr/brdf/bv/

- **Ward reflection model:** For calculating an image from a description of the shape, the illumination, and the BRDF

The Ward model is a physically realizable cousin of the Phong model.

Subscripts $i$ and $e$ below indicate incoming and outgoing rays, respectively.

$$L_e(\theta_e, \phi_e) = \int \int L_i(\theta_i, \phi_i) \rho(\theta_i, \phi_i, \theta_e, \phi_e) \cos \theta_i \sin \phi_i d\theta_i d\phi_i$$

$$\rho(\theta_i, \phi_i, \theta_e, \phi_e) = \frac{\rho_d}{\pi} + \rho_s \frac{e^{-\tan^2(\delta)/a^2}}{4 \pi a^2 \sqrt{\cos \theta_i \cos \theta_e}}$$

$\delta$ is the angle between the viewer and the vector defining the mirror reflection of the incident ray (i.e. where the angle of
reflection equals the angle of incidence). $\alpha$ can be thought of as a measure of "roughness", and $\rho_d$ and $\rho_s$ give the amounts of diffuse and reflected contributions.

![Image of specular and matte finishes](23.SurfaceMaterial.nb)

**Non-uniform materials: Texture**

Note: "texture" sometimes refers to low-level cues or statistics useful for inferring properties like slant and shape, but it is also used to refer to surface material properties that are useful to estimate because they represent view-invariant object properties. In other words, sometimes it refers to a cue (measurement to support an estimate) and other times to an estimate itself. Thus confusingly, sometimes "texture" refers to an image features, and other times to 3D surface properties.

In this lecture, we focus on texture as a material property.

Textures can:

- be regular ("herringbone pattern") or stochastic ("fur")
- "cohere" e.g. asphalt vs. sand & gravel

Textures can be due to:

- reflectance/pigment variations or bump (small geometric) variations
  - perceptually it isn't always easy to tell the difference, and may not matter depending on visual function.
  - For example, consider the visual and tactile differences between real wood and synthetic wood finishes.
  - (Note that image texture can also result from a completely uniform (shiny) material reflecting a textured environment)

Key characteristics of texture:

- spatial variations are small with respect to the global scale of the surface structure
- spatial homogeneity
- **Appearance-based measurements**

How can one characterize the generative model? Much more complicated because of small, but not micro-scale surface non-uniformity.


- **Random synthesis and learning of textures**

There has been considerable work in computer graphics, computer vision, and perception on the problem of texture synthesis. One approach is to assume that textures are defined by statistics with respect to a set of spatial filters--a basis set. So for example, assume that the filters are the collection of V1 simple cell receptive fields. Suppose we have N neurons that span a range of spatial frequencies and orientations.

The idea is that two different images that have the same texture (e.g. “tiger fur”) should have the same statistics. What does this mean? Textures are by definition spatially homogeneous and typically have a characteristic scale (and sometimes more than one). Divide up the image into patches whose size is on the order of the scale of the texture. Compute the responses of the N neurons over all the patches and assemble them into N histograms. If we repeat the process with the second image, its collection of histograms should be similar.

This suggests that we could make a texture synthesizer using a technique closely related to histogram equalization. Start off with 1) a texture sample and 2) a random noise image. Compute the histograms for the texture sample, and now adjust the noise image to have the same histograms as the sample. See Heeger and Bergen (1995).

Recently, Freeman and Simoncelli method has been used to generate random samples of images in peripheral vision that have the same “texture”. They called these “metamers”. See Freeman, J., & Simoncelli, E. P. (2011). “Metamers of the ventral stream.” Nature Neuroscience. They did psychophysics to conclude that area V2
### Reflectance estimation & lightness

In this section we will look at the simplest generative model. We’ll assume a flat world consisting of surfaces with uniform reflectance $R$ ($0 \leq R \leq 1$; related to $\rho$ above), and with illumination level $E$. Then the generative model for luminance $L$, is simply: $L = R \cdot E$. Luminance has a precise physical definition. Lightness refers to the psychological appearance of the level of “grayness” of a substance.

### Introduction

Historically, much experiment and thought went into accounting for the phenomena of color appearance over the last century and a half. However, the problem of what color vision is for, received less attention.

Although people have made various conjectures about the function of color vision, the advent of computational vision helped to clarify and motivate research into color’s function. One idea is that it could aid in segmentation—the localization of boundaries in the absence of luminance contours. Another idea is that color could provide a surface attribute, relatively invariant over illumination variations useful for recognition. So just like shape is informative for object
recognition, so might surface color. Color constancy refers to the observation that the color (of an object) can remain relatively unchanged with both spatial and chromatic changes in illumination. This second explanation gives us a different slant on color constancy—because in order to have a reliable surface attribute, we must be able to compute it given variations in secondary variables. Surface color is not given to the eye directly because the color and spatial distribution of the illumination typically varies. If we computed the color of an object by simply registering its wavelength composition, the object would rarely appear the same as it was moved about the room, or from indoors to outdoors. To obtain some measure of color constancy, vision discounts illumination as a secondary variable. The neural mechanisms of color vision support the estimation of invariant intrinsic surface properties that are in some sense closer to the parameters of the BRDF than to the physical light input to the eye.

If color constancy is a result of the neural system's attempt to estimate a surface attribute, then what is that attribute, and could neural networks compute it? Let's look at the one dimensional the problem—in particular, lightness constancy. Historically there have been two types of models, one in which the goal is to model the perceptual appearance, i.e. lightness, and the second (computer vision), to assume an underlying physical generative model and estimate reflectance.

**Functional vs. mechanistic explanations**

- Overview of lightness effects

  http://web.mit.edu/persci/demos/Lightness/gaz-teaching/index.html

- Simultaneous contrast

  ![Simultaneous contrast](http://web.mit.edu/persci/demos/Lightness/gaz-teaching/flash/contrast-movie.swf)

**Lightness & spatially uniform illumination**

- Simple constancy: simultaneous contrast mechanisms vs. functional algorithms

  Empirical observations show that local contrast (ratios of the luminance of the inside disk to annulus) can (under certain
Empirical observations show that local contrast (ratios of the luminance of the inside disk to annulus) can (under certain conditions) predict apparent lightness matches:

Can we understand this from the point of view of reflectance estimation?

Spatially uniform illumination. $L = RE$.

We assume a simple generative model, together with a task assumption that vision values an invariant object property, $R$.

This suggests that $R$ should be a better predictor of lightness than $L$.

$\text{Lightness} \rightarrow R$, where $R$ is between 0 and 1.

Let $L_1$ and $L_2$ be the luminance of the small center disks, and $R_1$ and $R_2$ be their reflectances.

Relative reflectance and local contrast: $L_1/L_2 = (R_1E)/(R_2E) = R_1/R_2$

So perceived ratios of lightness should match luminance ratios.

What about the sense that lightness as a particular absolute value, e.g. "white", "black", "medium gray"?

Normalization or anchoring problem (see Gilchrist).

Estimate of $R_1 \sim L_1/L_{avg}$

or $R_1 \sim L_1/L_{max}$?

There is a physical constraint on reflectance. In the natural world a typical range is about 10 to 1, or with really white and really black surfaces up to 30 to 1.

See Appendix for a simple Bayesian model of reflectance estimation.
Spatially varying illumination

- **Craik-O’Brien-Cornsweet effects**

```math
size = 256; y[x_] := \frac{1.\text{Abs}[\frac{x}{2}]+6}{\text{size} - 1}; y1 = \text{Table}[y[x], \{x, 0, \text{size}/2\}];
```

```math
y12 = \text{Join}[\text{Reverse}[y1], y1 - 0.03];
ListPlot[y12 + 0.5, \text{PlotRange} \to \{-1, 1\}, \text{Joined} \to \text{True}]
```

- **Land & McCann's "Two squares and a happening"**

```math
size = 256; \text{Clear}[y]; \text{slope} = 0.0005;
y[x_] := \text{slope} x + 0.5 \;/; x < \text{size}/2
y[x_] := \text{slope} (x - 128) + 0.5 \;/; x > \text{size}/2
```
The left half looks lighter than the right half. But, let's plot the intensity across a horizontal line:

```
new = picture;
new[[128, All]] = 0;
GraphicsRow[{ArrayPlot[new, PlotRange -> {0, 1}],
   g0 = ListPlot[ picture[[128]], PlotJoined -> True, PlotRange -> {0.2, .8}]}]
```

Lightness algorithms in "flat land"

The Appendix provides some examples of historical approaches to computing lightness.

The two ramps are identical...tho' not too surprising in that that is how we constructed the picture. How can we explain this illusion based on what we've learned so far about human contrast sensitivity as a function of spatial frequency—in terms of a single-channel model?

One explanation is that the visual system takes a spatial derivative of the intensity profile. Recall from calculus that the second derivative of a linear function is zero. So a second derivative should filter out the slowly changing linear ramp in the illusory image. We approximate the second derivative with a discrete kernel (-1,2,-1).
The steps are: 1) take the second derivative of the image; 2) threshold out

\[
\text{filter} = \{-1, 2, -1\};
\]

(*Take the second derivative at each location*)
\[
f\text{picture} = \text{ListConvolve}[\text{filter}, \text{picture}[[128]]];
\]
\[
g1 = \text{ListPlot}[f\text{picture}, \text{PlotJoined} \rightarrow \text{True}, \text{PlotRange} \rightarrow \{-0.1, .1\},
\text{Axes} \rightarrow \text{False}];
\]

(*Now integrate twice--to undo the second derivative and "restore" the picture*)
\[
i\text{ntegratefpicture} = \text{FoldList}[\text{Plus}, f\text{picture}[[1]], f\text{picture}];
\]
\[
i\text{ntegratefpicture2} = \text{FoldList}[\text{Plus}, \text{i}\text{ntegratefpicture}[[1]],
\text{i}\text{ntegratefpicture}];
\]
\[
g2 = \text{ListPlot}[\text{i}\text{ntegratefpicture2}, \text{PlotJoined} \rightarrow \text{True}, \text{Axes} \rightarrow \text{False}];
\]
\[
\text{GraphicsRow}[\{g0, g1, g2\}, \text{ImageSize} \rightarrow \text{Large}]
\]

To handle gradients that aren't perfectly linear, we could add a threshold function to set small values to zero before re-integrating:

\[
\text{threshold}[x\_0, \varepsilon\_] := \text{If}[x > \varepsilon, x, 0]; \text{SetAttributes[threshold, Listable]};
\]
\[
f\text{picture} = \text{threshold}[f\text{picture}, 0.025];
\]

Or one can take just the first derivative, followed by the threshold function

The problem of edge cause: the same intensity gradient means different things depending on context

- "Two cylinders and no happening"

But is edge enhancement and and spatial filtering a good way to explain the lightness effect? Up until the early 1990's many people thought so, and this was a standard textbook explanation of these kinds of lightness illusions.
What if we measure the intensity across a horizontal line in the "slab" on the left, and the "two-cylinders" on the right?

They are also the same! They would both look something like this:

But the perceived lightness contrast for the slabs is significantly stronger than it is for the two cylinders. A spatial convolution/derivative model would predict the same for both. The spatial convolution operation won't work as an explanation!

One interpretation of this observation is that the visual system has knowledge of the type of edge—i.e. whether it is due to pigment or to self-occlusion/contact. (See Knill and Kersten, 1991).

**Visual cortex: Respond to luminance or lightness change?**

If we could measure the activity in the first cortical area, V1, would responses there correspond to intensity change or lightness change?

Using functional magnetic resonance imaging, we can image V1 activity in subjects viewing a contrast-reversing Craik-O'Brien illusion. The result is that V1 responds to lightness contrast with almost the same strength as to an equivalent luminance change.


The animation below shows what contrast-reversing lightness illusion looks like:
Reflectance estimation & indirect lighting

How sophisticated is our perceptual system to the causes of illumination? Does the visual system take into account the geometry of reflected light? Consider indirect lighting such as would arise in a corner. Below is a photograph of a corner consisting of a white paper on the left and a red paper on the right. The white paper looks pinkish (consistent with the physical spectrum induced by the light landing on it from the red paper). Normally we don't notice the color of reflected light, perhaps because given sufficient cues to shape, it can discount the color of indirect lighting. How can we test this?


Imagine making the following card using a color printer:
Fold it, arrange the lighting as show below, and then look at it from above. The physics of the situation is illustrated below.

Now if you look at the paper steadily, you would experience a spontaneous reversal in the shape going from a concave corner to a convex "roof". When the paper looks like a roof, the white side appears more pinkish than when the paper appears to be a concave. Why is this so?
Two generative models

Bloj et al. measured the perceptual effect and produced a quantitative explanation showing that the visual system seemed to have

"built-in" knowledge about the effects of indirect vs. direct lighting. They used the following generative models to produce a Bayesian estimate of surface color matches:

Indirect plus direct lighting (1 bounce, Funt & Drew, 1991)

\[
I(\lambda) = E(\lambda)\rho_1(\lambda)\left[\cos(\alpha_1) + f_{21}(x)\rho_2(\lambda)\cos(\alpha_2)\right] + n
\]

\[
f_{21}(x) = \frac{1}{2}\left[1 + \frac{\cos(\beta) - (x/w)}{\sqrt{(x/w)^2 - 2(x/w)\cos(\beta)}}\right]
\]

Direct lighting only (0 bounce)

\[
I(\lambda) = E(\lambda)\rho_1(\lambda)\left[\cos(\alpha)\right] + n
\]

Bottom line: Human color matches consistent with built-in knowledge of the generative laws of reflection.

But we do not yet know how the visual areas of the brain might interact to use shape knowledge to estimate surface color.
Perception of more complex materials

- A severe invariance problem

http://gandalf.psych.umn.edu/~kersten/karsten-lab/demos/MatteOrShiny.html

One of the main results of this study was to show that human judgments of specular attributes increases in accuracy when a shiny object is placed in a complex but still naturalistic environment. What is "naturalistic"? One ingredient is that the images have the kurtotic histogram properties that we studied in an earlier lecture. This is consistent with the presence of edges being important. Bright points are important too. Recognizable reflected objects are not necessary. Fleming et al used the above Ward model and had human subjects estimate qualities related to the degree of specularity (the image of a point light source on a really shiny object is quite sharp, i.e. a point), and the relative amounts of specular to diffuse components. See $\alpha$ and $\rho_s$ in the Ward model above.


- **The role of motion: Shiny or matte?**

http://gandalf.psych.umn.edu/~kersten/kersten-lab/demos/MatteOrShiny.html


- **The brain?**

We are just beginning to discover which cortical areas are involved in extracting information about object material properties. fMRI evidence suggests that a region, the collateral sulcus (CoS) overlapping with the parahippocampal place area (PPA) is involved in the computation of material property (Cant et al., 2008; 2011). How it is done is a challenge for the future.
Appendices

- **Simple constancy: Bayesian reflectance estimation of one isolated patch in flatland**

This simple example shows how marginalization or integrating out secondary variables can constrain an otherwise unconstrained problem...even without hypothesizing explicit priors on reflectance or illumination distributions. (Freeman, 1994)

\[ L = R \times E_l + \text{noise}. \]

Given L, what is R? El is the secondary variable that we want to discount by marginalization.

Let the illumination range be [0,10], and the reflectance range [0,1]. Then the luminance range is also [0,10].

Let the luminance noise be Gaussian with a standard deviation less than 10% of L, say 1 for simplicity. Then the probability of an observation L given R and El is proportional to:

\[
\text{likeli}[L, R, E_l] := \exp\left(-0.5 \times (L - R \times E_l)^2 \right) / \sqrt{2 \times \pi};
\]

\[
\text{prior}[R] := \text{PDF}[\text{UniformDistribution}\{0, 1\}, R]
\]

where we assume that the noise has a Gaussian distribution.

Here is a plot of the likelihood for a luminance value of 1:

\[
\text{Plot3D}[\text{prior}[R] \times \text{likeli}[1, R, E_l], \{R, 0.1, 0.9\}, \{E_l, 0.1, 10\},
\text{AxesLabel} \rightarrow \{"R", "E", "p"\}]
\]
Marginalize over illumination, $\text{El}$ to get the likelihood of $\text{R}$ for a given value of $\text{L}$:

\[
\text{pr}[\text{L}_-, \text{R}_-] := \text{Evaluate[}\text{Integrate[\text{prior[R]*Exp[-(L-R*El)^2]}, \text{El, 0, 10]}]}\text{]}
\]
Here is the relative probability of R given L = 0.75

```math
pt = {{r0 = R /. NMinimize[-pr[.75, R][[2]], 0], {r0, 10}};
Plot[pr[0.75, R], {R, 0, 1}, PlotRange -> {0, 10},
     Epilog -> {Red, Thick, Line[pt]]
```
Some notes on color illusions

- Munker-White illusion

http://web.mit.edu/persci/people/bart/DemoLinks.html

Neon color spreading, etc.

![Image of neon color spreading]

From: http://neuro.caltech.edu/~carol/VanTuijl.html


http://www.michaelbach.de/ot/col_neon/

Land, Horn and others

Given \( L(x,y) = S(x,y)E(x,y) \), where \( L \) is the intensity/luminance data of the image (using an achromatic world), we attempt to estimate \( S(x,y) \).

Rather than seeking a spatial filter explanation (e.g. do edge detection, and then fill in the region up to the edges with the color of the edges), consider the following functional explanation of this illusion:

The lightness value we assign is correlated with \( S \), not with \( L \). So how can we estimate \( S \)?

The idea is to assume that the image intensity changes (or changes in \( r, b, \) or \( g \)) are due to slowly varying illumination together with piece-wise constant reflectances. The slowly varying illumination needs to be filtered out. Land's scheme was to use ratios:
We want to estimate

\[
\frac{L_1}{L_5} = \frac{L_1}{L_2} \cdot \frac{L_2}{L_3} \cdot \frac{L_3}{L_4} \cdot \frac{L_4}{L_5}
\]

\[
\frac{L_1}{L_5} = \frac{S_1 E_1}{S_2 E_2} \cdot \frac{S_2 E_2}{S_3 E_3} \cdot \frac{S_3 E_3}{S_4 E_4} \cdot \frac{S_4 E_4}{S_5 E_5}
\]

But we would like to discount small changes in \(L\), so we can use the rule:

\[
\text{if } \left| 1 - \frac{L_i}{L_{i+1}} \right| < t
\]

\[
\text{then set } \frac{L_i}{L_{i+1}} = \frac{S_i E_i}{S_{i+1} E_{i+1}} = 1
\]

\[
1 \cdot 1 \cdot \frac{L_3}{L_4} \cdot 1 = 1 \cdot 1 \cdot \frac{S_3 E_3}{S_4 E_4} \cdot 1 \approx \frac{S_3}{S_4} = \frac{S_1}{S_5}
\]

and thus by using luminance ratios that are sufficiently large in the product, we obtain an estimate of the relative reflectance

\[
S_5 \approx S_1 \left( \frac{L_4}{L_1} \right)
\]

where the luminance ratio is measureable. We can obtain estimates for \(i = 1, 2, 3, 4, 6\). (See Appendix to see how Land extended this lightness algorithm model to color).

**Horn's algorithm**

Luminance \((L) = \text{reflectance} (S) \times \text{illumination} (E)\)

1) Take logs to turn the multiplication into addition:
1) \( C(x, y) = \log(L(x, y)) = \log(SE) = \log(S(x, y)) + \log(E(x, y)) = S' + E' \)

2) High-pass filter to amplify the edges

\[ \nabla^2 C(x, y) = \nabla^2 S' + \nabla^2 E' \] (or \( \nabla^2 G \ast C \))

3) Threshold all values below some finite threshold

\[ t(x, y) = T[\nabla^2 C] = T[\nabla^2 S' + \nabla^2 E'] = \nabla^2 S'(x, y) \]

Using Poisson's equation, solve for \( S(x, y) \).

\[ S' = t \ast g \]

\[ F[S'] = F[t]F[g] \]

The mathematical complication is because the problem is two-dimensional. In one dimension, only beginning calculus is required to understand how to solve a simple differential equation—just integrate.

Both Horn's method and Land's have some problems:

1) Normalization (anchoring problem) is actually more complicated, because we have taken second derivatives, leaving an extra degree of freedom in the integration process.

2) Spatial scale and threshold

3) Restricted to flatland.

In fact most of the alternatives face the same problems. One could imagine various ways of filtering out the illumination, for example, using spatial frequency representations of the image, but this does not help.

**Mathematica demonstration of a 1D lightness calculation in flatland**

One explanation is that the visual system takes a spatial derivative of the intensity profile. Recall from calculus that the second derivative of a linear function is zero. So a second derivative should filter out the slowly changing linear ramp in the illusory image. We approximate the second derivative with a discrete kernel \((-1, 2, -1)\). Let's apply this to a line across the Craik-O'Brien illusion above.

The steps are: 1) take the second derivative of the image;

```mathematica
filter = {1, -2, 1};
(* Take the second derivative at each location *)
fspicture = ListConvolve[filter, picture[[128]]];
```

2) Threshold. To handle gradients that aren't perfectly linear, we add a threshold function to set small values to zero before re-integrating:

```mathematica
threshold[x_, τ_] := If[Abs[x] > τ, x, 0];
SetAttributes[threshold, Listable];
fspicture = threshold[fspicture, 0.0025];
```
3) re-integrate

```math
ListPlot[fspicture, Joined -> True, PlotRange -> {-0.1, 0.1}];
integratefspicture = FoldList[Plus, fspicture[[1]], fspicture];
integratefspicture2 = FoldList[Plus, integratefspicture[[1]],
   integratefspicture];
ListPlot[integratefspicture2, Joined -> True, Axes -> False]
```

### Color constancy

**Land's demonstrations**

Beginning in the 1950's, Edwin Land has shown the sophistication of human color constancy in a number of striking demonstrations (Land, E.H., 1983). In one experiment, three lights (long, medium, and short wave lamps) illuminate a Mondrian consisting of a collection of patches of paper of various colors.

```
L (r)  
M (g)  
S (b)  
```

interference filters
We consider two phases, each characterized by a different global illumination of the whole Mondrian. In the first phase, we pick out two patches, a white (W) and a yellow (Y) one, on which to focus our attention. A radiometer is used to measure the amount of each of the three components radiating off the yellow patch. Now, in the second phase, we adjust the irradiance of each of the colored lights so that we get the same readings for the white patch as we had for the yellow patch in the first phase. And as a consequence, the spectral composition of the yellow patch changes too, because it is now receiving the same changed illumination as the white patch. Based on spectral composition, we might predict that the white patch of the first phase would be made to appear yellow in the second phase. but it doesn’t. color constancy is maintained, and the white patch appears white, and the yellow appears yellow. How can this be done?

Kraft and Brainard (1999) have measured color constancy under nearly natural viewing conditions. Their results rule out all three classic hypotheses: local adaptation, by adaptation to the spatial mean of the image, or by adaptation to the most intense image region. What more is needed to explain to constancy beyond these simple visual mechanisms?

References

- Other links

  http://www.cs.princeton.edu/~smr/cs348c-97/surveypaper.html
  http://www.ciks.nist.gov/appmain.htm
  http://www_graphics.cornell.edu/research/measure/

  For examples using BRDF measurements of human skin see:

  http://www_graphics.cornell.edu/online/measurements/


Perception as Bayesian Inference,: Cambridge University Press.


kerten.org