

# Information theory and the limits on color vision in natural scenes

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David H. Foster  
Computational Neuroscience Group  
University of Manchester, M60 1QD, U.K.

d.h.foster@umist.ac.uk  
<http://www.op.umist.ac.uk/dhf.html>  
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Kinjiro Amano  
Computational Neuroscience Group  
University of Manchester  
M60 1QD, U.K.



Sérgio M. C. Nascimento  
Department of Physics  
University of Minho  
4710-057 Braga, Portugal

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# Local surface-color information

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What limits our ability to identify surfaces despite changes in color of light on scene?

Three issues:

1. Number of different colors.
2. How surfaces are coded neurally.
3. How well such codings label uniquely surfaces under different lights.

Theoretical limits, then experimental ...

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# Local surface-color information



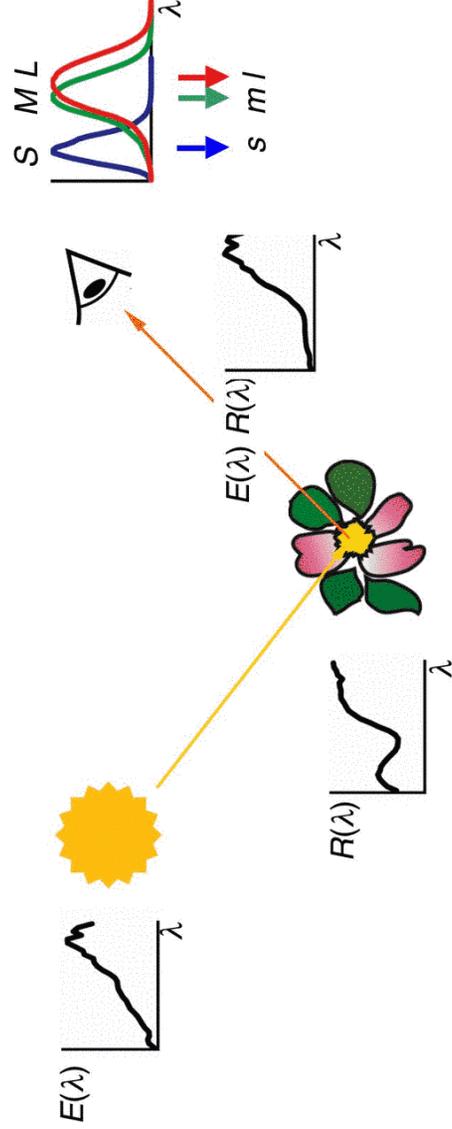
With just two surfaces, little confusion.

As number increases, risk of confusion increases:

1. Chance of similar reflectance spectra increases.
2. Codings not perfectly invariant under illuminant changes.
3. Physical, not perceptual or cognitive factors. ...

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# Basic optics



L-cone activity  $l = \int E(\lambda)R(\lambda)L(\lambda) d\lambda$

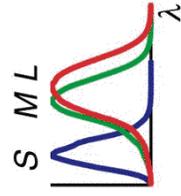
M-cone activity  $m = \int E(\lambda)R(\lambda)M(\lambda) d\lambda$

S-cone activity  $s = \int E(\lambda)R(\lambda)S(\lambda) d\lambda$

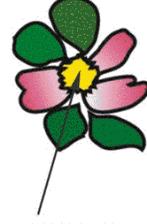
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## Problem of recovery

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From triple  $(l, m, s)$



Want something like

More precisely, want corresponding  $(l_0, m_0, s_0)$  values under some standard illuminant  $E_0 \dots$

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## Illuminant-invariant codes

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Estimate in relation to spatial average ...

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## Illuminant-invariant codes

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Take ratios for each cone class ...

target — comparison

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## Scaling

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Comparisons affected by:

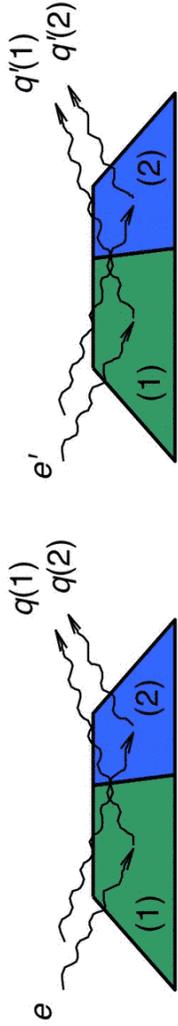
- distance
- contrast
- gamut

Pairwise comparisons capture all illuminant-invariant operations.

How invariant? ...

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## Cone-excitation ratios



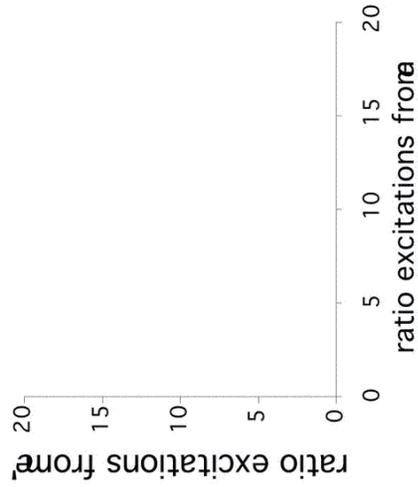
$$r = q(1) / q(2)$$

$$r' = q'(1) / q'(2)$$

Now plot  $r'$  against  $r$  ...

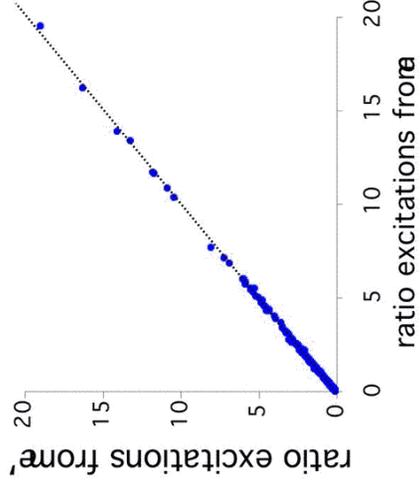
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## Scatterplot ratios (S-cones)



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## Scatterplot ratios (S-cones)



- Illuminants  $e$  and  $e'$  drawn at random from range 4300K to 25000K.
- Subset of 200 from 1000 surfaces drawn at random from natural scenes.
- Relative deviations for natural rural scenes:  $|r - r'|/\min\{r, r'\} \sim 4\%$
- Ratios are stable, but the error is important ...

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## Labelling



How much information is captured by color-labeling objects in a scene? ...

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## Labelling by ratios

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Represent surface colors as a collection of ratios  $r_1$

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## Labelling by ratios

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Represent surface colors as a collection of ratios  $r_1, r_2$

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## Labelling by ratios

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Represent surface colors as a collection of ratios  $r_1, r_2, r_3$

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## Labelling by ratios

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Represent surface colors as a collection of ratios  $r_1, r_2, r_3, \dots, r_{16}$ .

Or, if local grey-world normalization ...

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## Labelling by grey-world normalization

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Represent surface colors as a collection of ratios  $r_1$

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## Labelling by grey-world normalization

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Represent surface colors as a collection of ratios  $r_1, r_2$

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## Labelling by grey-world normalization

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Represent surface colors as a collection of ratios  $r_1, r_2, r_3$

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## Labelling by grey-world normalization

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Represent surface colors as a collection of ratios  $r_1, r_2, r_3, \dots, r_{16}$ .

Can think of these 16 points carrying 4 bits of information.

If  $n$  points, then  $\log_2 n$  bits ...

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## Now change illuminant

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Suppose illuminant changed, is information preserved by eye?

Change to cone-ratio pairs as easier to see ...

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## Preserving information?

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Under warm light 4300K.

Change to cold light 25000K ...

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## Preserving information?

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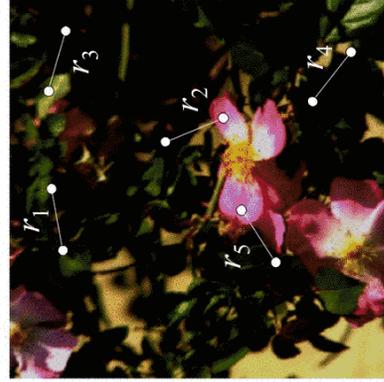
Under cold light 25000K.

How well do ratios to identify original surfaces? ...

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## Preserving information?

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Suppose just 5 pairs under old illuminant.

Suppose perfect recovery under new illuminant ...

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# Preserving information?



old illuminant:

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# Perfect recovery



old illuminant: 1 → 2 → 3 → 4 → 5

new illuminant: 1 → 2 → 3 → 4 → 5

No information lost.

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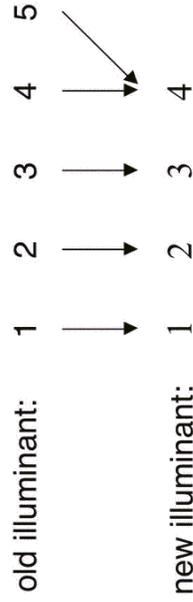
## Imperfect recovery



old illuminant:

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## Imperfect recovery

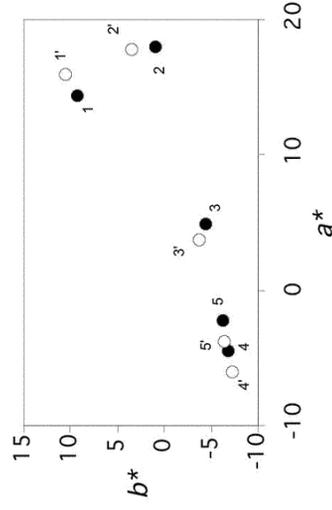


Now information lost: from (4) cannot determine original reliably ...

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## Imperfect recovery

In a suitable color space:



In general, need to describe identifications by probabilities ...

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## Information available vs number



If  $p(i, j)$  is probability of identifying point  $j$  under illuminant  $E_2$  with point  $i$  under illuminant  $E_1$ , then information preserved:

$$I(1;2) = \sum_i \sum_j p(i, j) \log p(i, j) / (p(i)p(j)),$$

where  $p(i) = \sum_j p(i, j)$  and  $p(j) = \sum_i p(i, j)$ .

Evaluate for  $i, j = 1, .. n$ , by numerical simulation ...

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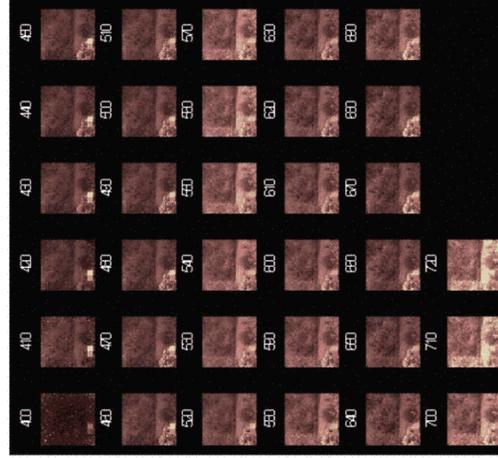
## Information available vs number



- How does  $I$  vary with scene?
- How does  $I$  vary with coding?
- Need reflectance data at each point in scene ...

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## Hyperspectral imaging



- Spectral samples at 10-nm intervals over 400–720 nm.
- Avoids temporal variations in illuminant or position.
- Spatial resolution similar to eye ( $\leq 1$  arcmin  $\times \leq 1$  arcmin) ...

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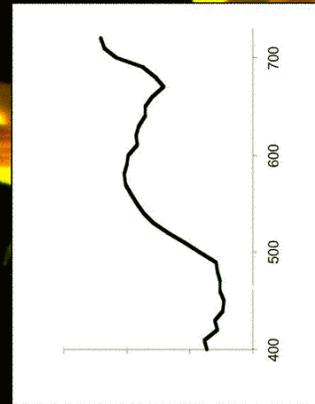
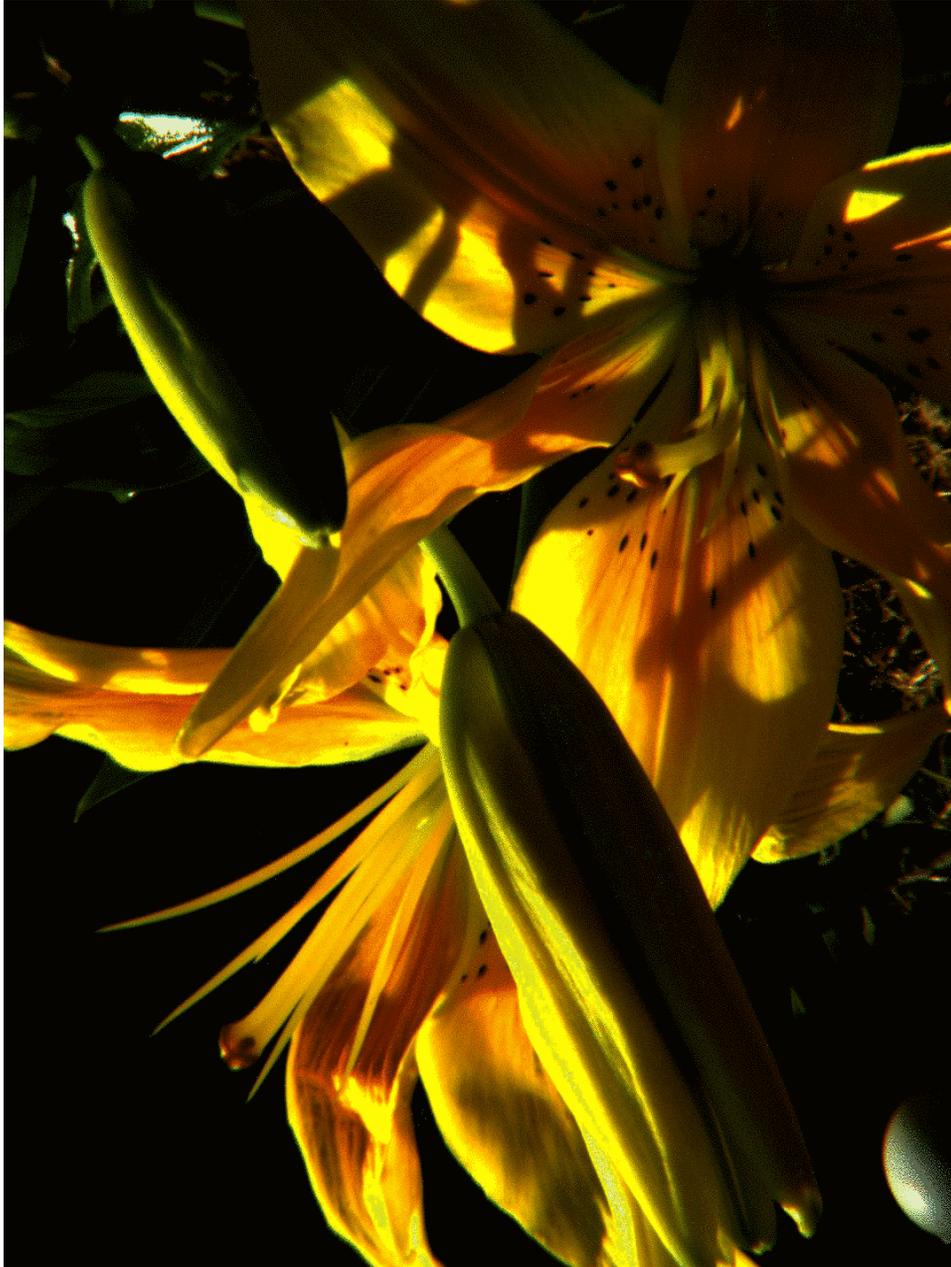
## On location

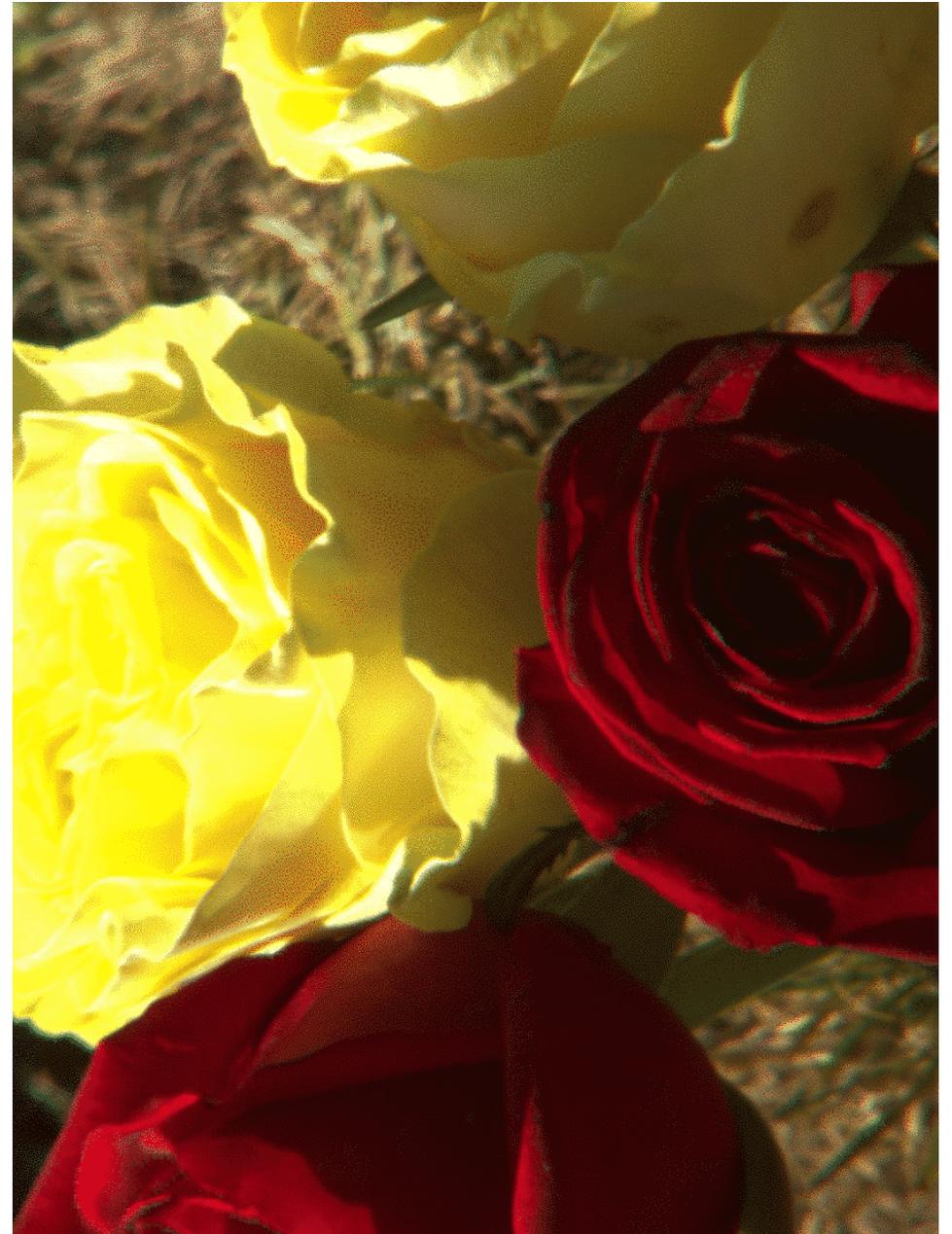
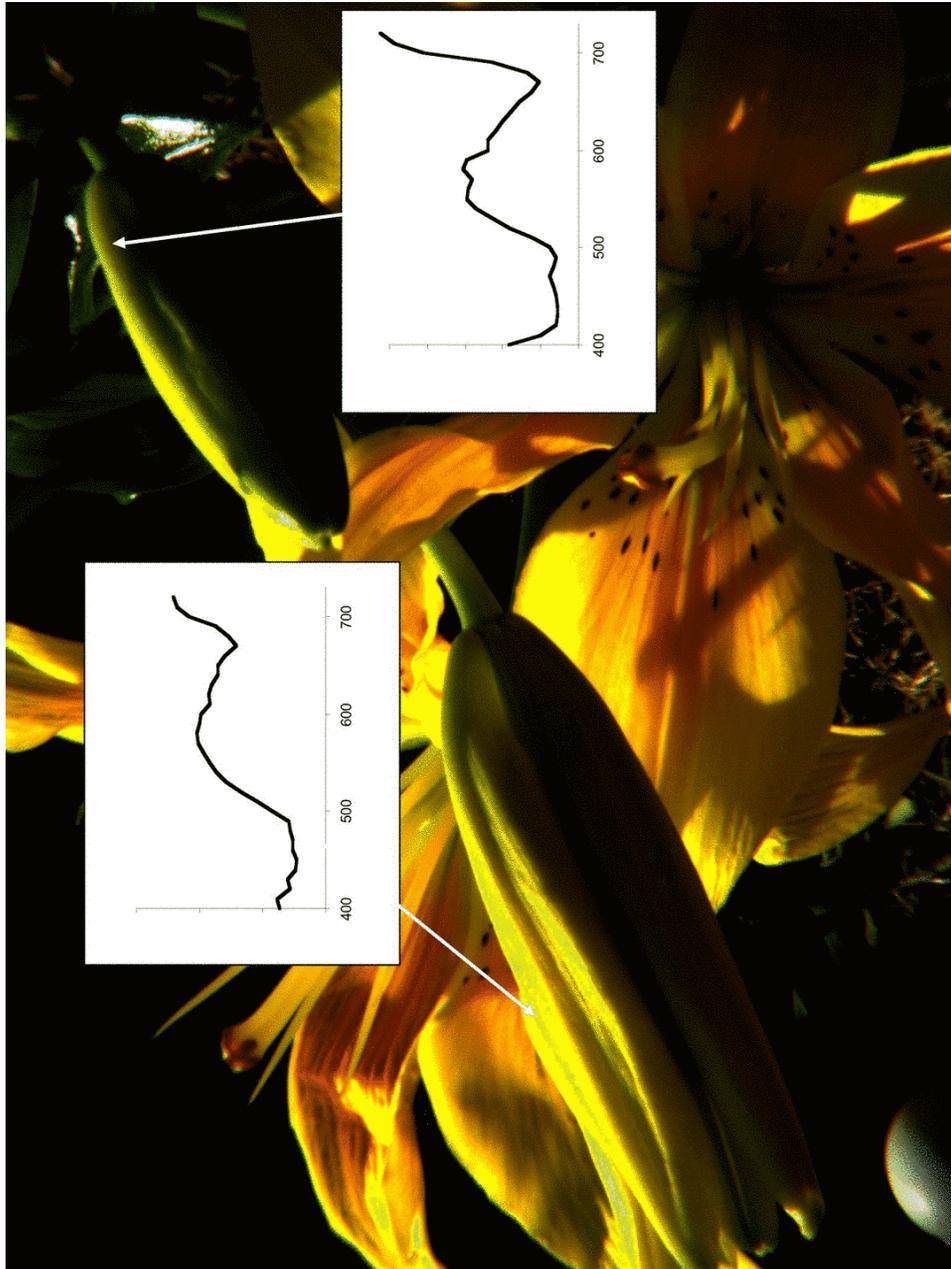


- Recorded during summers of 2002 and 2003.
- Almost always under clear sky.
- Particular care taken to avoid scenes containing movement ...

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## Hyperspectral reconstruction

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y Lilly1b



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## Hyperspectral reconstruction

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y Rose1b

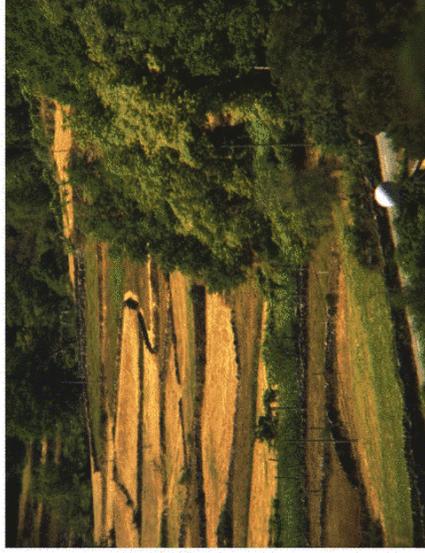


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## Hyperspectral reconstruction

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brufe1b

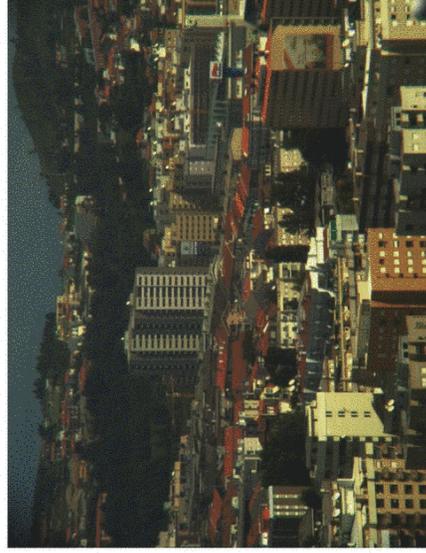


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## Hyperspectral reconstruction

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braga1b

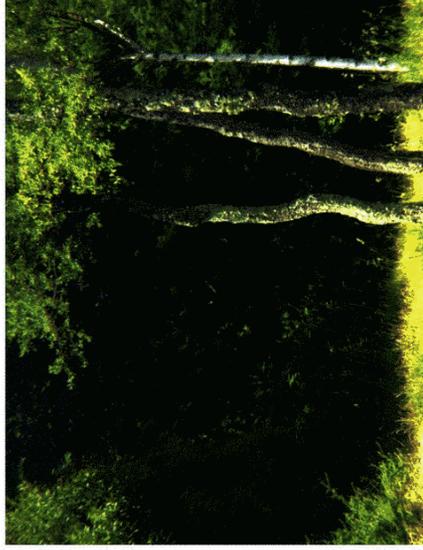


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## Hyperspectral reconstruction

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crown 3bb



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## Hyperspectral reconstruction

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crown4bbbb



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## Hyperspectral reconstruction

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ruivaes1b



47

## Hyperspectral reconstruction

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mosteiro4b



48

## Hyperspectral reconstruction

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ribeira1bb



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## Hyperspectral reconstruction

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farne1a



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## Hyperspectral reconstruction

ruivaes1b

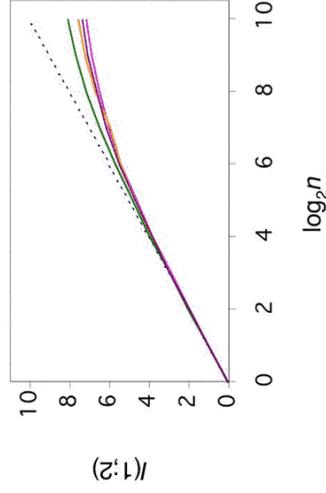


Plot mutual information  $I(1;2)$  against number  $n$  of sample surfaces ...

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## Mutual information $I(1;2)$ vs sample $n$

town buildings leaves fields



- Estimated  $I(1;2)$  increases monotonically.
- Similar values for four types of scenes.
- Each tends towards asymptote.
- Unreliable estimates with small  $p(i, j)$  and large  $n$ .
- Fortunately, when  $n$  so large that distribution of code values continuous, can approximate by additive Gaussian channel ...

$$I(1;2) = \sum_i \sum_j p(i, j) \log p(i, j) / (p(i)p(j)),$$

with  $i, j = 1, \dots, n$ .

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## Additive Gaussian channel



Suppose each point coded as triple of cone responses  $(l_1, m_1, s_1)$  under illuminant  $E_1$

Under illuminant  $E_2$ , triple becomes  $(l_1+\Delta l, m_1+\Delta m, s_1+\Delta s)$ .

Let  $K_1$  be covariance of  $(l_1, m_1, s_1)$  and  $K_\Delta$  covariance of  $(\Delta l, \Delta m, \Delta s)$ .

Then  $\max_{l(1; 2)} = C$ , where

$$C = -\log\{\det(K_1 + K_\Delta) / \det(K_1)\}.$$

If noise not Gaussian, then still max if nearest-neighbor identification (Lapidoth, 1996).

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## Information capacity

| illuminant change | grey-world         | ratios      |
|-------------------|--------------------|-------------|
| 25000K – 6500K    | mean C    11.43    | 11.02       |
|                   | S.d. C <b>0.76</b> | <b>0.69</b> |
| 4000K – 6500K     | mean C    11.78    | 11.37       |
|                   | S.d. C <b>0.72</b> | <b>0.69</b> |

data based on 25 rural and urban scenes, 1344 × 1024 pixels.

- Despite variety of scenes,  $C$  remarkably stable.
- Suggests performance in using color information can be optimized independent of location for any particular range of illuminants ...

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## Implications

- Fundamental limit on use of surface color to label objects in scenes.
- Can estimate ideal match for any given surface by minimizing variance in cone-excitation ratios.
- Are human observers' matches as good as these limiting values?
- Traditionally, use computer-controlled images of geometric displays or more recently of natural scenes, but gamut problem ...

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## Gamut problem

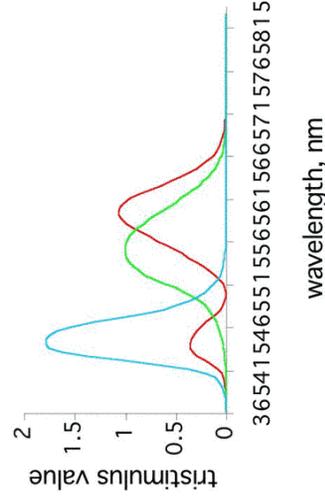
To specify colors, use CIE chromaticity diagram.

Need XYZ tristimulus values for arbitrary spectral distribution  $f(\lambda)$ :

$$X = \int f(\lambda) \bar{x}(\lambda) d\lambda$$

$$Y = \int f(\lambda) \bar{y}(\lambda) d\lambda$$

$$Z = \int f(\lambda) \bar{z}(\lambda) d\lambda$$



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## Gamut problem

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Normalize to get chromaticity coordinates:

$$x = X/(X + Y + Z) \quad (\text{"red"})$$

$$y = Y/(X + Y + Z) \quad (\text{"green"})$$

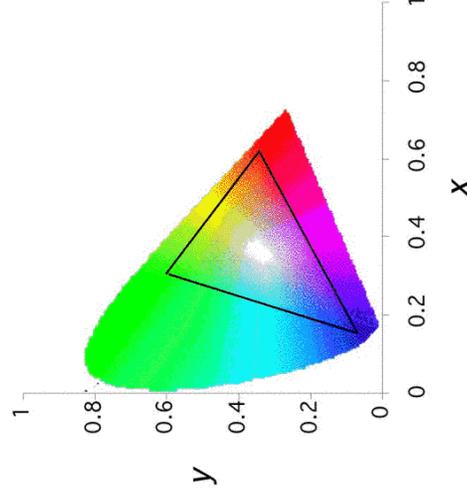
$$z = 1 - x + y \quad (\text{"blue"})$$

Now plot phosphor gamut ...

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## Gamut problem

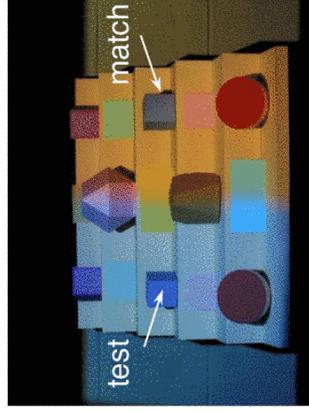
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Displayable monitor colors contained within triangle of three phosphors.  
Instead, as a more realistic test, use real surfaces with optical projection device ...

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## Real 3-dimensional physical surfaces



Left-side illuminant 25000 K; right-side, 4000 K.

Right-side cube is a virtual 3D image.

Subject adjusts apparent color until surface matches surface of left-side cube (measure of "color constancy")

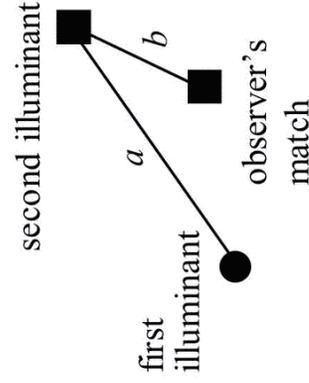
...

de Almeida, Fiadeiro, Nascimento (2004)

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## Constancy index

In a suitable color space (CIE 1976  $L^*u^*v^*$  space)

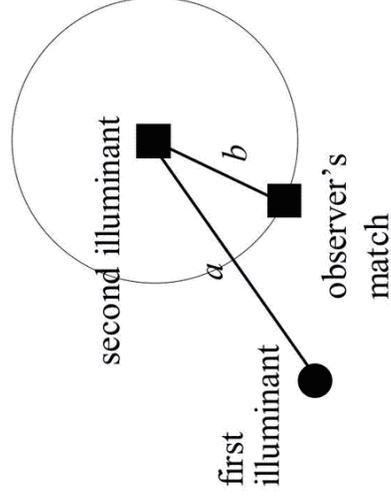


$$CI = 1 - b/a$$

## Constancy index

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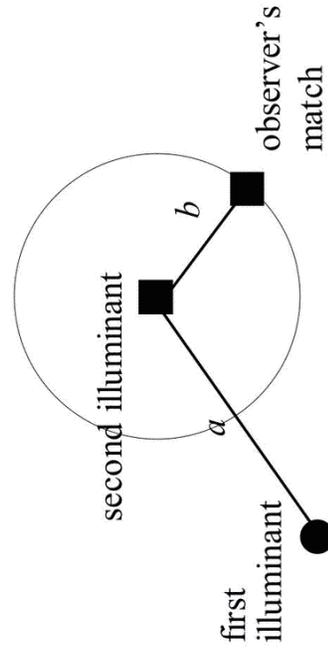
$$CI = 1 - b/a$$



## Constancy index

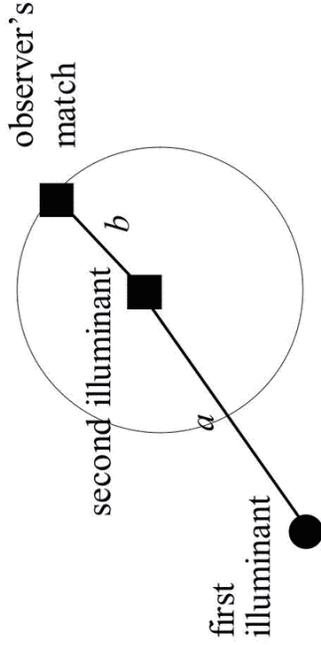
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$$CI = 1 - b/a$$



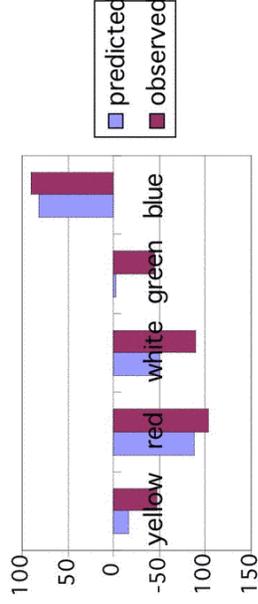
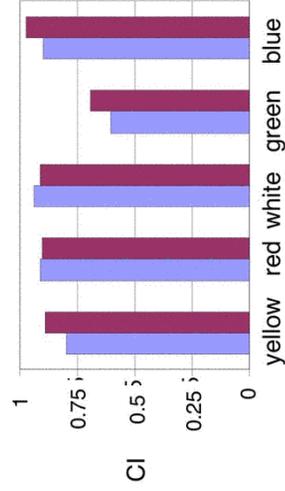
# Constancy index

$$CI = 1 - b/a$$



Measure both CI and angular error ...

# Constancy index and angular error



Nascimento, de Almeida, Fiadeiro, and Foster (2004)

- Typical color-constancy indices 0.4-0.8.
- Residual bias towards color of illuminant of fixed comparison surface, suggesting light-based matching.
- No parameters in predicted fit ...

## Summary

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- Despite variation in scenes, information capacity remarkably stable.
- Reveals physical limit on observers' surface-color matching.
- Previous models of surface-color matching involve multiple empirically determined parameters.
- Minimum-variance principle requires only chromatic specification of stimuli: no free parameters.
- Variation in constancy and directional biases generally well reproduced  $\rho_1$