# Color Constancy and Understanding

# Overview

- Color Basics
- Color Constancy
  - Gamut mapping
  - More methods
- Deeper into the Gamut
  - Matte & specular reflectance
  - Color image understanding

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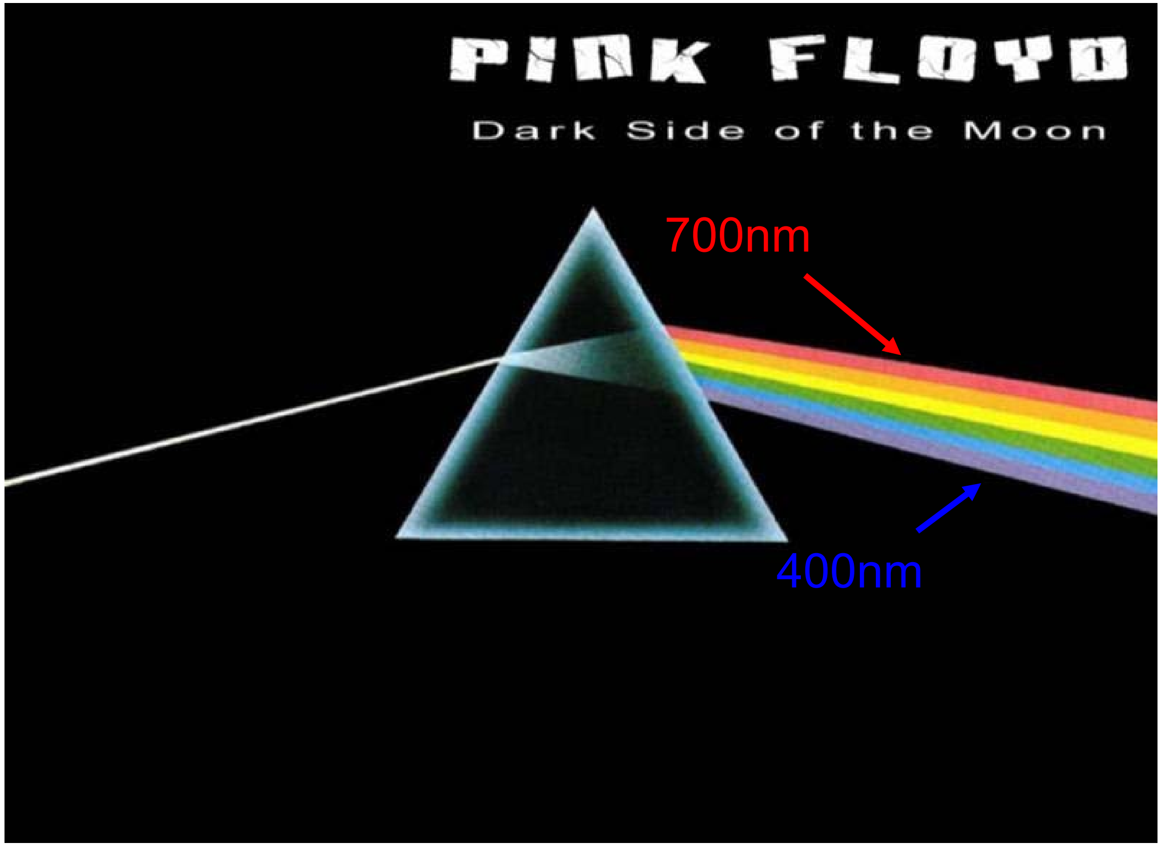
# What is Color?

- Energy distribution in the visible spectrum

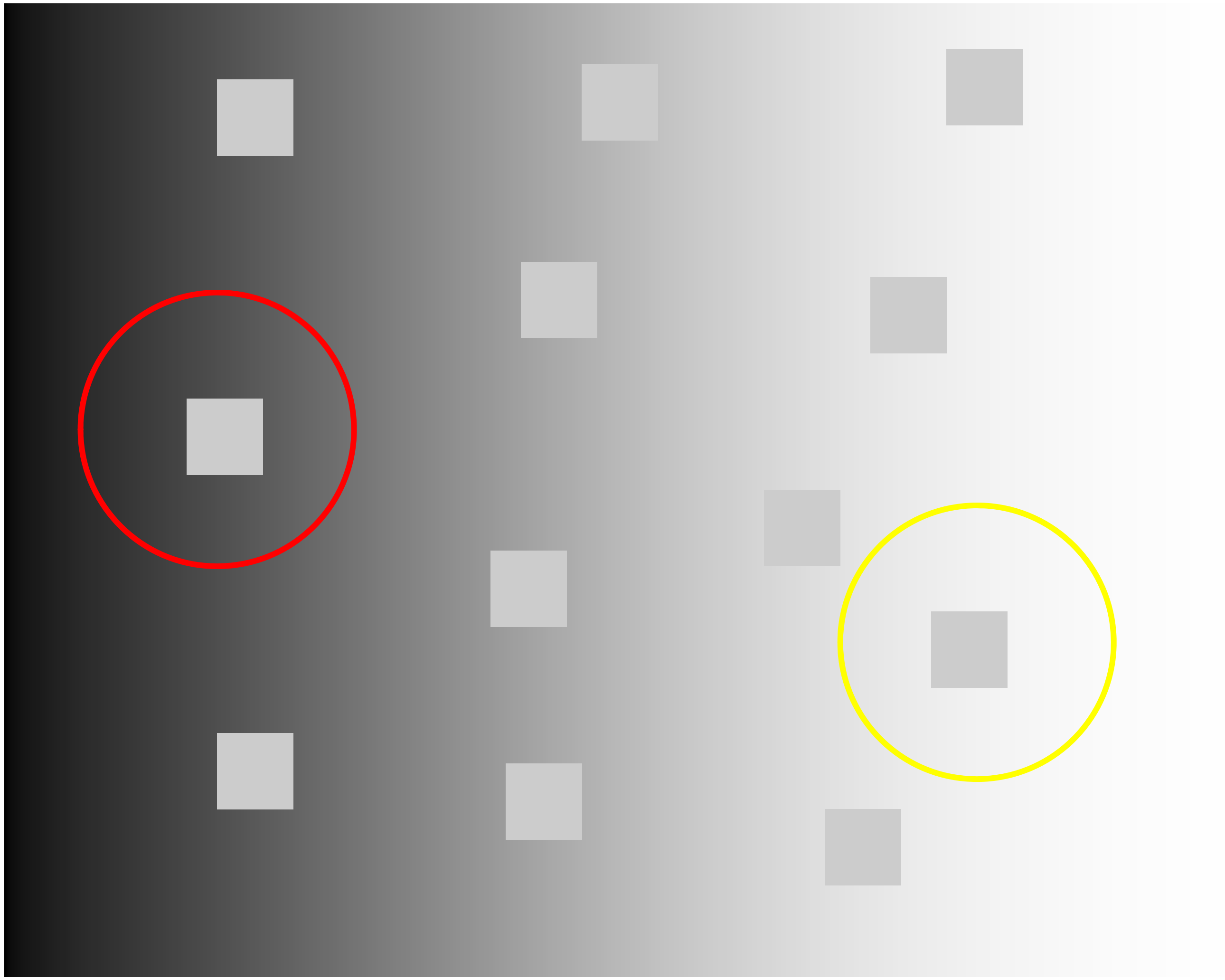
  ~400nm - ~700nm

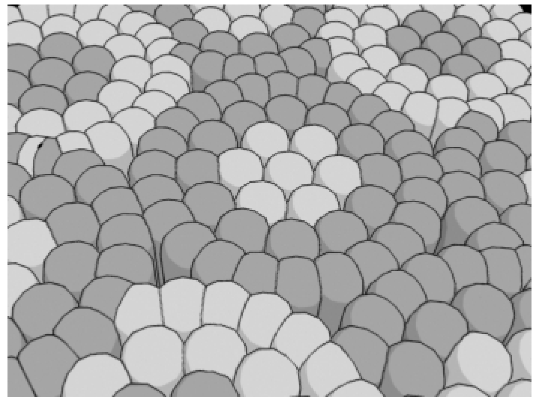


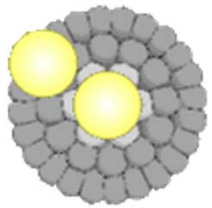
# Do objects have color?

- NO - objects have pigments
- Absorb all frequencies except those which we see
- Object color depends on the illumination

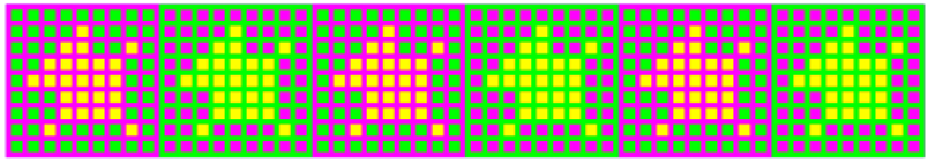
# Brightness perception

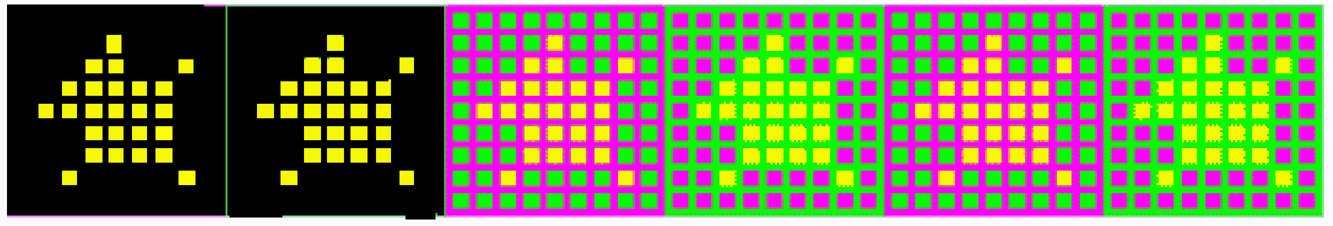






# Color perception





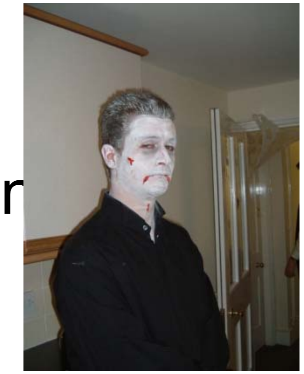
Cells in the retina combine the colors of nearby areas

Color is a perceptual property

# Why is Color Important?

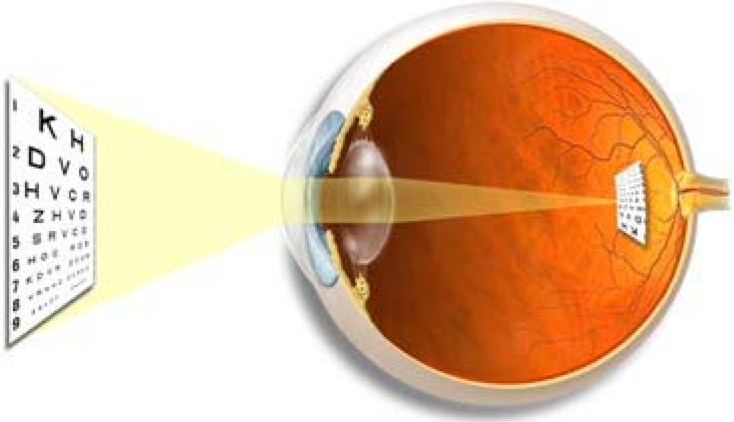
- In animal vision
  - food vs. nonfood

  - identify predators and prey
  - check health, fitness, etc. of other ir



- In computer vision
  - Recognition [Schiele96, Swain91 ]
  - Segmentation [Klinker90, Comaniciu97]

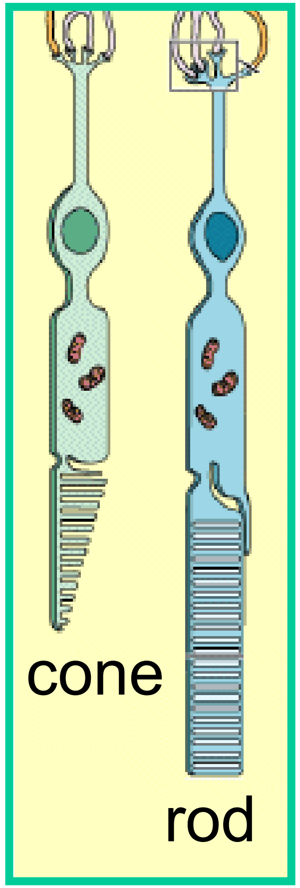
# How do we sense color?



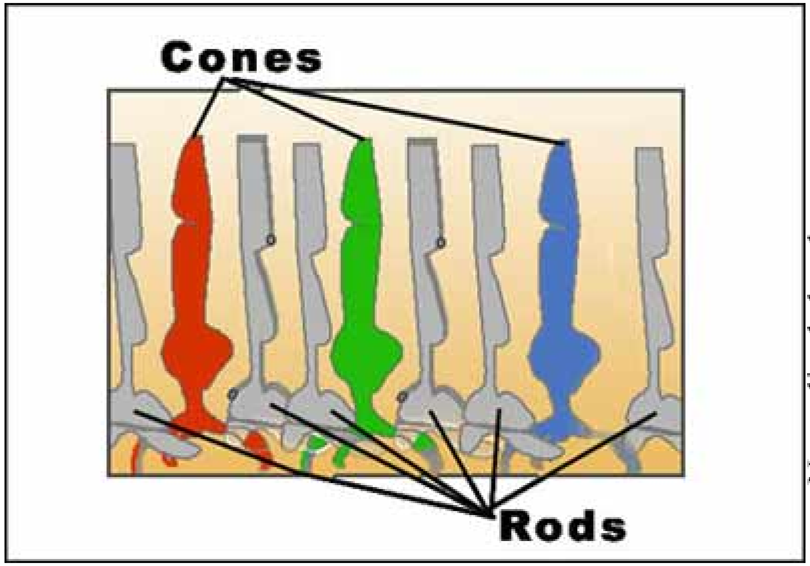
Rods
- Very sensitive to light
- But don’t detect color

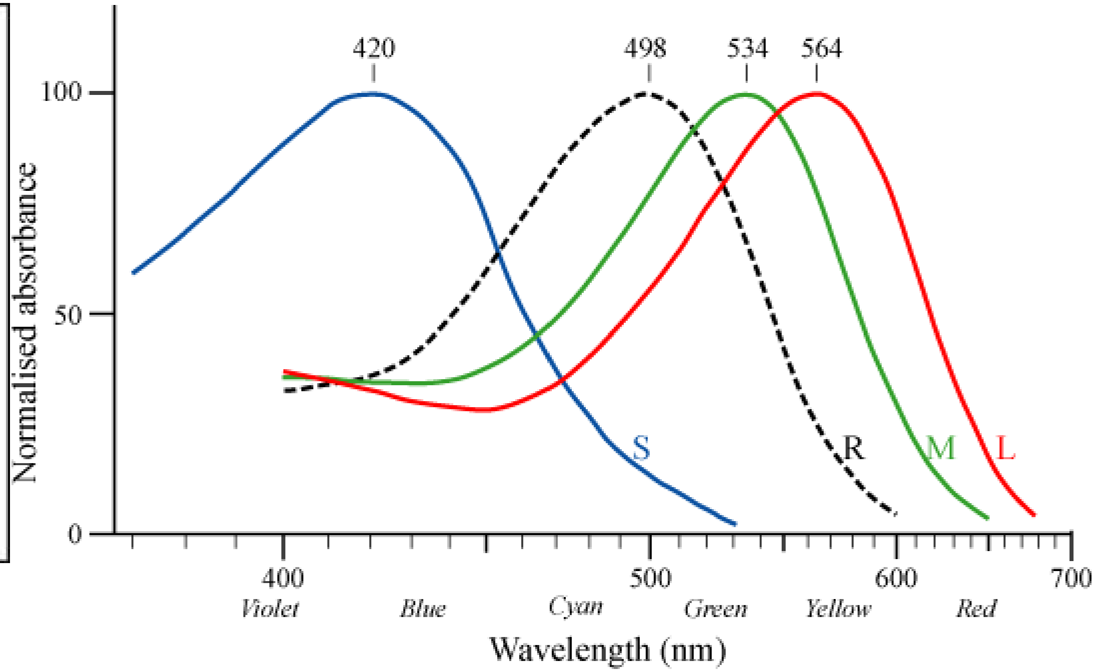
Cones
- Less sensitive
- Color sensitive

- Colors seems to fade in low light



# What Rods and Cones Detect

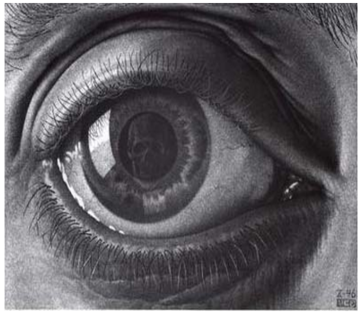


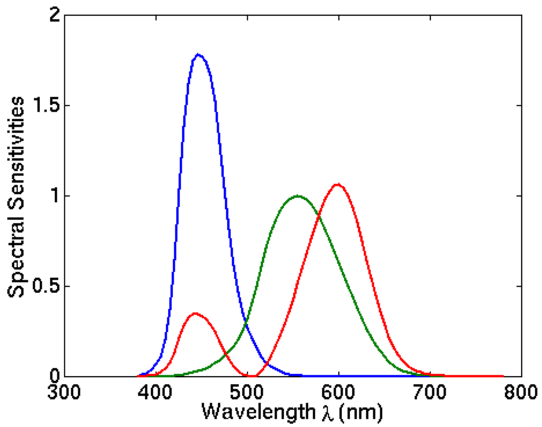




Responses of the three types of cones largely overlap

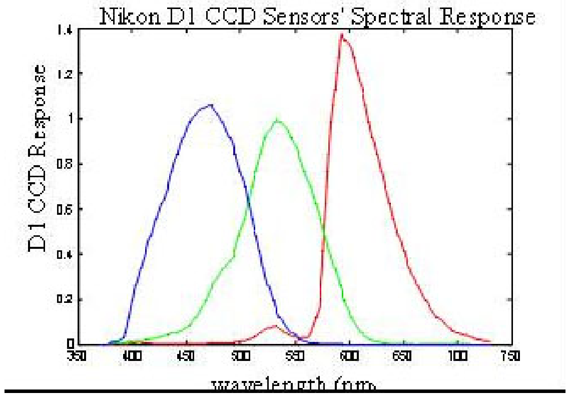
# Eye / Sensor

Eye

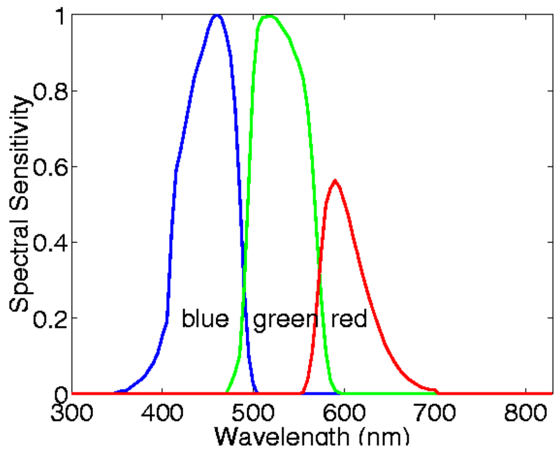





Sensor



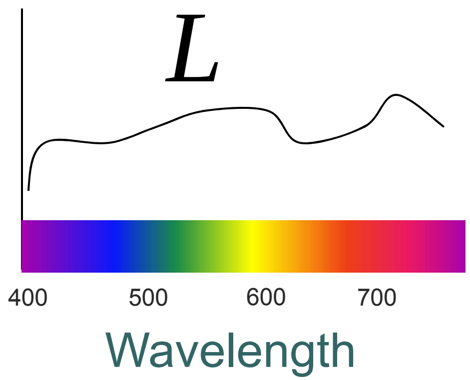





# Finite dimensional color representation

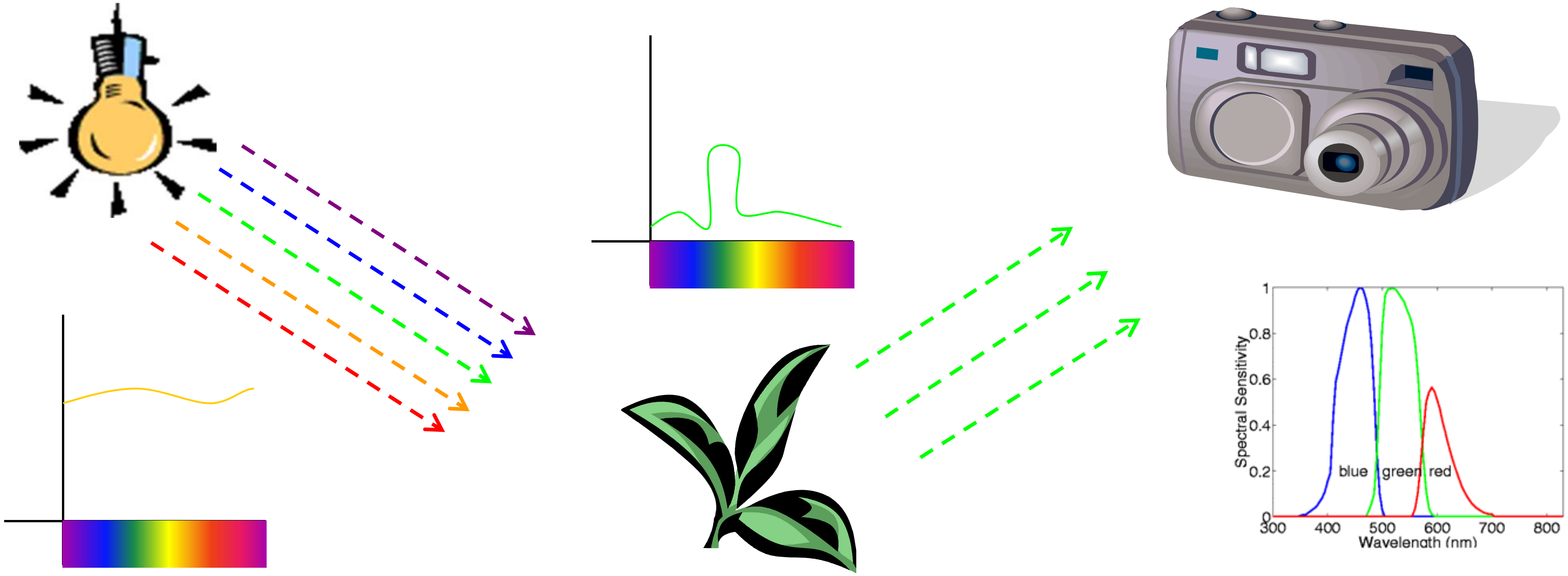
- Color can have infinite number of frequencies.

- Color is measured by projecting on a finite number of sensor response functions.




$$\begin{aligned} &\Rightarrow \langle L, \phi_R \rangle \\ &\Rightarrow \langle L, \phi_G \rangle \\ &\Rightarrow \langle L, \phi_B \rangle \end{aligned} \Rightarrow \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

# Reflectance Model




Multiplicative model:
(What the camera mesures )

# Image formation

Image color

$$E_k = \int_\lambda e(\lambda)s(\lambda)\rho_k(\lambda)d\lambda$$

$\boldsymbol{k} = \boldsymbol{R,G,B}$

Illumination

object reflectance

Sensor respons e

# Overview

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  - More methods
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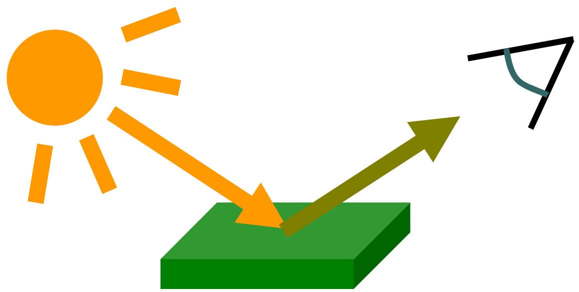
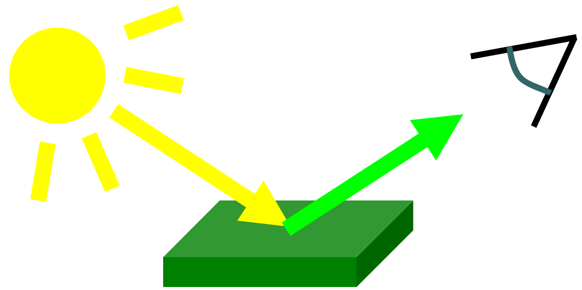
# Color Constancy

If Spectra of Light
Source Changes

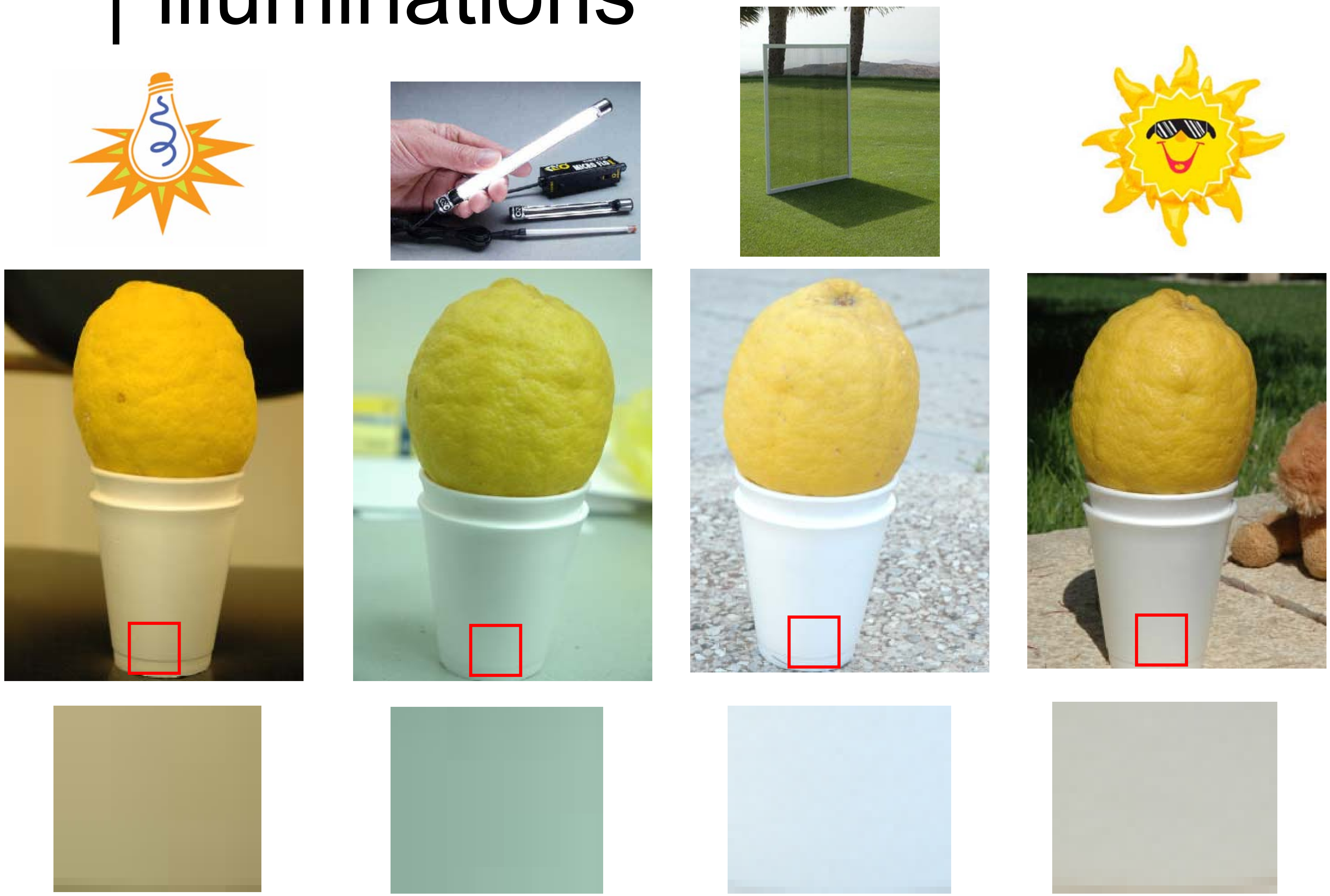


Spectra of Reflected Light
Changes



The goal : Evaluate the surface color as
if it was illuminated with white light (canonical)

# Color under different illuminations



# Color constancy by Gray World

# Color constancy by Gamut mapping

D. A. Forsyth. A Novel Algorithm for Color Constancy. International Journal of Computer Vision, 1990.

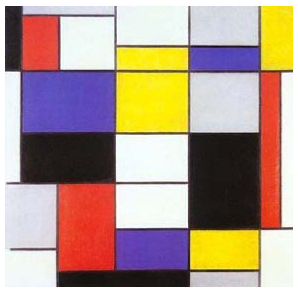
# Assumptions: summary

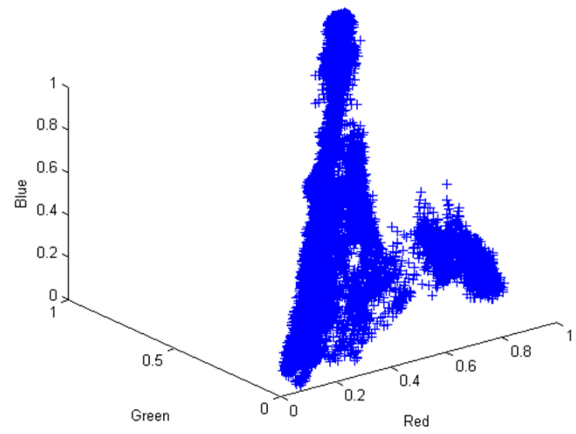
- Planar frontal scene (Mondrian world)
- Single constant illumination
- Lambertian reflectance
- Linear camera

# Gamut

(central notion in the color constancy algorithm)

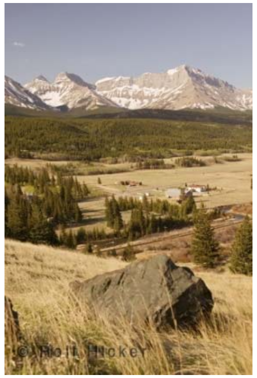
- Image: a small subset object colors under a given light.

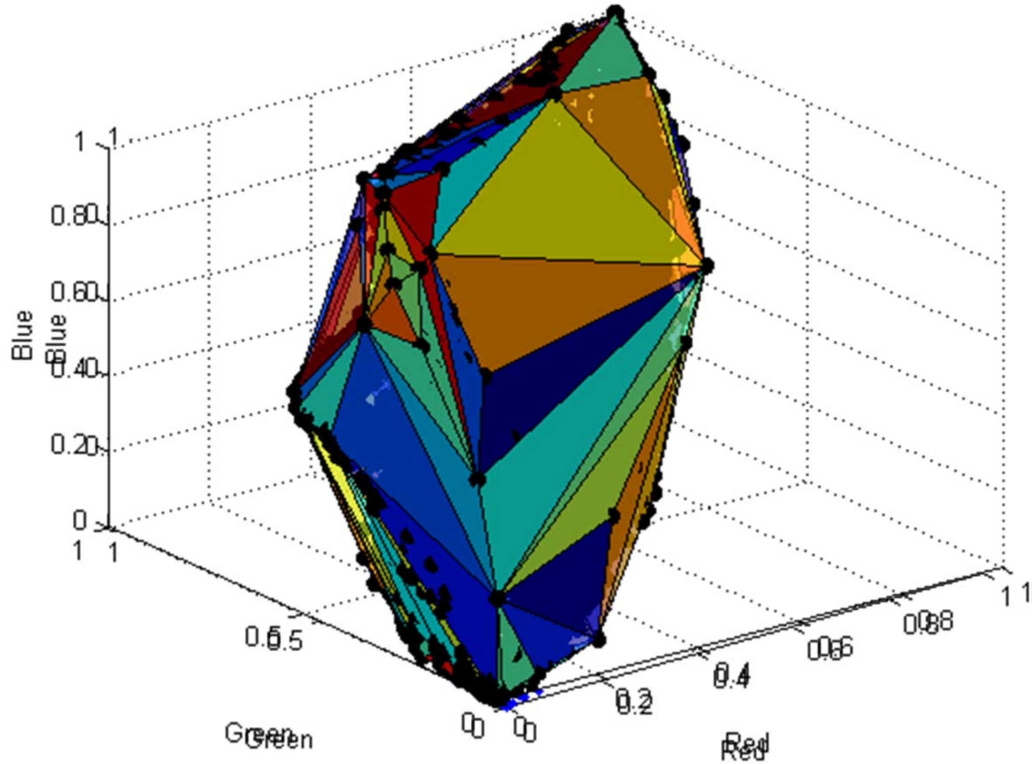





- Gamut : All possible object colors imaged under a given light.

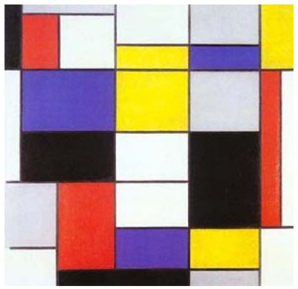
# Gamut of outdoor images

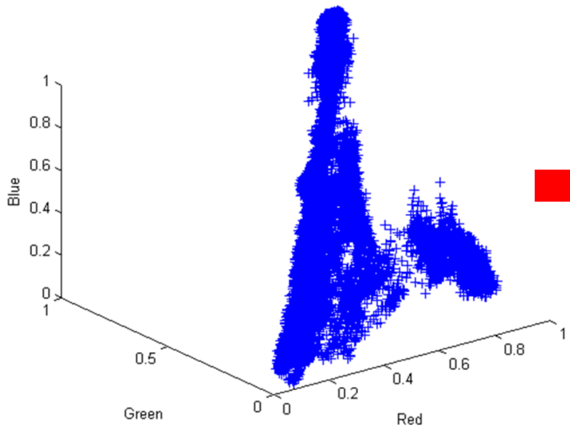


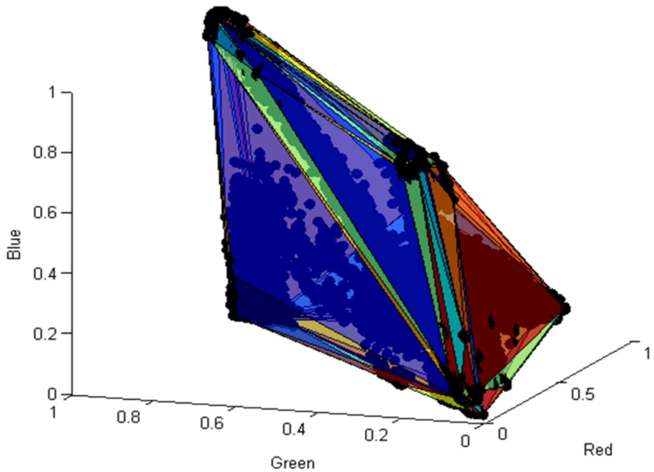


# All possible !?
# (Gamut estimation)

- The Gamut is convex.
  - Reflectance functions: $f(\lambda)$ such that $0 \leq f(\lambda) \leq 1$
  - A convex combination of reflectance functions is a valid reflection function.
- Approximate Gamut by a convex hull:

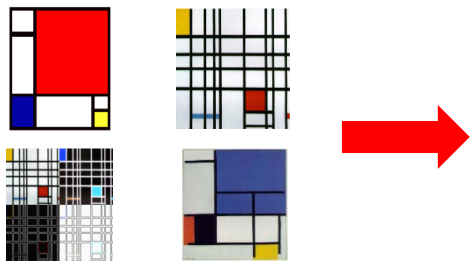


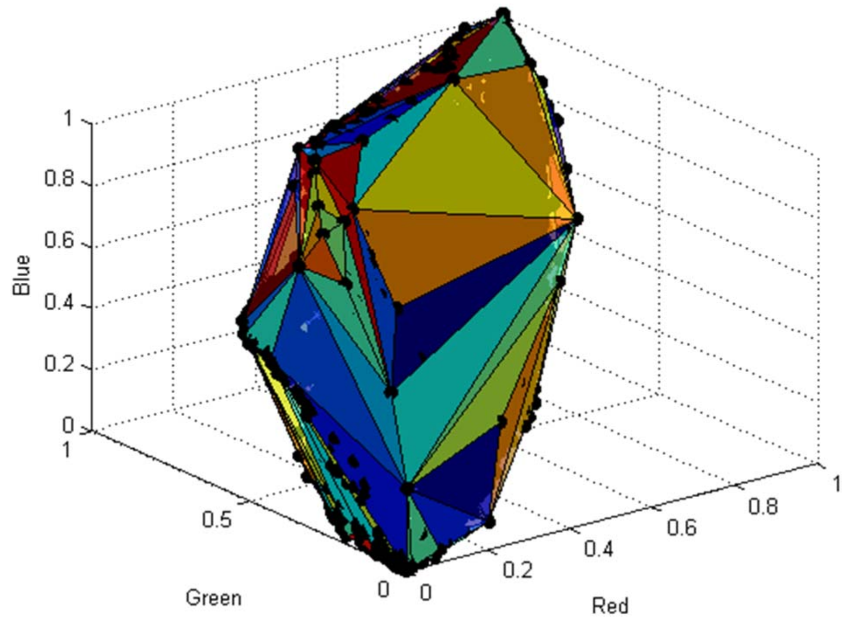


# Color Constancy via Gamut mapping

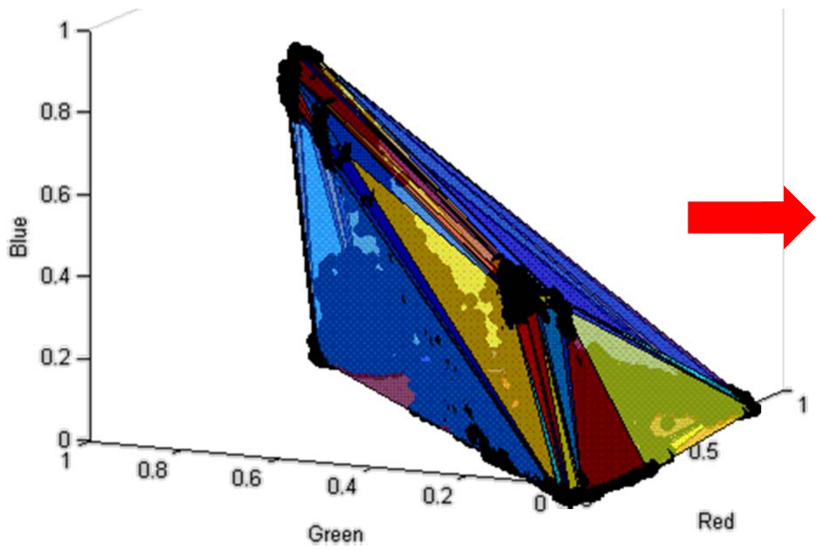
- Training – Compute the Gamut of all possible surfaces under canonical light.



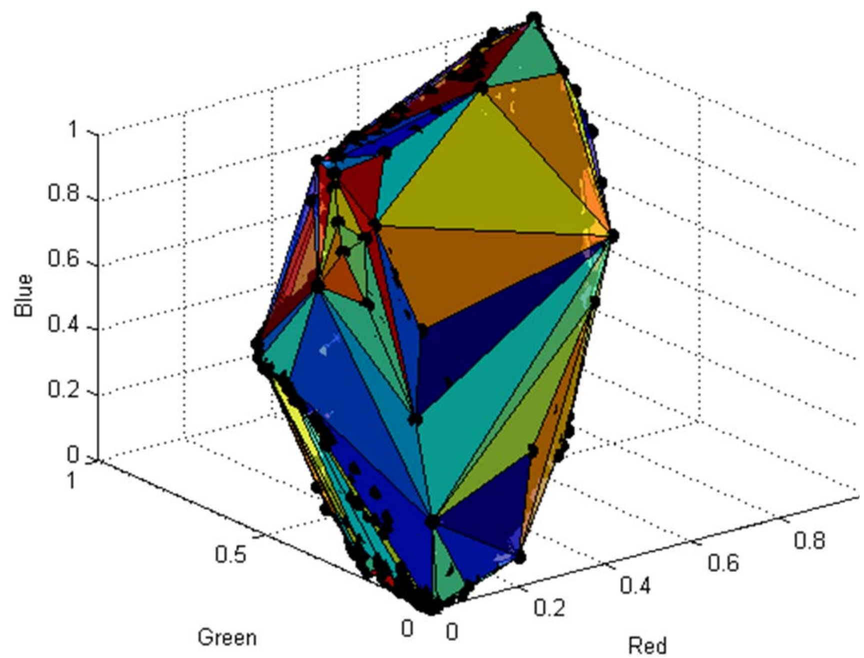


# Color Constancy via Gamut mapping

- The Gamut under unknown illumination maps to a **inside** of the canonical Gamut.




Unknown illumination

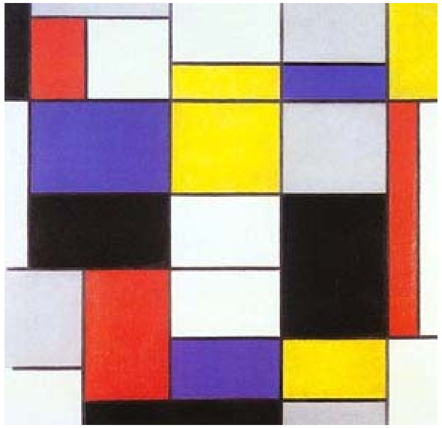



Canonical illumination

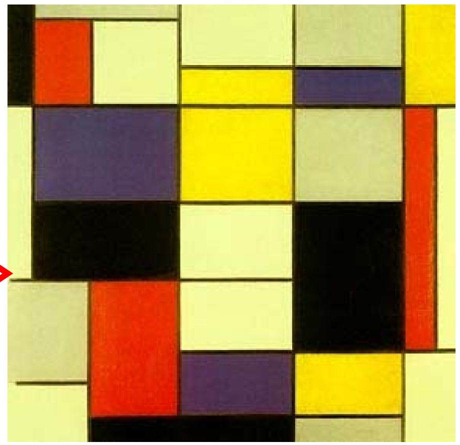
D. A. Forsyth. A Novel Algorithm for Color Constancy. International Journal of Computer Vision, 1990.

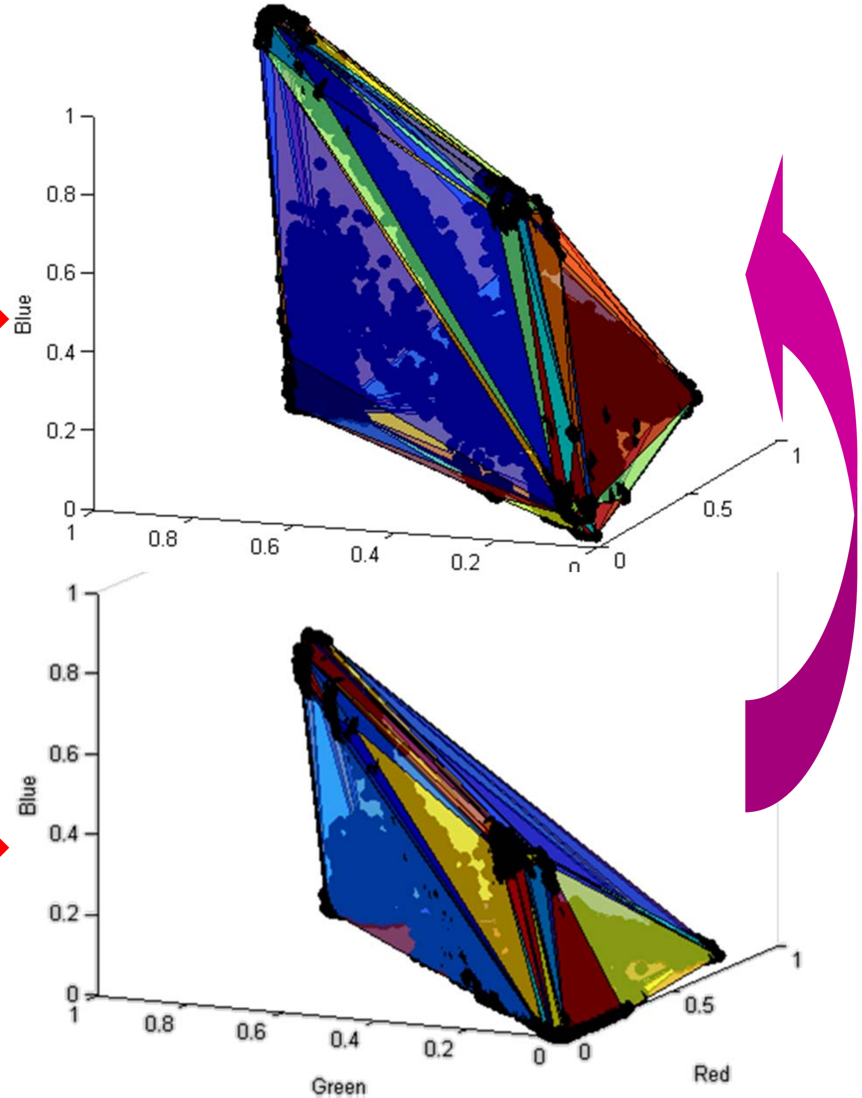
# Color Constancy via Gamut mapping

Canonical illumination



Unknown illumination



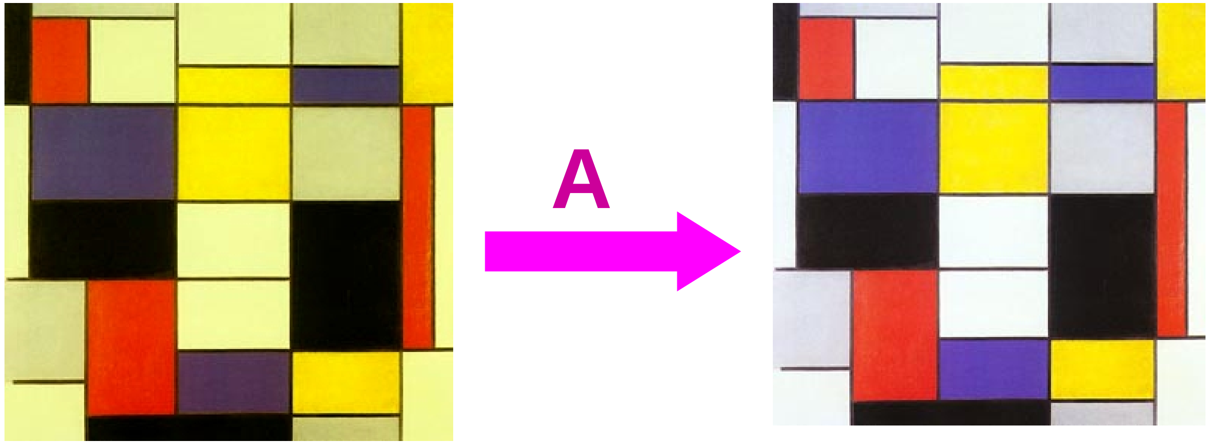


# Color constancy: theory

1. Mapping:
   - Linearity
   - Model
2. Constraints on:
   - Sensors
   - Illumination

# What type of mapping to construct?

- We wish  to find a mapping such that




$$A(\vec{E}) = \vec{E}^{c}$$

In the paper:

$$\Psi^{-1} = A$$

# What type of mapping to construct? (Linearity)

- The response of one sensor k in one pixel under known canonical light (white)

Canonical Illumination

Sensor response

object reflectance

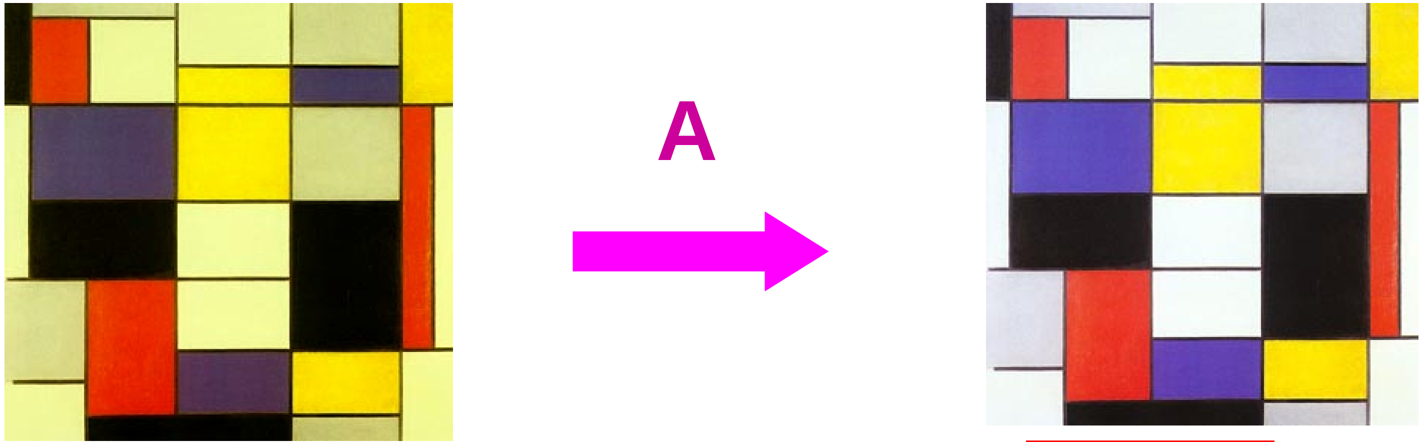
$$E_k^c = \int_\lambda e^c(\lambda)\rho_k(\lambda)s(\lambda)d\lambda$$

**k = R,G,B**

$$E_k^c = < \Phi_k^c(\lambda), s(\lambda) > \qquad \Phi_k^c(\lambda) = e^c(\lambda)\rho_k(\lambda)$$

(inner product )

# What type of mapping to construct? (Linearity)



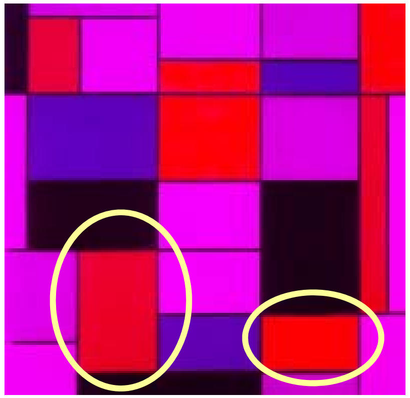

$$E_k =< \boxed{\Phi_k(\lambda)}, s(\lambda) > \qquad E_k^c =< \boxed{\Phi_k^c(\lambda)}, s(\lambda) >$$

Requires: $span\{\Phi_1, \Phi_2, \Phi_3\} = span\{\Phi_1^c, \Phi_2^c, \Phi_3^c\}$

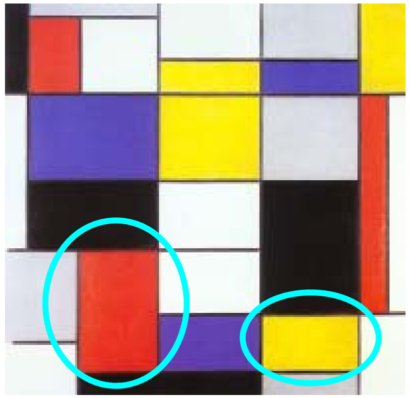
D. A. Forsyth. A Novel Algorithm for Color Constancy. International Journal of Computer Vision, 1990.

# Motivation

red-blue light



white light



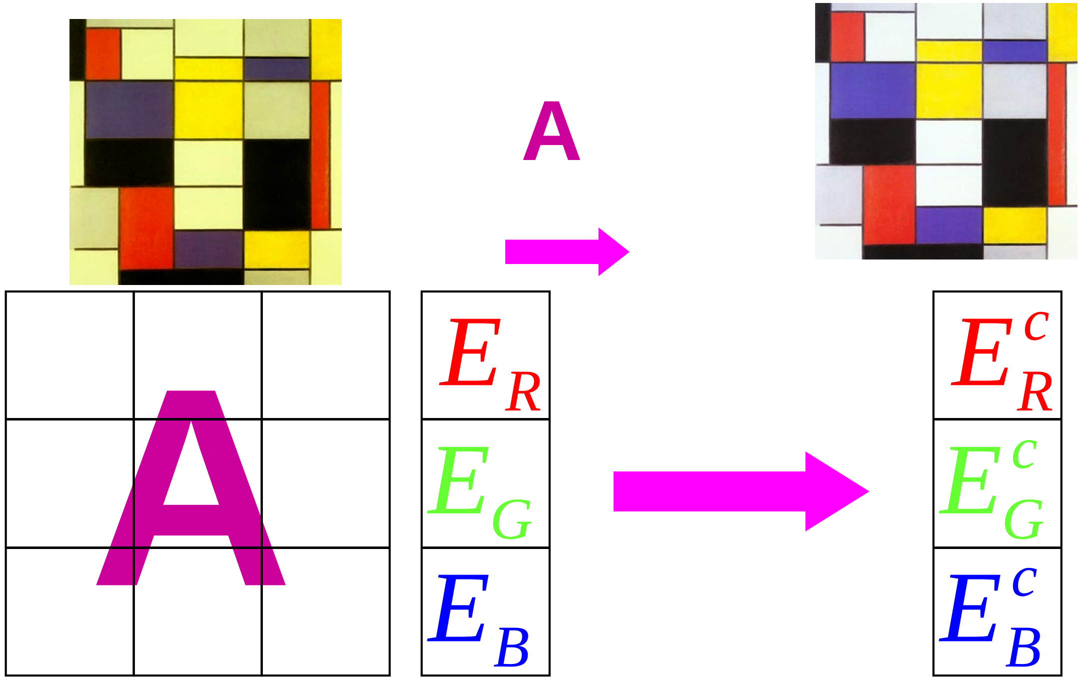
$$span\ \ \{\Phi_R, \Phi_G, \Phi_B\} = span\ \ \{\Phi_R, \Phi_B\} \neq span\ \ \{\Phi_R^c, \Phi_G^c, \Phi_B^c\}$$

# What type of mapping to construct? (Linearity)

- Then we can write them as a linear combination:

$$\Phi_k(\lambda) = \sum_{j=1}^{3} \alpha_{kj} \Phi_j^c \quad \Rightarrow \quad E_k = \sum_{j=1}^{3} \alpha_{kj} E_j^c$$

# What type of mapping to construct? (Linearity)




Linear Transformation

What about Constraints?

# Mapping model

Recall: $\vec{\Phi}(\lambda) = Sensor * \text{illumination}$

$$\vec{\Phi}^c(\lambda) = A\vec{\Phi}(\lambda)$$ (Span constraint)

Expand Back

$$e^c(\lambda)\vec{\rho}(\lambda) = A\vec{\rho}(\lambda)e(\lambda)$$

$$\frac{e^c(\lambda)}{e(\lambda)}\vec{\rho}(\lambda) = A\vec{\rho}(\lambda)$$

EigenValue of $A$

EigenVector of $A$

# Mapping model

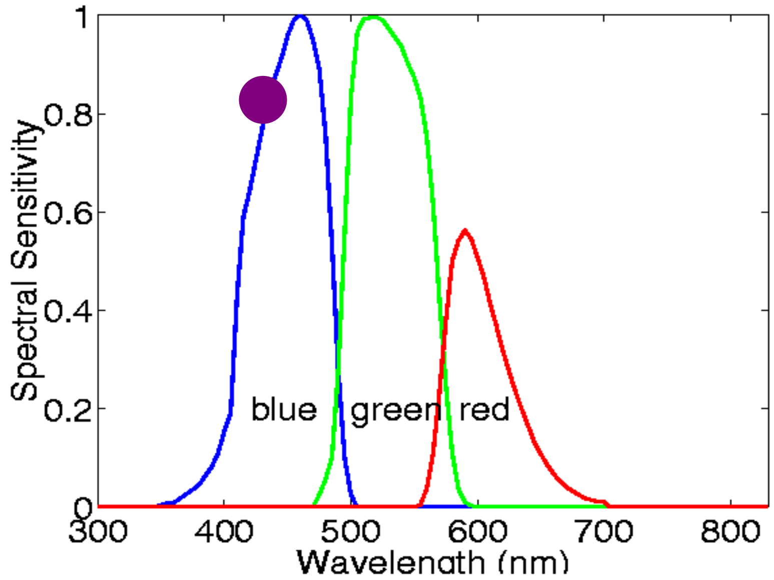
$$\frac{e^{c}(\lambda)}{e(\lambda)}\vec{\rho}(\lambda) = A\vec{\rho}(\lambda)$$

EigenValue of $A$

EigenVector of $A$

For each frequency the response originated from one sensor.

$$\vec{\rho}(\lambda_0) \in \left\{ \begin{bmatrix} 0 \\ 0 \\ b \end{bmatrix}, \begin{bmatrix} 0 \\ g \\ 0 \end{bmatrix}, \begin{bmatrix} r \\ 0 \\ 0 \end{bmatrix} \right\}$$




The sensor responses are the eigenvectors of a diagonal matrix

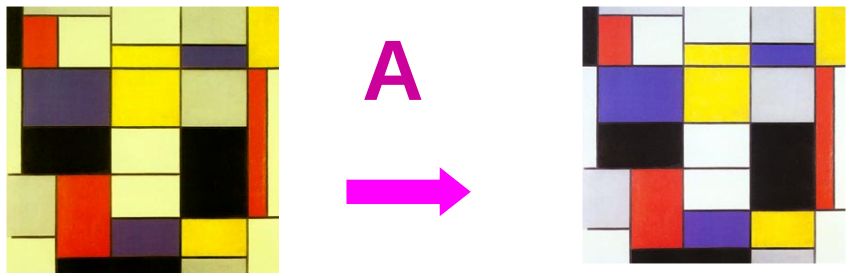
# The resulting mapping

$A$ is a diagonal mapping

$$\begin{bmatrix} K_R & & \\ & K_G & \\ & & K_B \end{bmatrix} \begin{bmatrix} E_R \\ E_G \\ E_B \end{bmatrix} \Rightarrow \begin{bmatrix} E_R^c \\ E_G^c \\ E_B^c \end{bmatrix}$$

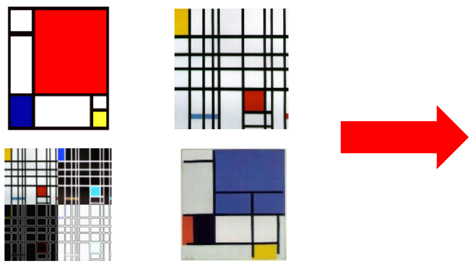
# C-rule algorithm: outline

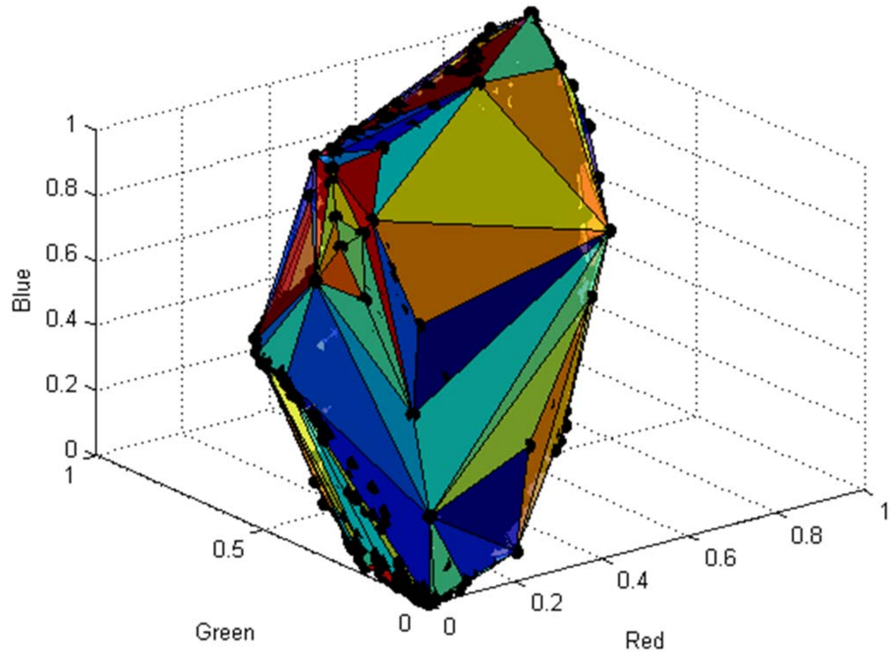
- Training: compute canonical gamut
- Given a new image:
  1. Find mappings which map each pixel to the inside of the canonical gamut.
  2. Choose one such mapping.
  3. Compute new RGB values.



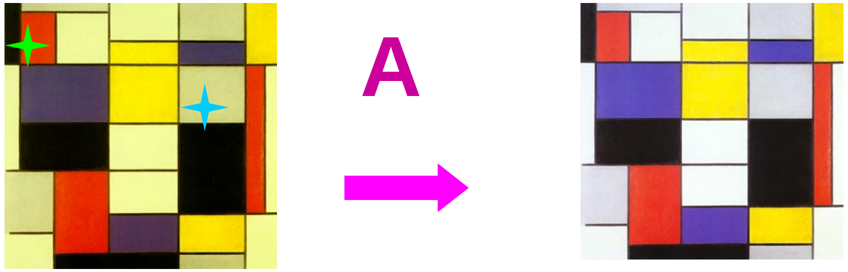
# C-rule algorithm

- Training – Compute the Gamut of all possible surfaces under canonical light.

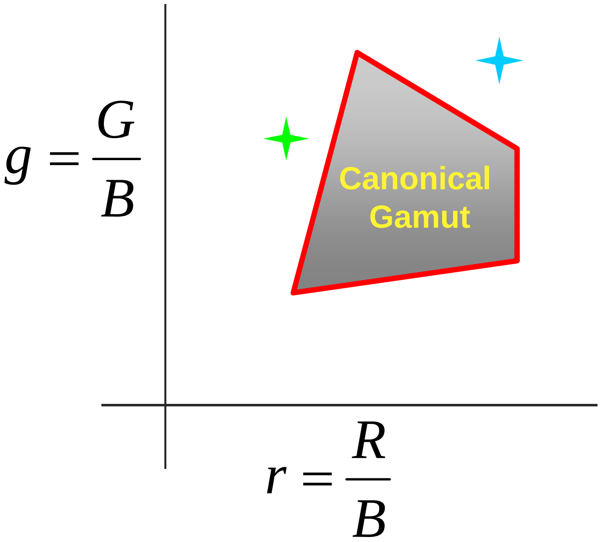


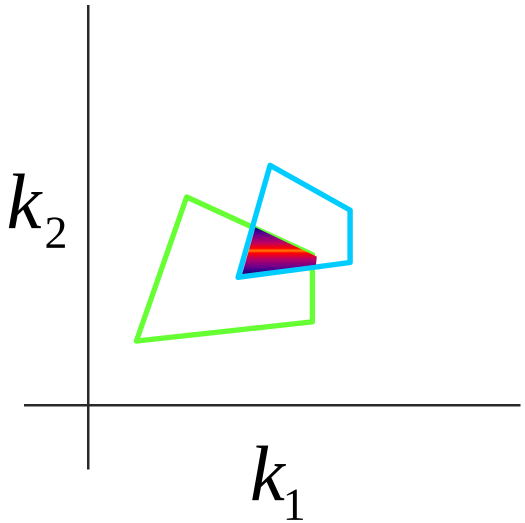


# C-rule algorithm




$$\begin{bmatrix} k_1 & 0 \\ 0 & k_2 \end{bmatrix} \begin{bmatrix} r \\ g \end{bmatrix} = \begin{bmatrix} k_1 r \\ k_2 g \end{bmatrix}$$



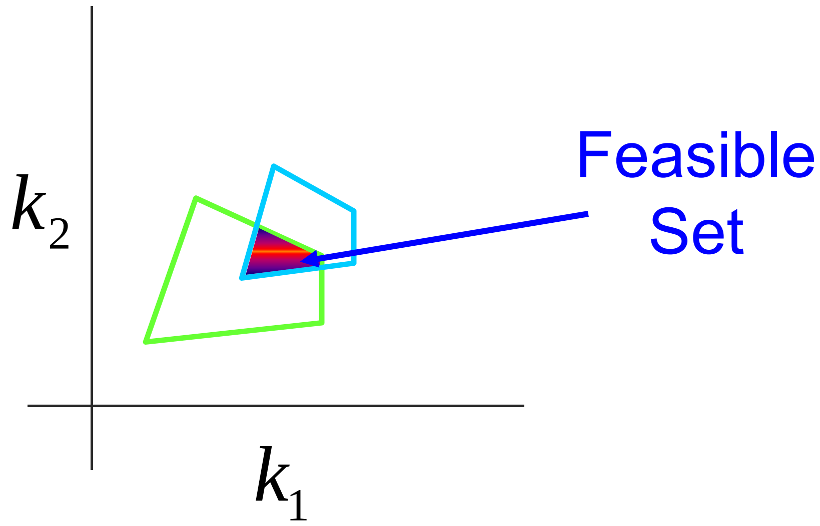




D. A. Forsyth. A Novel Algorithm for Color Constancy. International Journal of Computer Vision, 1990.

Finlayson, G. Color in Perspective, PAMI Oct 1996. Vol 18 number 10, p1034-1038

# C-rule algorithm

$$\begin{bmatrix} k_1 & 0 \\ 0 & k_2 \end{bmatrix} \begin{bmatrix} r \\ g \end{bmatrix} = \begin{bmatrix} k_1 r \\ k_2 g \end{bmatrix}$$



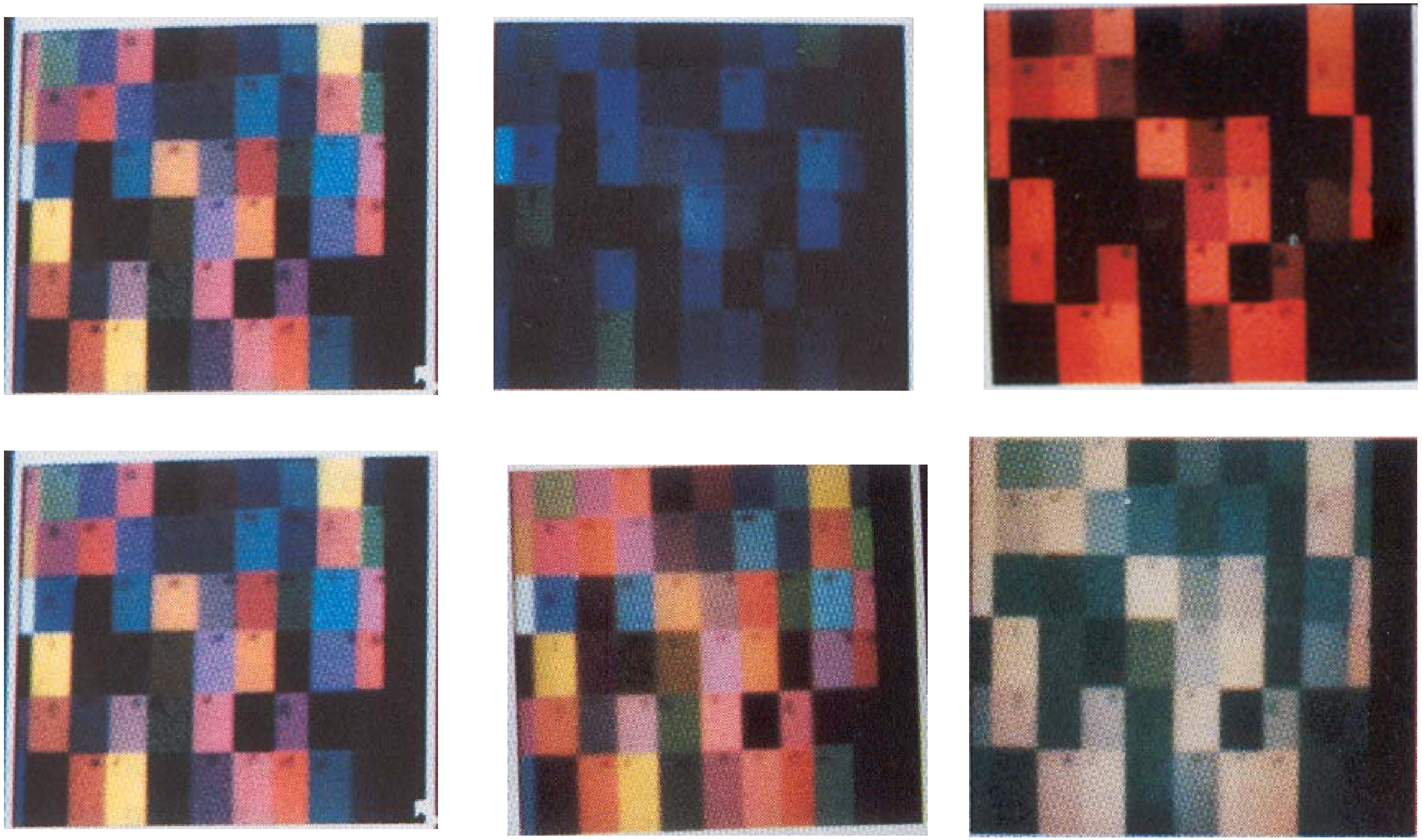

**Heuristics: Select the matrix with maximum trace**
**i.e. max(k1+k2)**

# Results (Gamut Mapping)

White — Blue- Green — Red

input

output

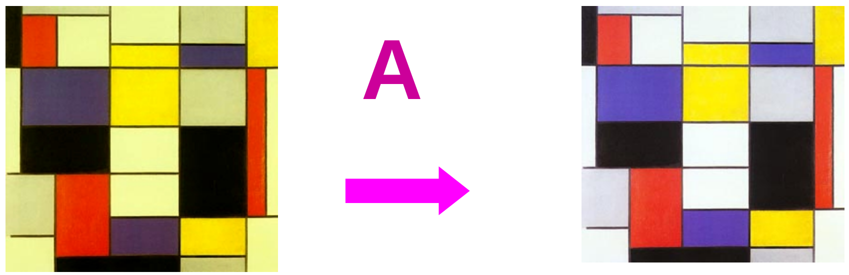


D. A. Forsyth. A Novel Algorithm for Color Constancy. International Journal of Computer Vision, 1990.

# Algorithms for Color Constancy

General framework and some comparison

# Color Constancy Algorithms: Common Framework




- Most color constancy algorithms find *diagonal* mapping

- The difference is *how to choose the coefficients*

# Color Constancy Algorithms: Selective list

All these methods find *diagonal transform*
(gain factor for each color channel)

- Max-RGB [Land 1977]
  Coefficients are 1 / maximal value of each channel
- Gray world [Buchsbaum 1980]
  Coefficients are 1 / average value of each channel
- Color by Correlation [Finlayson et al. 2001]
  Build database of color distributions under different illuminants.
  Choose illuminant with maximum likelihood.
  Coefficients are 1 / illuminant components.
- Gamut Mapping [Forsyth 1990, Barnard 2000, Finlayson&Xu 2003]
  (seen earlier; several modifications)

S. D. Hordley and G. D. Finlayson, "Reevaluation of color constancy algorithm performance," JOSA (2006)

K. Barnard et al. "A Comparison of Computational Color Constancy Algorithms"; Part One&Two, IEEE Transactions in Image Processing, 2002

# Color Constancy Algorithms: Comparison (real images)

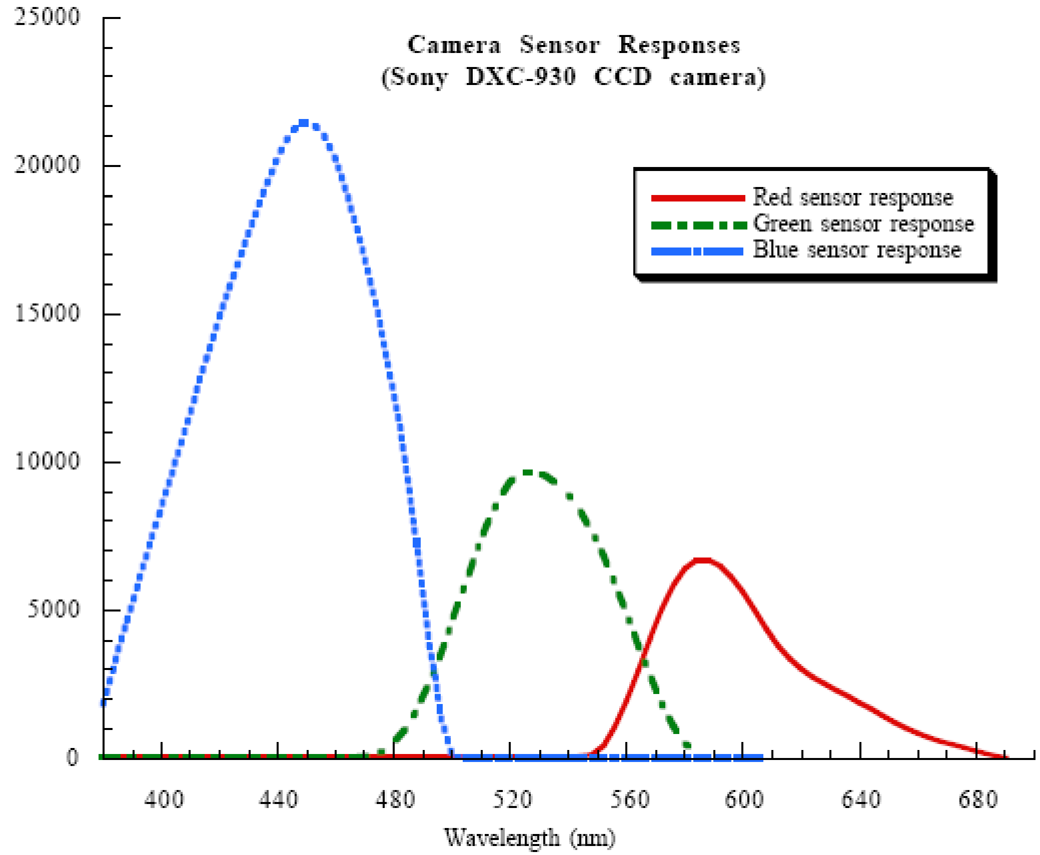

S. D. Hordley and G. D. Finlayson, "Reevaluation of color constancy algorithm performance," JOSA (2006)

K. Barnard et al. "A Comparison of Computational Color Constancy Algorithms"; Part One&Two, IEEE Transactions in Image Processing, 2002

# Diagonality Assumption

Requires *narrow-band disjoint* sensors

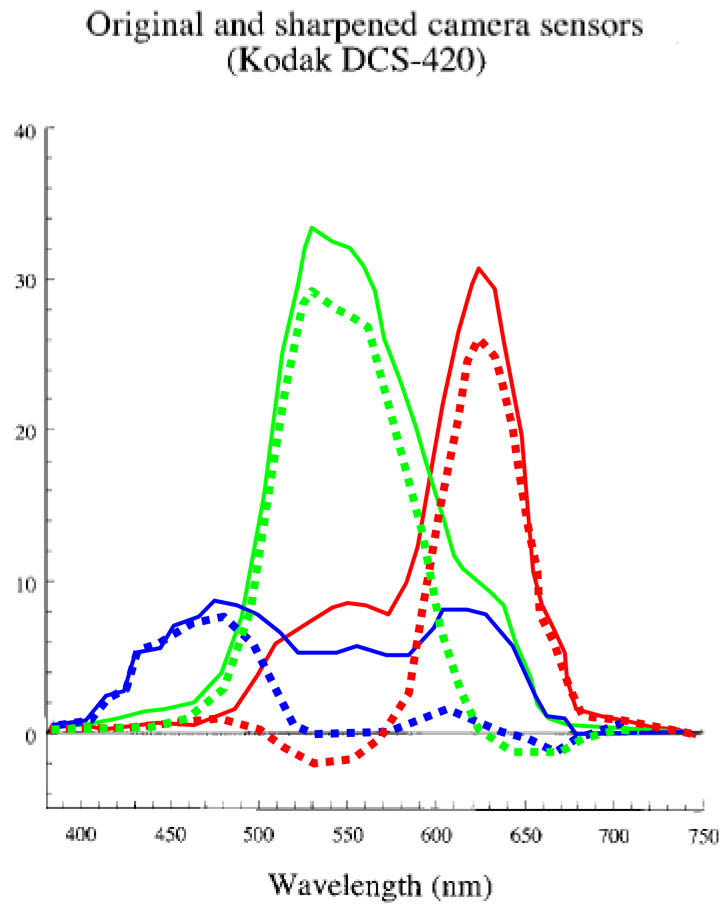
- Use hardware that gives disjoint sensors
- Use software




Sensor data by Kobus Barnard

# Disjoint Sensors for Diagonal Transform: Software Solution

- "Sensor sharpening": linear combinations of sensors which are as *disjoint* as possible
- Implemented as *post-processing*: directly transform RGB responses

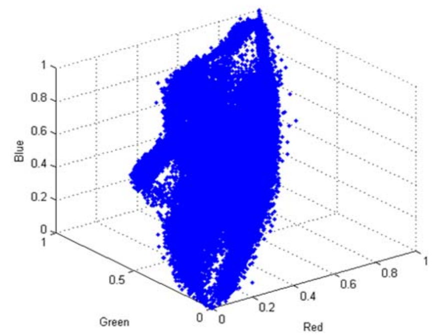



G. D. Finlayson, M. S. Drew, and B. V. Funt, "Spectral sharpening: sensor transformations for improved color constancy," JOSA (1994)

K. Barnard, F. Ciurea, and B. Funt, "Sensor sharpening for computational colour constancy," JOSA (2001).

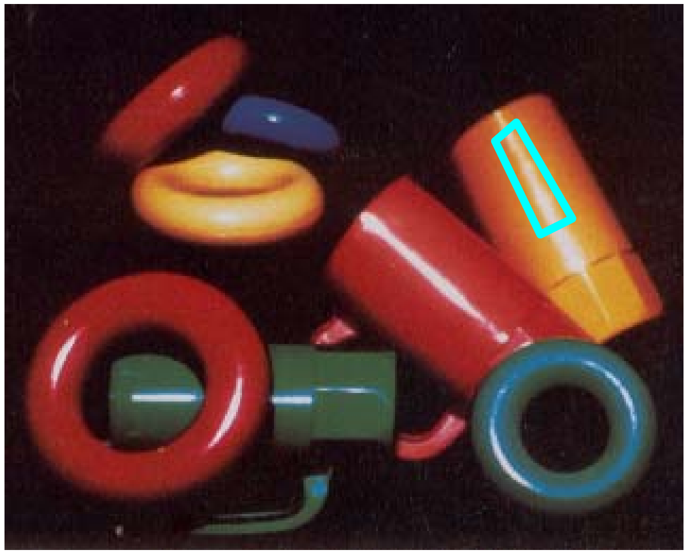
# Overview

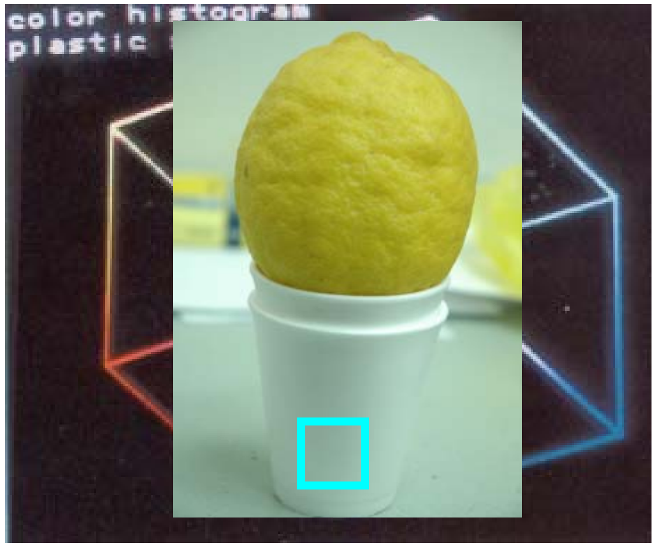
- Color Basics
- Color constancy
  - Gamut mapping
  - More methods
- Deeper into the Gamut
  - Matte & specular reflectance in color space
  - Object segmentation and photometric analysis
  - Color constancy from specularities



# Goal: detect objects in color space

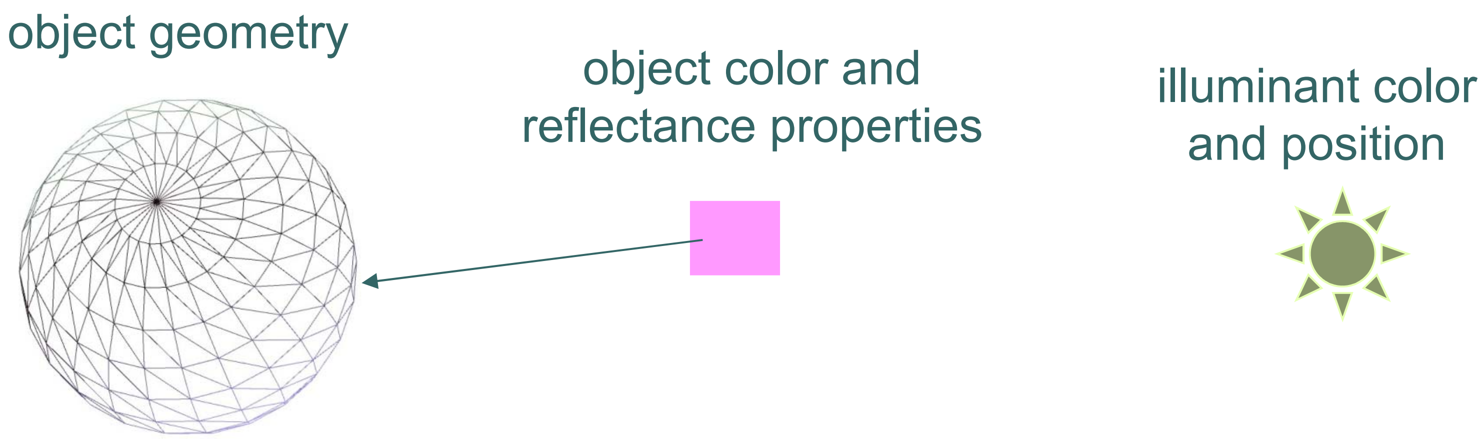
- Detect / segment objects using their representation in the color space





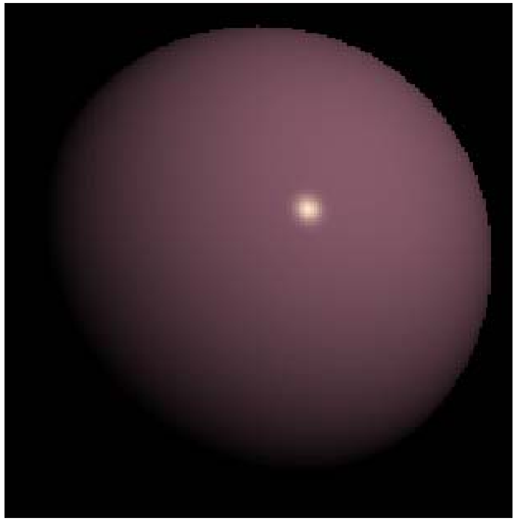

G. J. Klinker, S. A. Shafer and T. Kanade. A Physical Approach to Color Image Understanding. International Journal of Computer Vision, 1990.

# Physical model of image colors: Main variables



# Two reflectance components

- total = matte + specular



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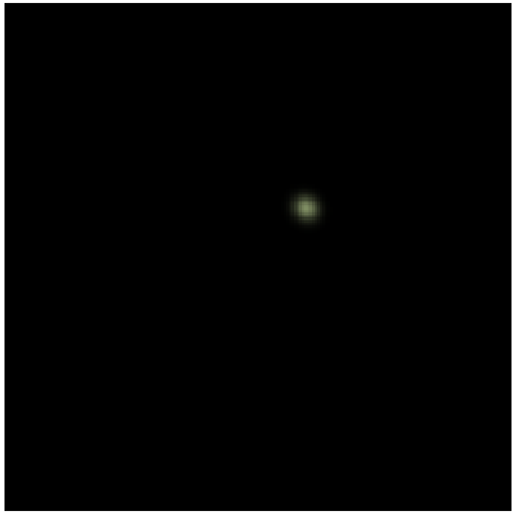
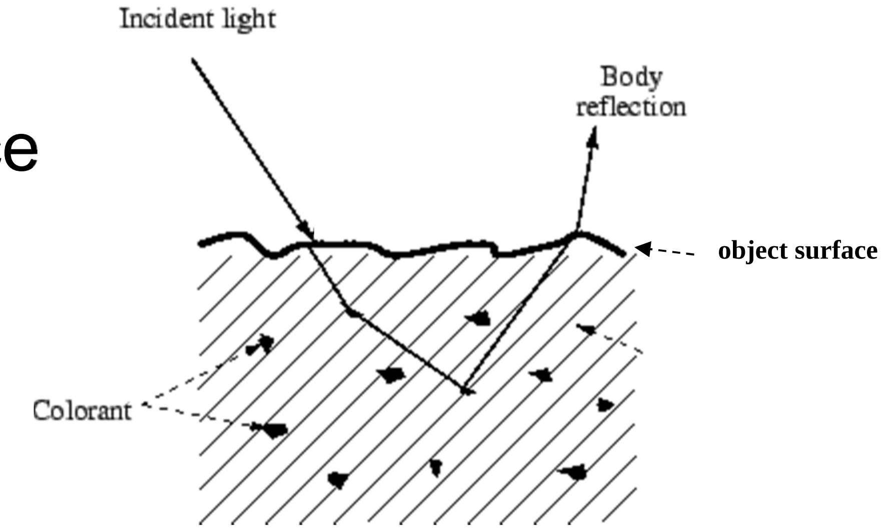


# Matte reflectance

- Physical model: "*body*" reflectance



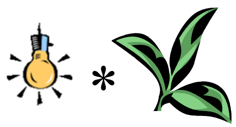

Separation of brightness and color:

L (wavelength, geometry) = c (wavelength) * m (geometry)

reflected light

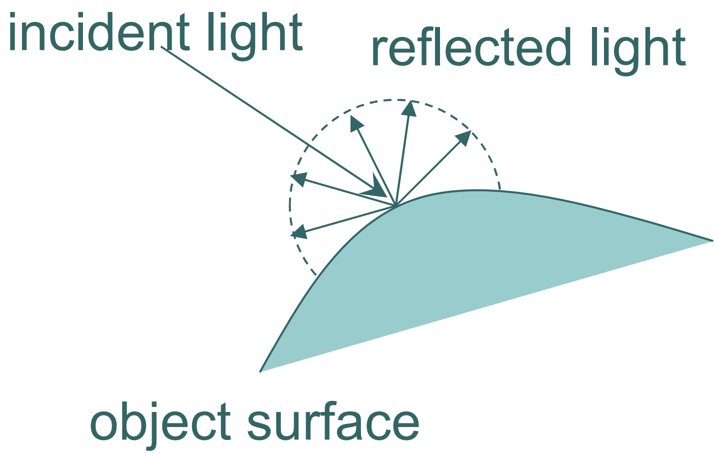
color

brightness



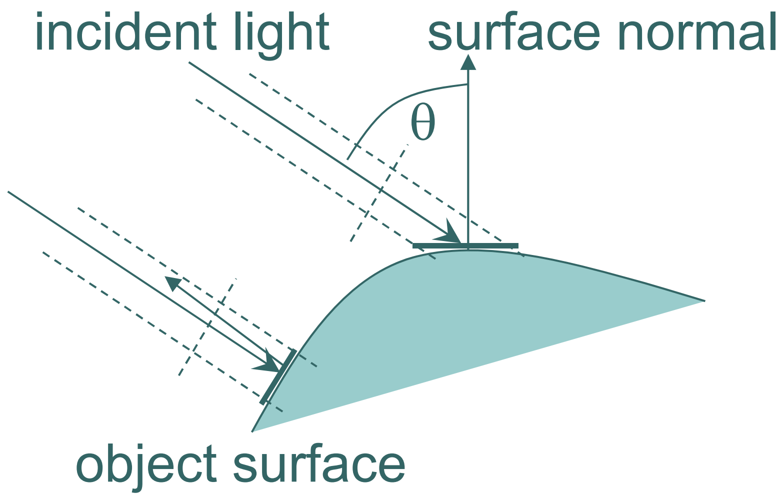
# Matte reflectance

- Dependence of brightness on geometry:
  - *Diffuse* reflectance: the same amount goes in each direction (intuitively: chaotic bouncing)



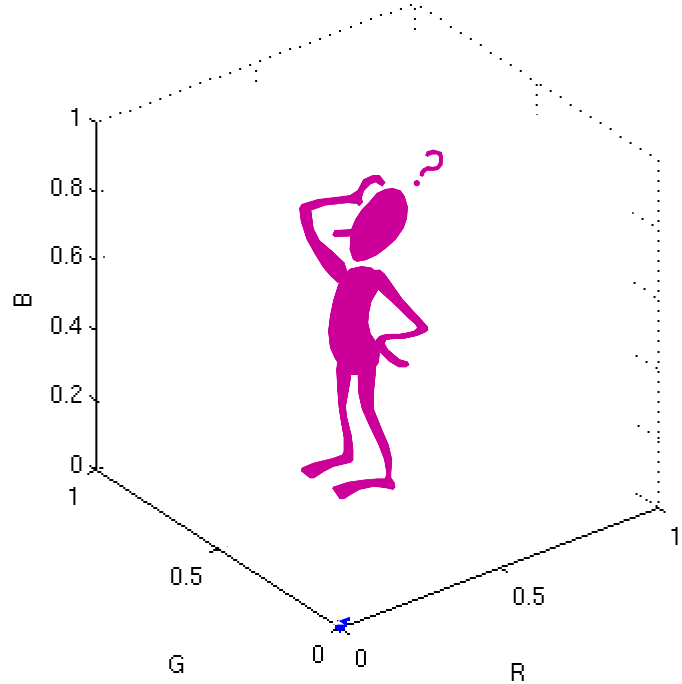
# Matte reflectance

- Dependence of brightness on geometry:
  - *Diffuse* reflectance: the same amount goes in each direction
  - Amount of incoming light depends on the falling angle (*cosine law* [J.H. Lambert, 1760])



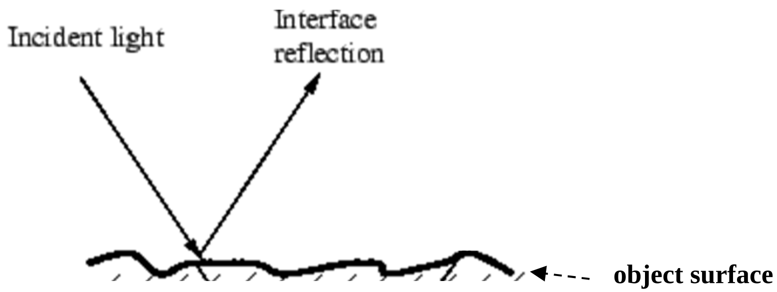

# Matte object in RGB space

- Linear cluster in color space



# Specular reflectance

- Physical model:
  "surface" reflectance




Separation of brightness and color:

L (wavelength, geometry) = c (wavelength) * m (geometry)

reflected light

color

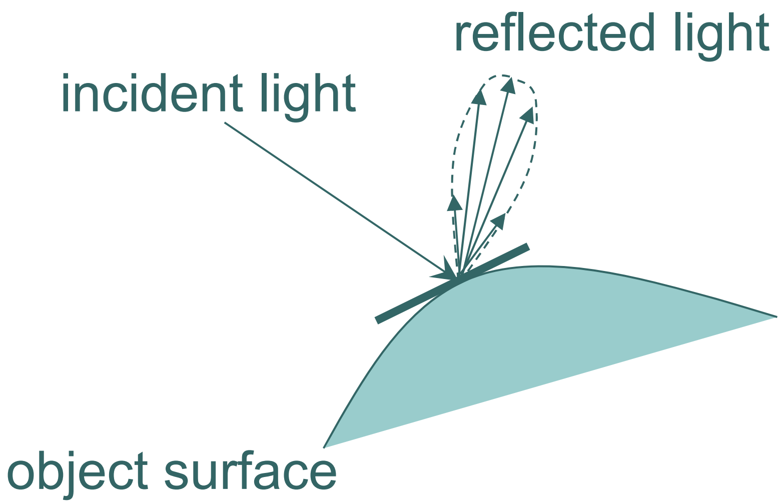
brightness

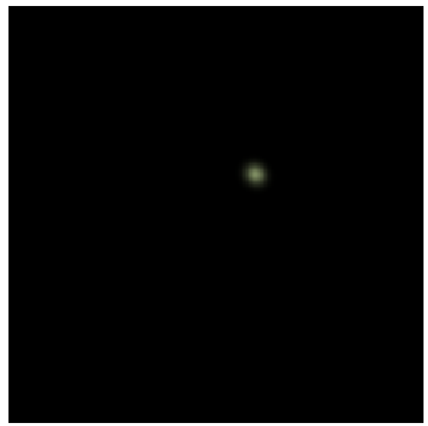
Light is reflected (almost) as is:

*illuminant color = reflected color*

# Specular reflectance

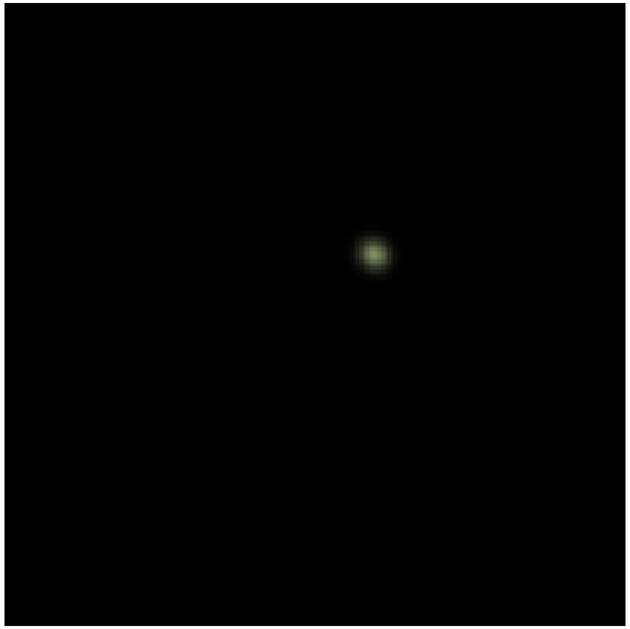
- Dependence of brightness on geometry:
  - Reflect light *in one direction* mostly

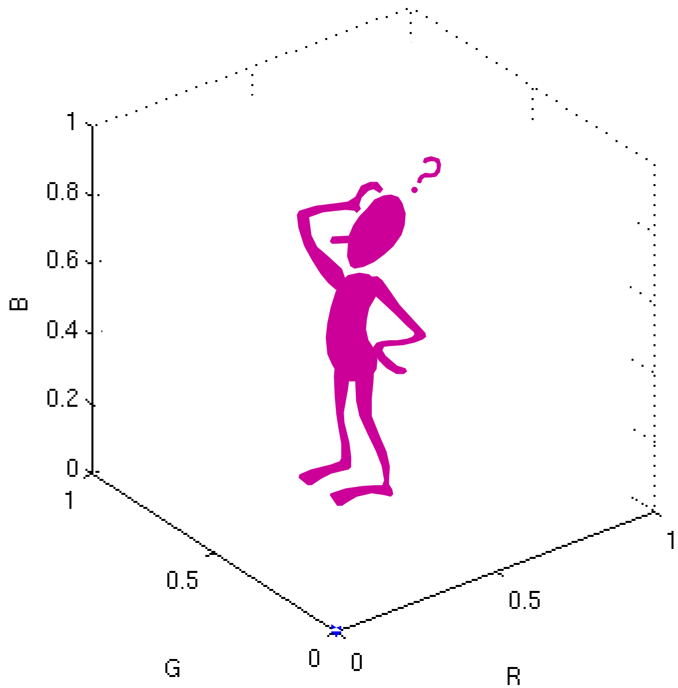


# Specular object in RGB space

- Linear cluster in the direction of the illuminant color

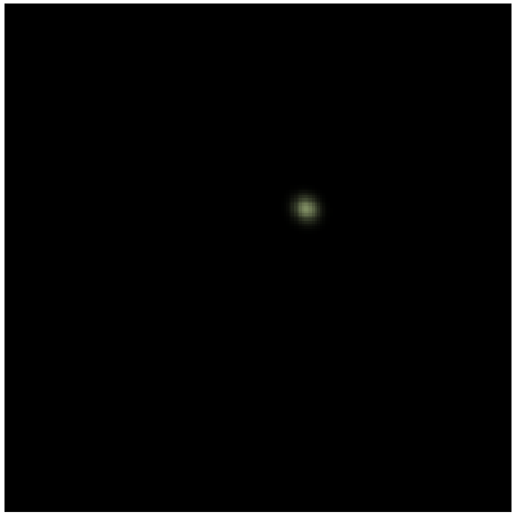




# Combined reflectance

- total  = body (matte) + surface (specular)

+



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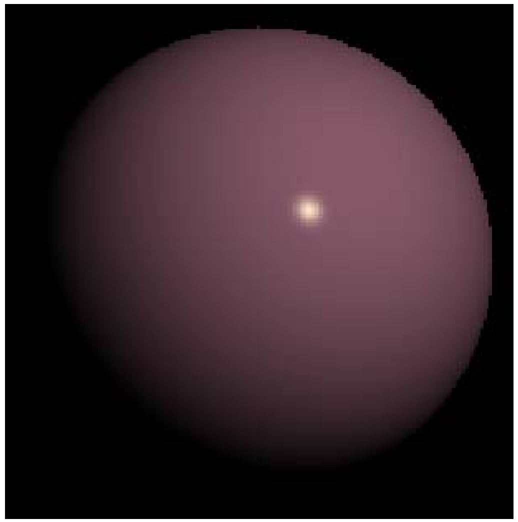
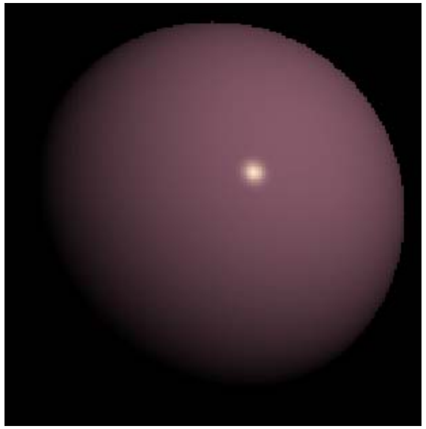
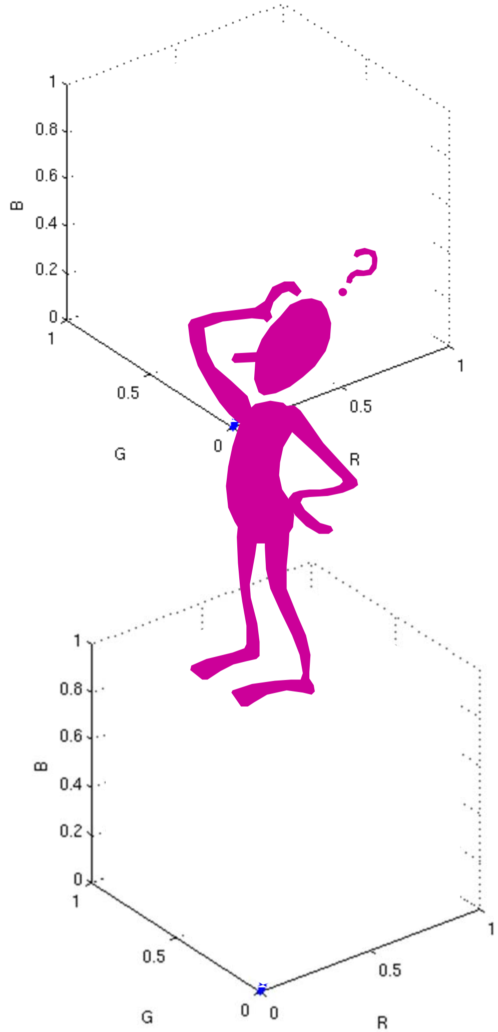


# Combined reflectance in RGB space

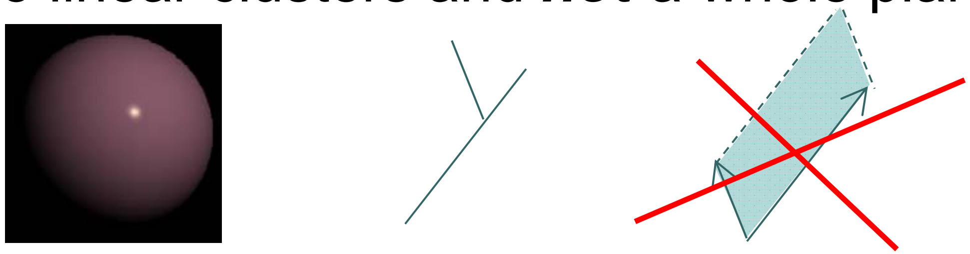




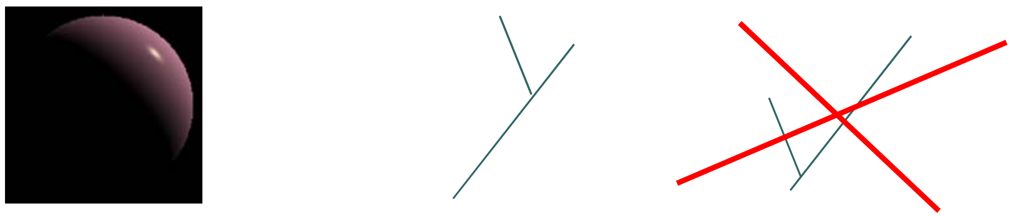

“Skewed T”

# Skewed-T in Color Space

- Specular highlights are very *localized*
  => two linear clusters and ***not*** a whole plane



- *Usually* T-junction is on the bright half of the matte linear cluster



# Color Image Understanding Algorithm

G. J. Klinker, S. A. Shafer and T. Kanade. *A Physical Approach to Color Image Understanding*. ICJV, 1990.

# Color Image Understanding Algorithm: Overview

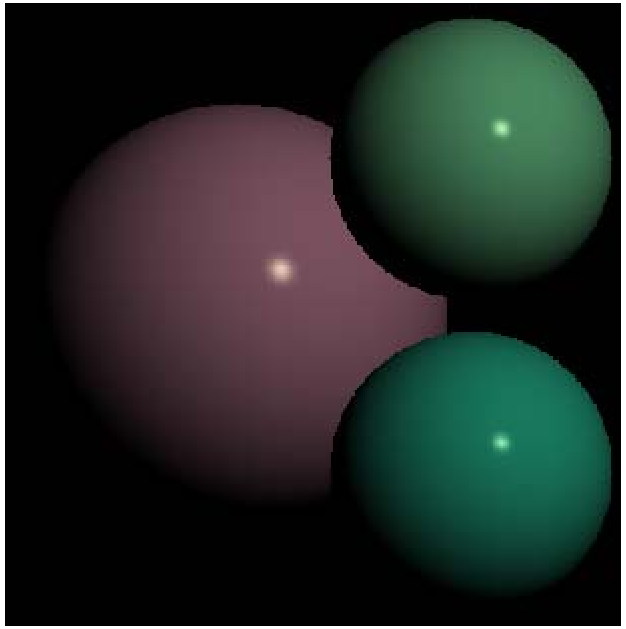
- Part I: Spatial segmentation
  - Segment *matte regions* and *specular regions* (linear clusters in the color space)
  - Group regions belonging to the same object ("skewed T" clusters)
- Part II: Reflectance analysis
  - Decompose object pixels into matte + specular

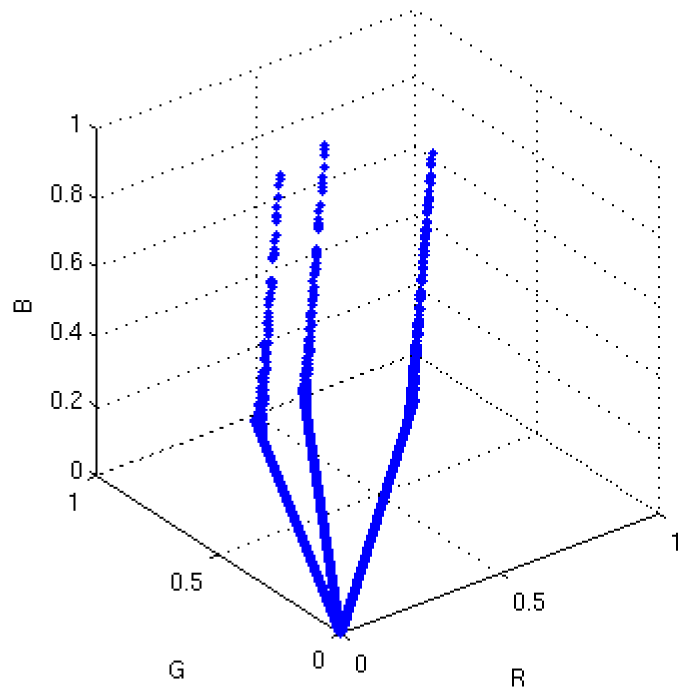
    - valuable for: shape from shading, stereo, color constancy
  - Estimate illuminant color
    - from specular component

G. J. Klinker, S. A. Shafer and T. Kanade. *A Physical Approach to Color Image Understanding.* International Journal of Computer Vision, 1990.

# Part I: Clusters in color space

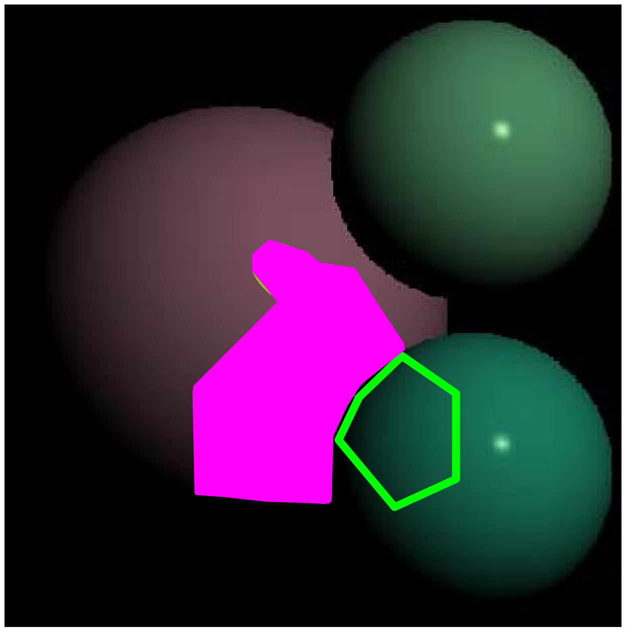
- Several T-clusters
- Specular lines are parallel

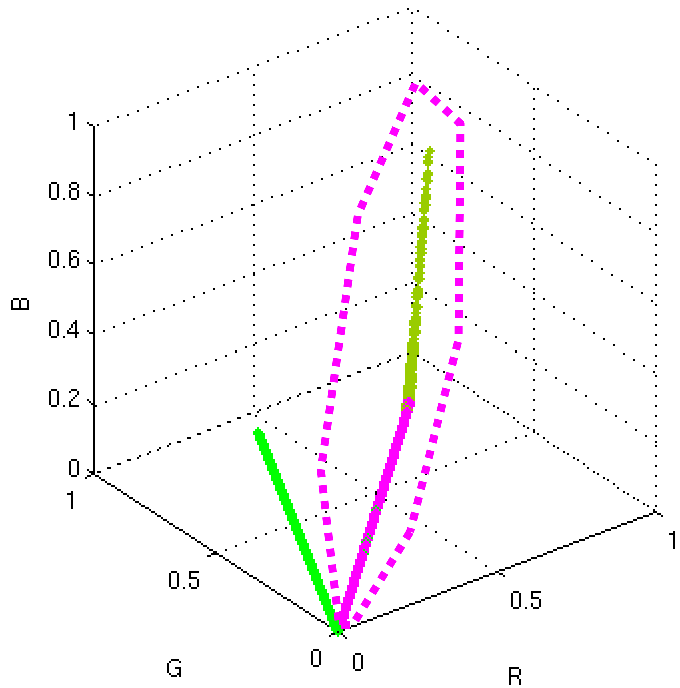




# Region grouping

- Group together matte and specular image parts of the same object
- Do not group regions from different objects

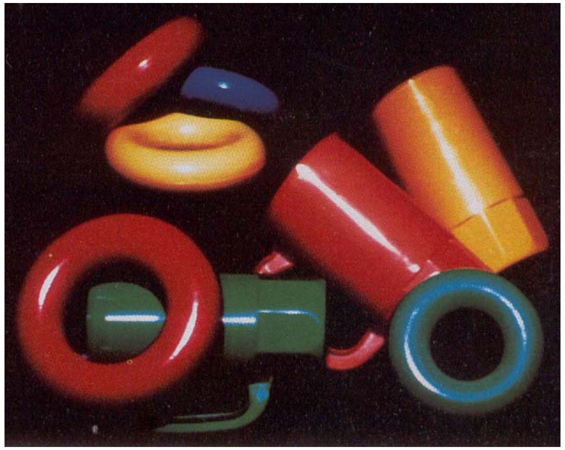




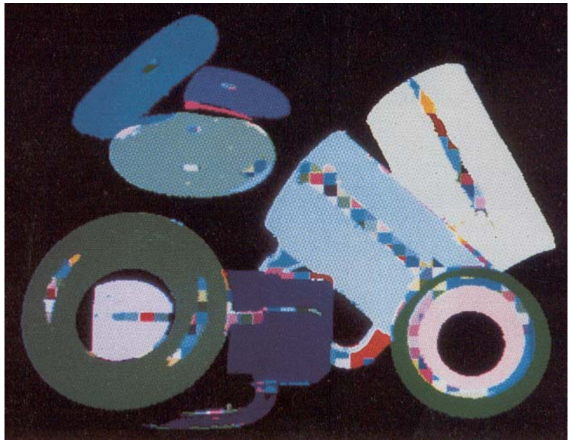
# Algorithm, Part I: Image Segmentation

Grow regions in image domain so that to form clusters in color domain.

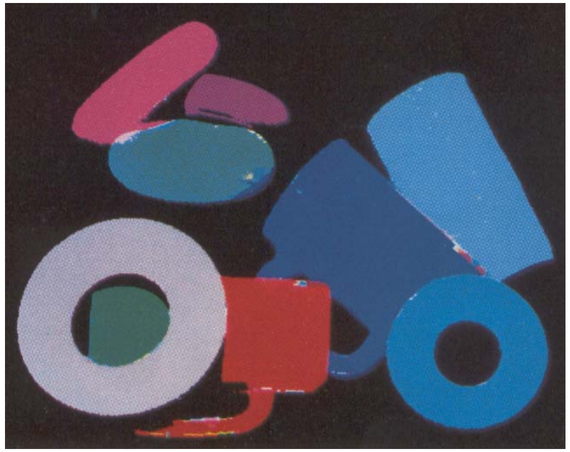
input image



“linear” color clusters



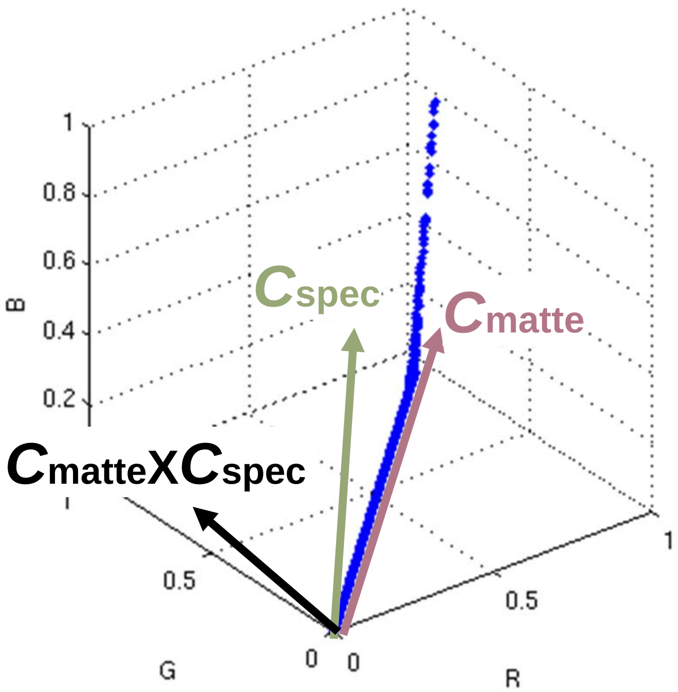
“skewed-T” color clusters



G. J. Klinker, S. A. Shafer and T. Kanade. *A Physical Approach to Color Image Understanding.* International Journal of Computer Vision, 1990.

# Part II: Decompose into matte + specular

- Coordinate transform in color space




$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \left[ C_{matte} \middle| C_{spec} \middle| C_{matte} \times C_{spec} \right] \begin{bmatrix} matte \\ specular \\ noise \end{bmatrix}$$

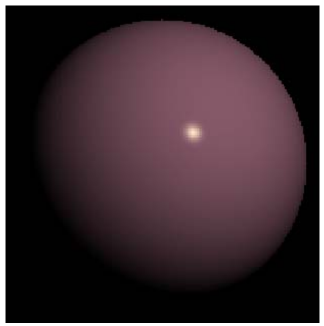
$$\Downarrow$$

$$\begin{bmatrix} matte \\ specular \\ noise \end{bmatrix} = \left[ C_{matte} \middle| C_{spec} \middle| C_{matte} \times C_{spec} \right]^{-1} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

# Decompose into matte + specular (2)

$$\left[ C_{matte} \middle| C_{spec} \middle| C_{matte} \times C_{spec} \right]^{-1} *$$

in RGB space



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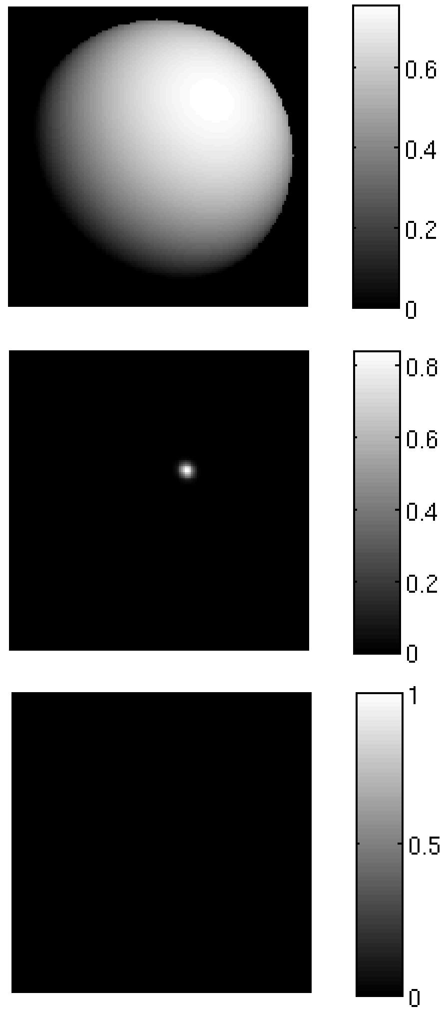
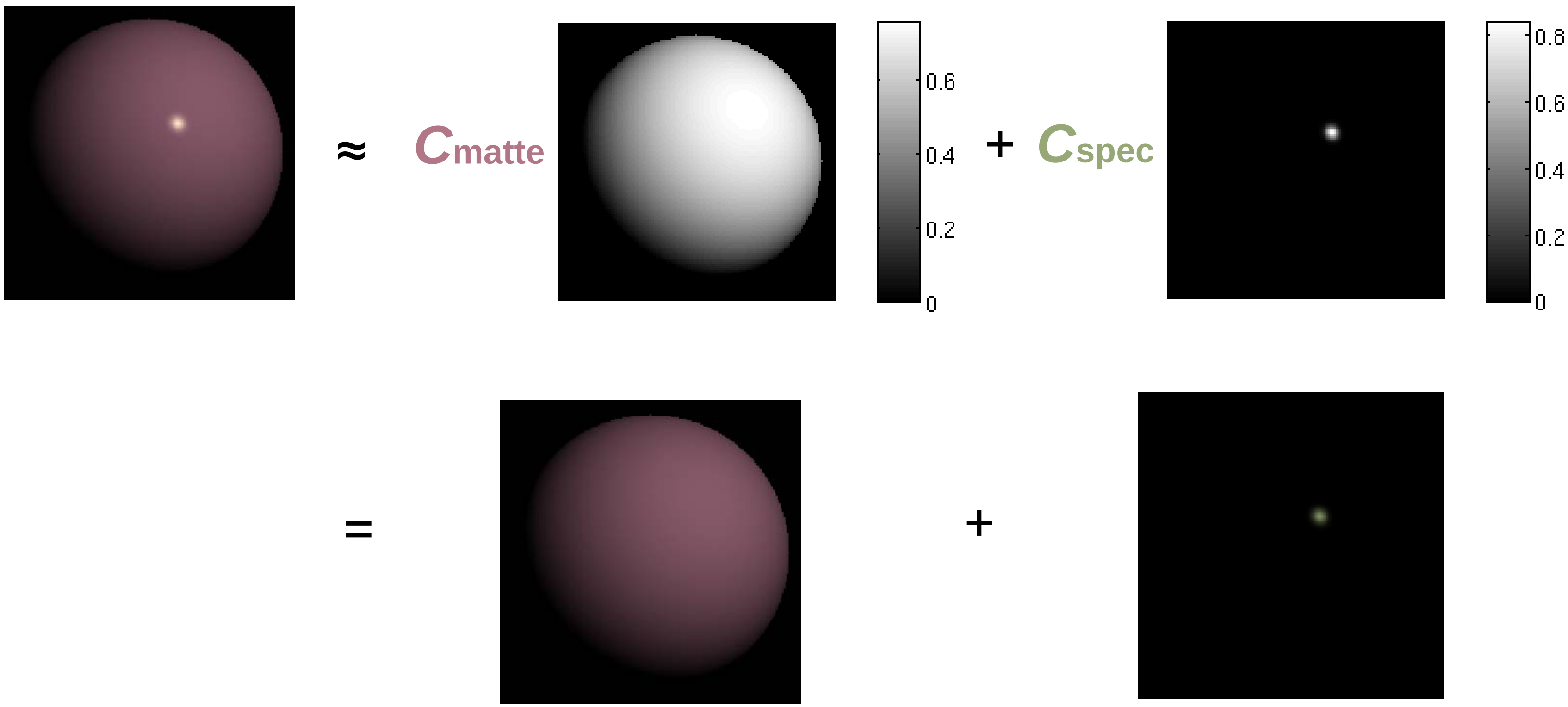
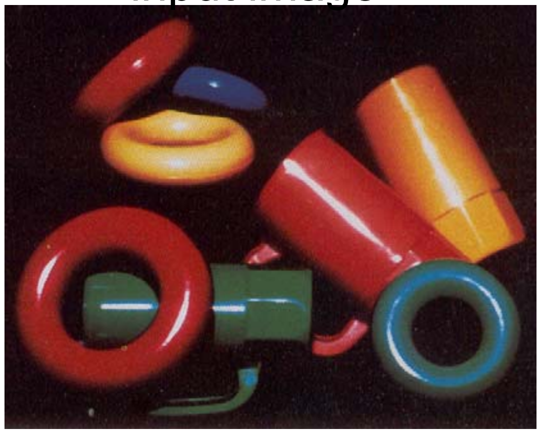


# Decompose into matte + specular (3)



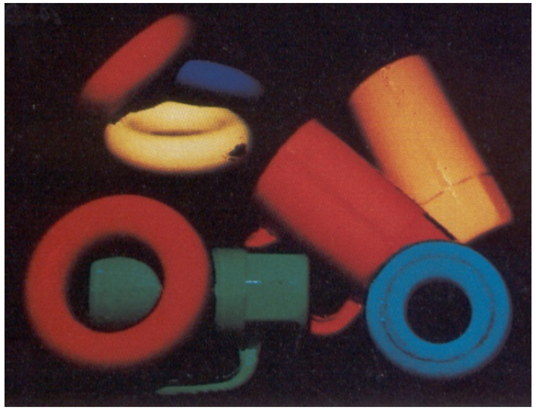
# Algorithm, Part II: Reflectance Decomposition

input image



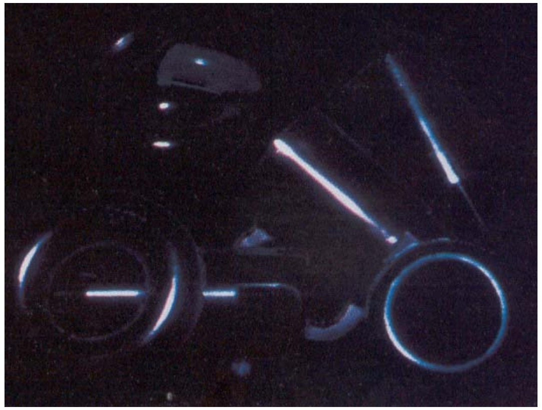
=

matte component

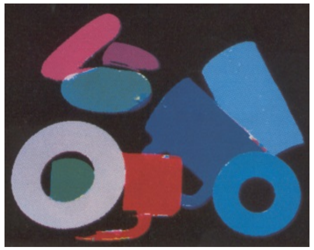


+

specular component



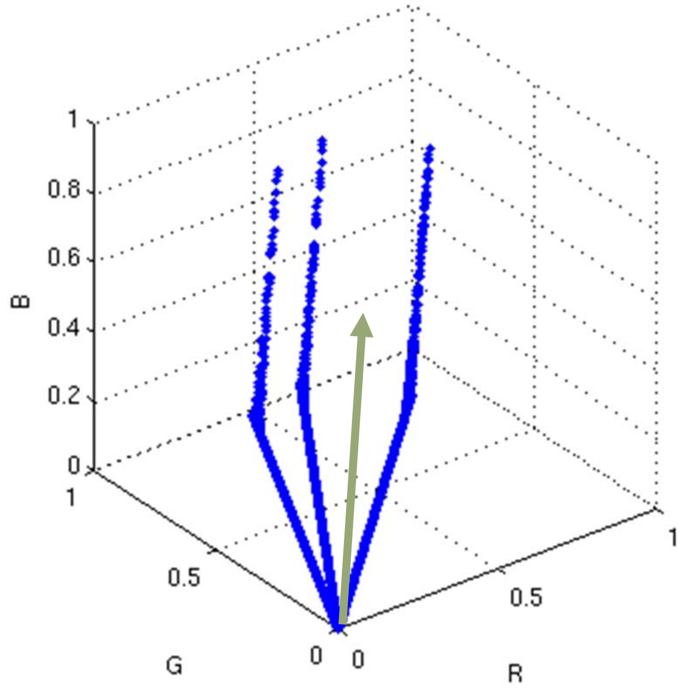
(Separately for each segment)



G. J. Klinker, S. A. Shafer and T. Kanade. *A Physical Approach to Color Image Understanding.* International Journal of Computer Vision, 1990.

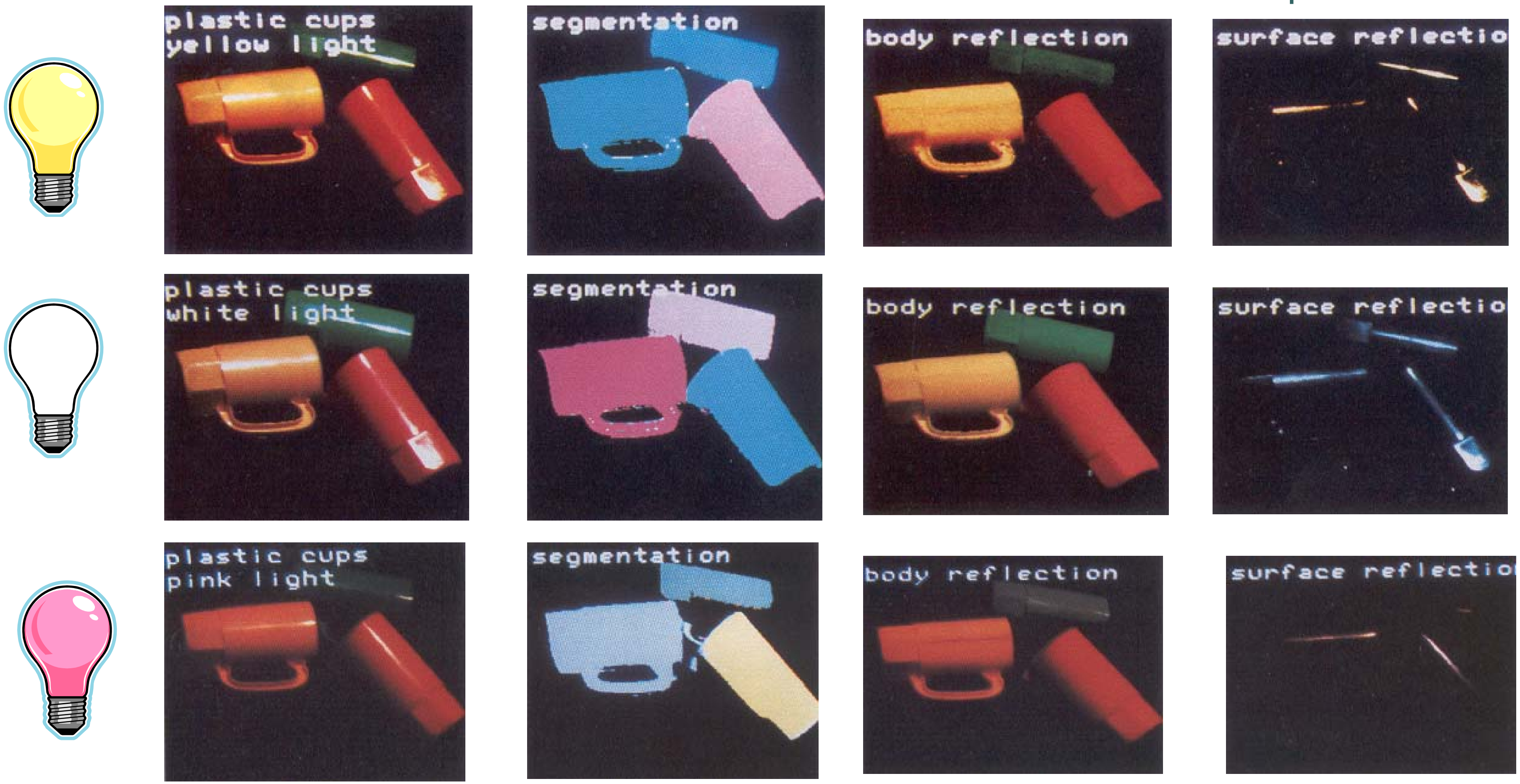
# Algorithm, Part II: Illuminant color estimation

- From specular components
- Note: can use for color constancy!
  - Diagonal transform = 1 ./ illuminant color



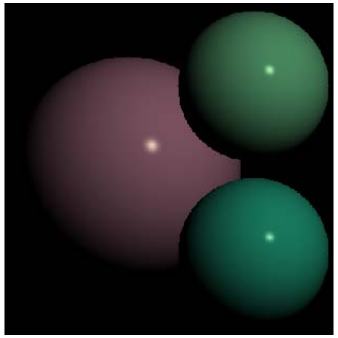
# Algorithm Results: Illumination dependence

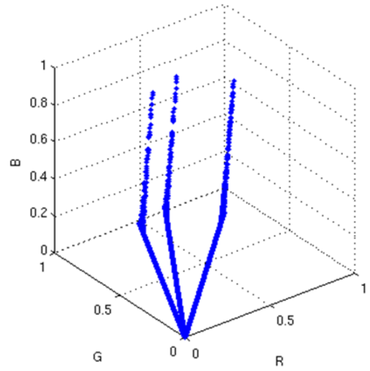
input | segmentation | matte | specular




G. J. Klinker, S. A. Shafer and T. Kanade. A Physical Approach to Color Image Understanding. IJCV, 1990.

# Summary






- Geometric structures in color space
  - Glossy uniformly colored convex objects are "*skewed T*"
  - The bright (highlight) part is in the direction of the illumination color
- This can be used to:
  - *segment* objects
  - separate *reflectance components*
  - implement *color constancy*

# Lecture Summary

- Color:
  - spectral distribution of energy
  - …projected on a few sensors
- Color Constancy:
  - done by linear transform of sensor responses (color values)
  - often diagonal (or can be made such)
- Color Constancy by Gamut Mapping:
  - find possible mappings by intersecting convex hulls
  - choose one of them
- Objects in Color Space
  - linear clusters or “skewed T” (specularities)
  - can segment objects and decompose reflectance
  - color constancy from specularities

# The End

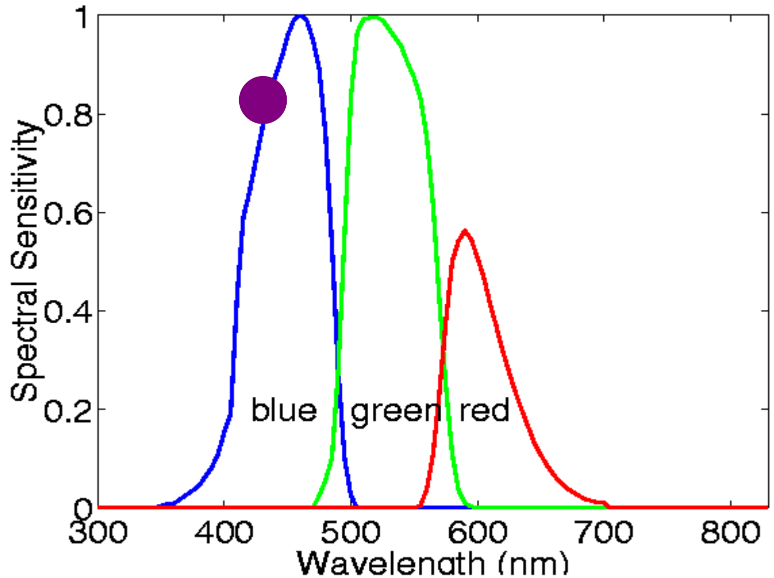
# Illumination constraints

$$\frac{e^c(\lambda)}{e(\lambda)}\vec{\rho}(\lambda) = A\vec{\rho}(\lambda)$$

EigenValue of $A$

EigenVector of $A$

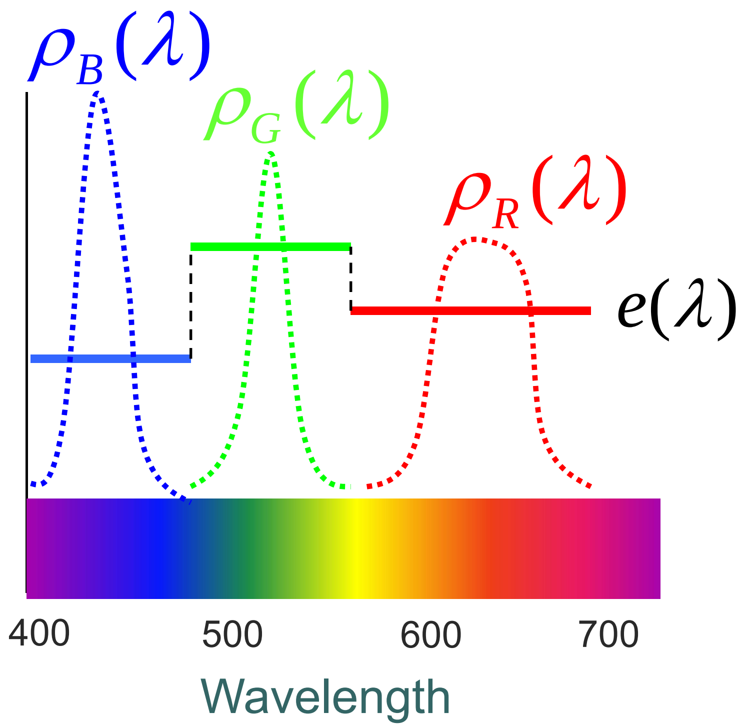
Constant over each sensor's spectral support



# Illumination constraints

Illumination power spectrum should be constant over each sensor's support

$$(e^c(\lambda) = 1)$$



# Illumination constraints

More narrow band sensors – less illumination constraints