Color Constancy

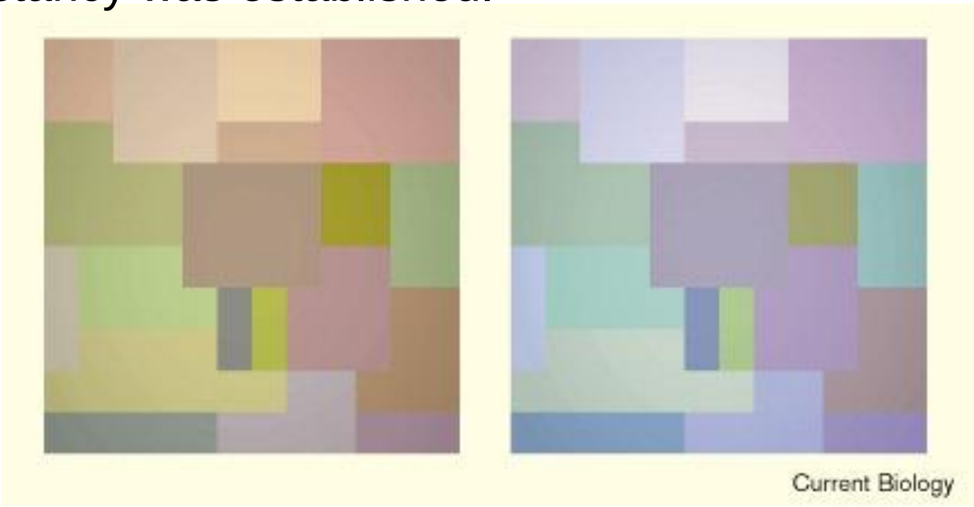
- bottom-up color constancy
- top-down color constancy
- color constant features

slides: Joost van de Weijer

Color Constancy Research in Human Vision

Often Mondrian images were used as stimuli in color constancy experiments. Humans were asked to match patches in the scene to isolated patches under white light.

From these images the importance of color statistics, spatial mean, maximum flux for color constancy was established.



Human color constancy was still only partially explained by these experiments.

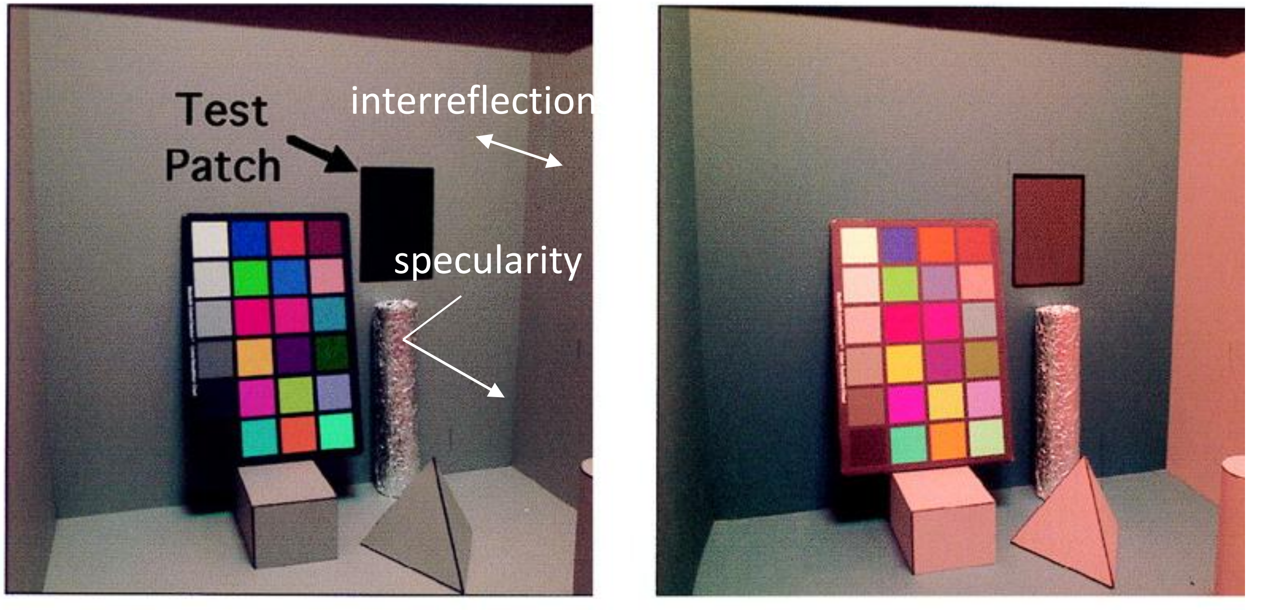
Drawbacks: do not resemble real 3D surfaces, no interreflections, no specularities, shading etc.

Edwin Lan. The retinex, Am Sci 1964
Anya Hurlbert: Is colour constancy real ? Current Biology 1999

Color Constancy Research in Human Vision

Kraft and Brainard designed a more realistic setting for color constancy. Where illuminant and test patch color could be adjusted.

Obeservers task to adjust the colour of the test patch to be achromatic.



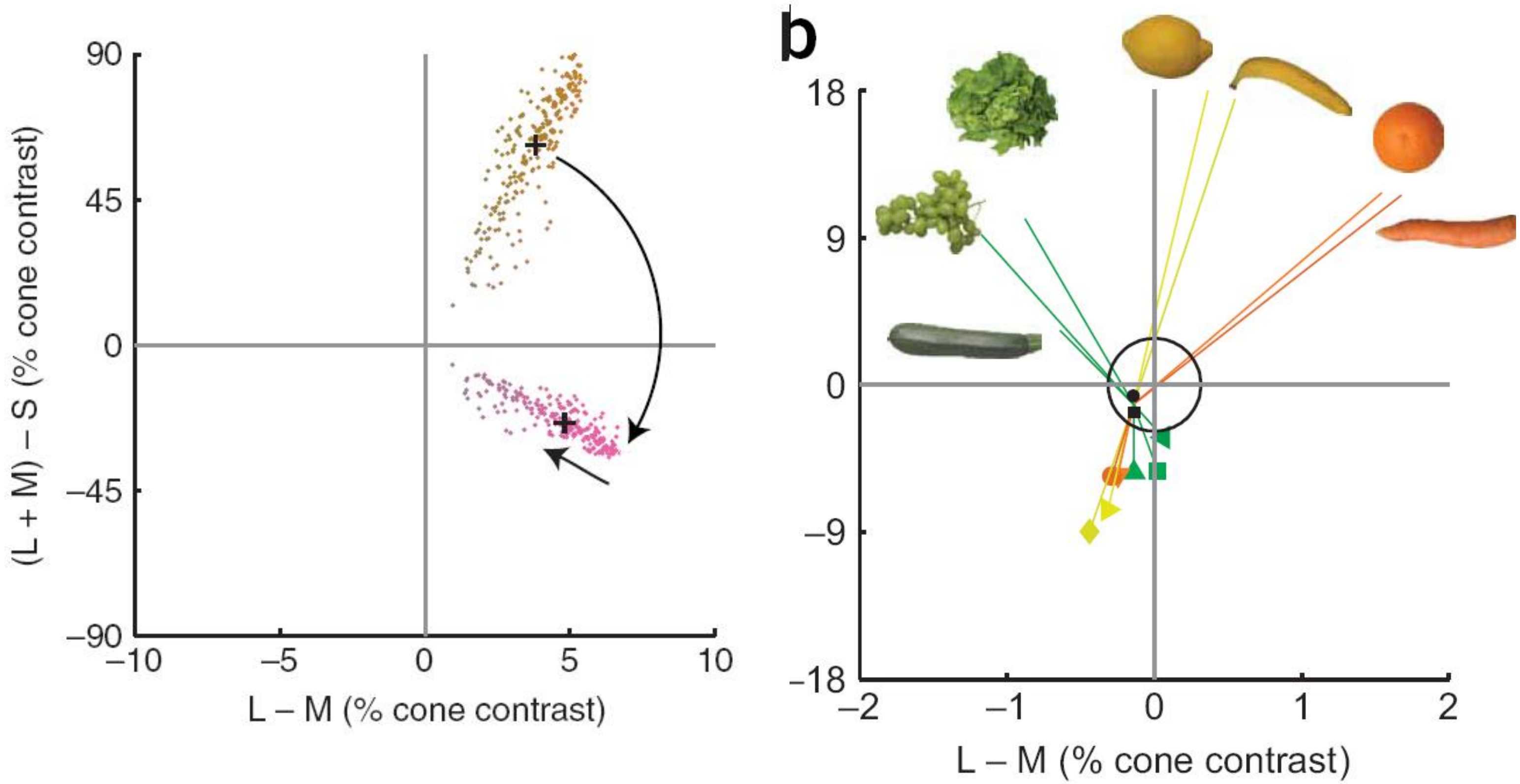
Successive subtraction of cues found them all to be important

- local contrast
- global contrast
- interreflections, specularities

Kraft J M , Brainard D H PNAS 1999;96:307-312
Anya Hurlbert: Is colour constancy real ? Current Biology 1999

Color Constancy Research in Human Vision

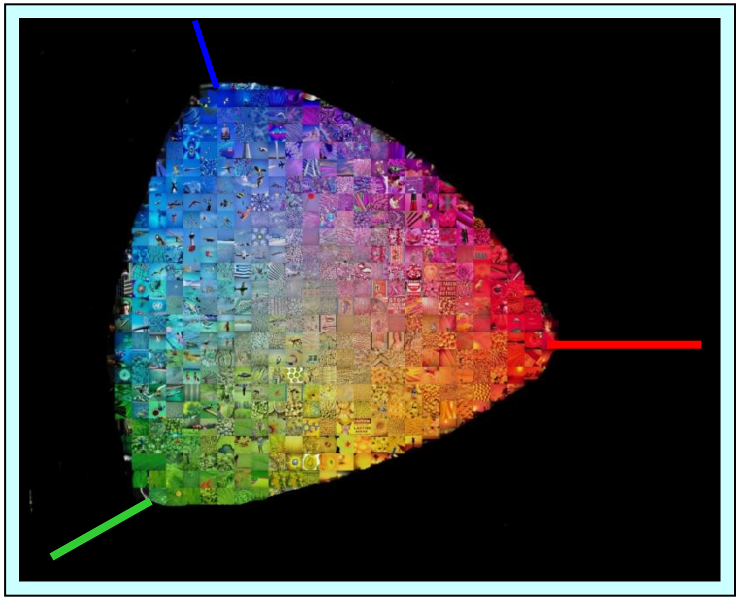
Observers were asked to adjust the colors of fruits to make them achromatic.



Fruits were considered grey when they physically had a color opposite to its natural color.

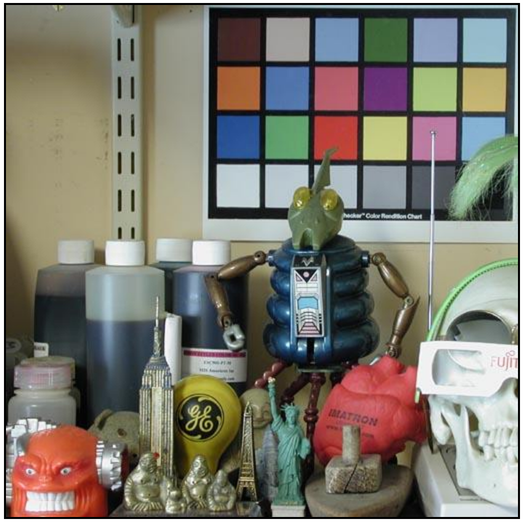
Hansen et al. “Memory modulates color appearance”, *nature neuroscience*, 2006.

Color Constancy at a Pixel



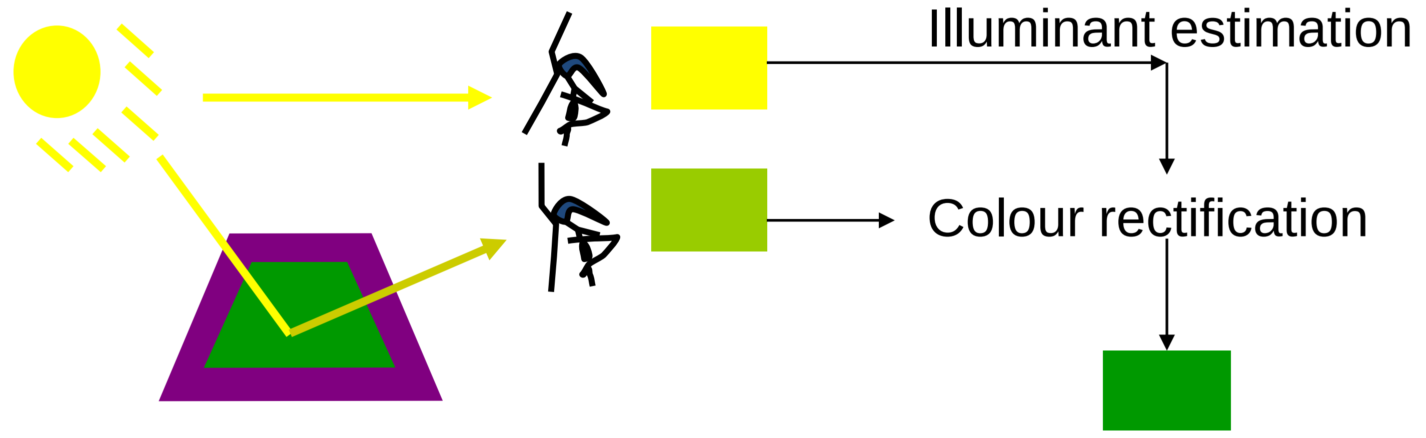
problem statement

How do we recognize colors to be the same under varying light sources ?

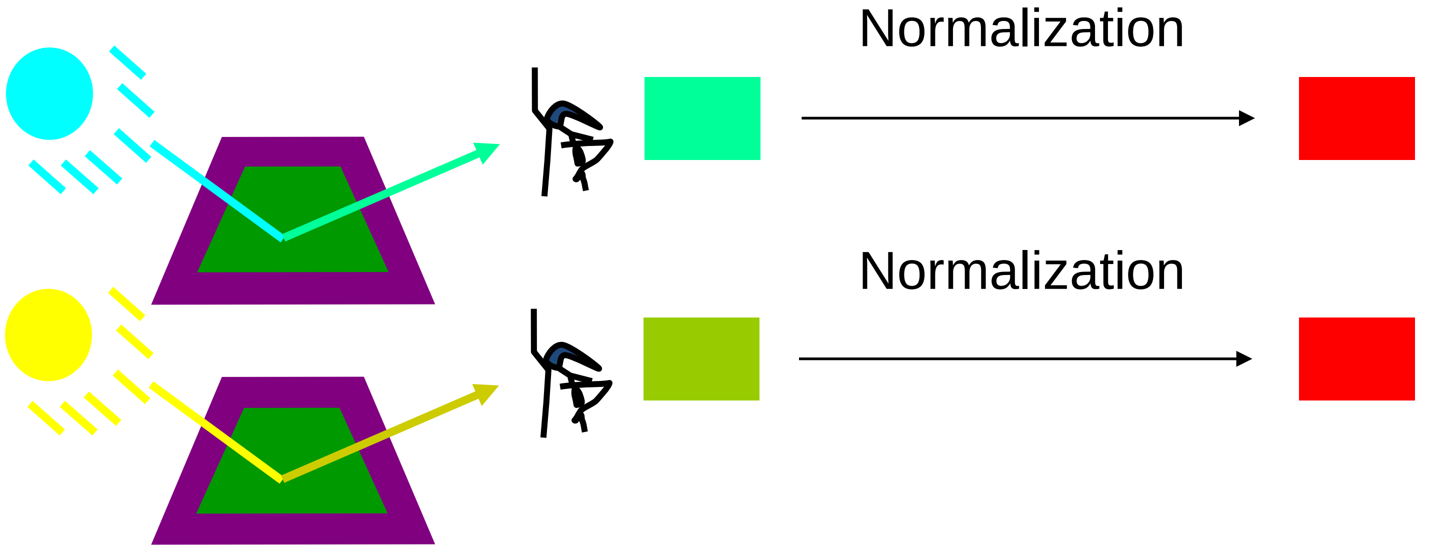


color constancy : the ability to recognize colors of objects invariant of the color of the light source.

Colour constancy algorithms



Invariant Normalizations



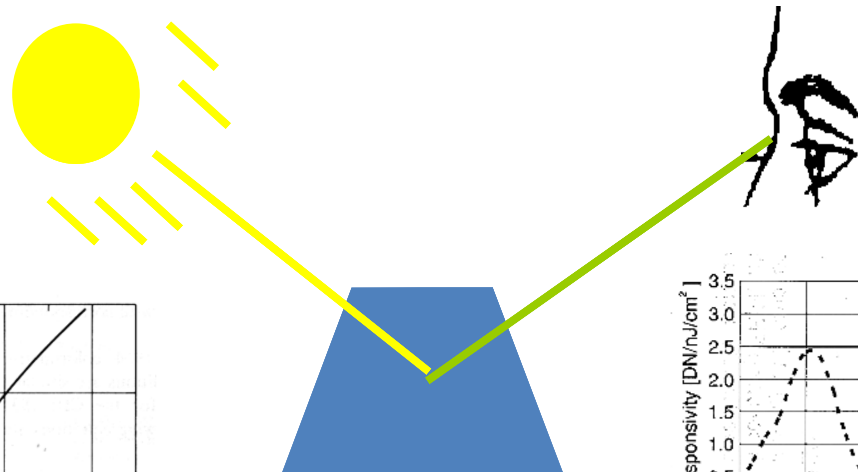
color constancy at a pixel

Assumptions :

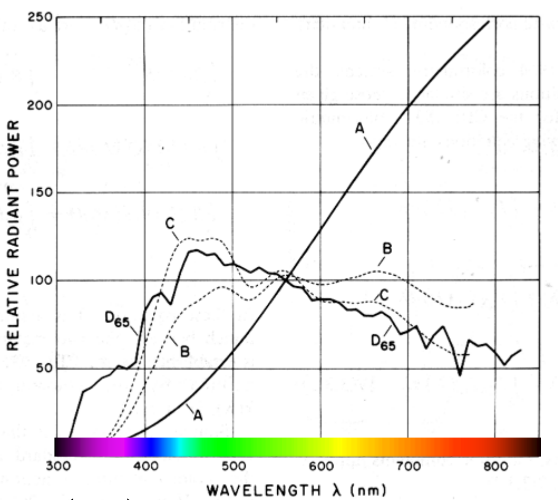
1. Lambertian model:
   - linear relation pixel values and intensity light.
   - no specularities and interreflections.
2. perfectly narrow-band sensors (Dirac delta functions).
3. the illuminants are Planckian.

However, the final algorithm is shown to be robust to deviations from the assumptions.

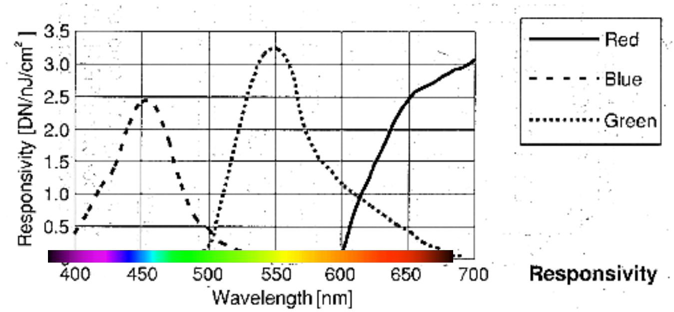
Surface reflectance



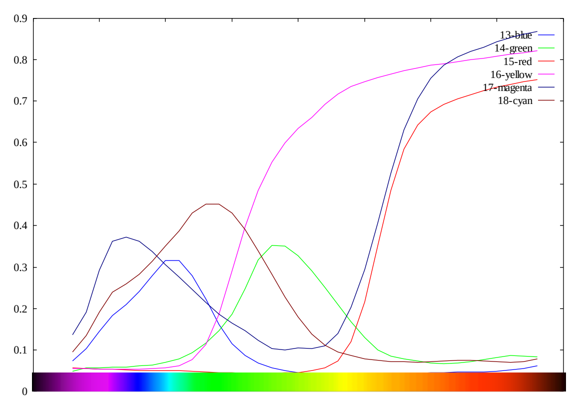
$\longrightarrow \{R, G, B\}$



$e(\lambda)$



$s(\lambda)$

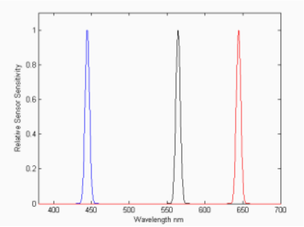


$c_b(\lambda)$

Dirac delta functions

$$p_k = \int_{\omega} e(\lambda) c_b(\lambda) s_k(\lambda) d\lambda$$

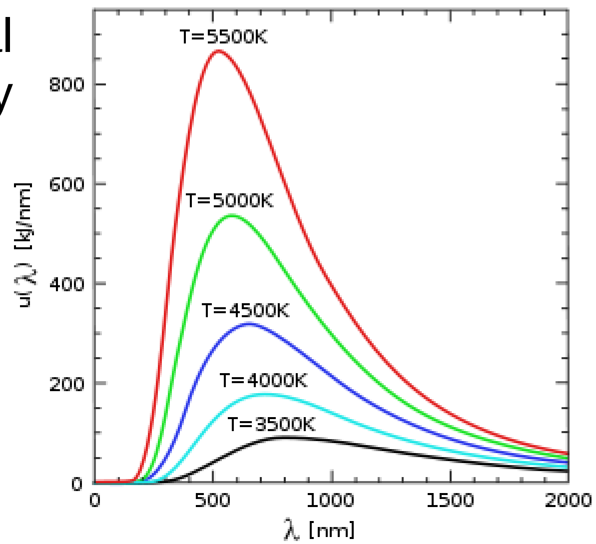
assumption: Dirac sensors



$$p_k = \int_{\omega} e(\lambda) c_b(\lambda) q_k \partial(\lambda - \lambda_k) d\lambda$$

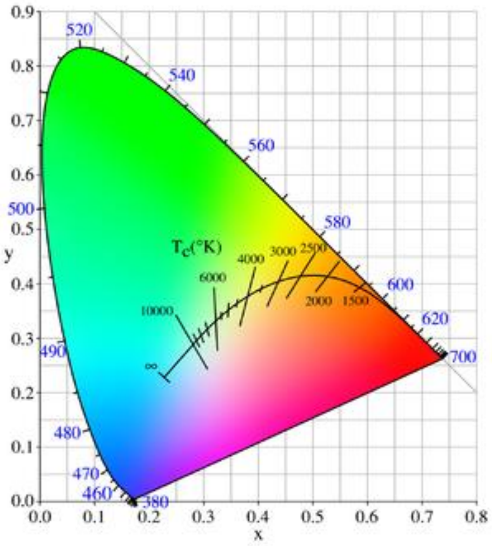
$$\boxed{p_k = e(\lambda_k) c_b(\lambda_k) q_k}$$

Planck's law of black body radiation states the spectral intensity of electromagnetic radiation from a black body at temperature T as a function of wavelength:

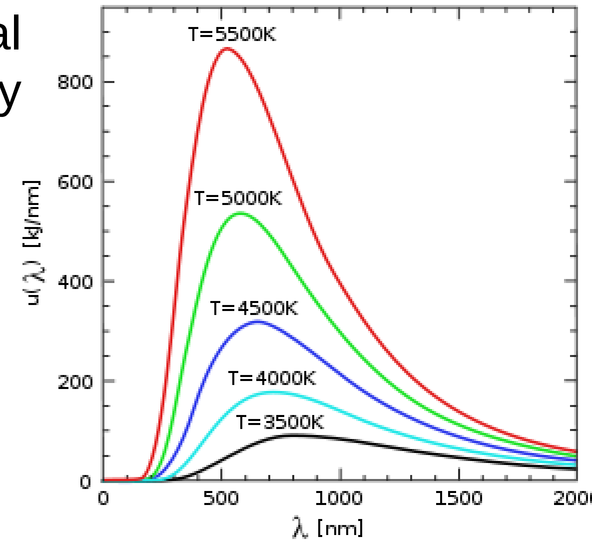


Wien's approx: $$E(\lambda,T)=\frac{c_1}{\lambda^5}e^{-\frac{c_2}{T\lambda}}$$

The **Planckian locus** is the path that the color of a black body as the blackbody temperature changes.



Planck's law of black body radiation states the spectral intensity of electromagnetic radiation from a black body at temperature T as a function of wavelength:



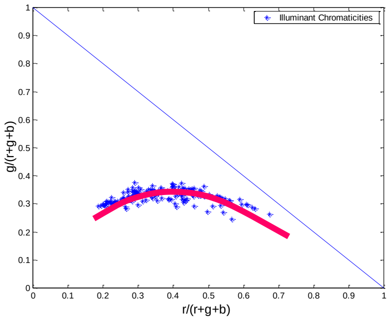
Wien's approx: $$E(\lambda,T)=\frac{c_1}{\lambda^5}e^{-\frac{c_2}{T\lambda}}$$

The **Planckian locus** is the path that the color of a black body as the blackbody temperature changes.

Daylight illuminants can be approximated by Planckian illuminants.

(indoor illuminants to some extend

2500K Household light bulbs
3000K Studio lights, photo floods
4000K Clear flashbulbs
5000K Typical daylight; electronic flash)



Color constancy at a pixel

Planckian light

$$p_k = e(\lambda_k)c_b(\lambda_k)q_k \longrightarrow p_k = \frac{c_1}{\lambda_k^5} e^{-\frac{c_2}{T\lambda}} c_b(\lambda_k)q_k$$

Consider the logarithm of the chromaticity coordinates:

$$\chi_j = \log\left(\frac{p_k}{p_p}\right) = \log\left(\frac{\lambda^{-5} e^{-\frac{c_2}{T\lambda}} c_b(\lambda_k)q_k}{\lambda^{-5} e^{-\frac{c_2}{T\lambda}} c_b(\lambda_p)q_p}\right)$$

$$\chi_j = \log\left(\frac{s_k}{s_p}\right) + \frac{1}{T}\left(e_k - e_p\right)$$

$$e_k \equiv -c_2/\lambda_k$$

$$s_k = \lambda_k^{-5} c_b(\lambda_k)q_k$$

$$\boldsymbol{\chi} = \mathbf{s} + \frac{1}{T}\mathbf{e}$$

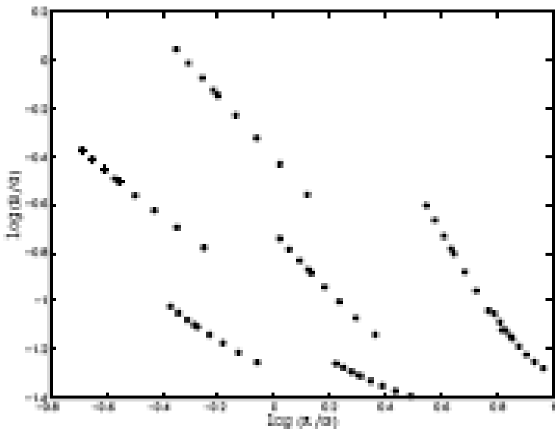
depends on surface color

depends on illuminant color

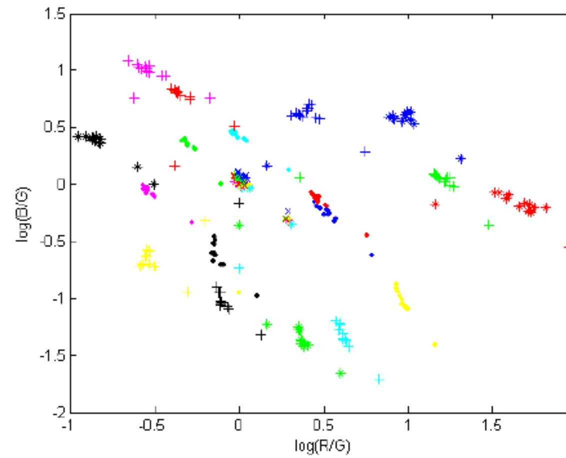
color constancy at a pixel - examples

examples log chromaticity plots:

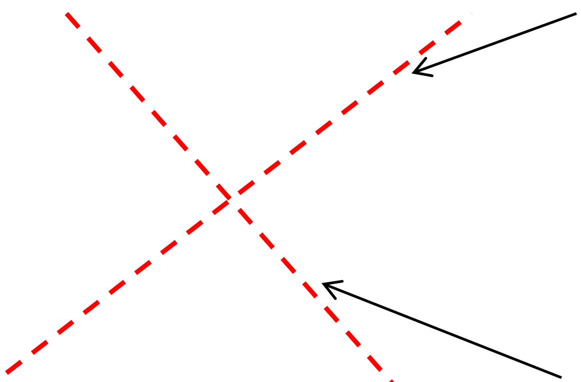
Macbeth Color Checker



HP912 Digital Still Camera



Nikon D-100



illuminant invariant direction axis

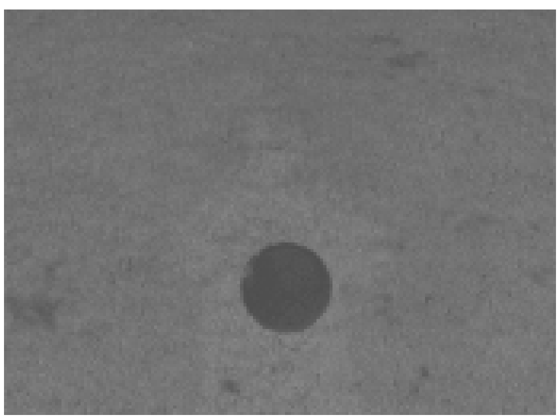
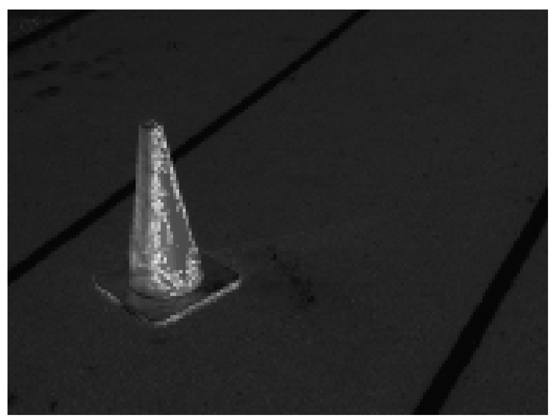
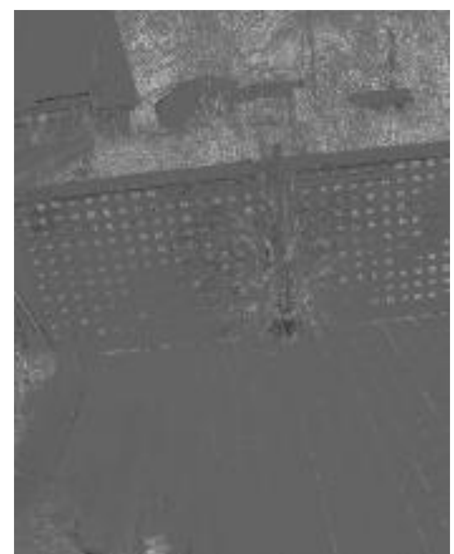
Every pixel can be represented in a illuminant invariant representation !

illuminant variant axis
(camera dependent)

images source: Eli Arbel

examples illuminant invariant

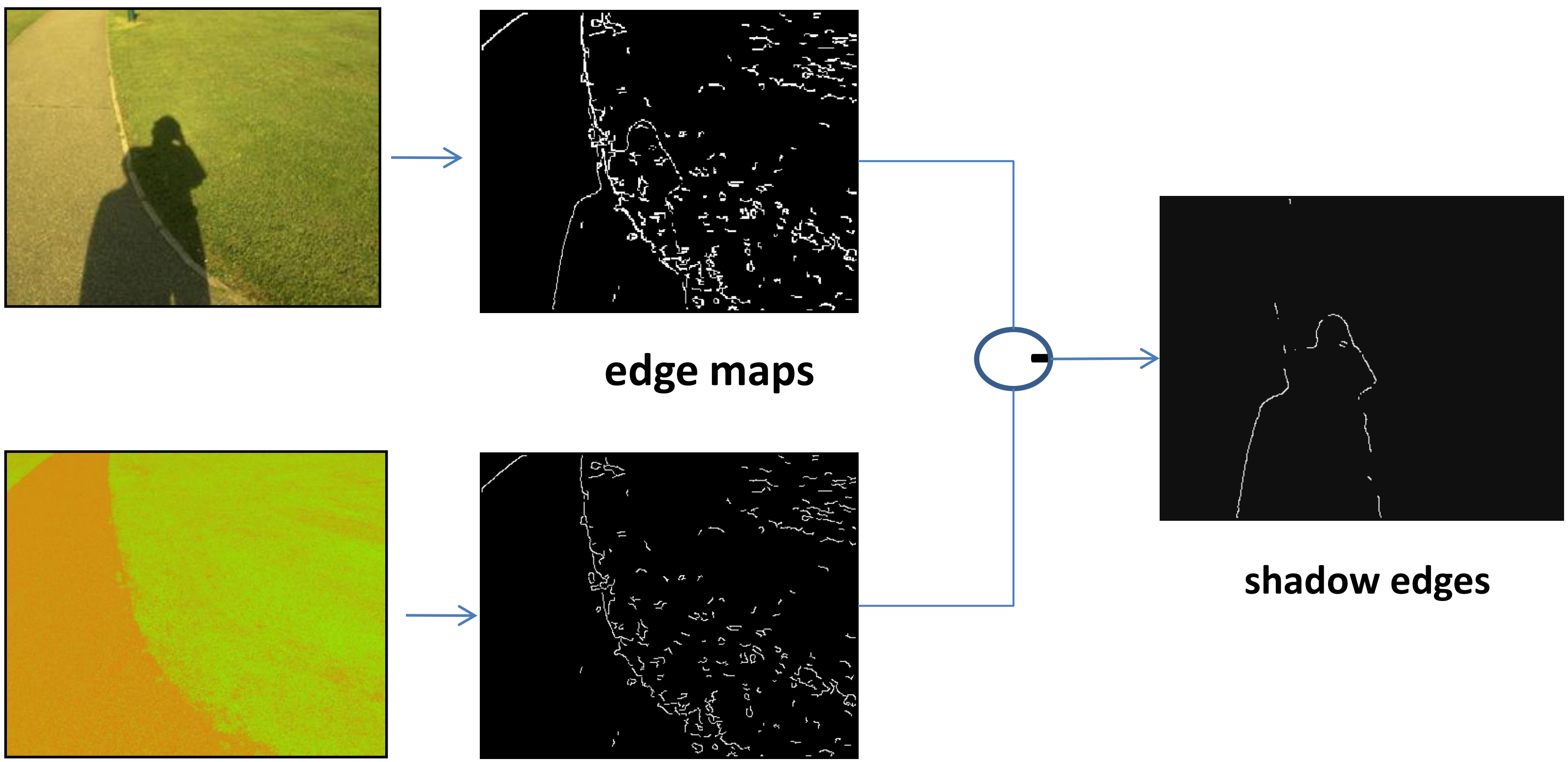


Since shadows are a change in illuminant these representation are shadow free.

shadow detection

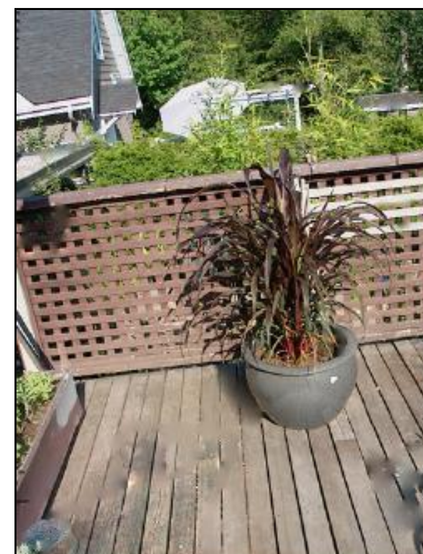
Comparison of the edge maps of the original and the shadow invariant image allows for shadow detection.



examples:

sky and sun light

sky light



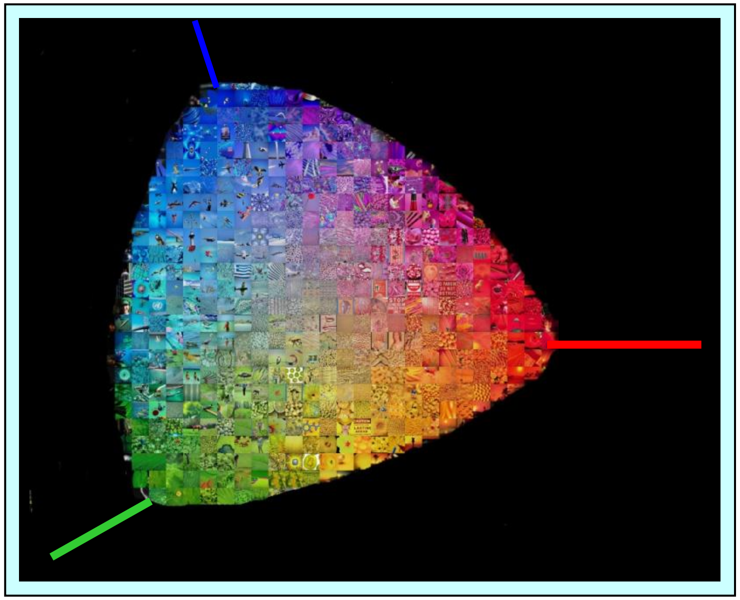
removal of colored shadow

shading is not effected

references:

1. B. H. Tenenbau. *Recovering intrinsic scene characteristics from images.* **Computer Vision Systems, 1978**.
2. Y. Weiss. *Deriving intrinsic images from image sequences*. **ICCV 2001**.
3. G. D. Finlayson, S.D. Hordley. *Color Constancy at a Pixel*. **JOSA 2001**.
4. G.D. Finlayson, S.D. Hordley, C. Lu, M.S. Drew, *On the reomoval of shadows from images*. **PAMI 2006**.
5. E. Arbel, H Hel-Or*, Texture-Preserving Shadow Removal in color Images Containing Curved Surfaces*. **CVPR 2007**.
6. F. Liu, M. Gleicher. *Texture-Consistent Shadow Removal.* **ECCV 2008**.

Gamut Mapping



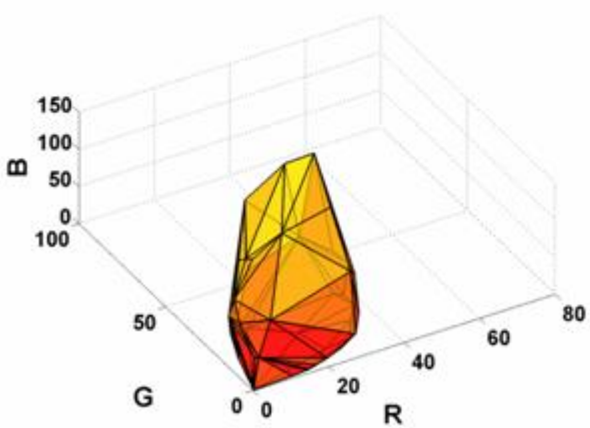
regular gamut mapping

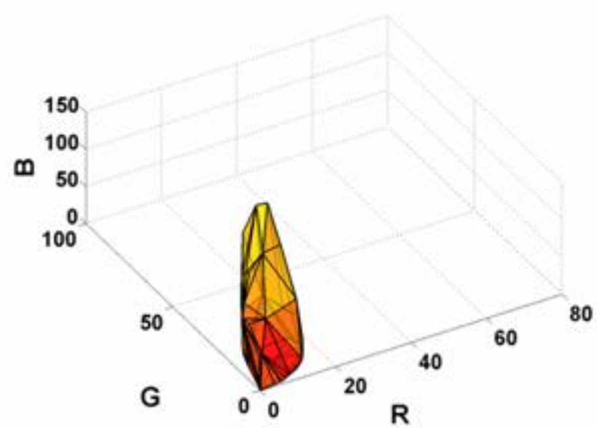
"In real-world images, for a given illuminant, one observes only a limited number of different colors."

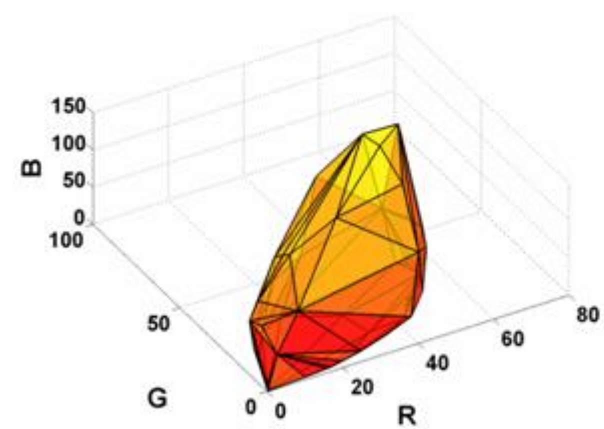
Solux 4700K

Solux 4700K + Roscolux filter

Sylvania Warm White Fluorescent







Slide credit: Theo Gevers

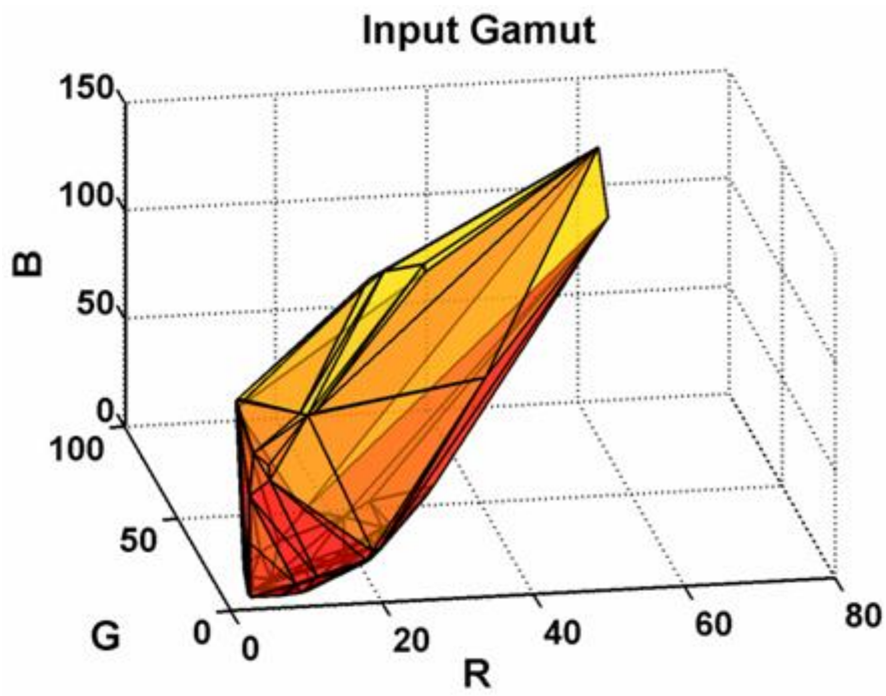
Gamut mapping algorithm:

- Obtain input image.

Slide credit: Theo Gevers

Gamut mapping algorithm:

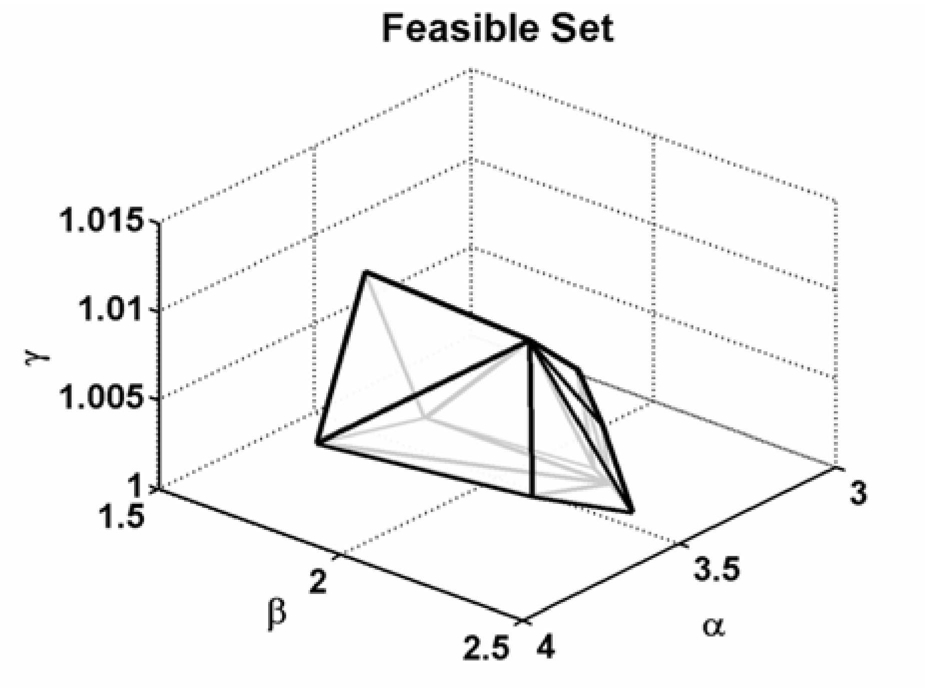
- Obtain input image.
- Compute gamut from image.



Slide credit: Theo Gevers

Gamut mapping algorithm:

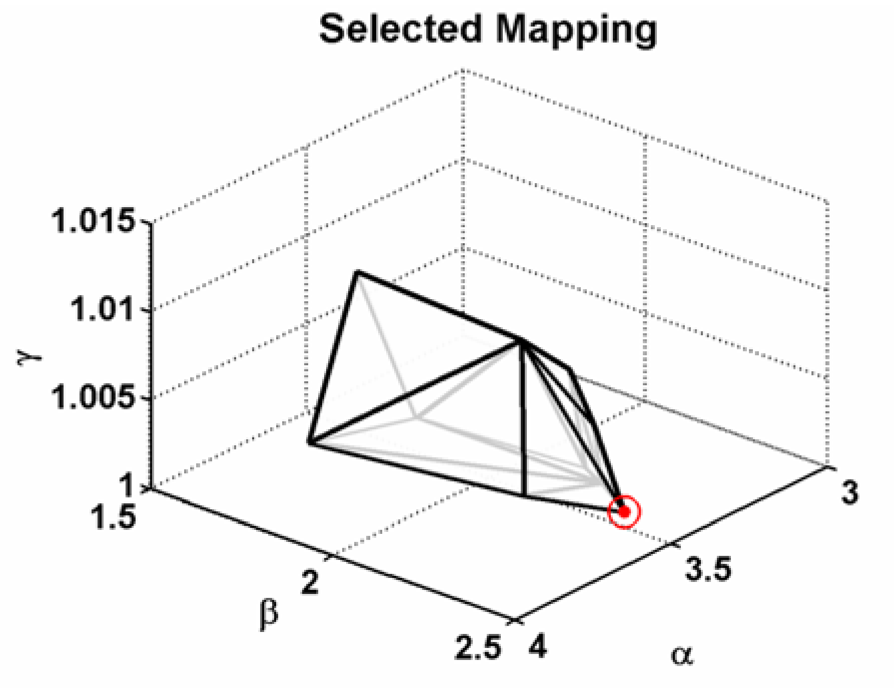
- Obtain input image.
- Compute gamut from image.
- Determine feasible set of mappings from input gamut to canonical gamut.



Slide credit: Theo Gevers

Gamut mapping algorithm:

- Obtain input image.
- Compute gamut from image.
- Determine feasible set of mappings from input gamut to canonical gamut.
- Apply some estimator, to select one mapping from this set.



Slide credit: Theo Gevers

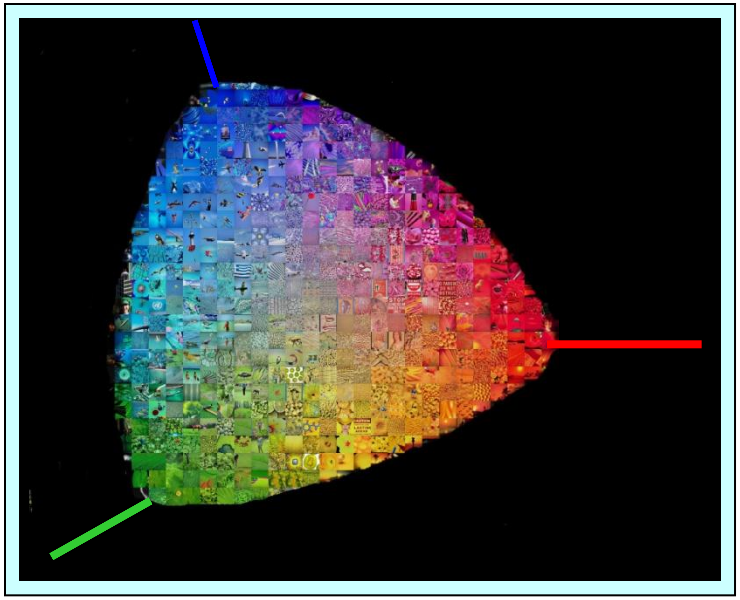
regular gamut mapping

Gamut mapping algorithm:

- Obtain input image.
- Compute gamut from image.
- Determine feasible set of mappings from input gamut to canonical gamut.
- Apply some estimator, to select one mapping from this set.
- Use mapping on input image to recover the corrected image, or on canonical illuminant to estimate the color of the unknown illuminant.

Slide credit: Theo Gevers

Color Constancy from Color Derivatives



Color Constancy

color constancy : the ability to recognize colors of objects invariant of the color of the light source.

Grey world hypothesis : the average reflectance in a scene is grey.

White patch hypothesis : the highest value in the image is white.

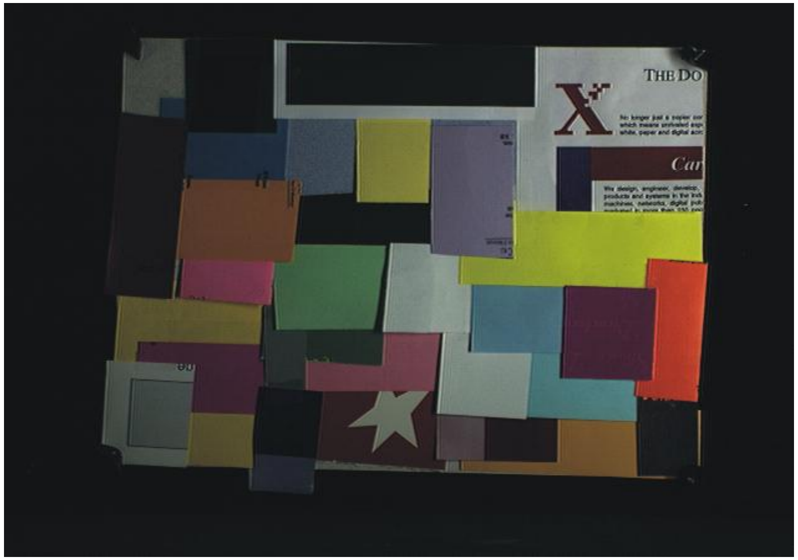
Grey-world: $\sum_{m=1}^{M} \mathbf{f}_i(\mathbf{x}) \propto \mathbf{c}$

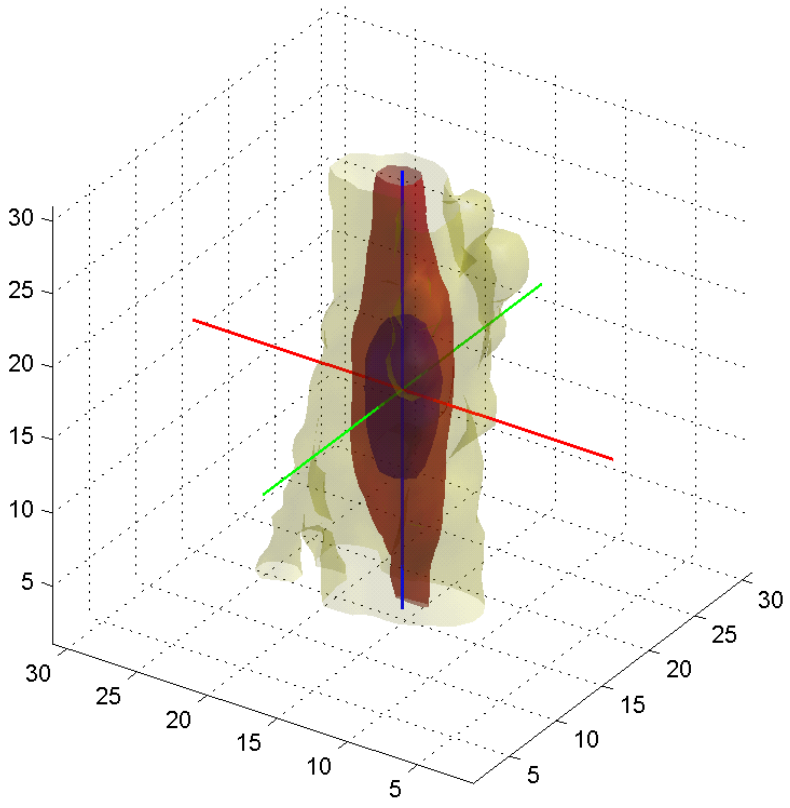
white-patch: $\left(\sum_{m=1}^{M} \left(\mathbf{f}_i(\mathbf{x}) \right)^{\infty} \right)^{\frac{1}{\infty}} \propto \mathbf{c}$

Shades of Grey hypothesis : the n-Minkowsky norm based average of a scene is achromatic.

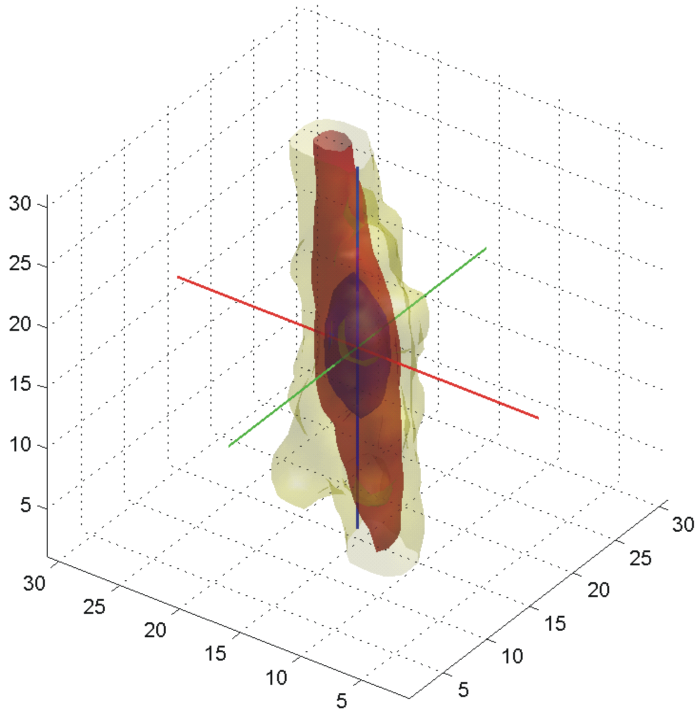
- unifies Grey-World and White Patch : $e^p \approx \sqrt[p]{\int \left| \mathbf{f}(\mathbf{x}) \right|^p d\mathbf{x}}$

Color Constancy

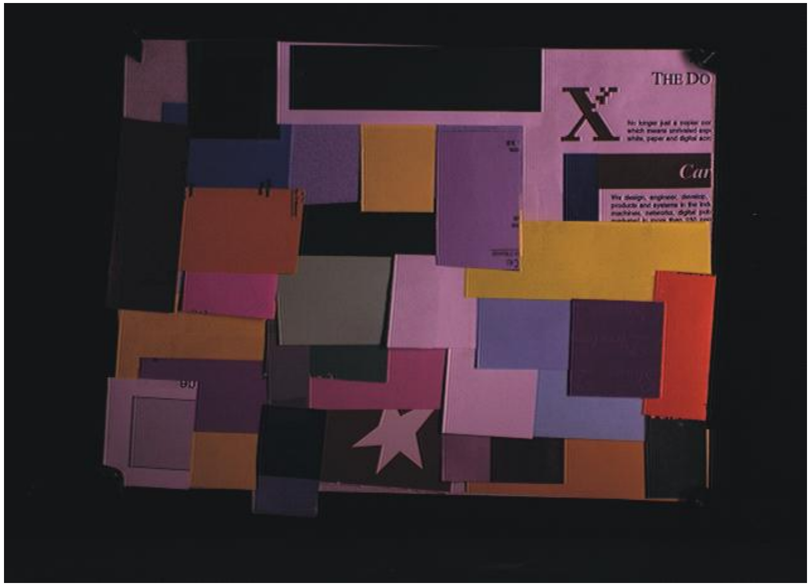


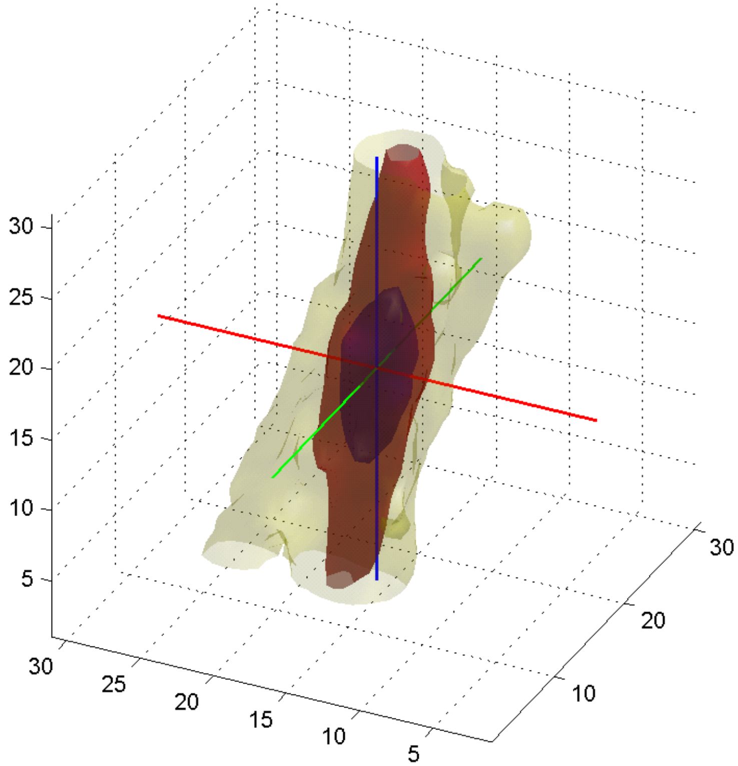


Color Constancy



Color Constancy





Color Constancy

color constancy : the ability to recognize colors of objects invariant of the color of the light source.

Grey world hypothesis : the average reflectance in a scene is grey.

White patch hypothesis: the highest value in the image is white.

generalization I: the L-norm:

$$\left(\sum_{m=1}^{M} \left(\mathbf{f}_i(\mathbf{x}) \right)^k \right)^{\frac{1}{k}} \propto \mathbf{c}$$

Grey edge hypothesis : the average edge in a scene is grey.

generalization II: L-norm + differentiation order:

$$\left(\sum_{i=1}^{M} \left| \frac{\partial^n \mathbf{f}_i(\mathbf{x})}{\partial \mathbf{x}^n} \right|^p \right)^{\frac{1}{p}} \propto \mathbf{c}$$

Color Constancy in 4 lines of matlab code !

```
Function Illuminant=GreyEdgeCC(im,mink,sigma,dif)

im  =  gauss_derivative(im,sigma,dif);
im  = reshape(im,size(im,1)*size(im,2),3);
Illuminant= 1./power( sum ( power( im, mink) ), 1/mink );
Illuminant = Illuminant./norm(Illuminant) ;
```

general color constancy framework

Low-level color constancy:

$$\left(\sum_{i=1}^{M} \left| \frac{\partial^n \mathbf{f}_i(\mathbf{x})}{\partial \mathbf{x}^n} \right|^p \right)^{\frac{1}{p}} \propto \mathbf{c}$$

$n=0,\ p=1$	$n=0,\ p=\infty$	$n=0,\ p=k$	$n=1,\ p=1$
$\sum_{m=1}^{M} \mathbf{f}_i(\mathbf{x}) \propto \mathbf{c}$	$\left(\sum_{m=1}^{M} (\mathbf{f}_i(\mathbf{x}))^{\infty} \right)^{\frac{1}{\infty}} \propto \mathbf{c}$	$\left(\sum_{m=1}^{M} (\mathbf{f}_i(\mathbf{x}))^{k} \right)^{\frac{1}{k}} \propto \mathbf{c}$	$\left(\sum_{m=1}^{M} \left| \frac{\partial \mathbf{f}_i(\mathbf{x})}{\partial \mathbf{x}} \right|^{p} \right)^{\frac{1}{p}} \propto \mathbf{c}$
grey-world	white-patch	shades-of-gray	grey-edge

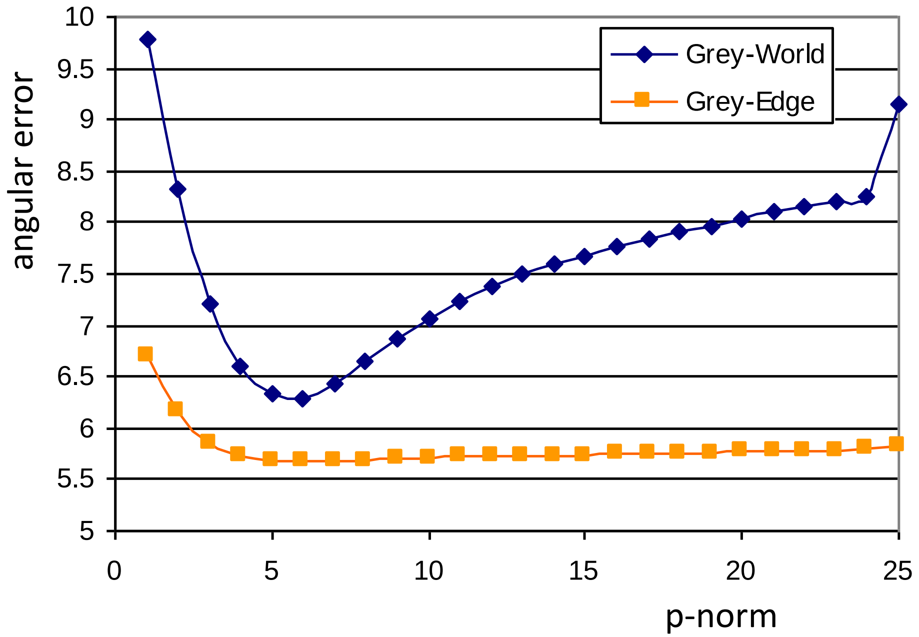
G. Finlayson, E. Trezzi, "Shades of gray and colour constancy", *CIC 2004*
J. van de Weijer, T. Gevers "Edge-Based Color Constancy", *IEEE IP 2007*

Color Constancy: experiment

- test set: 23 objects under 11 illuminants (Computational Vision Lab: Simon Fraser)

- $\text{angular error} = \cos(\hat{e} \cdot e)$

Color Constancy: experiment



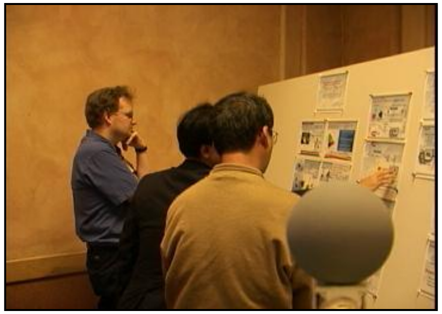
	error
Grey-World	9.8
White-Patch	9.2
General Grey-World	5.4
Grey-Edge	5.6
2nd order Grey-Edge	5,2
Color by Correlation	9,9
Gamut Mapping	5,6
GCIE, 11 Lights	4,9
GCIE, 87 Lights	5,3

Color Constancy: experiment

• real-world data set (F. Ciurea and B. Funt : Vision Lab - Simon Fraser)







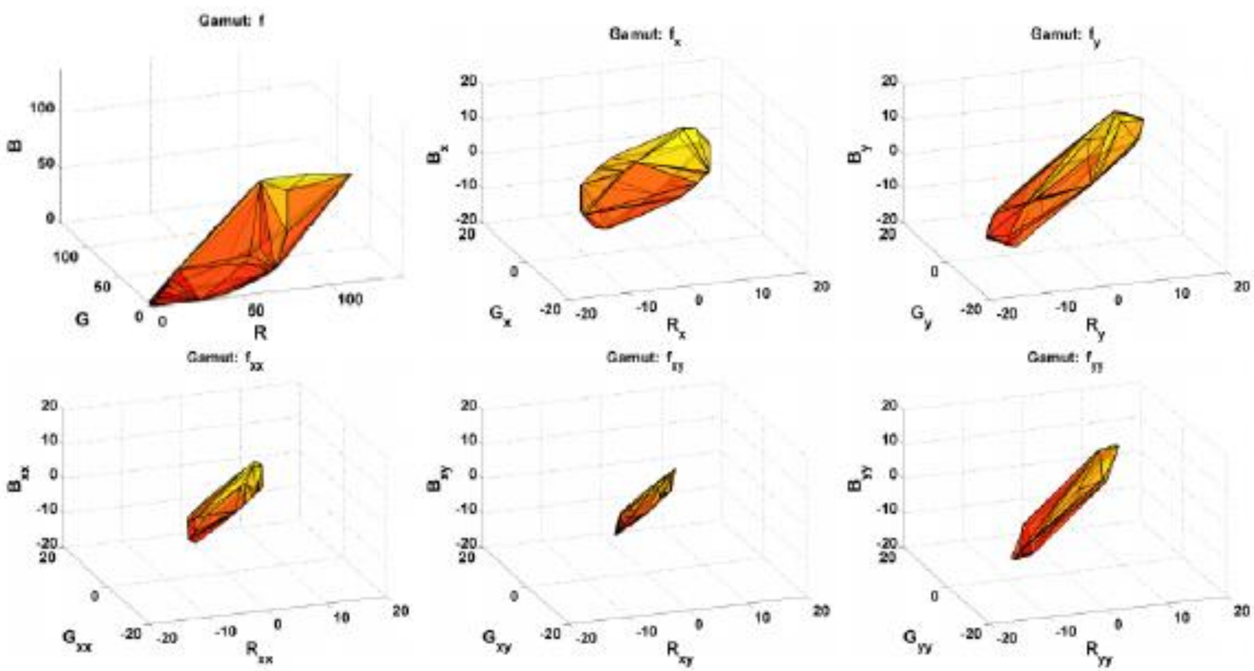
Color Constancy: experiment

• real-world data set (F. Ciurea and B. Funt : Vision Lab - Simon Fraser)

	median
Grey-World	7.3
White-Patch	6.7
General Grey-World	4.7
Grey-Edge	4.1
2nd order Grey-Edge	4.3

derivative-based gamut mapping

"In real-world images, for a given illuminant, one observes only a limited number of different colored edges."

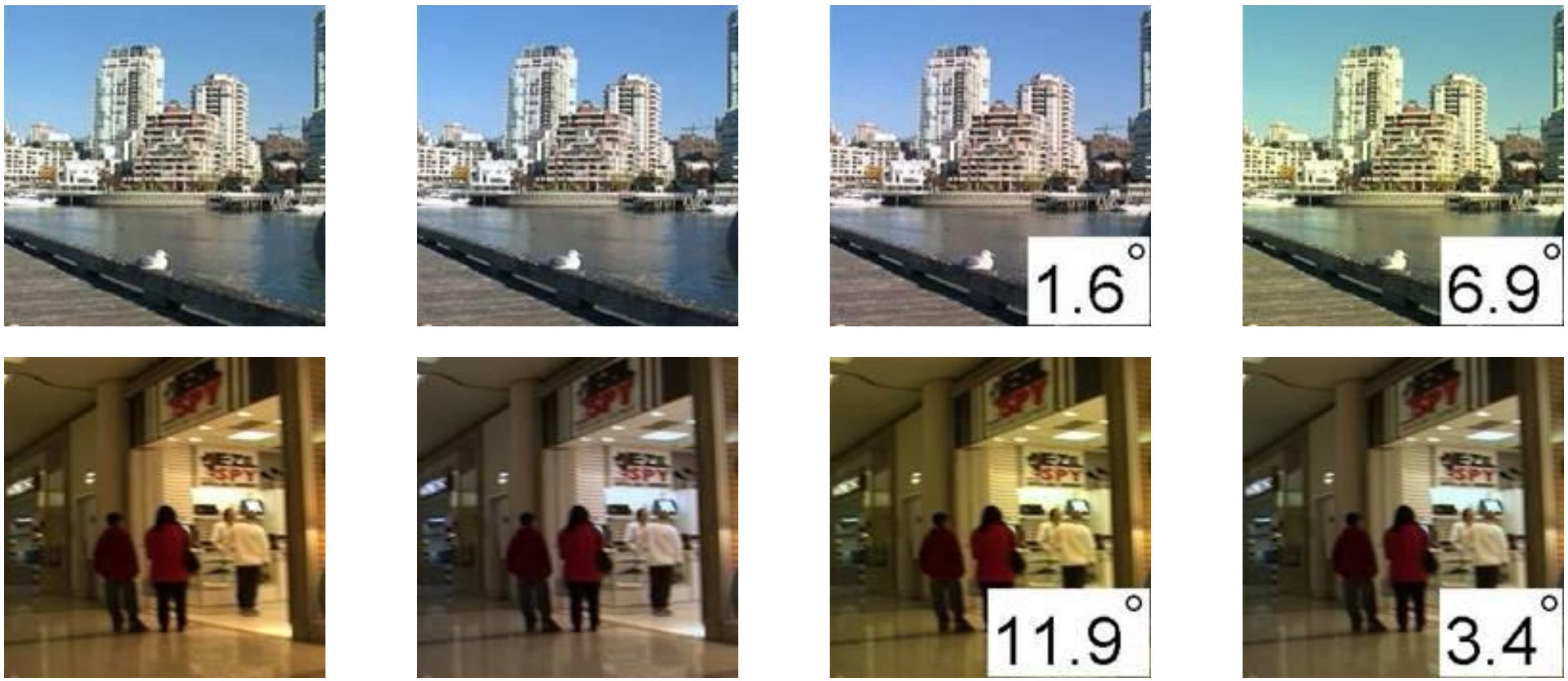


A. Gijsenij, T. Gevers, J. van de Weijer, "Generalized Gamut Mapping using Image Derivative Structures for Color Constancy ", *IJCV 2010*

Experiments (real-world images)

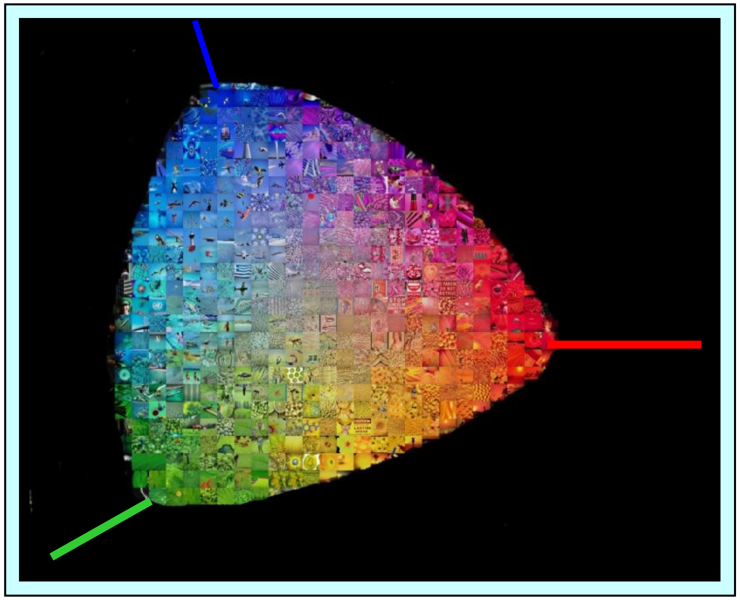
Some examples:

Original	Ideal	Derivative-based	Regular Gamut



How do you choose the best cc-algorithm ?

High-Level Color Constancy



Natural Image Statistics

- Could it be that different scenes prefer different color constancy methods ?

Geusebroek and Smeulders (2005) – Weibulls

Examples:

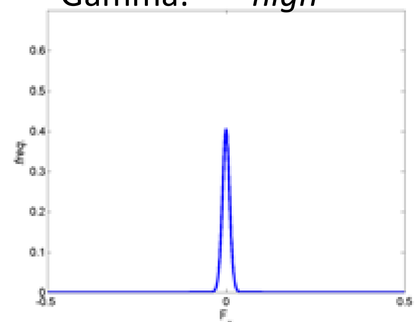
Natural Image Statistics

Distribution of edge responses follows Weibull distribution.

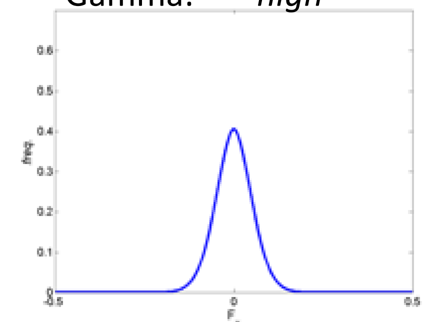
Two parameters:

- β – Contrast of the image. A higher value indicates more contrast.
- γ - Grain size. A higher value indicates more fine textures.

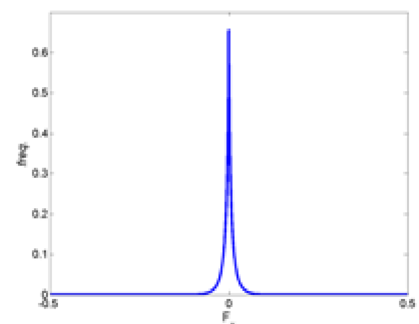
Beta: *low*
Gamma: *high*



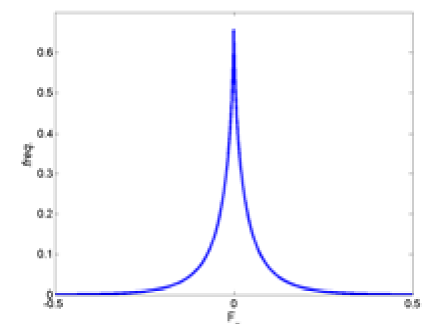
Beta: *high*
Gamma: *high*



Beta: *low*
Gamma: *low*



Beta: *high*
Gamma: *low*



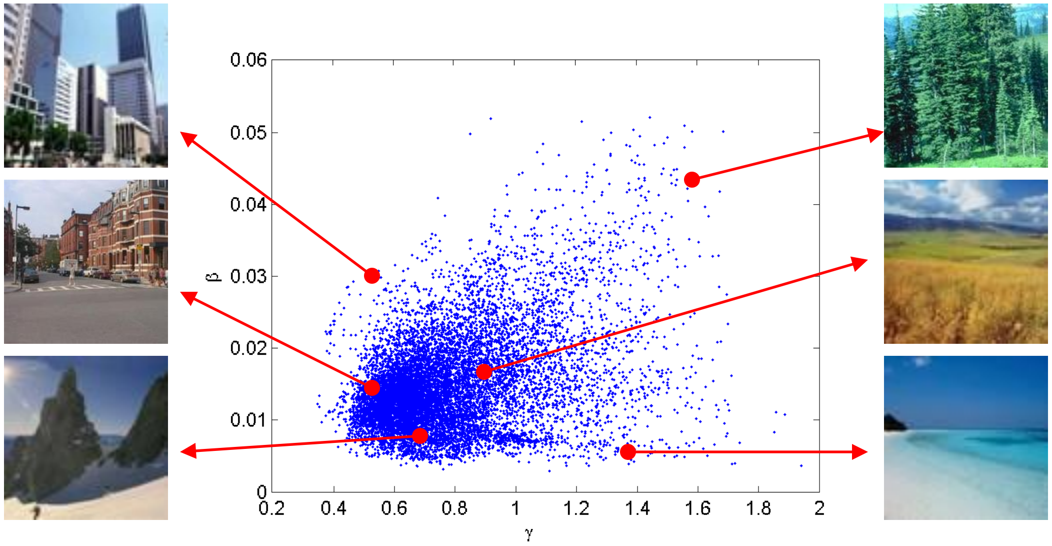
slide credit: Arjan Gijsenij

Color Constancy – Selection

Postsupervised Prototype

Classification:

Compute Weibull-parameters for all images



slide credit: Arjan Gijsenij

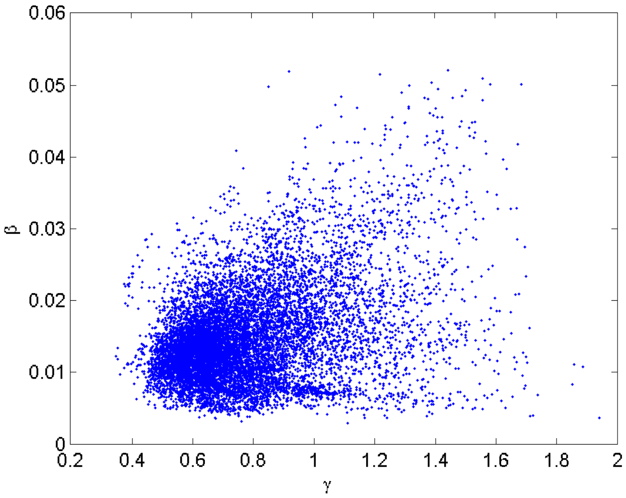
Color Constancy – Selection

Postsupervised Prototype

Classification:

Compute Weibull-parameters for
all images

Partition weibull-parameters using
k-means



slide credit: Arjan Gijsenij

Color Constancy – Selection

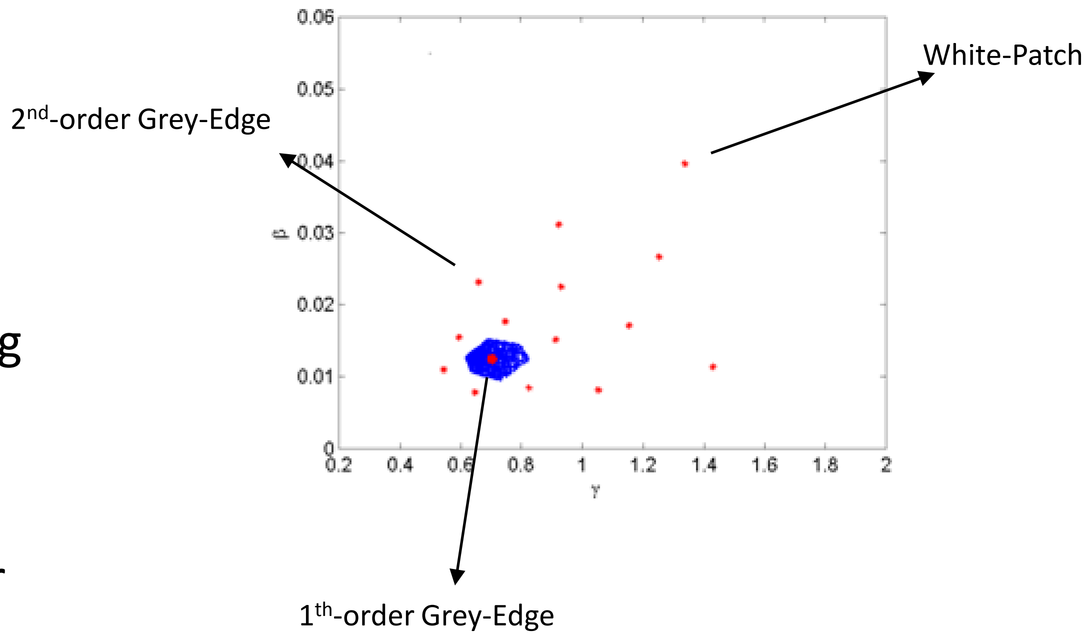
Postsupervised Prototype

Classification :

Compute Weibull-parameters for all images

Partition weibull-parameters using *k*-means

Label cluster centers according to the minimum mean angular error



slide credit: Arjan Gijsenij

Color Constancy – Selection

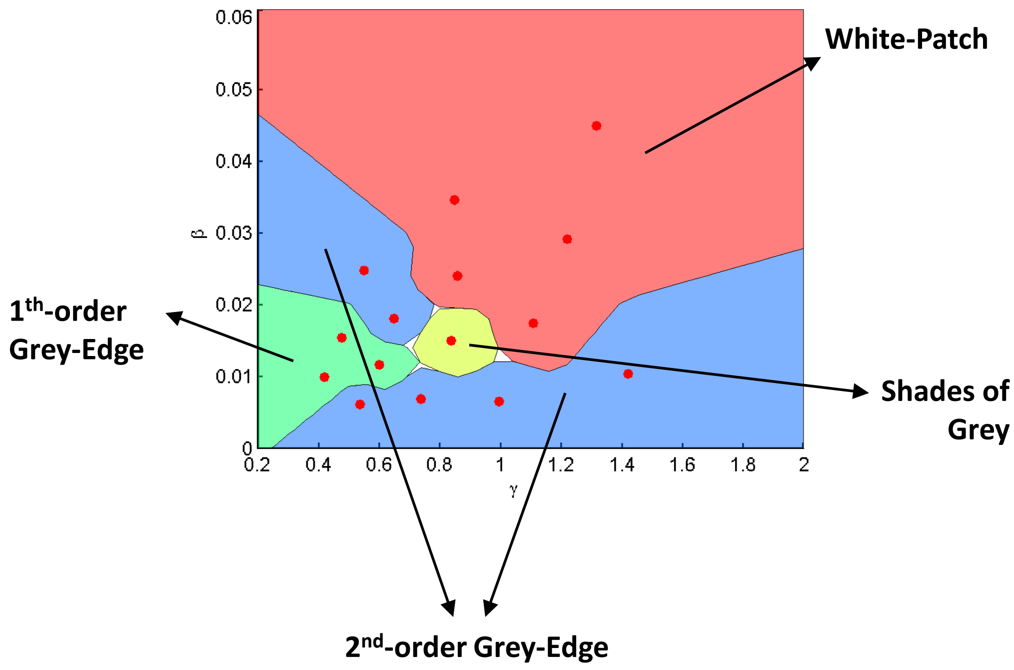
Postsupervised Prototype Classification :

Compute Weibull-parameters for all images

Partition weibull-parameters using *k*-means

Label cluster centers according to the minimum mean angular error

Build 1-NN Classifier on these cluster centers



slide credit: Arjan Gijsenij

Experiments

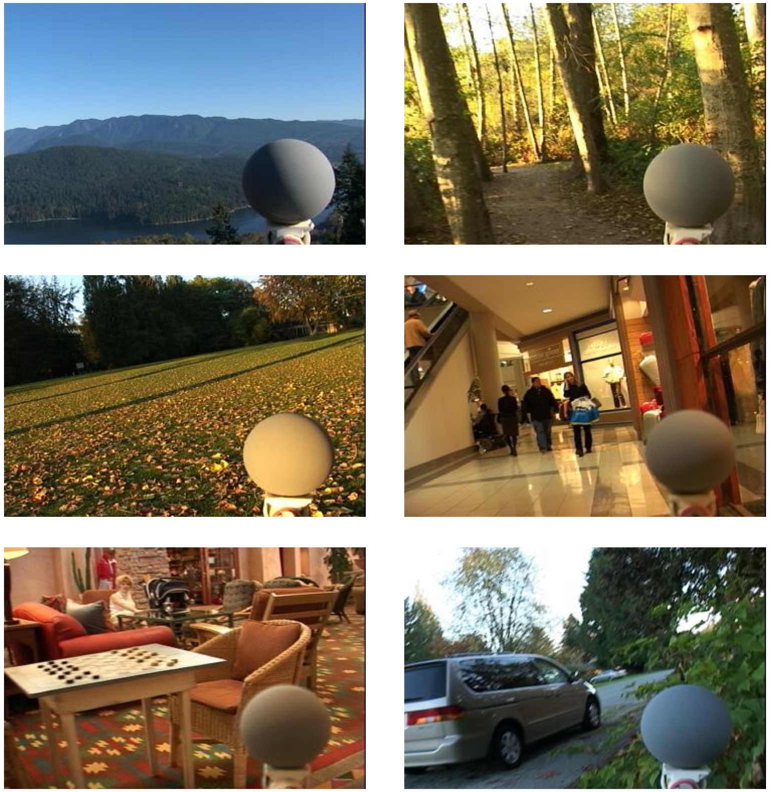
Data set consisting of 11000+ images

The *true* illuminants are known (ground truth)

Grey sphere is *masked during experiments*

Performance measure → **angular error:**

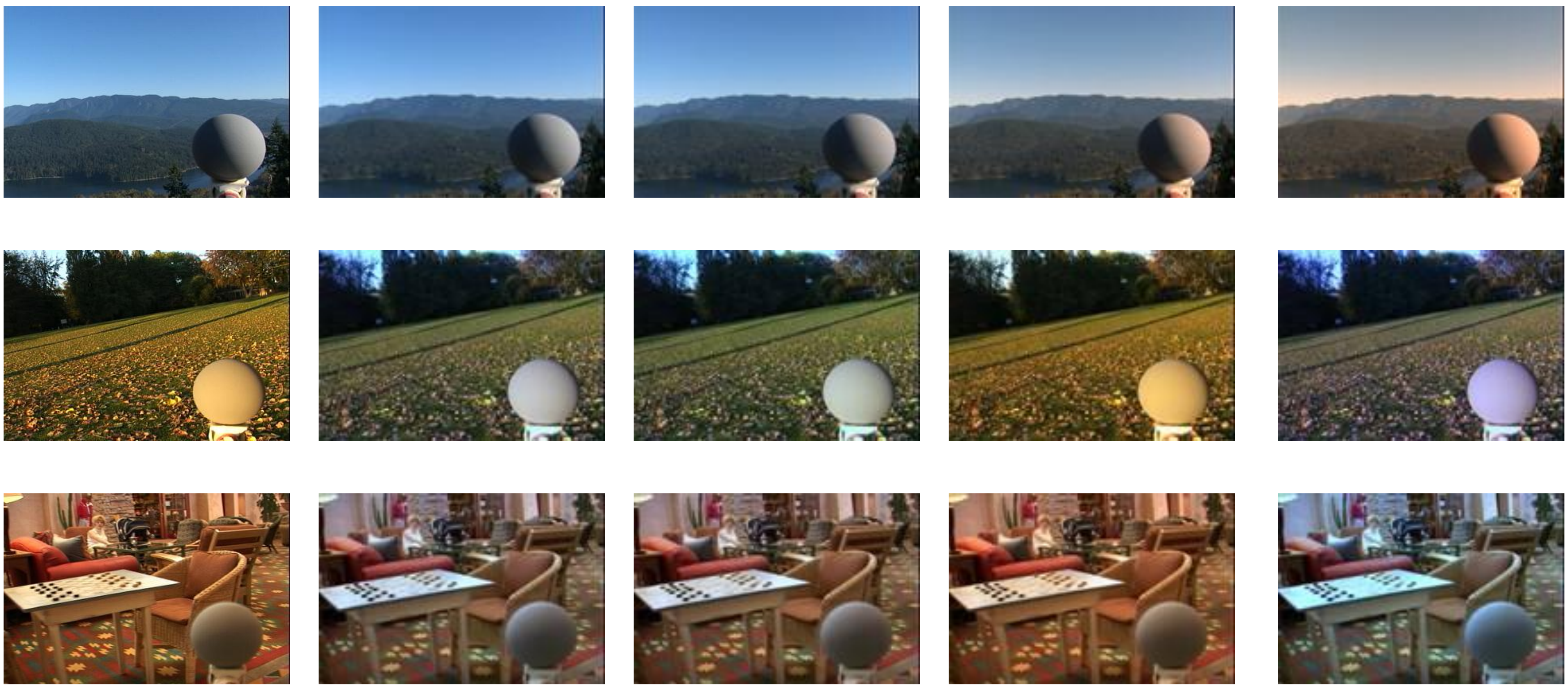
$$\cos^{-1}(\hat{\mathbf{e}}_l \cdot \hat{\mathbf{e}}_e)$$



slide credit: Arjan Gijsenij

Experiments – Results

Original	Ideal	Selection	White-Patch	Grey-World



slide credit: Arjan Gijsenij

Experiments – Performance

Method	Mean	Median
Grey-World	7.9^o	7.0^o
White-Patch	6.8^o	5.3^o
General Grey-World	6.2^o	5.3^o
1^{th}-Order Grey-Edge	6.2^o	5.2^o
2^{nd}-Order Grey-Edge	**6.1^o**	**5.2^o**
Gamut mapping	8.5^o	6.8^o
Color-by-Correlation	6.4^o	5.2^o

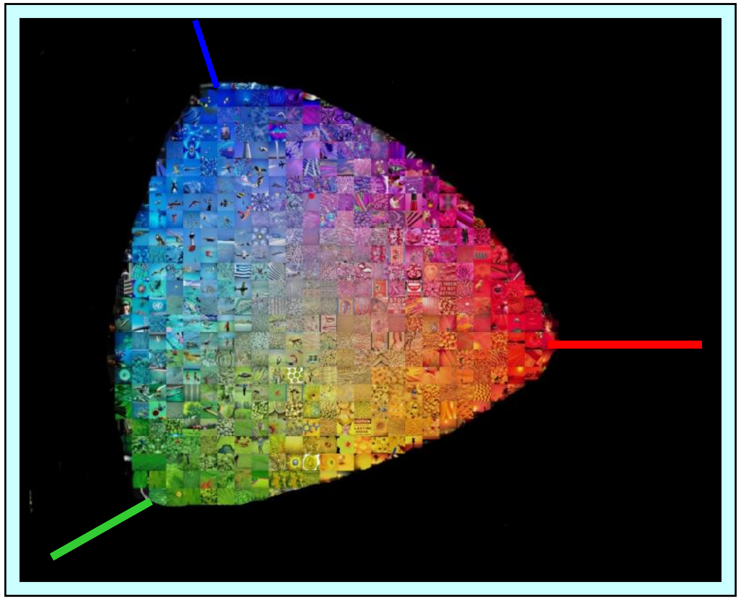
slide credit: Arjan Gijsenij

Experiments – Performance

Method	Mean	Median
2nd-Order Grey-Edge (baseline)	6.1^{o}	5.2^{o}
Selection – 5 methods	5.7^{o} (-7%)	4.7^{o} (-10%)
Combining – 5 methods	5.6^{o} (-8%)	4.6^{o} (-12%)
Combining – 75 methods	**5.0^{o}(-18%)**	**3.7^{o} (-29%)**

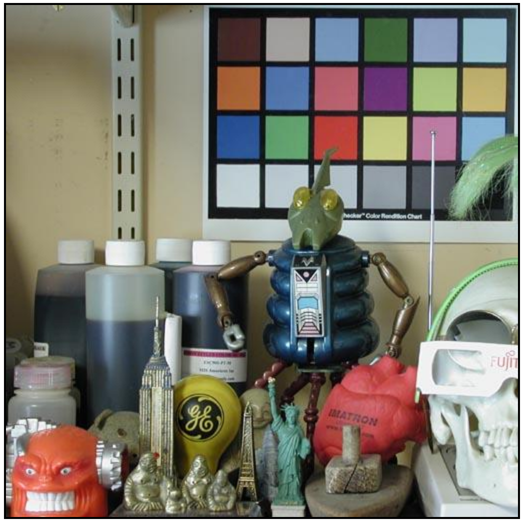
slide credit: Arjan Gijsenij

Color Constancy from High-Level Visual Information



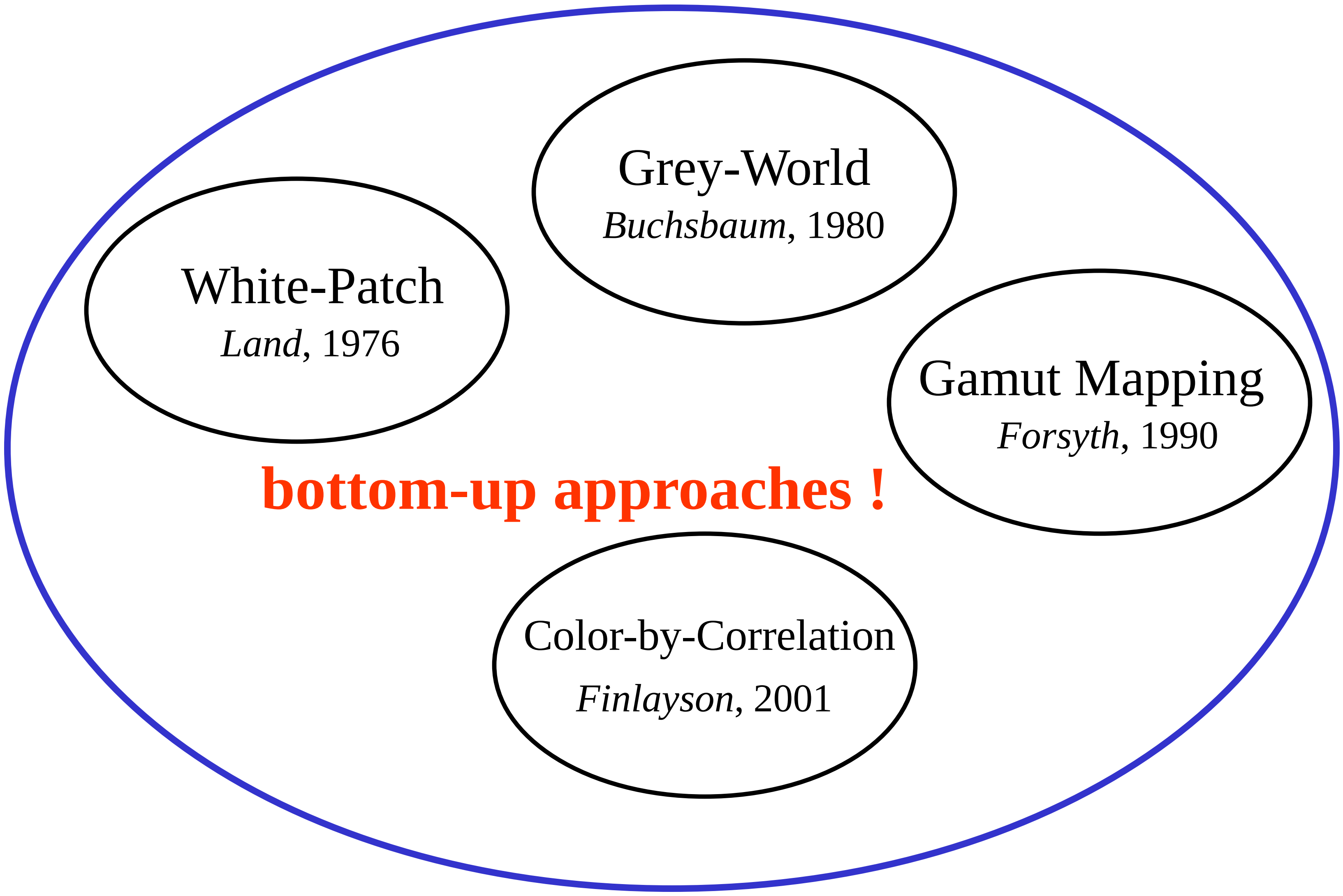
problem statement

How do we recognize colors to be the same under varying light sources ?



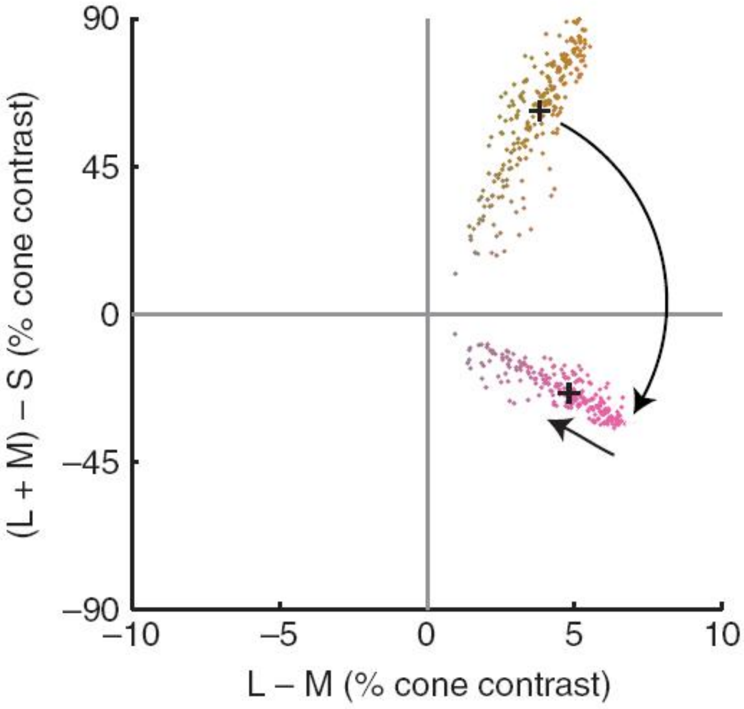
color constancy : the ability to recognize colors of objects invariant of the color of the light source.

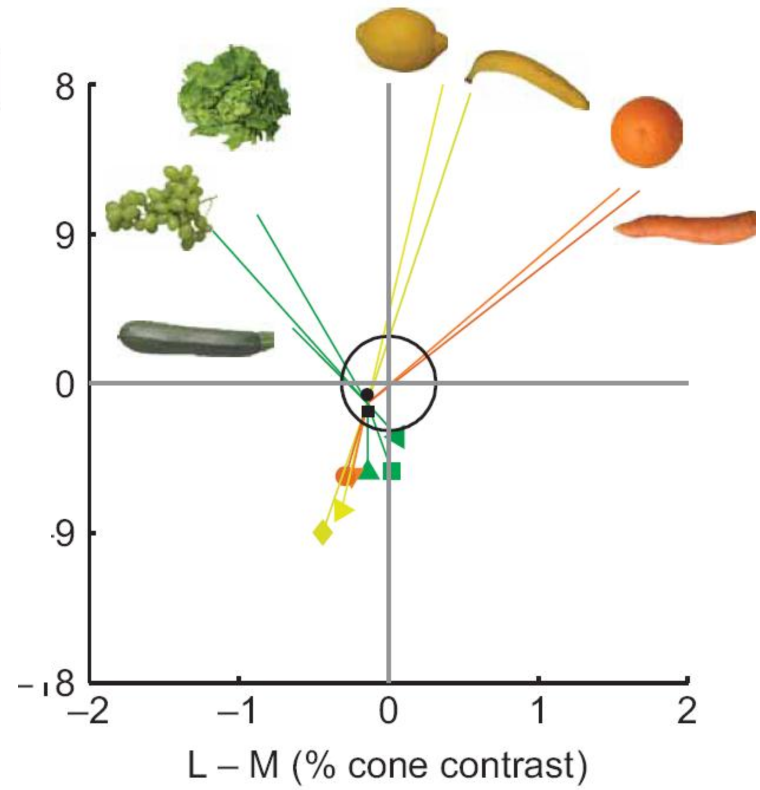
computational color constancy



top-down color constancy

psychophysical motivation:

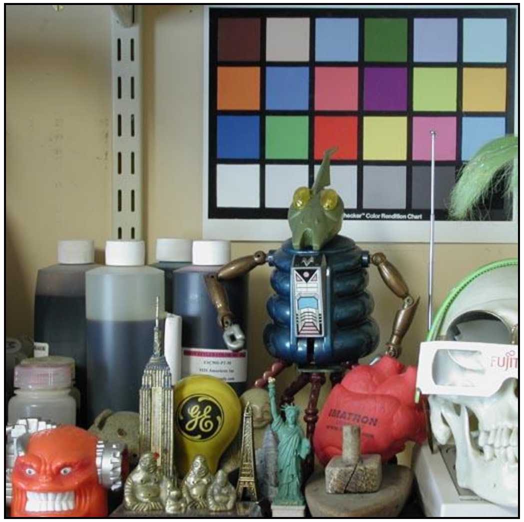




Hansen et al. "Memory modulates color appearance", *nature neuroscience*, 2006.

problem statement

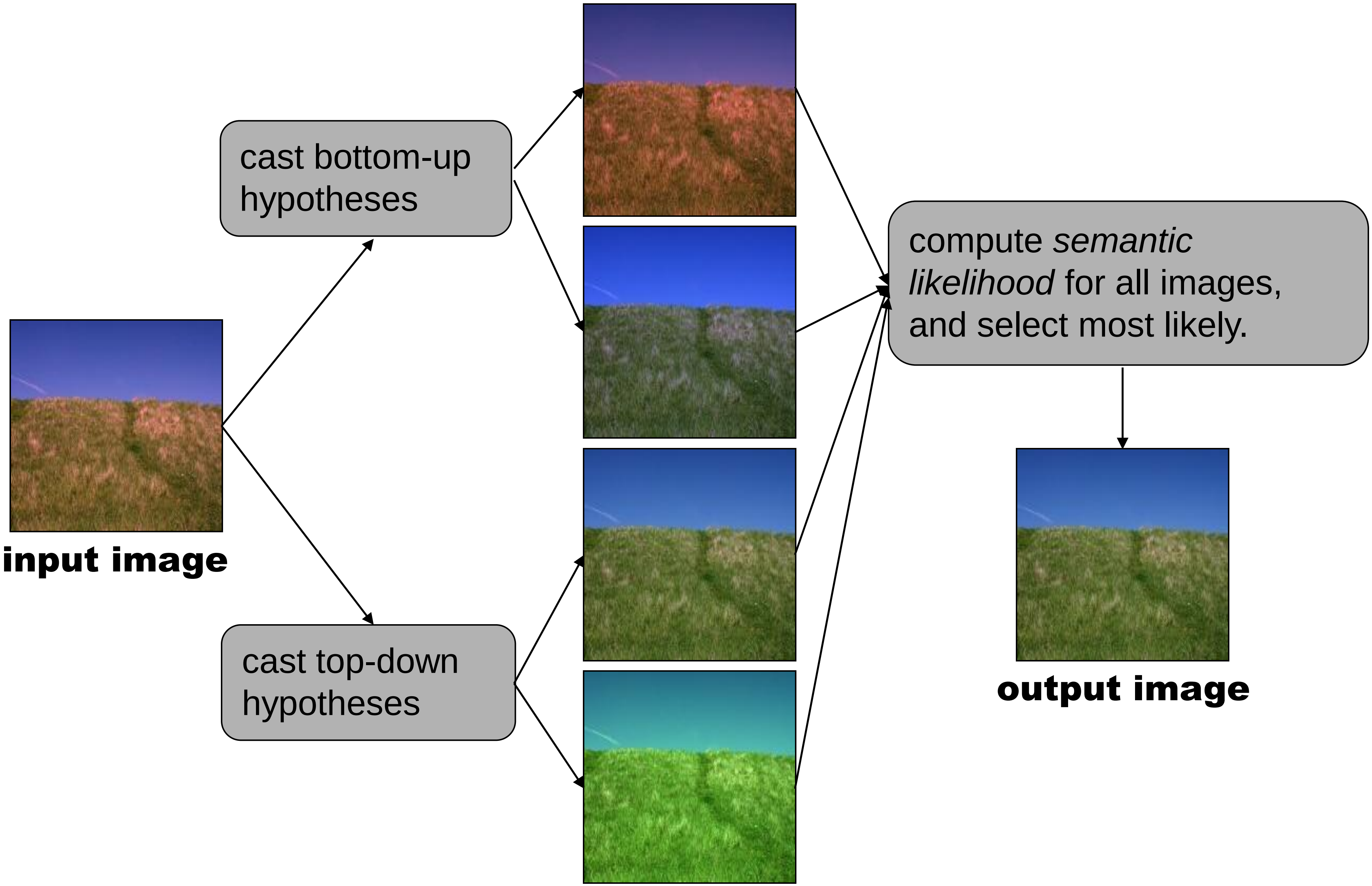
How do we recognize colors to be the same under varying light sources ?



color constancy : the ability to recognize colors of objects invariant of the color of the light source.

How can we apply high-level visual information for computational color constancy ?

overview our approach



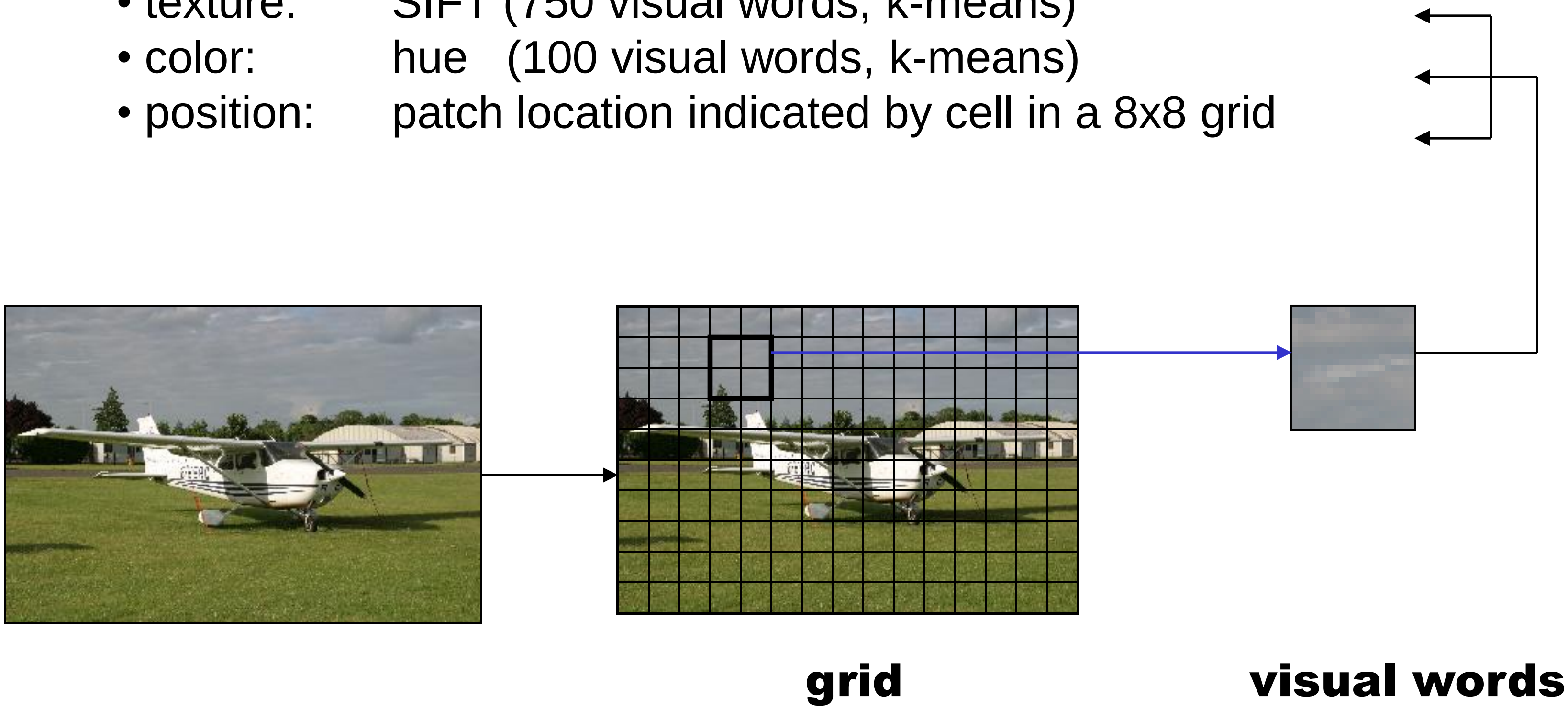
plsa-based image segmentation

- We use Probabilistic Latent Semantic Analysis (pLSA) to compute the semantic likelihood of an image.

Image representation

- dense extraction of 20x20 pixel patches on 10x10 pixel grid

- each patch described by discretized features, the words .
  - texture: SIFT (750 visual words, k-means)
  - color: hue (100 visual words, k-means)
  - position: patch location indicated by cell in a 8x8 grid



plsa-based image segmentation

- We use Probabilistic Latent Semantic Analysis (pLSA) to compute the semantic likelihood of an image.

An image is modeled as a mixture of semantic topics:

$$p(w|d) = \sum_{z} p(w|z)\, p(z|d)$$

image-specific mixture proportions

visual word **image** **semantic topics**

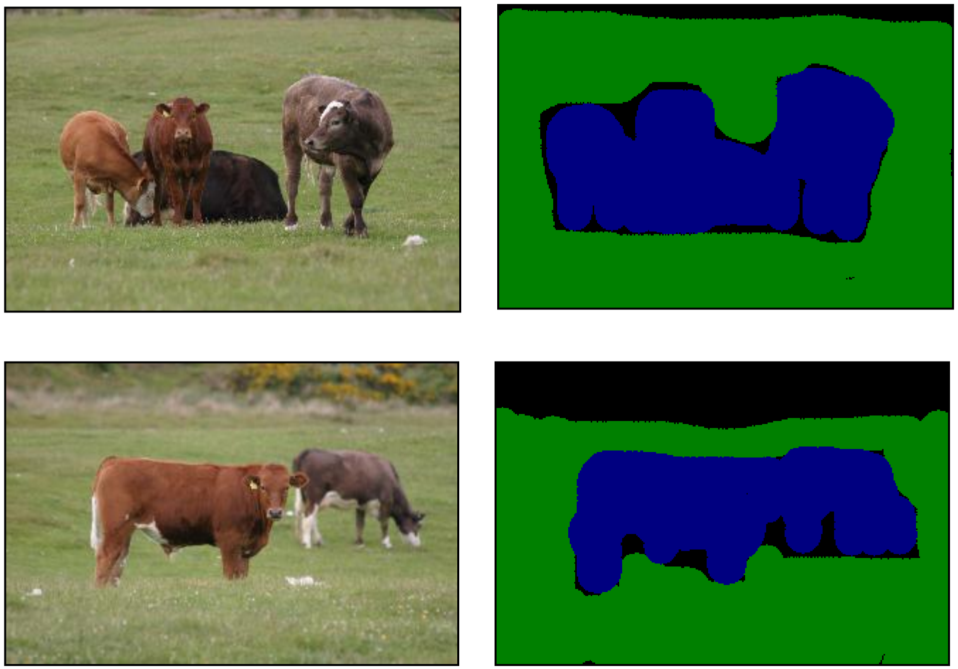
$$p(w|z) = \prod_{m=1}^{M} p(w^m|z)$$

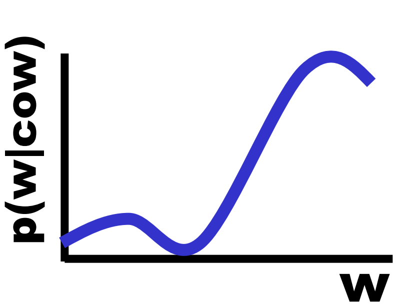
The $p(w^m|z)$ can either be learned supervised or unsupervised.
We assume them to be learned from images taken under a white illuminant.

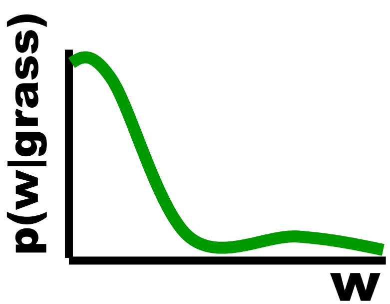
likelihood image $p(d) = \prod_{w} p(w|d)$

plsa-based image segmentation

supervised learning

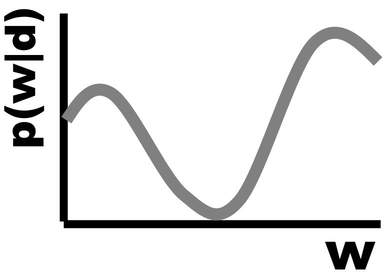






p(w|z)

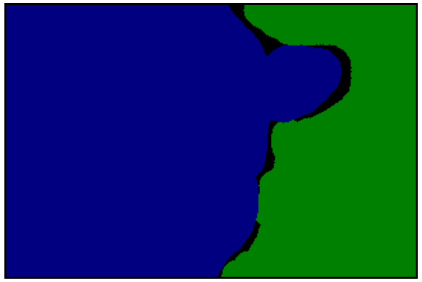
test image



$$p(w|d) = \sum_z p(w|z)\, p(z|d)$$

unknown

using EM: p(z|d)={0.6,0.4}

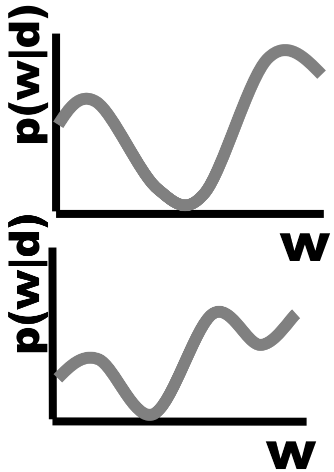


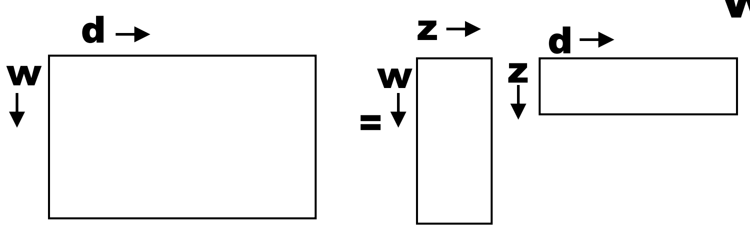
semantic image segmentation

plsa-based image segmentation

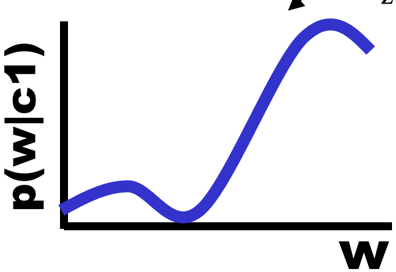
unsupervised learning

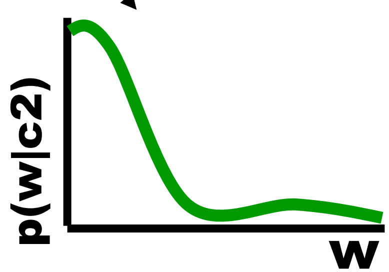






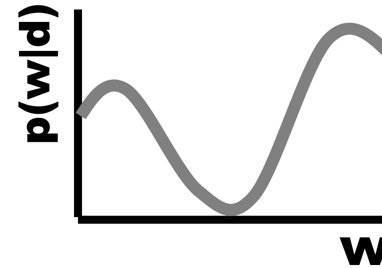
$$p\left(w|d\right)=\sum_{z}p\left(w|z\right)p\left(z|d\right)$$





p(w|z)

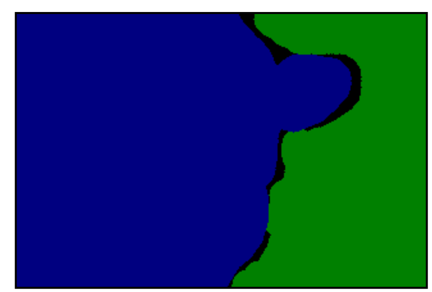
test image

$$p\left(w|d\right)=\sum_{z}p\left(w|z\right)p\left(z|d\right)$$

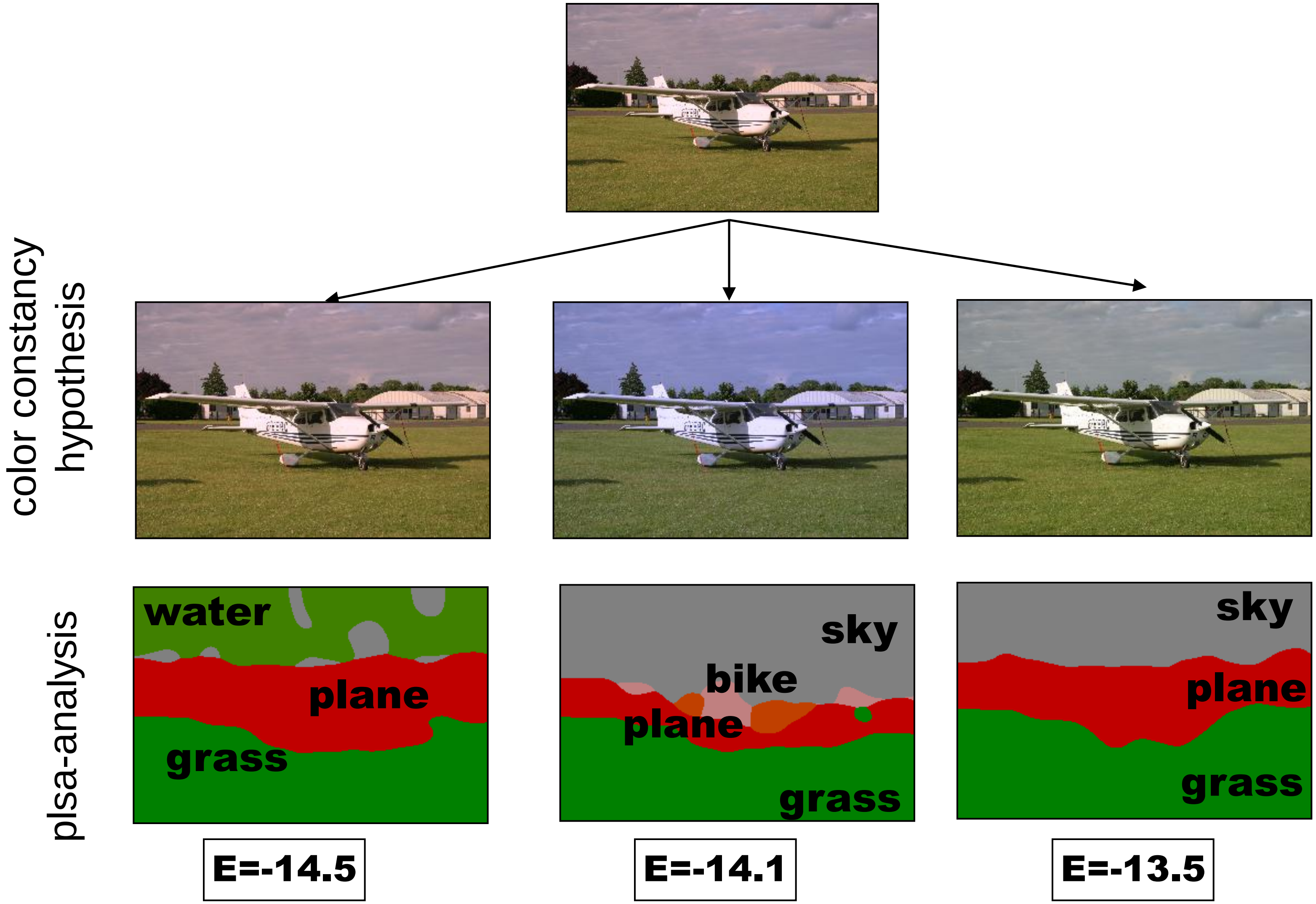
unknown

using EM: p(z|d)={0.6.0.4}



semantic image segmentation

semantic likelihood image



casting hypotheses: bottom-up

Low-level color constancy:

$$\left(\sum_{i=1}^{M} \left| \frac{\partial^n \mathbf{f}_i(\mathbf{x})}{\partial \mathbf{x}^n} \right|^p \right)^{\frac{1}{p}} \propto \mathbf{c}$$

$n=0,\ p=1$

$$\sum_{m=1}^{M} \mathbf{f}_i(\mathbf{x}) \propto \mathbf{c}$$

grey-world

white-patch

shades-of-gray

$n=1,\ p=1$

$$\left(\sum_{m=1}^{M} \left| \frac{\partial \mathbf{f}_i(\mathbf{x})}{\partial \mathbf{x}} \right|^p \right)^{\frac{1}{p}} \propto \mathbf{c}$$

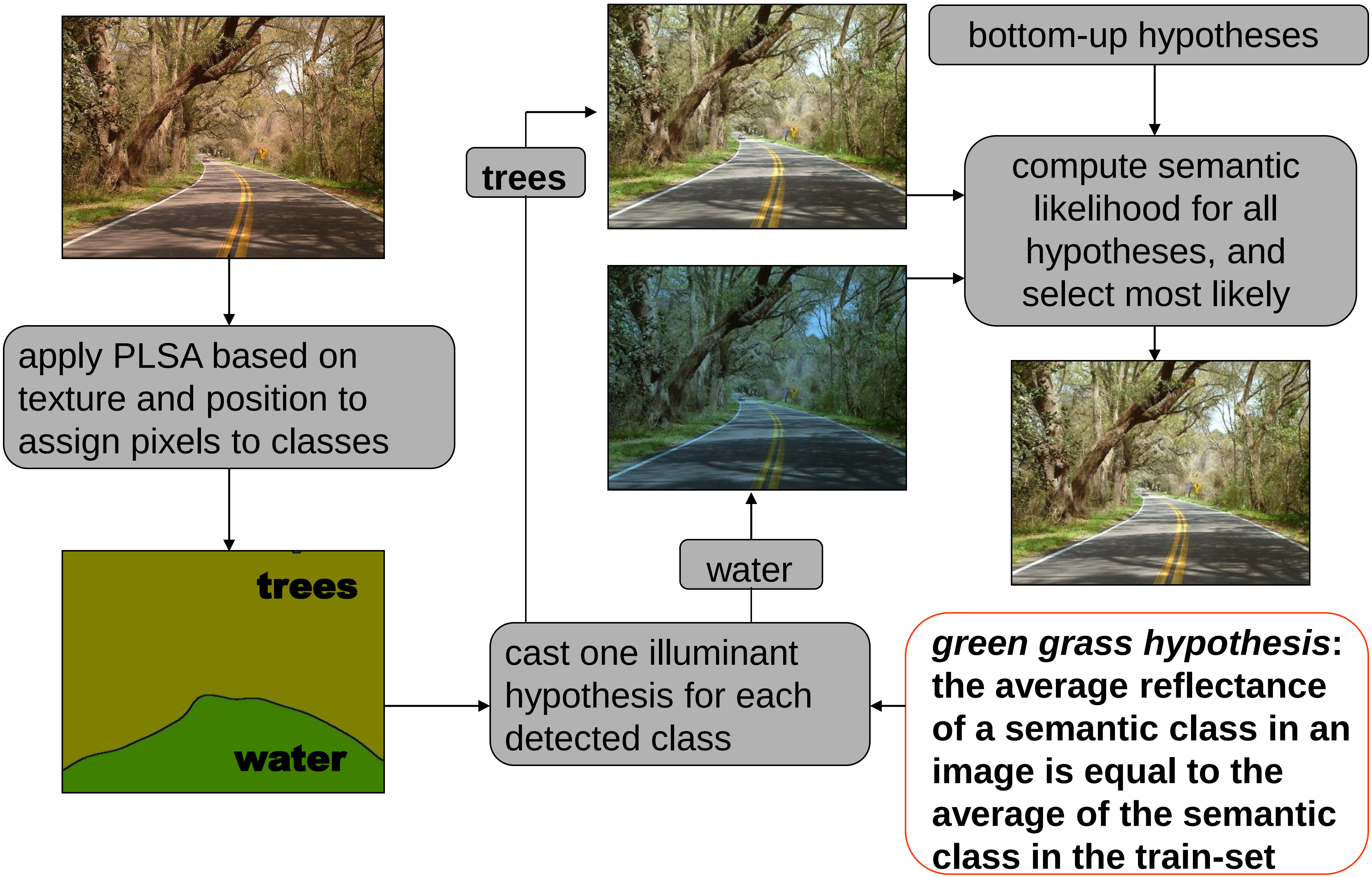
grey-edge

We will use n={0,1,2} and p={2,12} to cast a total of 6 bottom-up hypotheses.

G. Finlayson, E. Trezzi, "Shades of gray and colour constancy", ***CIC 2004***

J. van de Weijer, T. Gevers "Edge-Based Color Constancy", ***IEEE TIP 2007***

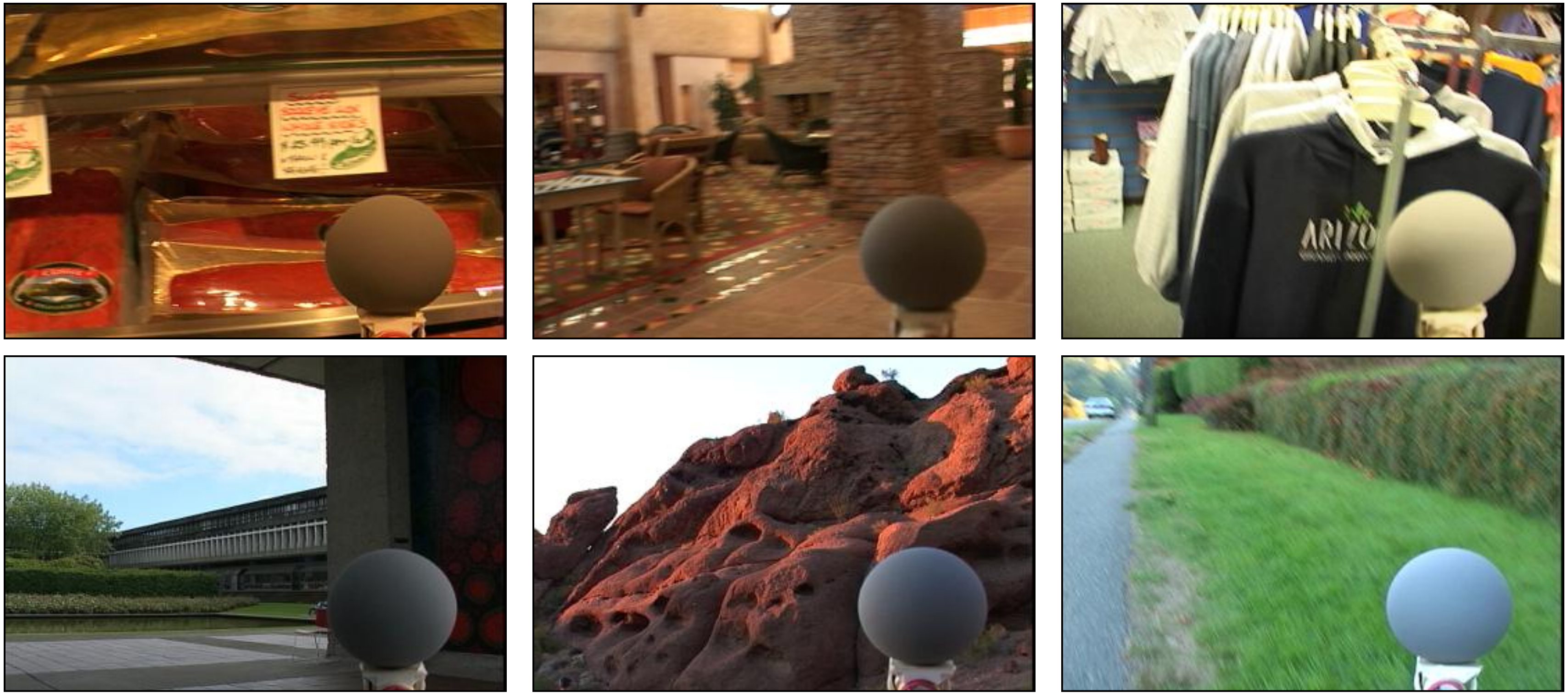
casting hypotheses: top-down



experiment: illuminant estimation

Data Set contains both indoor and outdoor scenes from a wide variety of locations (150 training, 150 testing)

Topic-word distributions are learned unsupervised on the texture and position cue (color is ignored in training).

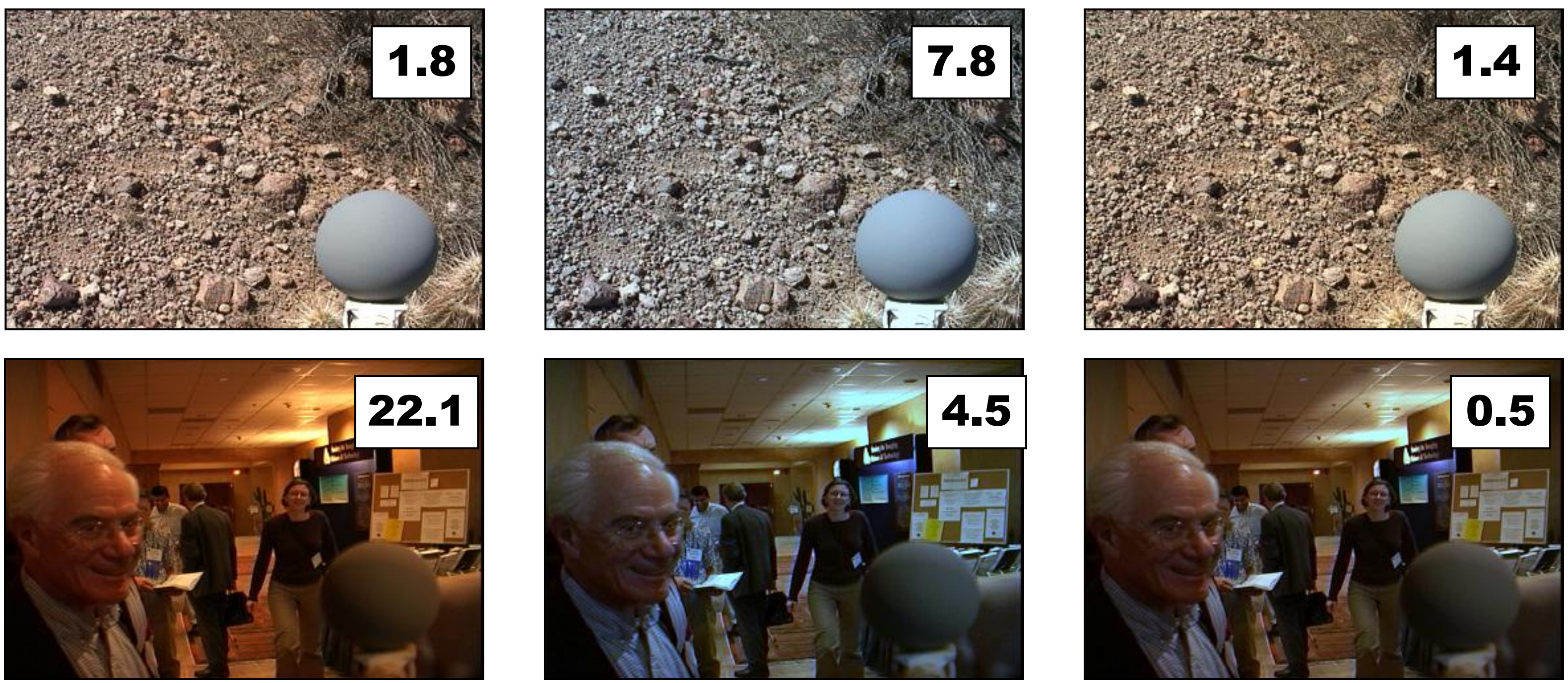


F. Ciurea and B. Funt “A large database for color constancy research”, ***CIC 2004.***

experiment: illuminant estimation

results in angular error:

		standard color constancy		high-level selection		
	no cc	worst BU	best BU	BU	TD	BU & TD
indoor	12.8	12.3	6.1	5.3	5.6	5.3
outdoor	5.5	7.4	4.9	4.7	4.7	4.5



input image bottom-up top-down

experiment: semantic segmentation

Data Set training: labelled images of Microsoft Research Cambridge (MSRC) set, together with ten images collected from Google Image for each class. Traning: 350 images. Test : 36 images.

Topic-word distributions are learned supervised.

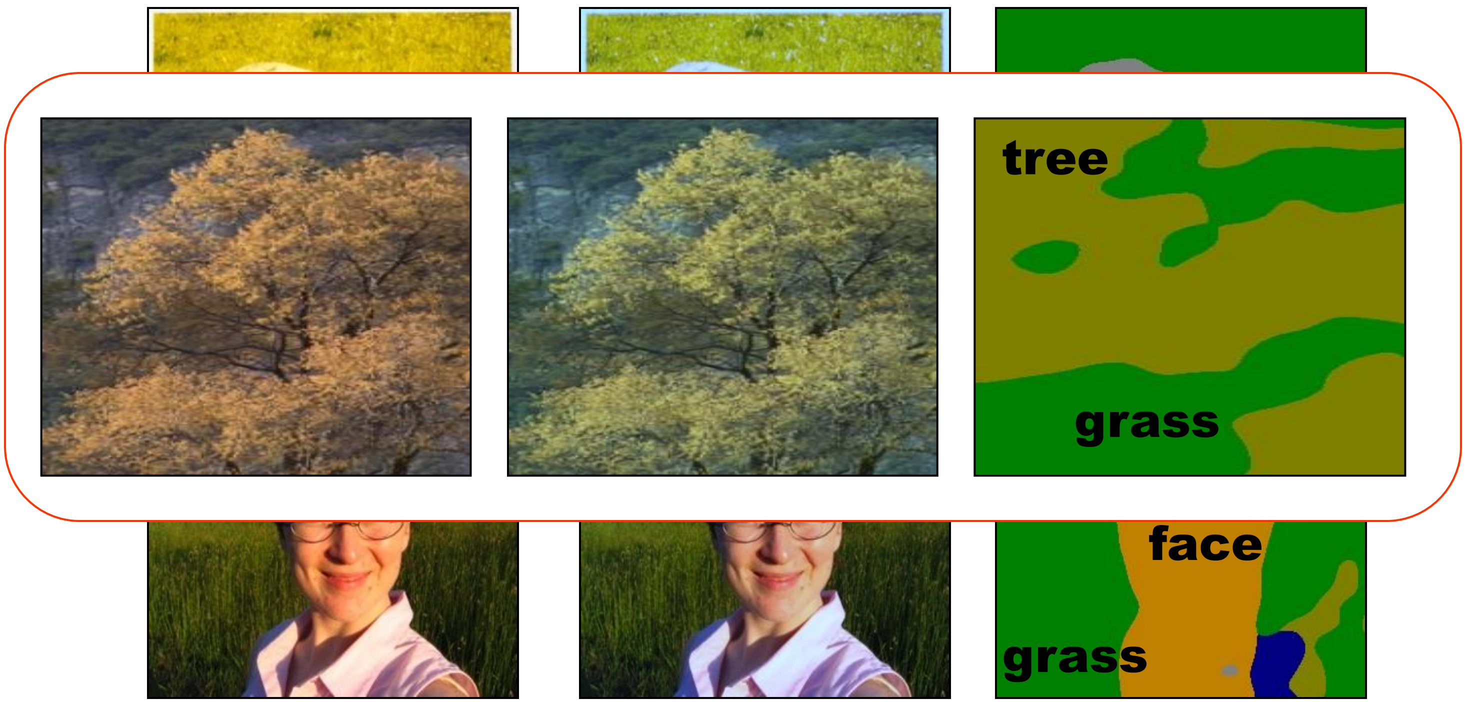
Classes: building, grass, tree, cow, sheep, sky, water, face and road.

J. Shotton et al. "Textonboost", ***ECCV 2006.***

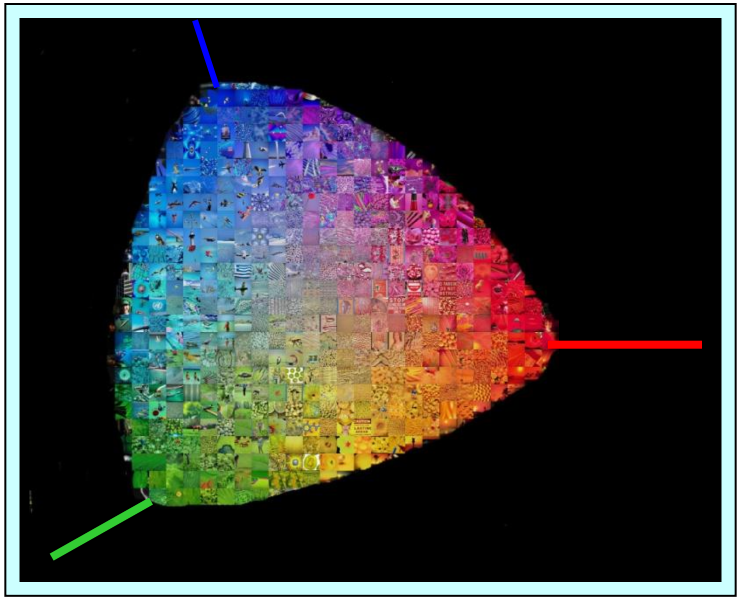
experiment: pixel classification

results pixel classification in %:

	standard color constancy		high-level selection		
no cc	worst BU	best BU	BU	TD	BU & TD
39.6	41.4	52.2	53.4	59.5	64.2

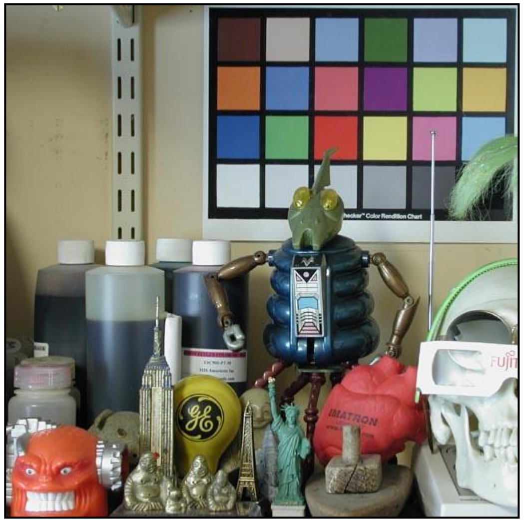


Blur Robust and Color Constant Image description

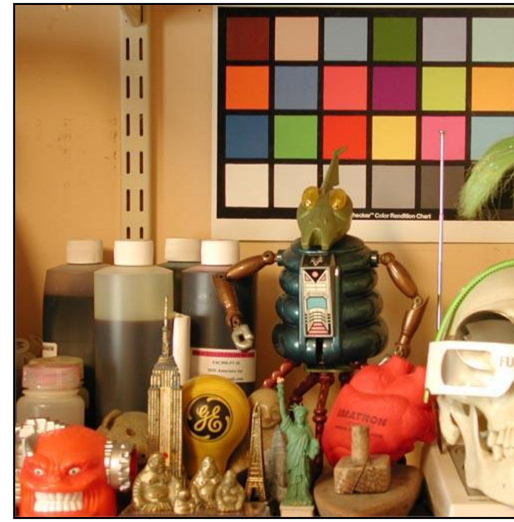


problem statement

How do we recognize colors to be the same under varying light sources ?



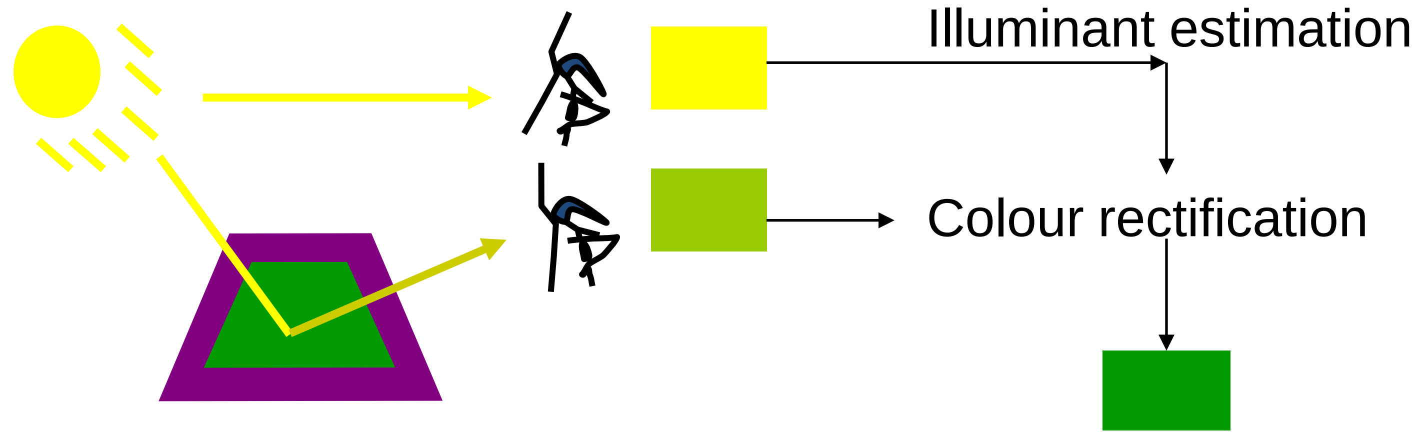
$$\begin{pmatrix} R' \\ G' \\ B' \end{pmatrix} = \begin{pmatrix} \alpha & 0 & 0 \\ 0 & \beta & 0 \\ 0 & 0 & \gamma \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$



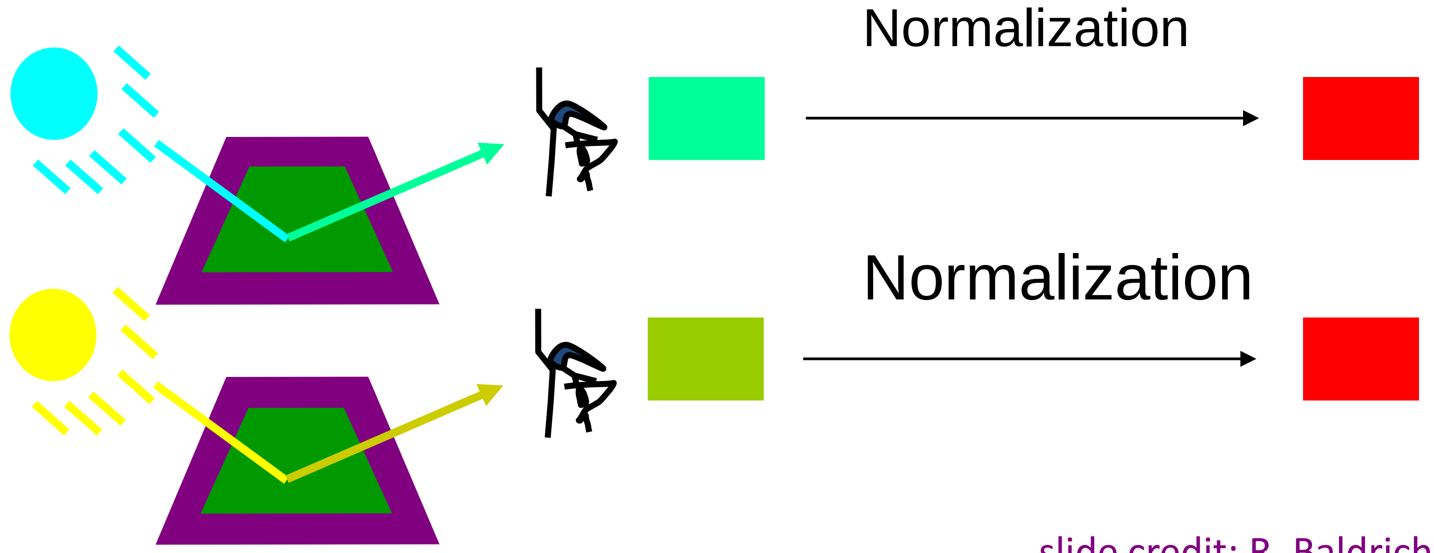
color constancy : the ability to recognize colors of objects invariant of the color of the light source.

Change of illuminant can be modeled by the *diagonal model*.

Colour constancy algorithms



Invariant Normalizations



slide credit: R. Baldrich

Color Constant Derivatives

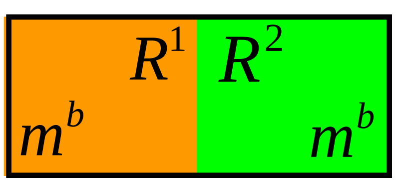
- A color constant representation of a single color patch is impossible.
- The difference between two color patches can be represented invariant to the color illuminant.

Funt and Finlayson:

Mondrian-world: $\mathbf{f}(\mathbf{x}) = m^b \mathbf{c}^b(\mathbf{x})\mathbf{e}$

$$p = \frac{R^1}{R^2} = \frac{m^b {c_1}^R e^R}{m^b {c_2}^R e^R} = \frac{{c_1}^R}{{c_2}^R}$$

$$\ln p = \ln \frac{R^1}{R^2} = \ln R^1 - \ln R^2 = \tfrac{\partial}{\partial x} \ln R$$

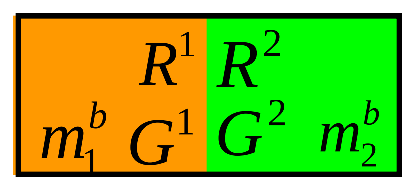


Gevers and Smeulders:

3D-world: $\mathbf{f}(\mathbf{x}) = m^b(\mathbf{x})\mathbf{c}^b(\mathbf{x})\mathbf{e}$

$$m = \frac{R^1 G^2}{R^2 G^1} = \frac{{m_1}^b {c_1}^R e^R}{{m_2}^b {c_2}^R e^R} \frac{{m_2}^b {c_2}^G e^G}{{m_1}^b {c_1}^G e^G} = \frac{{c_1}^R {c_2}^G}{{c_2}^R {c_1}^G}$$

$$\ln m = \ln \frac{R^1 G^2}{R^2 G^1} = \ln \frac{R^1}{G^1} - \ln \frac{R^2}{G^2} = \tfrac{\partial}{\partial x} \ln \frac{R}{G}$$



Color Constant Derivatives

- A color constant representation of a single color patch is impossible.
- The difference between two color patches can be represented invariant to the color illuminant.

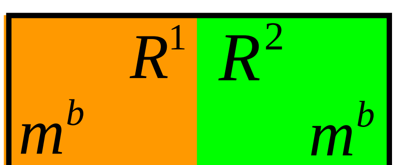
Monc

These theories overlook the fact that an edge operator measures two properties of the edge:

1. the color difference
2. the steepness of the edge

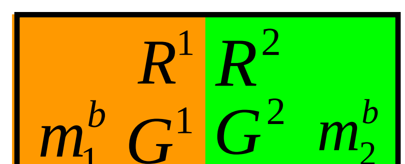
$$p = \frac{R^1}{R^2} = \frac{m^b c_1{}^R e^R}{m^b c_2{}^R e^R} = \frac{c_1{}^R}{c_2{}^R}$$

$$\ln p = \ln \frac{R^1}{R^2} = \ln R^1 - \ln R^2 = \tfrac{\partial}{\partial x} \ln R$$



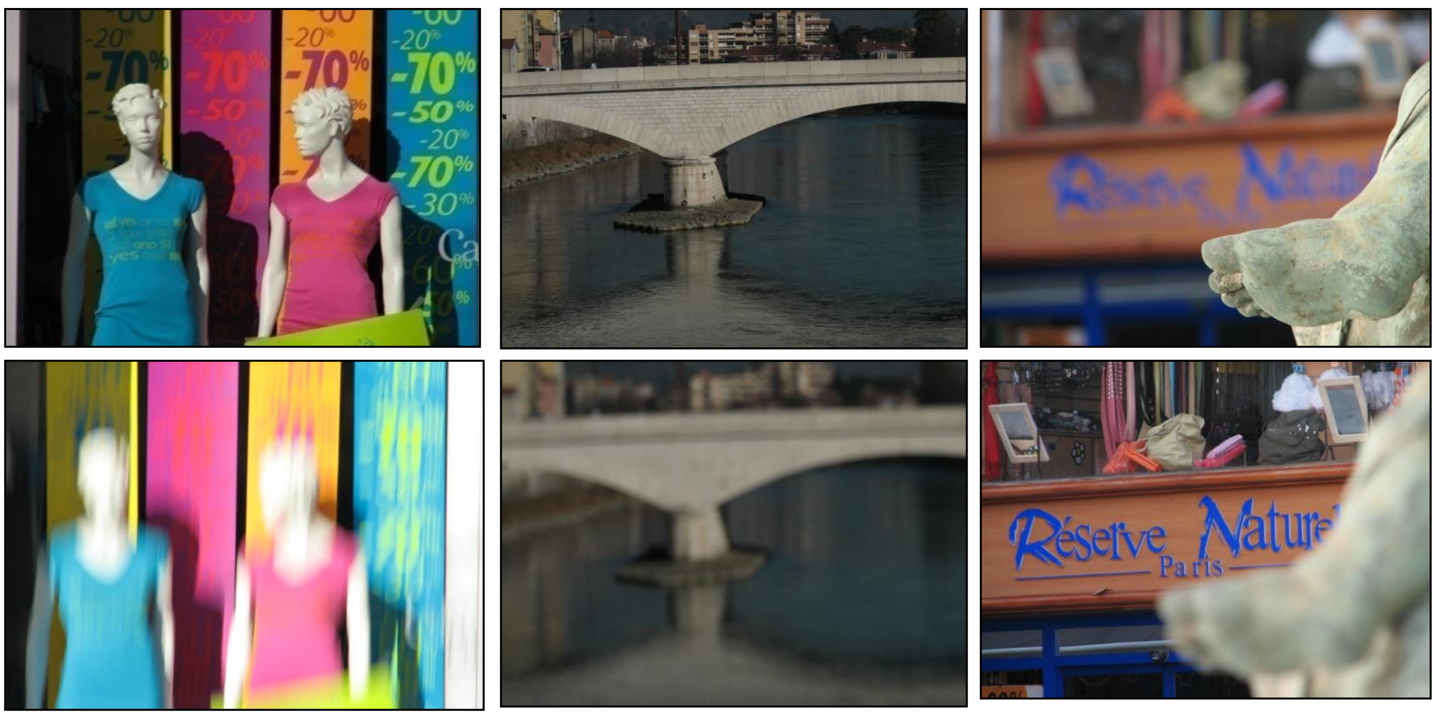
$$m = \frac{R^1 G^2}{R^2 G^1} = \frac{m_1{}^b c_1{}^R e^R}{m_2{}^b c_2{}^R e^R} \frac{m_2{}^b c_2{}^G e^G}{m_1{}^b c_1{}^G e^G} = \frac{c_1{}^R c_2{}^G}{c_2{}^R c_1{}^G}$$

$$\ln m = \ln \frac{R^1 G^2}{R^2 G^1} = \ln \frac{R^1}{G^1} - \ln \frac{R^2}{G^2} = \tfrac{\partial}{\partial x} \ln \frac{R}{G}$$



Why is this a problem ?

• Image blur is frequently encountered phenomenon.
• Possible causes are : out-of-focus, relative motion between camera and object, and aberrations of the optical system.



Obtaining Invariance to Image Blur

- A color constant representation of a single color patch is impossible.
- The difference between two color patches can be represented invariant to the color illuminant.

Funt and Finlayson:

Mondrian-world: $\mathbf{f}(\mathbf{x}) = m^b \mathbf{c}^b \mathbf{e}(\mathbf{x})$

$$p = \frac{R^1}{R^2} = \frac{m^b {c_1}^R e^R}{m^b {c_2}^R e^R} = \frac{{c_1}^R}{{c_2}^R}$$

$$\ln p = \ln \frac{R^1}{R^2} = \ln R^1 - \ln R^2 = \tfrac{\partial}{\partial x} \ln R$$

Consider a blurred image: $R' = R \otimes G^{\sigma_s}$

$$\frac{\partial}{\partial x}^{\sigma_d} \ln R = \frac{R_x^{\sigma_d}}{R^{\sigma_d}} \qquad \frac{\partial}{\partial x}^{\sigma} \ln R' = \frac{R_x^{\sqrt{\sigma_d^2+\sigma_s^2}}}{R^{\sqrt{\sigma_d^2+\sigma_s^2}}}$$

On the edge the following holds:

$$R^{\sqrt{\sigma_s^2}} = R^{\sqrt{\sigma_d^2+\sigma_s^2}} \qquad R_x^{\sqrt{\sigma_d^2}} = C(\sigma_s) R_x^{\sqrt{\sigma_d^2+\sigma_s^2}}$$

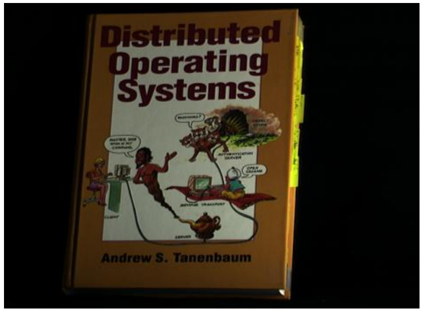
Robustness with respect to blur is obtained by:

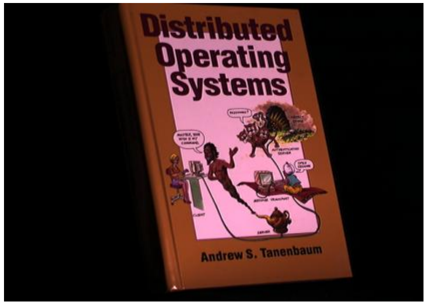
$$\varphi_p^1 = \arctan\left(\frac{R_x G}{G_x R}\right) \qquad \varphi_p^1 = \arctan\left(\frac{G_x B}{B_x G}\right)$$

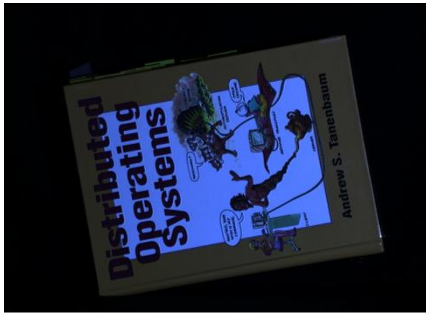
Retrieval Experiment I

• Twenty different objects where captured under 11 different object orientations and 11 different light sources (Simon Fraser).
• We compare the retrieval results of the color constant description with the color constant and blur robust description.
• Error given in Normalized Average Rank (NAR).

rank	1	2	>2	ANAR
p	180	5	15	0.010
φ_p	169	17	14	0.012
m	155	22	23	0.024
φ_m	115	23	65	0.049







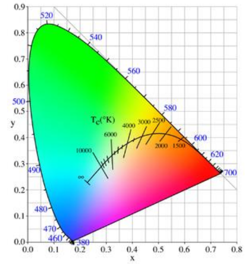
Retrieval Experiment II

• Twenty pairs of images with varying image blur.
• We compare the retrieval results of the color constant description with the color constant and blur robust description.

rank	1	2	>2	ANAR
p	7	2	11	0.365
φ_p	16	3	1	0.018
m	6	2	12	0.303
φ_m	13	1	6	0.053

Summary Color Constancy

- The Planckian locus describes natural light illuminants.



- Color constancy at the pixel allows for shadow removal.

- The general grey-world algorithm generalizes a set of low-level color constancy algorithms, including white patch, grey-world, grey-edge, and shades –of-grey.

$$\left(\sum_{i=1}^{M}\left|\frac{\partial^n \mathbf{f}_i(\mathbf{x})}{\partial \mathbf{x}^n}\right|^p\right)^{\frac{1}{p}} \propto \mathbf{c}$$

- Top-down information improves both color constancy performance and semantic segmentation results.

references: color constancy

- D.A. Forsyth, “*A novel algorithm for color constancy*.” IJCV, 1990.
- G.D. Finlayson, M.S. Drew, B.V. Funt, “*Color by correlation: A simple, unifying framework for color constancy*“, PAMI 2001.
- K. Barnard, L. Martin, B.V. Funt, “*A comparison of computational color constancy algorithms-part II: Experiments with data*” IEEE transactions on Image Processing, 2002.
- G.D. Finlayson, S.D. Hordley, and I. Tastl. “*Gamut constrained illuminant estimation*“, ICCV’03.
- G.D. Finlayson and E. Trezzi. “*Shades of gray and colour constancy*“, IS&T/SID, CIC’04.
- J. van de Weijer, Th. Gevers, A. Gijsenij, "*Edge-Based Color Constancy*", TIP 2005.
- A. Gijsenij, T. Gevers, “*Color Constancy using Natural Image Statistics*”,CVPR 2006.
- A. Chakrabarti, K. Hirakawa, T. Zickler, “*Color Constancy Beyond Bags of Pixels”*, CVPR 2008.
- A. Gijsenij, T. Gevers, J. van de Weijer, “Generalized Gamut Mapping using Image Derivative Structures”, *IJCV 2011.*