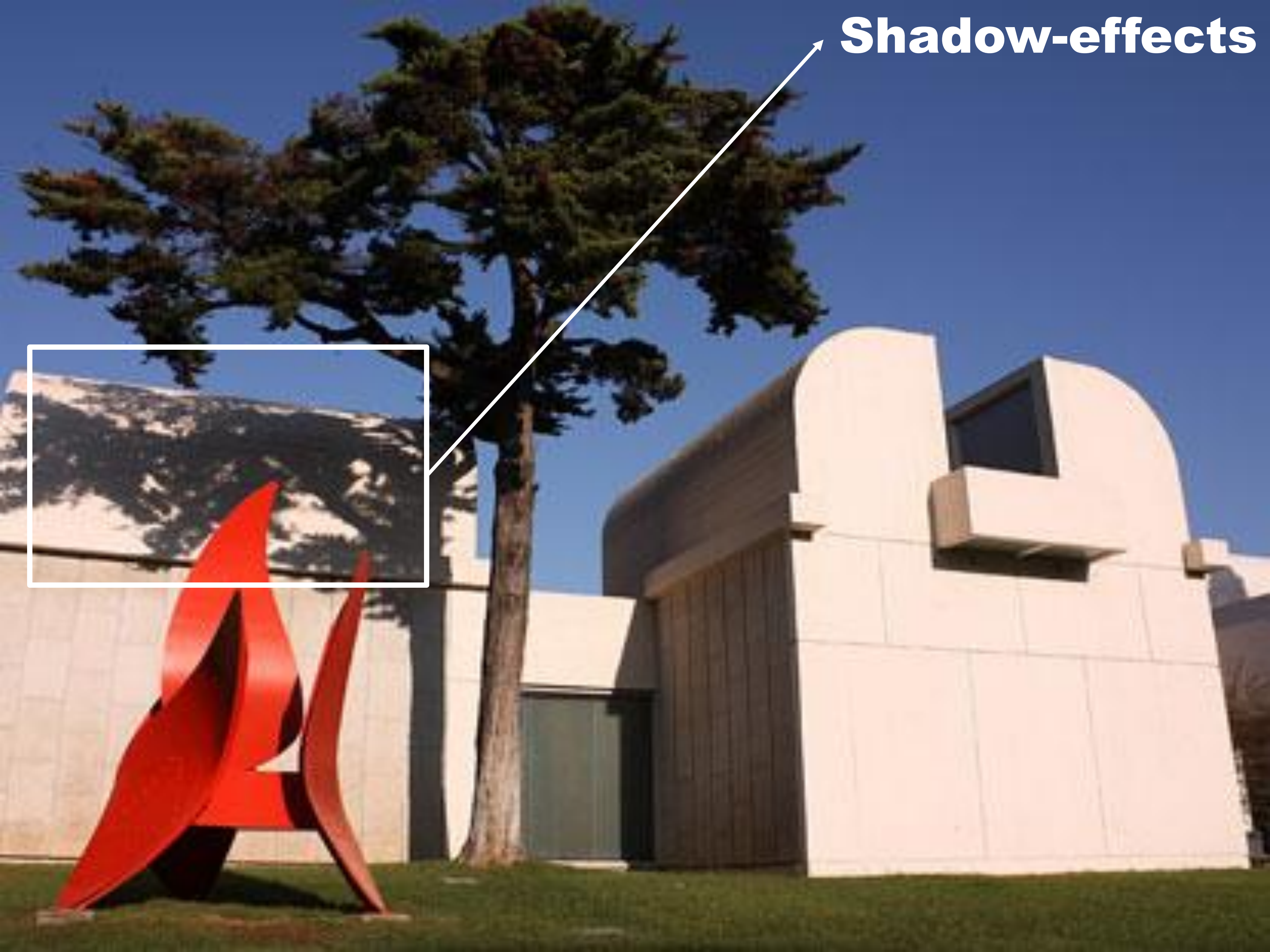
Color Image Understanding

from acquisition to
high-level image
understanding

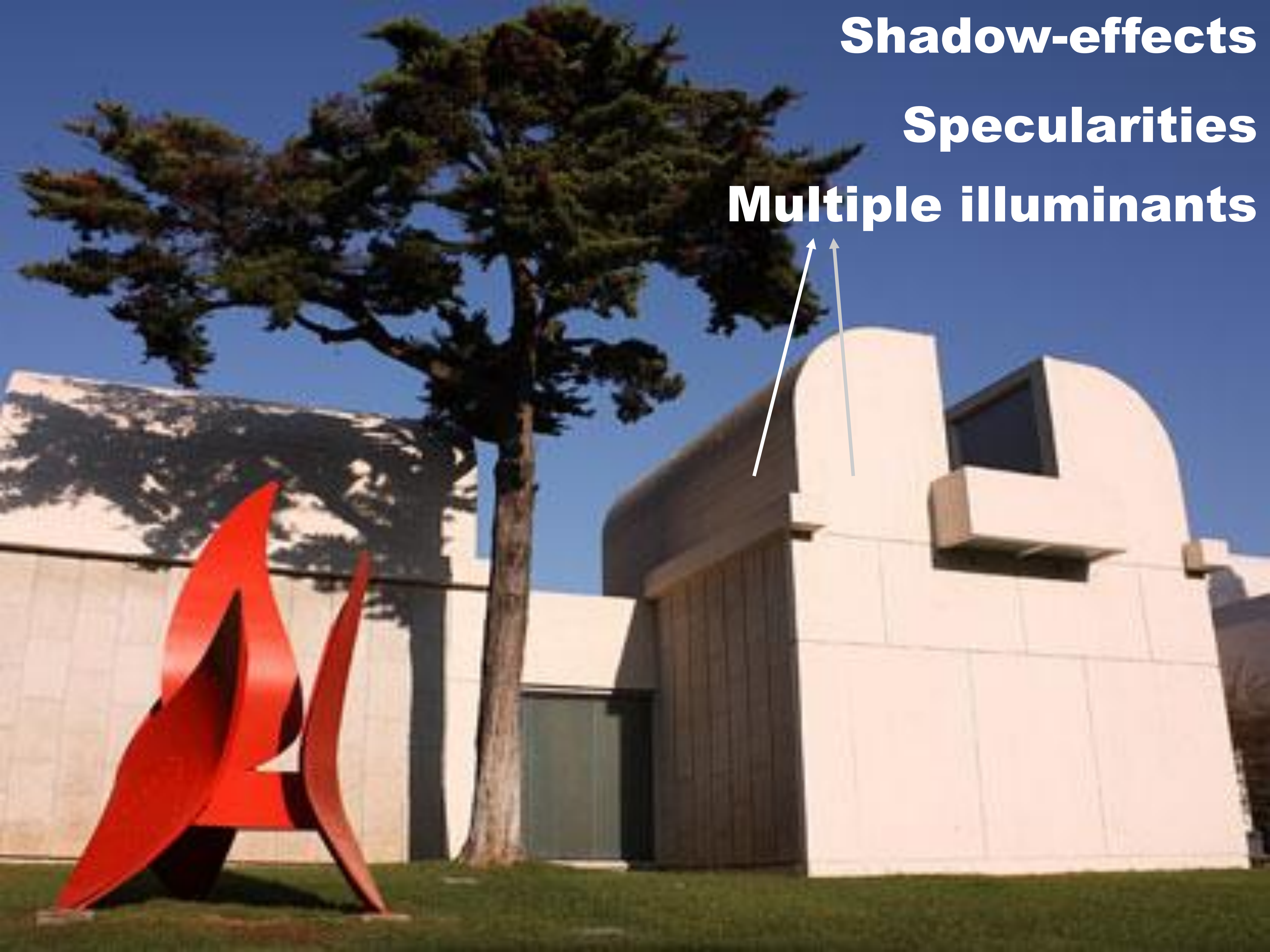
Theo Gevers
University of Amsterdam
Computer Vision Center Barcelona

Keigo Hirakawa
University of Dayton

Joost van de Weijer
Universitat Autònoma de Barcelona
Computer Vision Center Barcelona


Shadow-effects


Shadow-effects
Specularities


Shadow-effects
Specularities
Multiple illuminants

overview

PART I:
Color Image Acquisition

Keigo Hirakawa

• Color Image Sensor.

• Chrominance/luminance decompositions and demosaicking algorithms.

• Denoising before, during, and after demosaicking.

• Color fidelity issues due to noise and crosstalk.

PART II:
Color Image Processing fundamentals
Joost van de Weijer

• Dichromatic Reflection model.

• Photometric Invariance Color Features.

• Color constancy.

• Color Saliency.

PART III:
Applications

Theo Gevers

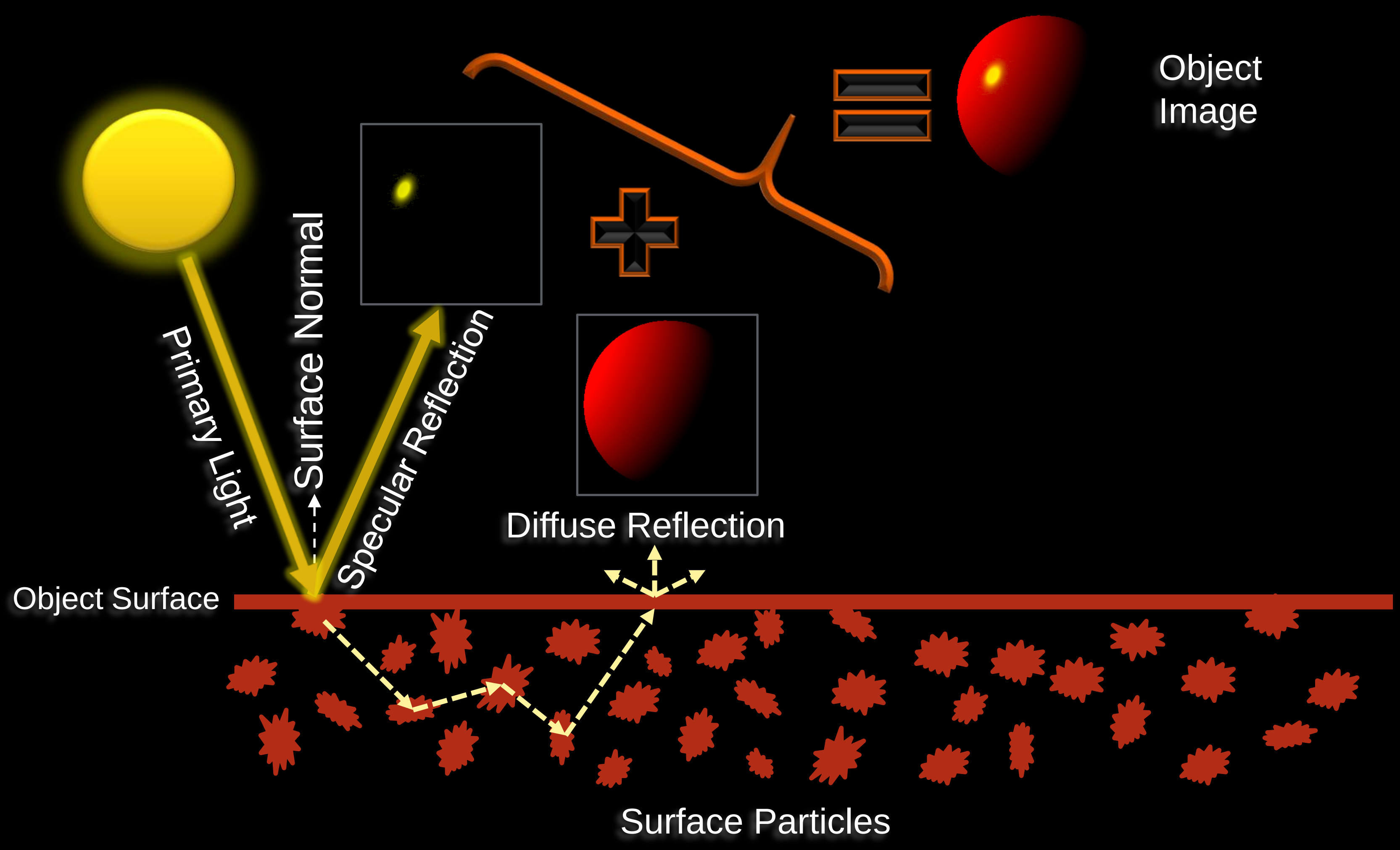
• Color Feature Detection.

• Color in Motion and Tracking.

• Color for Object Recognition.

• Color in Image/video Classification.

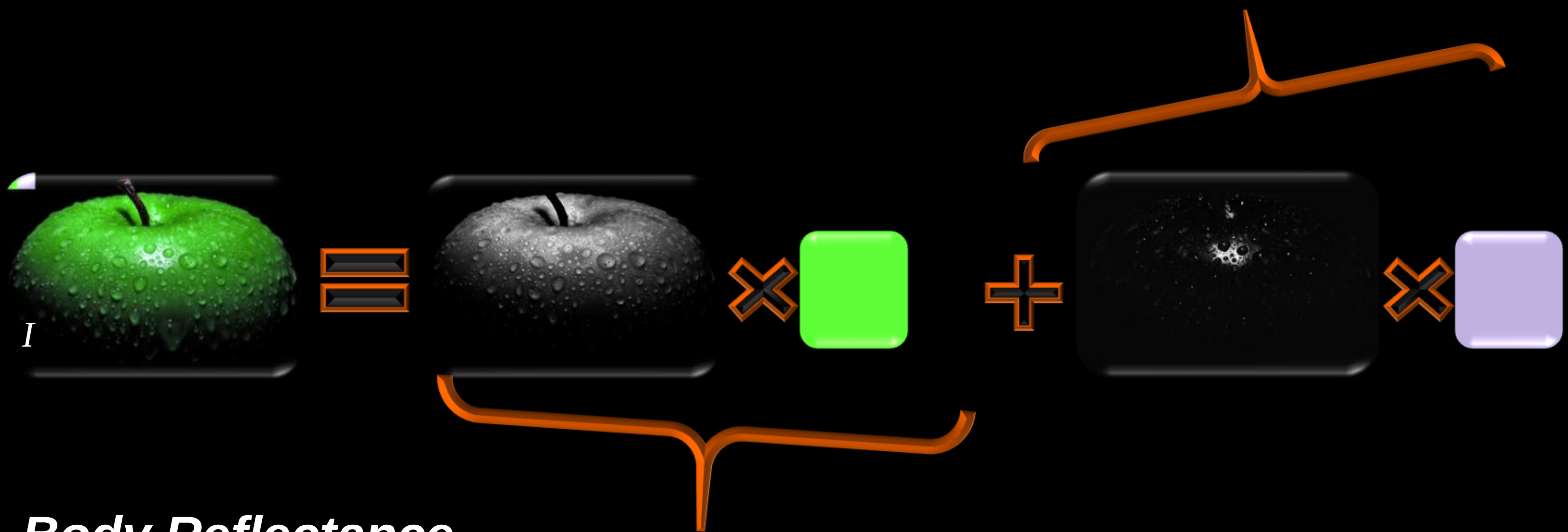
Dichromatic Reflection Model (DRM)



Dichromatic Reflection Model

Surface Reflectance

Specular reflection. The reflection angle is similar to the incident angle. Its spectral distribution depends on the illuminant

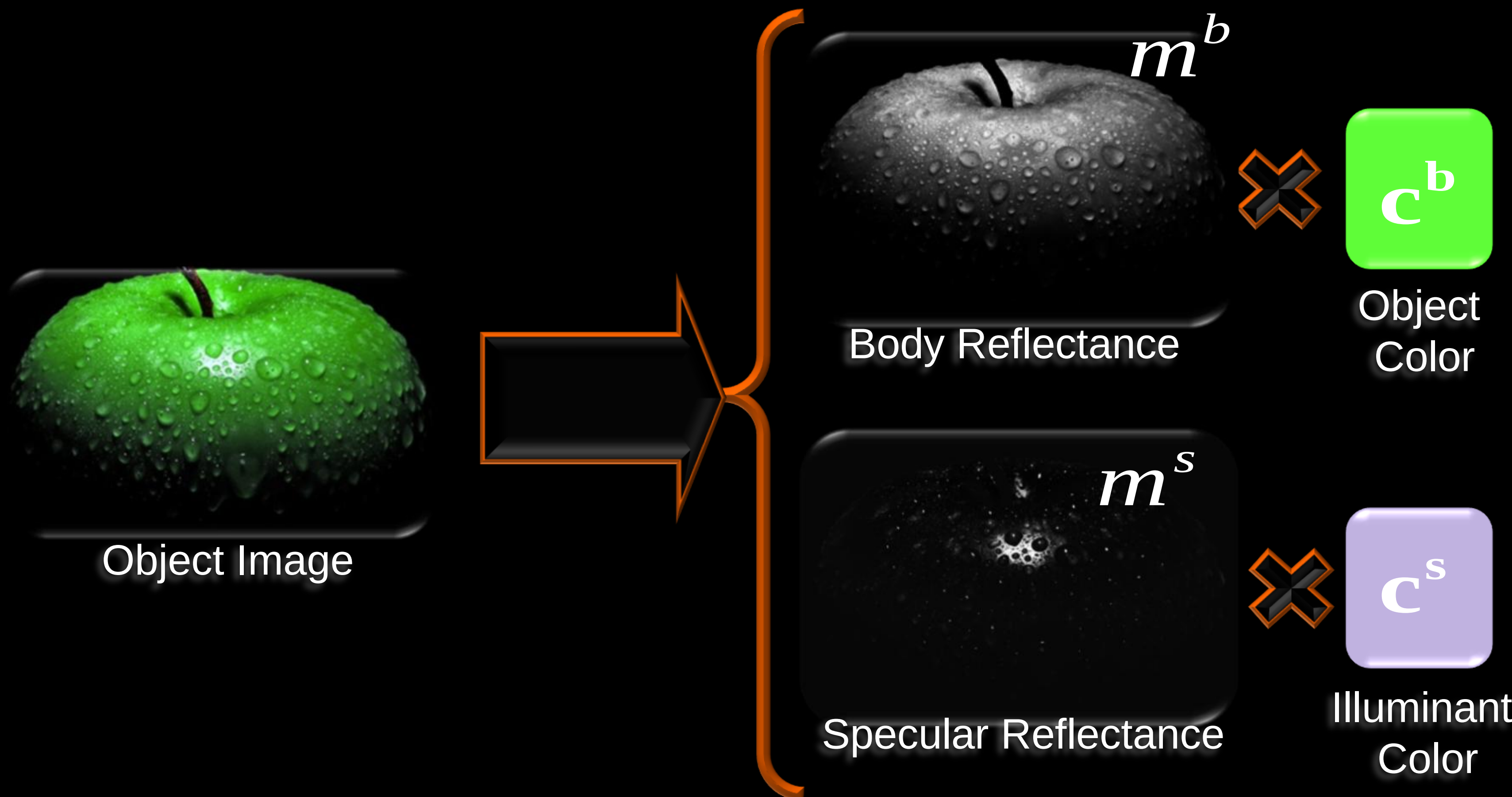


Body Reflectance

Diffuse reflection, isotropic reflection. The spectral distribution depends on colorants.

$$\boxed{\mathbf{f}(\mathbf{x}) = m^b(\mathbf{x})\mathbf{c}^{\mathbf{b}} + m^s(\mathbf{x})\mathbf{c}^{\mathbf{s}}}$$

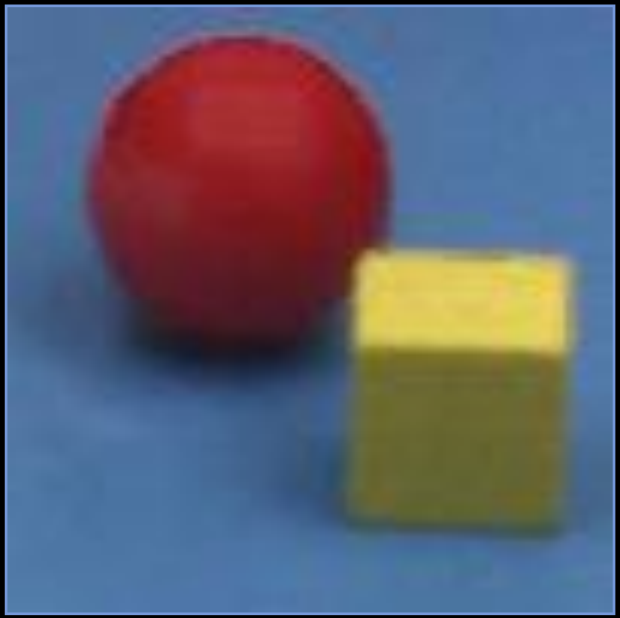
DICHROMATIC REFLECTION MODEL

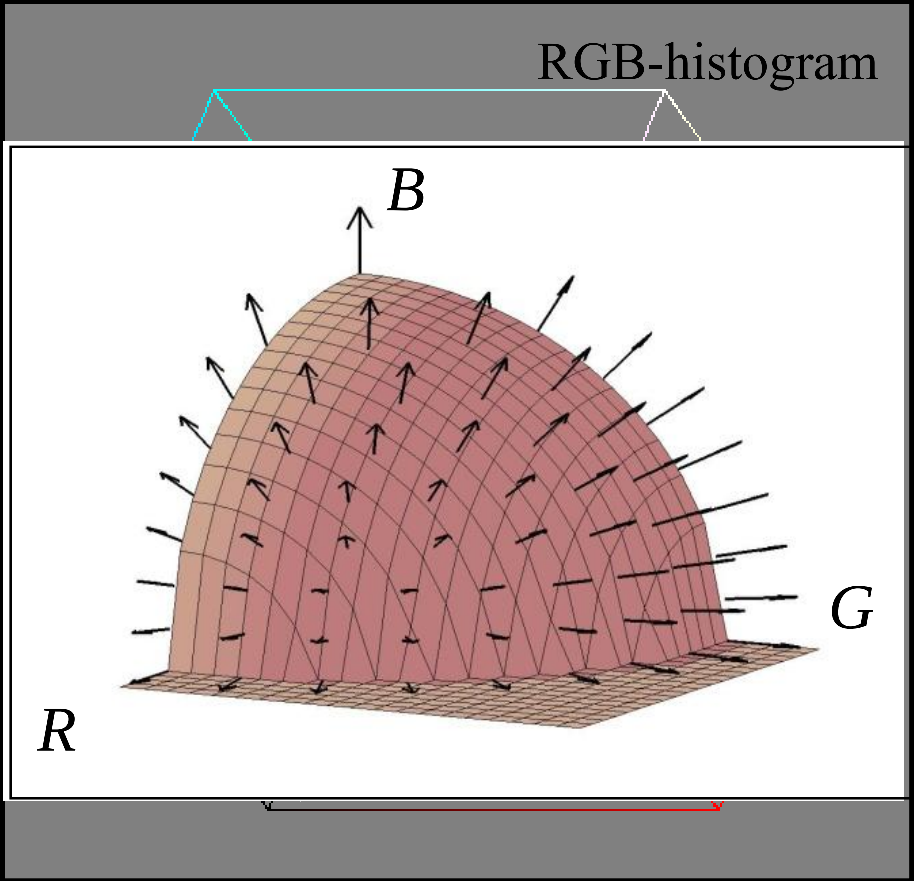


DICHROMATIC REFLECTION MODEL

dichromatic model for matte surfaces:

$$\mathbf{f} = m^b \mathbf{c}^\mathbf{b}$$

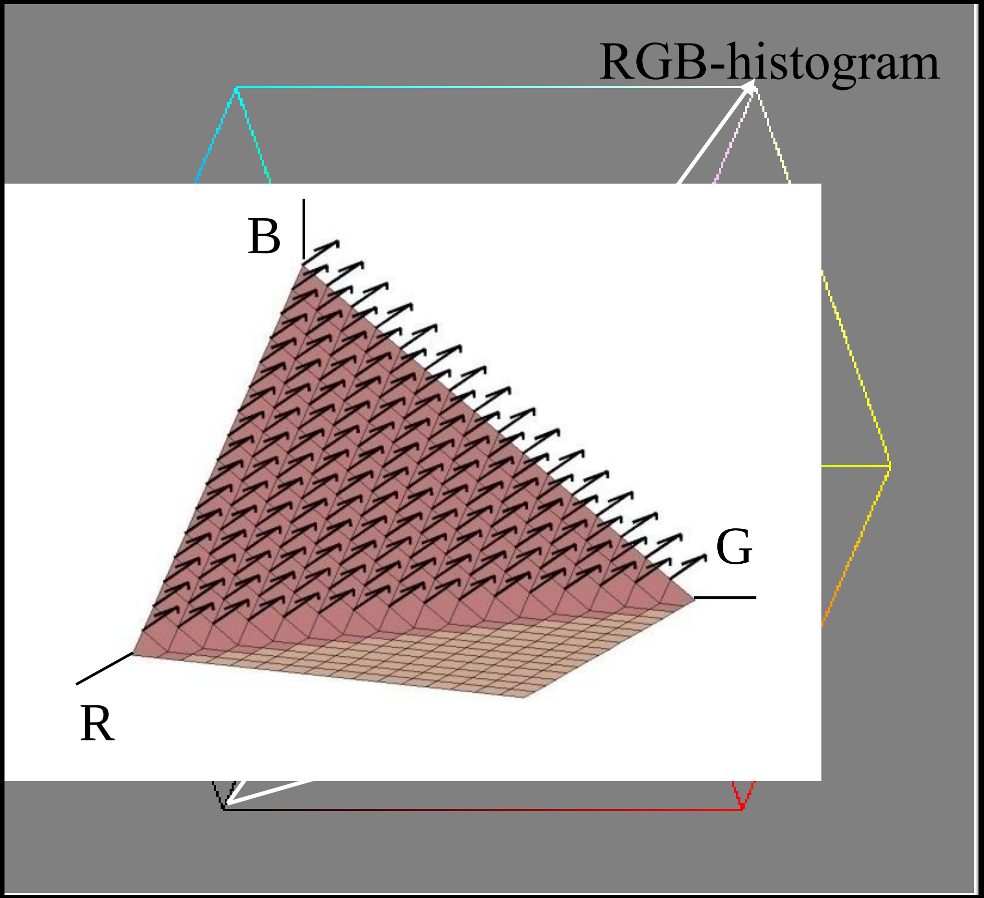




DICHROMATIC REFLECTION MODEL

dichromatic model for specular surfaces:

$$\mathbf{f} = m^b \mathbf{c}^\mathbf{b} + m^s \mathbf{c}^\mathbf{s}$$



Dichromatic Reflection Model

The model is valid for a wide variety of materials:

plastic

paper

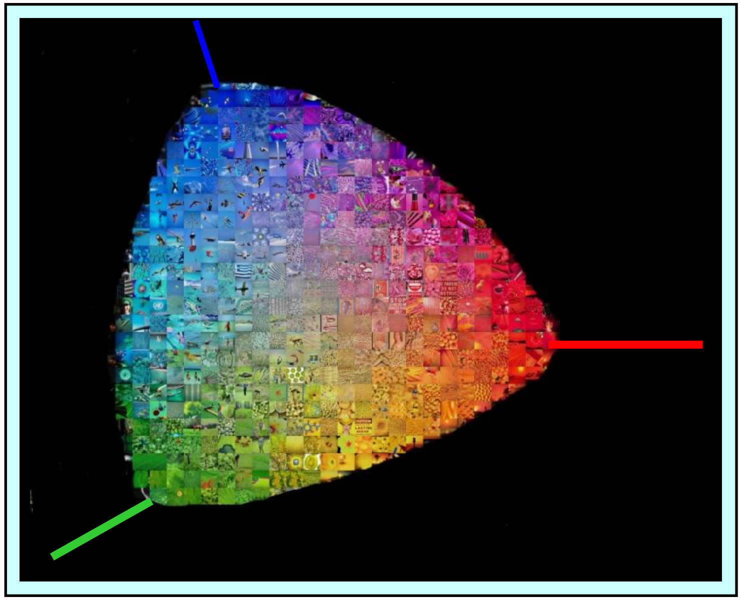
skin

wood

paint

fruit and vegetables

Photometric Invariant Features



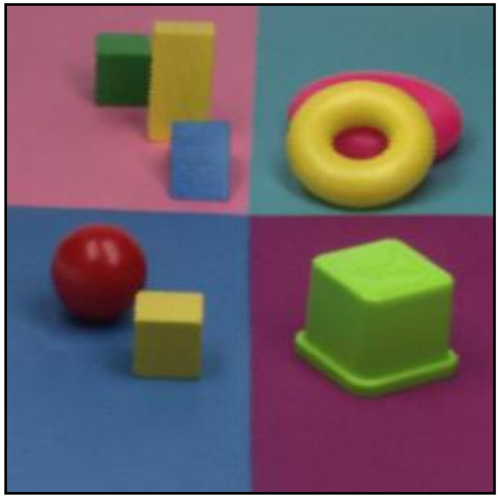
color spaces: normalized RGB

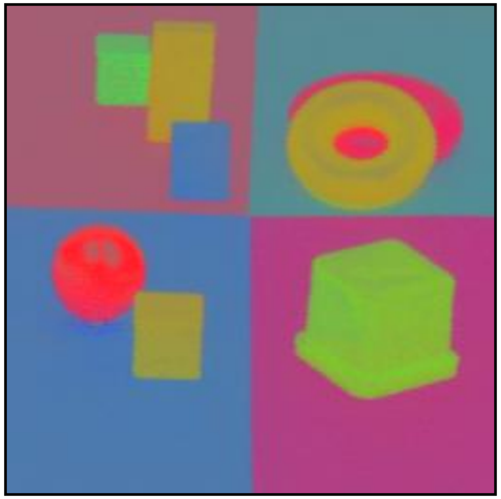
- normalized RGB is given by:

$$\{r,g,b\} = \{\frac{R}{R+G+B}, \frac{G}{R+G+B}, \frac{B}{R+G+B}\}$$

- invariant for shadow and shading variations (matte surfaces):

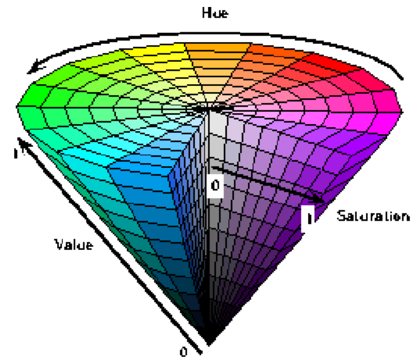
$$r = \frac{R}{R+G+B} = \frac{\cancel{m^b} c_R^b}{\cancel{m^b} c_R^b + \cancel{m^b} c_G^b + \cancel{m^b} c_B^b} = \frac{c_r^b}{c_r^b + c_g^b + c_b^b}$$





normalized RGB

color spaces: hue-saturation-intensity



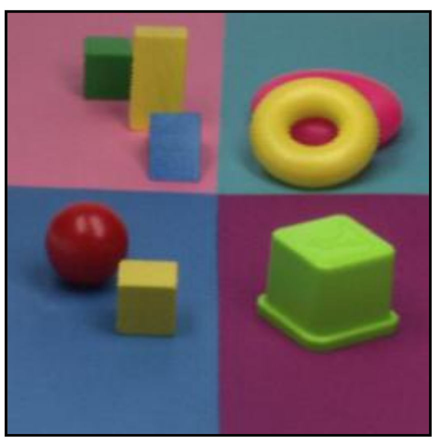
- defined as: $$hue = \arctan\left(\frac{\sqrt{3}(R-G)}{(R+G-2B)}\right)$$

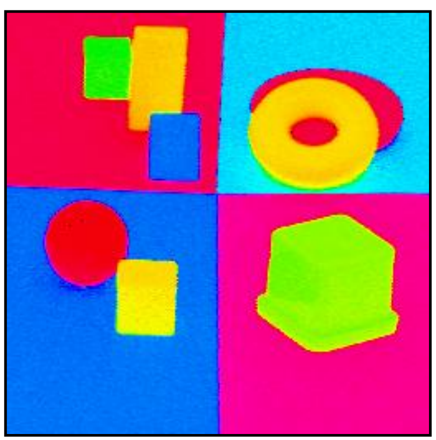
$$sat = \sqrt{\tfrac{2}{3}\left(R^2+G^2+B^2-RG-RB-GB\right)}$$

$$i = \frac{R+G+B}{\sqrt{3}}$$

- hue is invariant for shading variations and specularities under white light:

$$hue = \arctan\left(\frac{\sqrt{3}\cancel{m^b}\left(c_R^b+\cancel{c^s}-c_G^b-\cancel{c^s}\right)}{\cancel{m^b}\left(c_R^b+\cancel{c^s}+c_G^b+\cancel{c^s}-2c_B^b-2\cancel{c^s}\right)}\right)$$



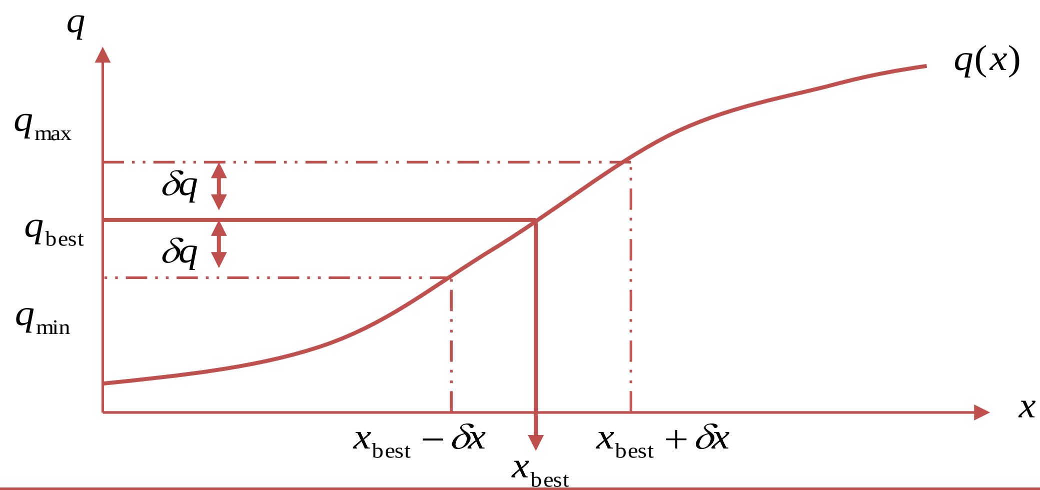


hue

Take care of instabilities

• when working in different color spaces always take instabilities into account !

• Error propagation is a convenient tool for instability evaluation:



Suppose that $u, \ldots, w$ are measured with corresponding uncertainties $\sigma_u, \ldots, \sigma_w$ to compute function $q(u, \ldots, w)$.

The predicted uncertainty is defined by :

$$\sigma_q = \sqrt{\left(\frac{\partial q}{\partial u}\sigma_u\right)^2 + \ldots + \left(\frac{\partial q}{\partial w}\sigma_w\right)^2}$$

Take care of instabilities

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• Error propagation is a convenient tool for instability evaluation:

Ex. 1

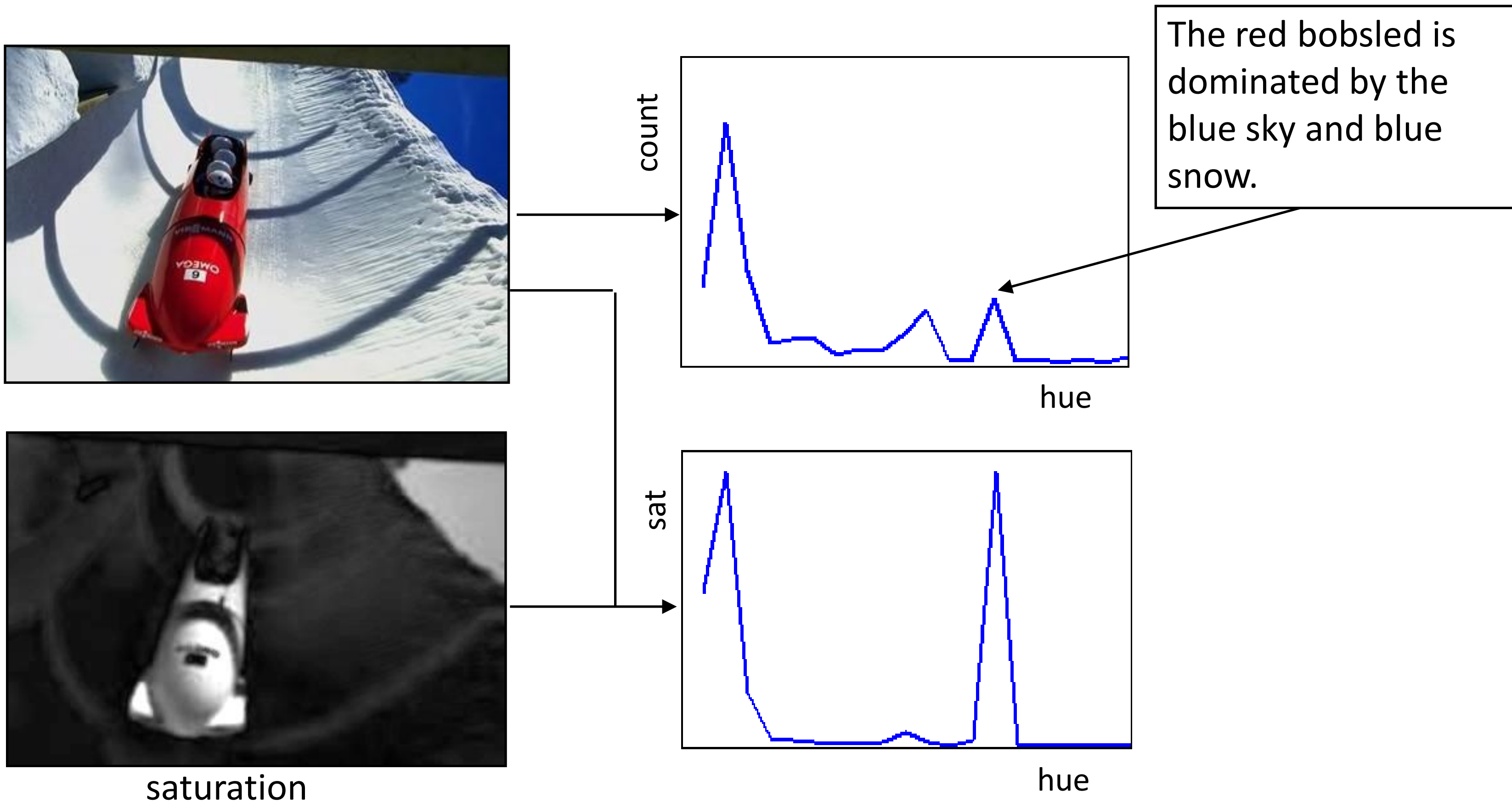
$$hue = \arctan\left(\frac{\sqrt{3}(R-G)}{(R+G-2B)}\right) \longrightarrow (\partial hue)^2 = \left(\partial\left(\arctan\left(\frac{\sqrt{3}(R-G)}{(R+G-2B)}\right)\right)\right)^2$$

$$(\partial hue)^2 = \left(\frac{\partial hue}{\partial R}\right)^2 \partial^2 R + \left(\frac{\partial hue}{\partial G}\right)^2 \partial^2 G + \left(\frac{\partial hue}{\partial B}\right)^2 \partial^2 B$$

$$= \frac{1}{sat^2}\partial^2 R \text{ (assuming } \partial^2 R = \partial^2 G = \partial^2 B)$$

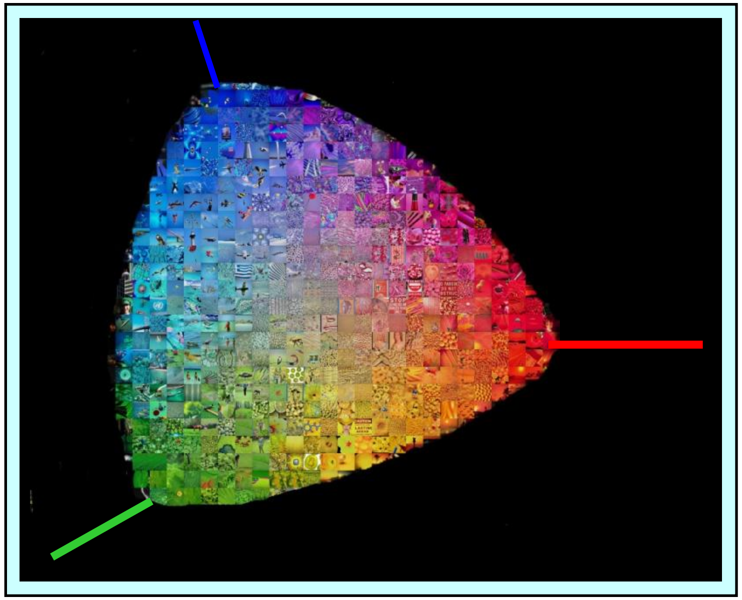
Take care of instabilities

- when working in different color spaces always take instabilities into account !
- Error analysis is a convenient tool for instability evaluation:



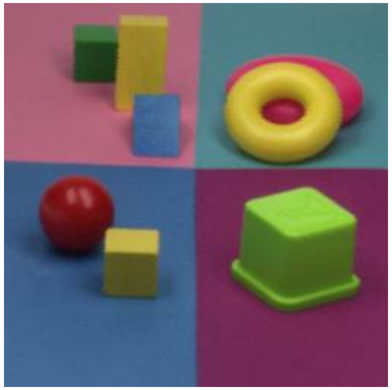
Coloring Local Feature Extraction, ECCV 2006

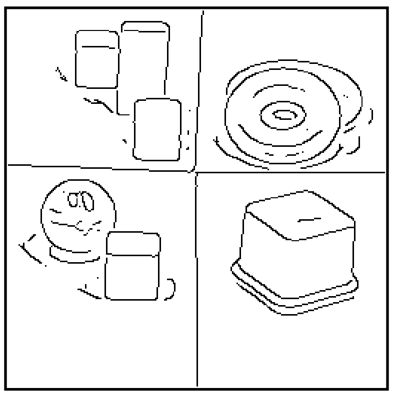
Color Differential Structure

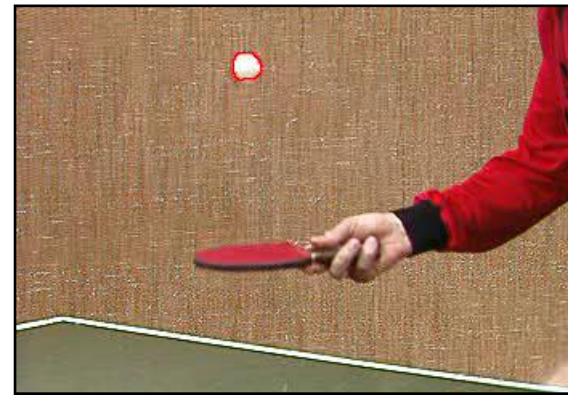


Edge and Corner Detection by Photometric Quasi-Invariants, PAMI 2005.
Robust Photometric Invariant Features from the Color Tensor, TIP 2006.

differential-based computer vision

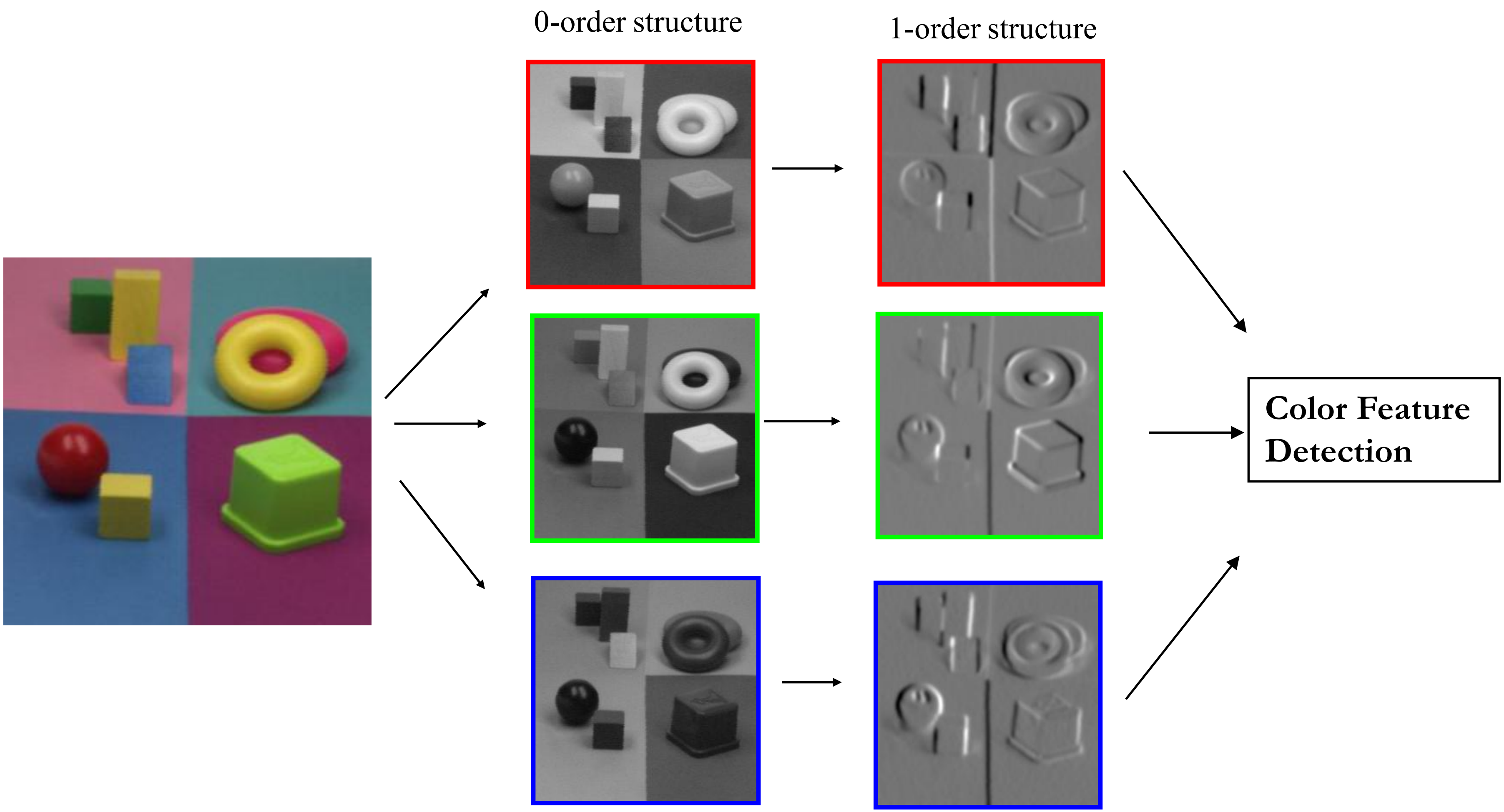






1. How do we combine the differential structure of the various color channels ?
2. How do we incorporate color invariance theory into the measurements of the differential structure while maintaining robustness ?

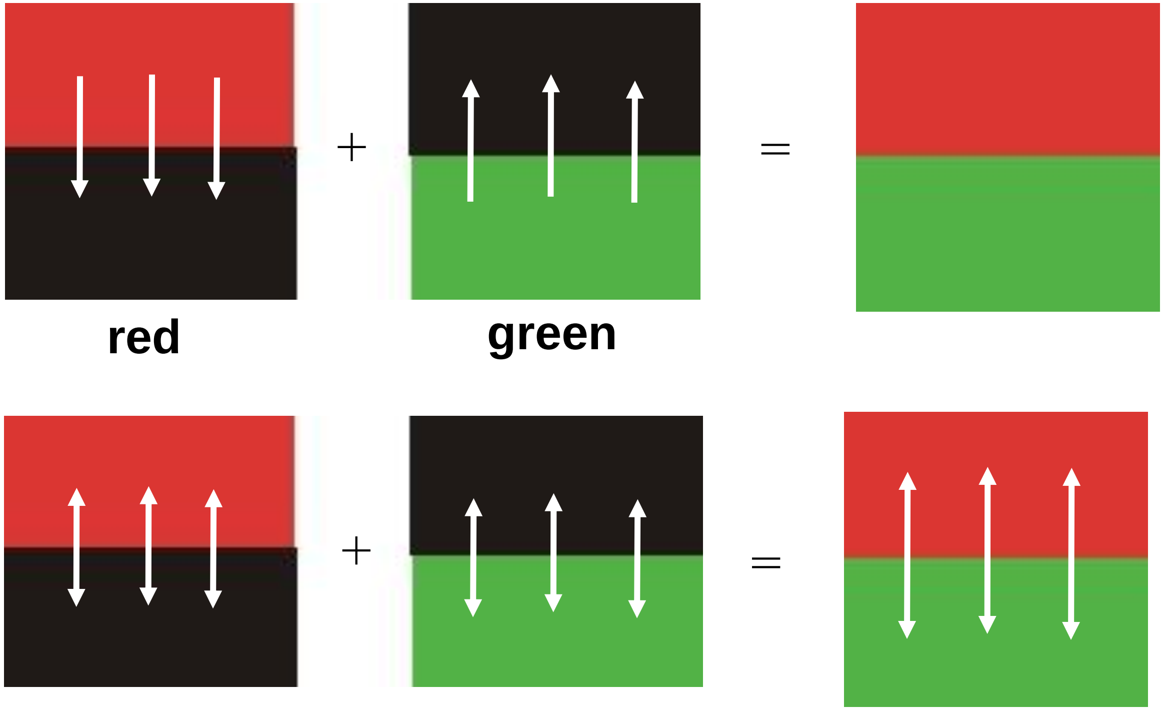
Color Feature Detection



from luminance to color

$$\textit{vector:}\quad R_x + G_x = 0$$

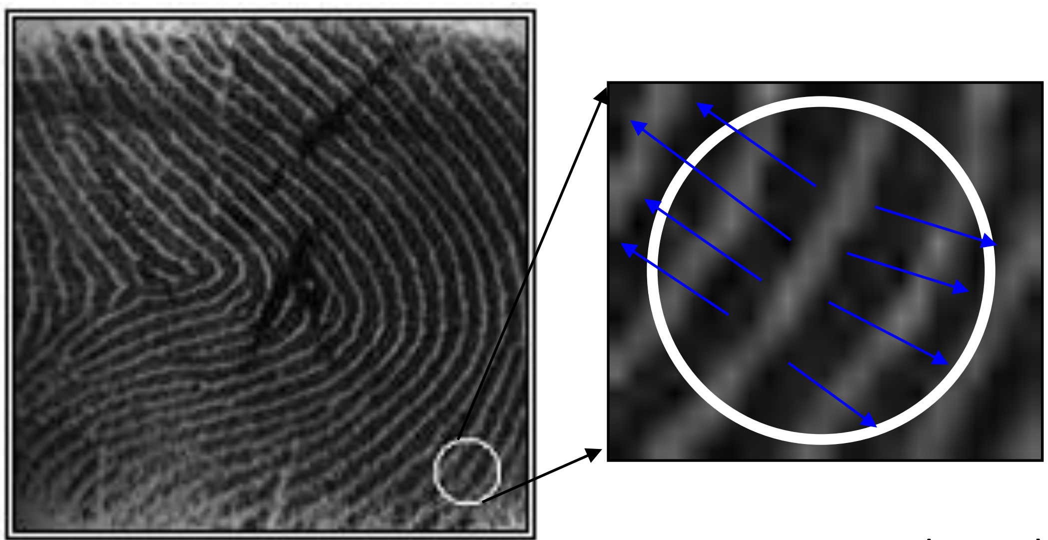
2-channel test-image



$$\textit{tensor:}\quad \begin{pmatrix} R_x^2 & R_xR_y \\ R_xR_y & R_y^2 \end{pmatrix} + \begin{pmatrix} G_x^2 & G_xG_y \\ G_xG_y & G_y^2 \end{pmatrix} = \begin{pmatrix} R_x^2+G_x^2 & R_xR_y+G_xG_y \\ R_xR_y+G_xG_y & R_y^2+G_y^2 \end{pmatrix}$$

DiZenzo. “Note on the Gradient of a Multi-Image”, *Computer Vision, Graphics, and Image Processing*, 1986.

feature detection in oriented patterns



oriented texture

more tensor-based features:

- Harris corner points
- symmetry points
  (star and circle structures)
- optical flow
- orientation estimation
- curvature estimation
- ...

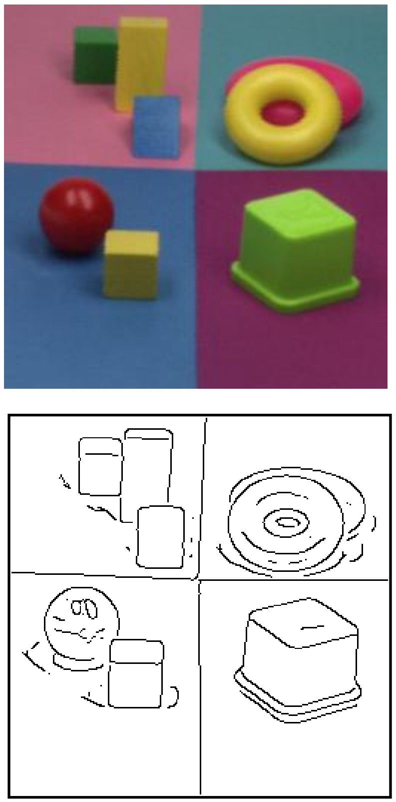
traditional orientation estimation:

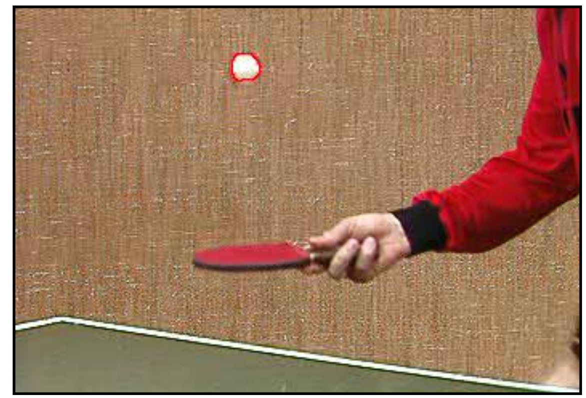
$$\theta = \arctan\left(\frac{f_y}{f_x}\right) \rightarrow \bar{\theta} = \arctan\left(\frac{\overline{f_y}}{\overline{f_x}}\right)$$

tensor-based orientation estimation:

$$\theta = \arctan\left(\frac{2 f_x f_y}{f_x^2 - f_y^2}\right) \rightarrow \bar{\theta} = \arctan\left(\frac{2\overline{f_x f_y}}{\overline{f_x^2 - f_y^2}}\right)$$

differential-based computer vision



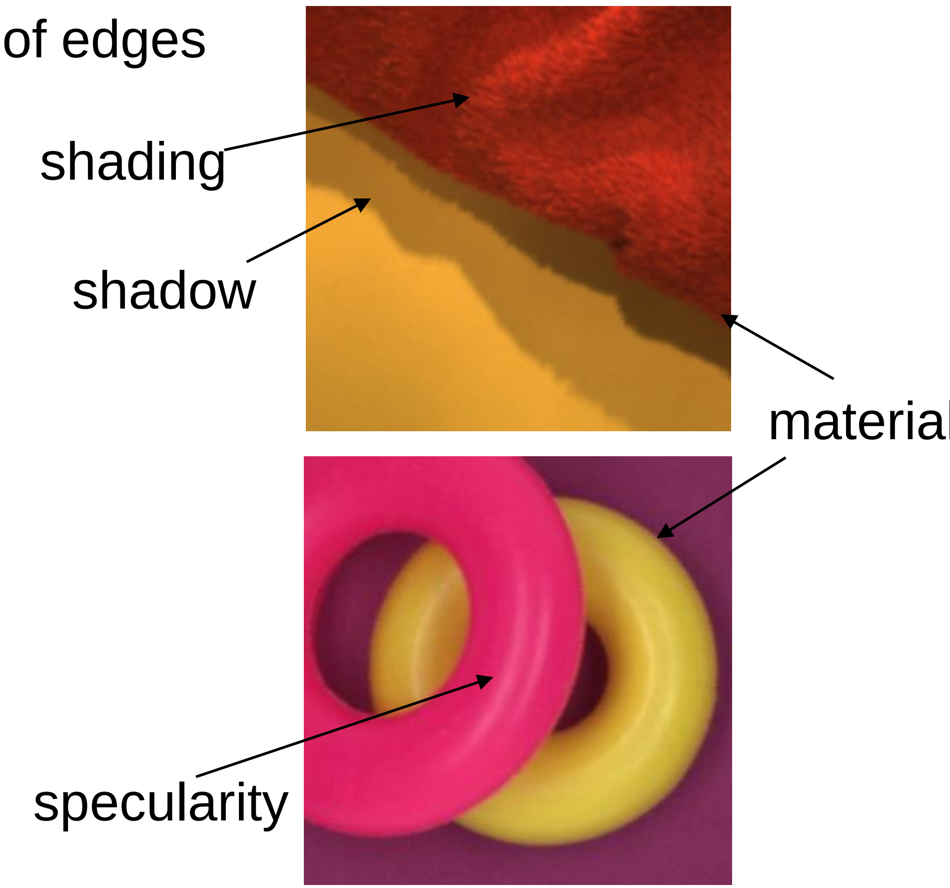


1. How do we combine the differential structure of the various color channels ?
2. How do we incorporate color invariance theory into the measurements of the differential structure while maintaining robustness ?

Photometric Invariant Edge Detection

- we differ between three types of edges
  1. material edge
  2. shadow/shading edge
  3. specular edge

- assumptions:
  1. white illumination
  2. neutral interface reflection
  3. shadows are not colored.



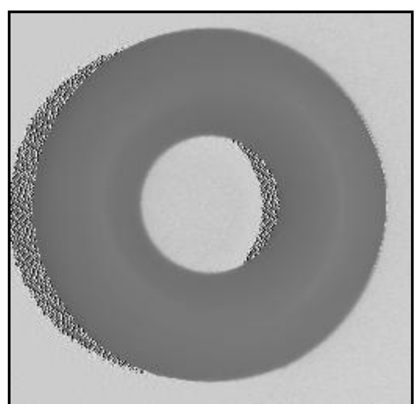
Computation of quasi-invariance

nonlinear transformation

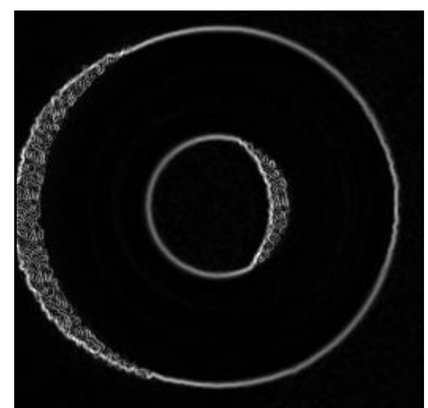
IMAGE → FULL INVARIANT → FULL INVARIANT DERIVATIVE

linear operation

IMAGE → DERIVATIVES → QUASI- INVARIANT DERIVATIVE



hue



hue_x

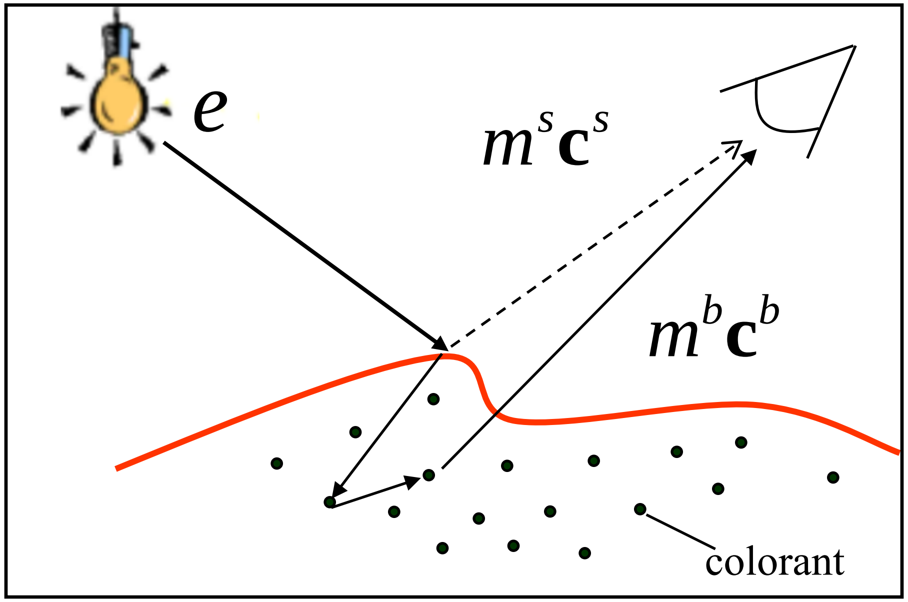
Dichromatic Model

- dichromatic model:

$$\mathbf{f} = e\left(m^b \mathbf{c}^\mathbf{b} + m^s \mathbf{c}^\mathbf{s}\right)$$

body + specular

intensity illuminant



- first order photometric structure:

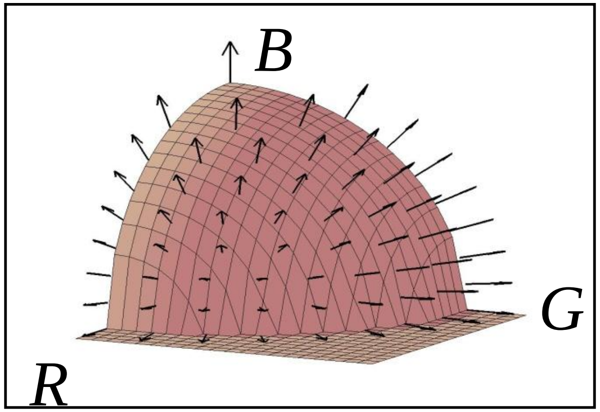
$$\mathbf{F}_x = \{R_x, G_x, B_x\} = m^b \mathbf{c}_x^b + \left(e_x m^b + e m_x^b\right)\mathbf{c}^b + e m_x^s \mathbf{c}^s$$

material + (shadow + shading) + specular

spherical coordinates

- For matte surfaces : $\mathbf{f} = m^b \mathbf{c}^b$

- all shadow-shading variation is in the radial direction

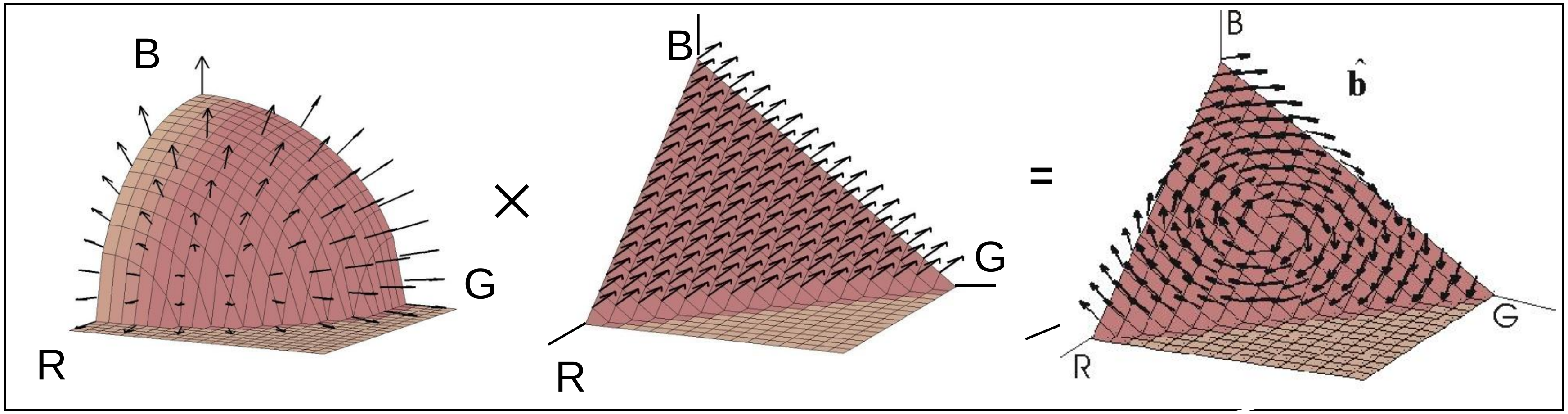


shadow/shading direction

uncertainty of c_x

$$\mathbf{f}_x = \begin{pmatrix} R_x \\ G_x \\ B_x \end{pmatrix} \xrightarrow{spherical} \begin{pmatrix} r_x \\ r\varphi_x \\ \sin\varphi\,\theta_x \end{pmatrix} = \begin{pmatrix} r_x \\ 0 \\ 0 \end{pmatrix} + r \begin{pmatrix} 0 \\ \varphi_x \\ \sin\varphi\,\theta_x \end{pmatrix} \longrightarrow \mathbf{c}_x = \begin{pmatrix} 0 \\ \varphi_x \\ \sin\varphi\,\theta_x \end{pmatrix}$$

Shadow-Shading-Specular Quasi-Invariant



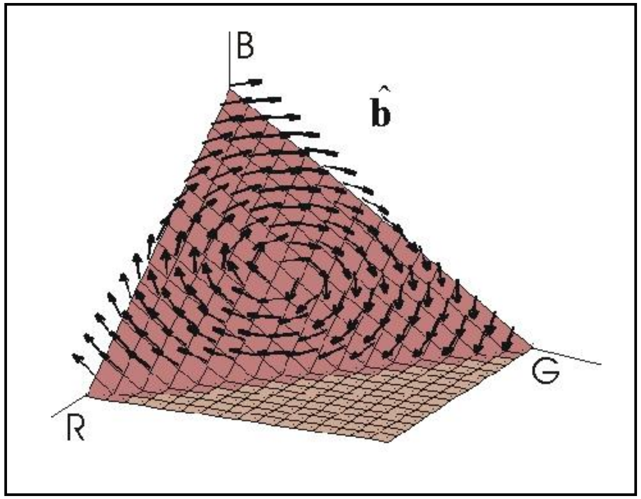
spherical coordinates *opponent colors* *hue-saturation-intensity*

shading variant	specular variant	shading-specular variant
shading invariant	specular invariant	shading-specular invariant

hue-saturation-intensity

• For specular surfaces : $\mathbf{f} = m^b \mathbf{c}^b + m^s \mathbf{c}^s$

• there is no specular-shadow-shading variation in the hue-direction.



the hue direction

uncertainty of h_x

$$\mathbf{f}_x = \begin{pmatrix} R_x \\ G_x \\ B_x \end{pmatrix} \xrightarrow{hsi} \begin{pmatrix} sh_x \\ s_x \\ i_x \end{pmatrix} = \begin{pmatrix} 0 \\ s_x \\ i_x \end{pmatrix} + s \begin{pmatrix} h_x \\ 0 \\ 0 \end{pmatrix} \longrightarrow \mathbf{h}_x = \begin{pmatrix} h_x \\ 0 \\ 0 \end{pmatrix}$$

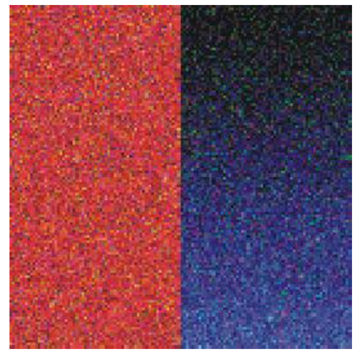
Instabilities

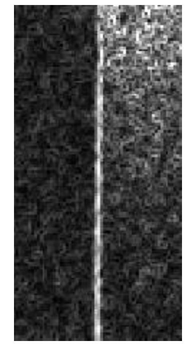
invariant

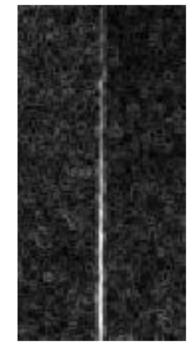
test-image | full | quasi

shadow-shading invariance:

$$\lim_{\{R,G,B\}\to 0}$$

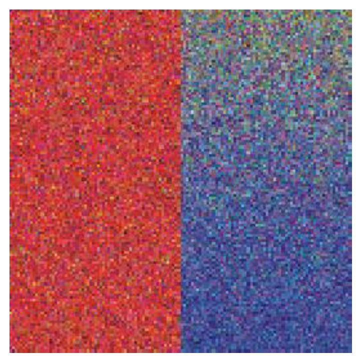


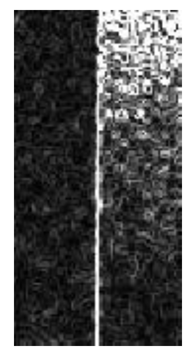


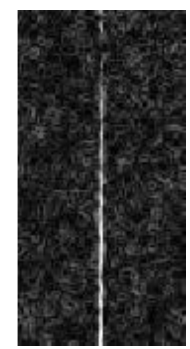


specular-shadow-shading invariance:

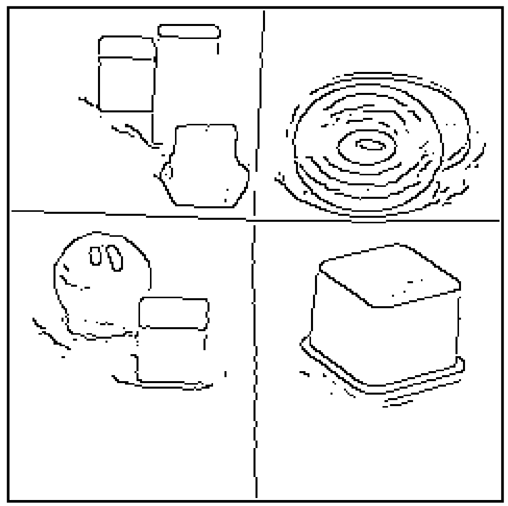
$$\lim_{\{R,G,B\}\to \alpha\{1,1,1\}}$$



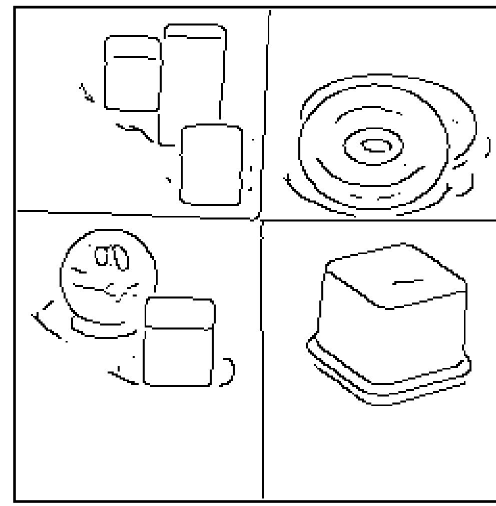




experiments : canny edge detection

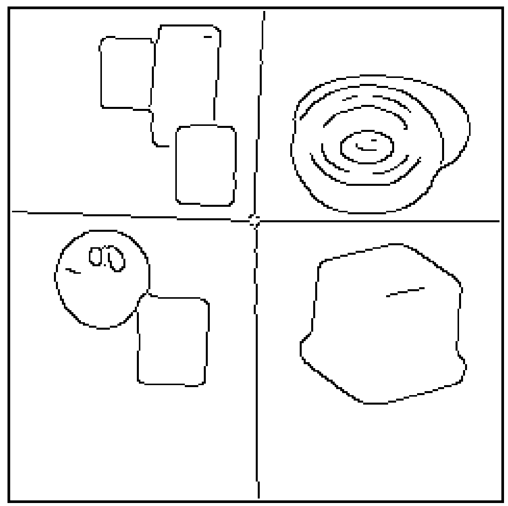


luminance-gradient

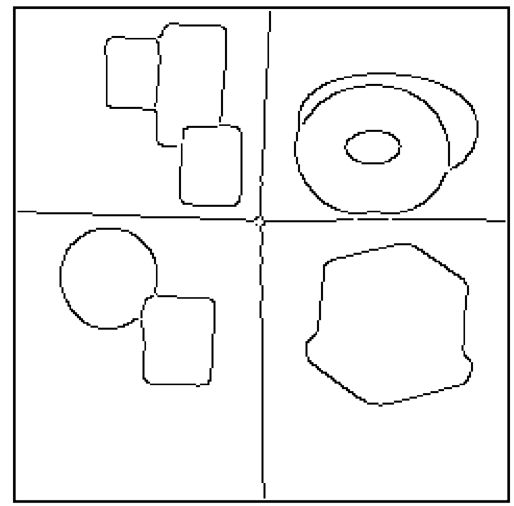


RGB-gradient

experiments : canny edge detection

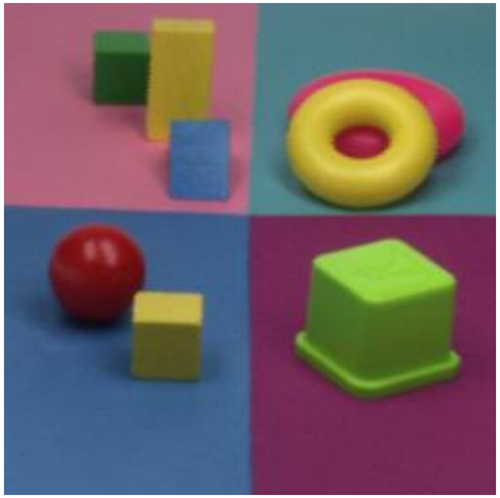


shadow-shading quasi-invariant

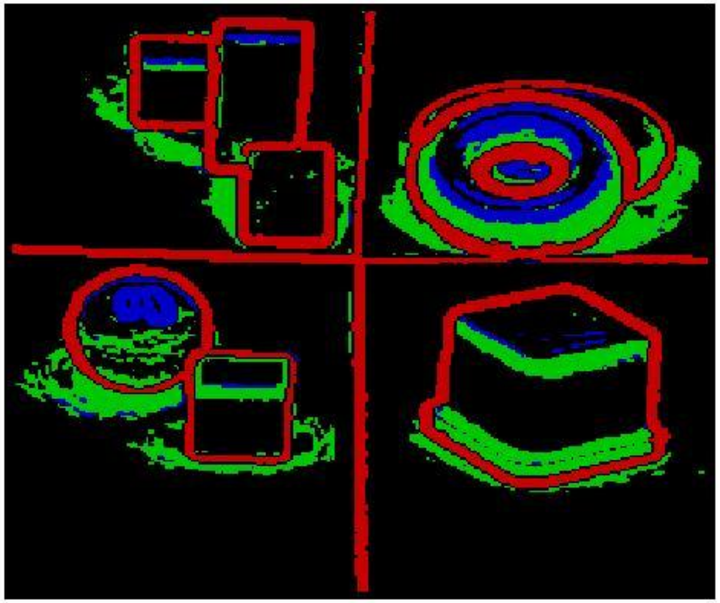


shadow-shading-specular quasi-invariant

Edge Classification

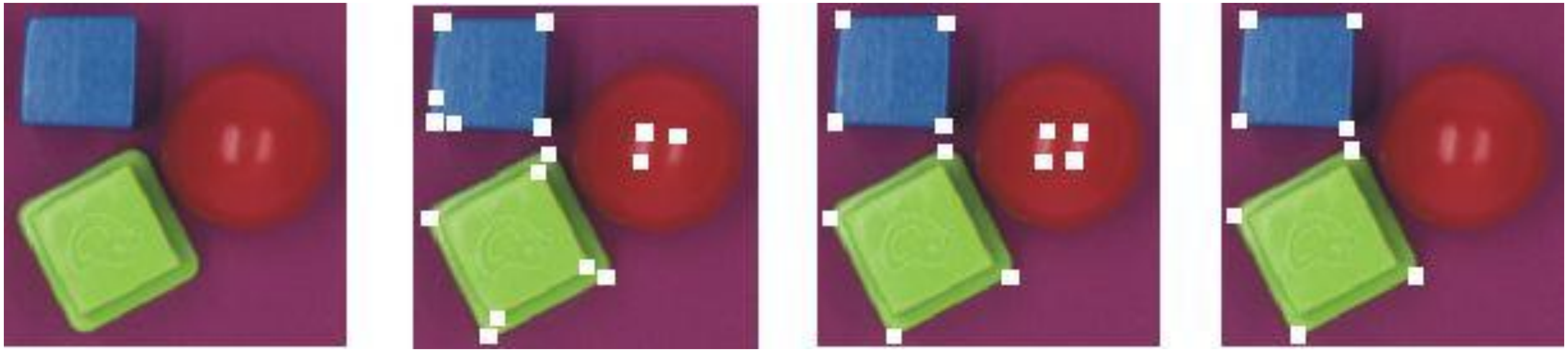


red - object edge
green-shading/shadow edge
Blue – specular edge



Photometric Invariant Corner Detection

• Harris corner detector combined with the quasi-invariants allows for photometric invariant corner detection

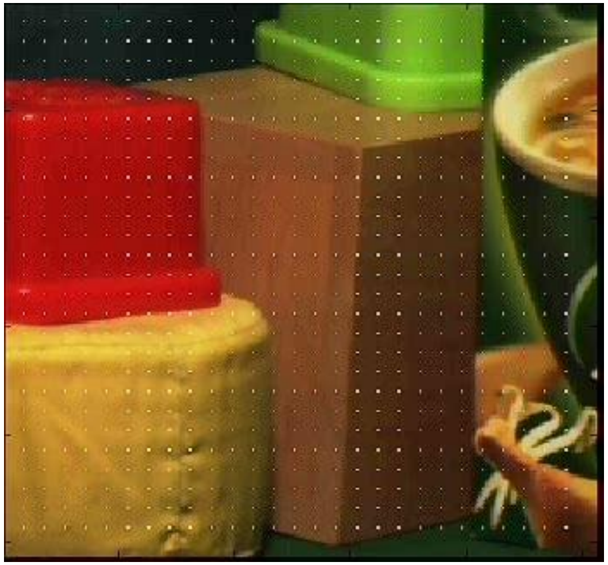


RGB

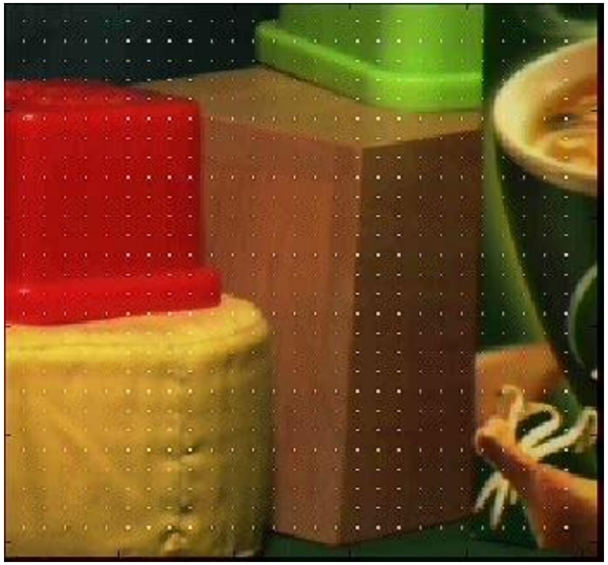
shadow-shading

specular-shadow-shading

Photometric Invariant Optical Flow



RGB



shadow-shading
invariance

overview

PART I:
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Keigo Hirakawa

• Color Image Sensor.

• Chrominance/luminance decompositions and demosaicking algorithms.

• Denoising before, during, and after demosaicking.

• Color fidelity issues due to noise and crosstalk.

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Joost van de Weijer

• Dichromatic Reflection model.

• Photometric Invariance Color Features.

• **Color constancy.**

• Color Saliency.

PART III:
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Theo Gevers

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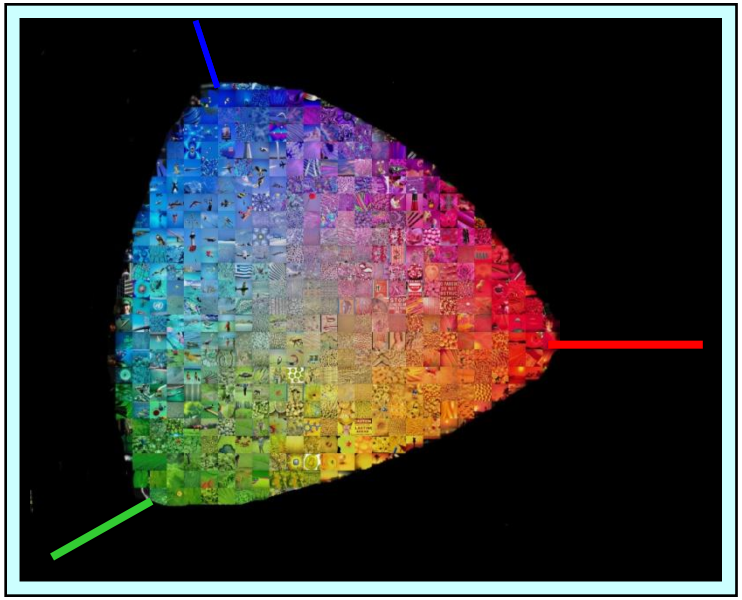
• Color for Object Recognition.

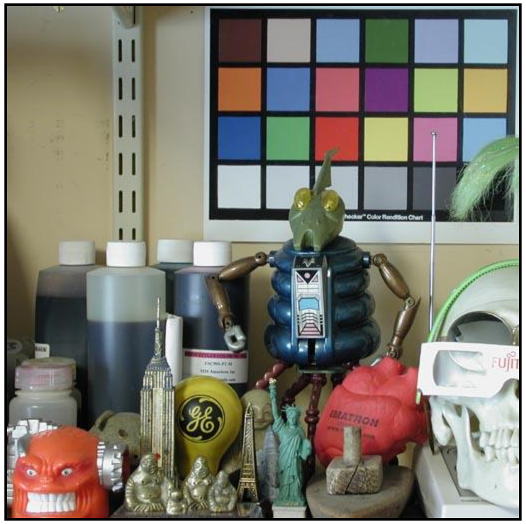
• Color in Image/video Classification.

Color Constancy



problem statement

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

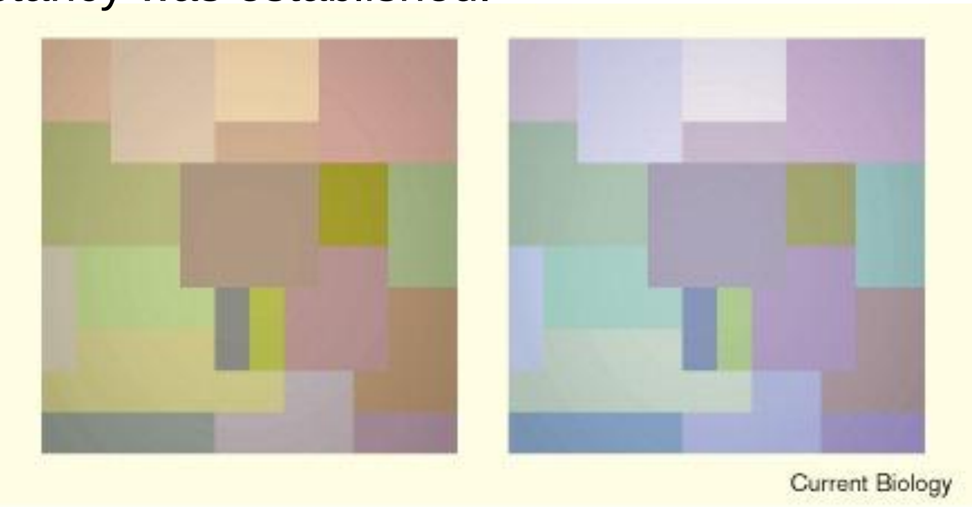


color constancy : the ability to recognize colors of objects invariant of the color of the light source.

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.

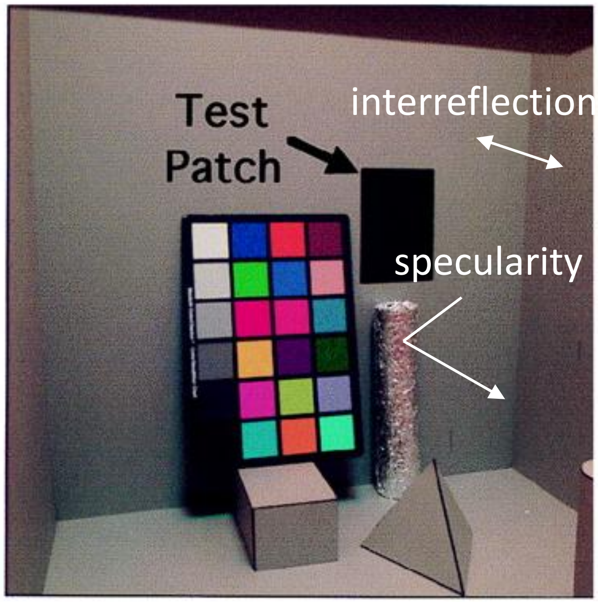
Drawbacks: do not resemble real 3D surfaces, no interreflections, no specularities, shading etc.

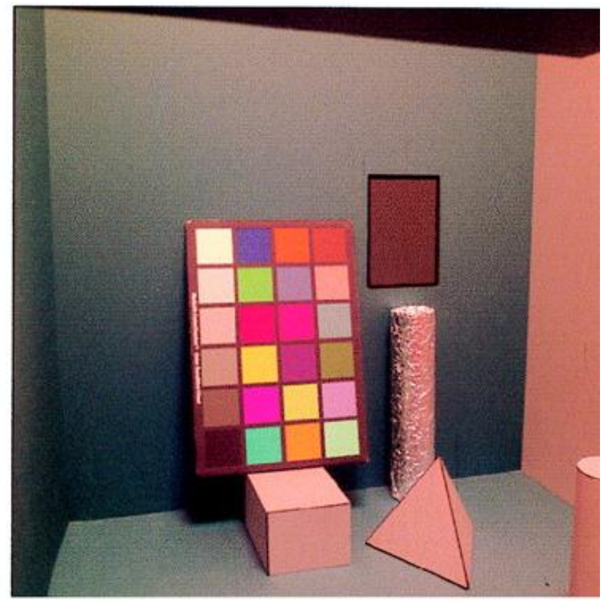
Edwin Lan. The retinex, Am Sci 1964
Anya Hurlbert: Is colour constancy real ? Current Biology 1999

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.



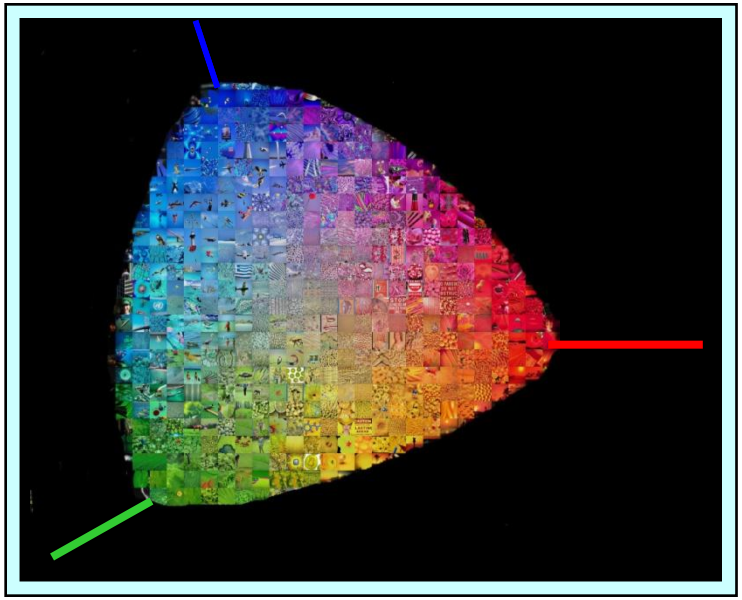


Successive subtraction of cues found them all to be important

- 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

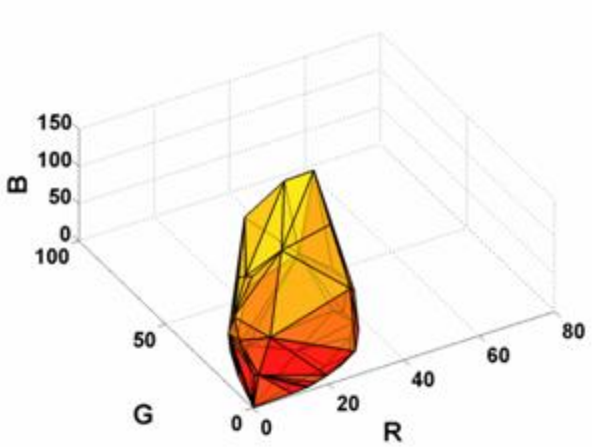
Gamut Mapping



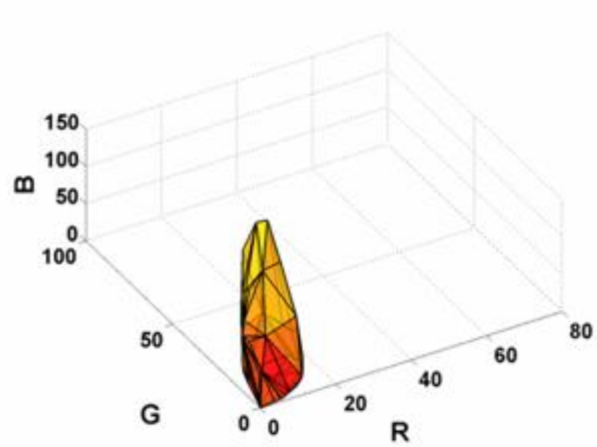
regular gamut mapping

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

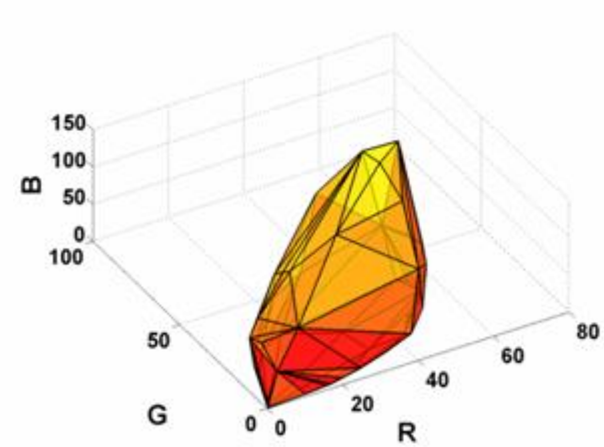
Solux 4700K



Solux 4700K + Roscolux filter



Sylvania Warm White Fluorescent



Slide credit: Theo Gevers

regular gamut mapping

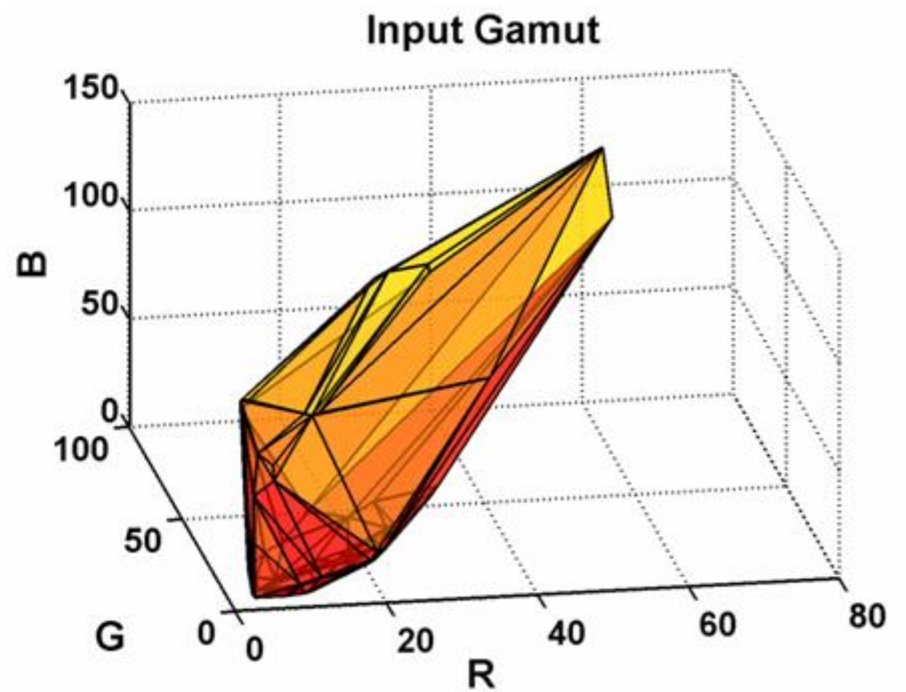
Gamut mapping algorithm:

- Obtain input image.

Slide credit: Theo Gevers

Gamut mapping algorithm:

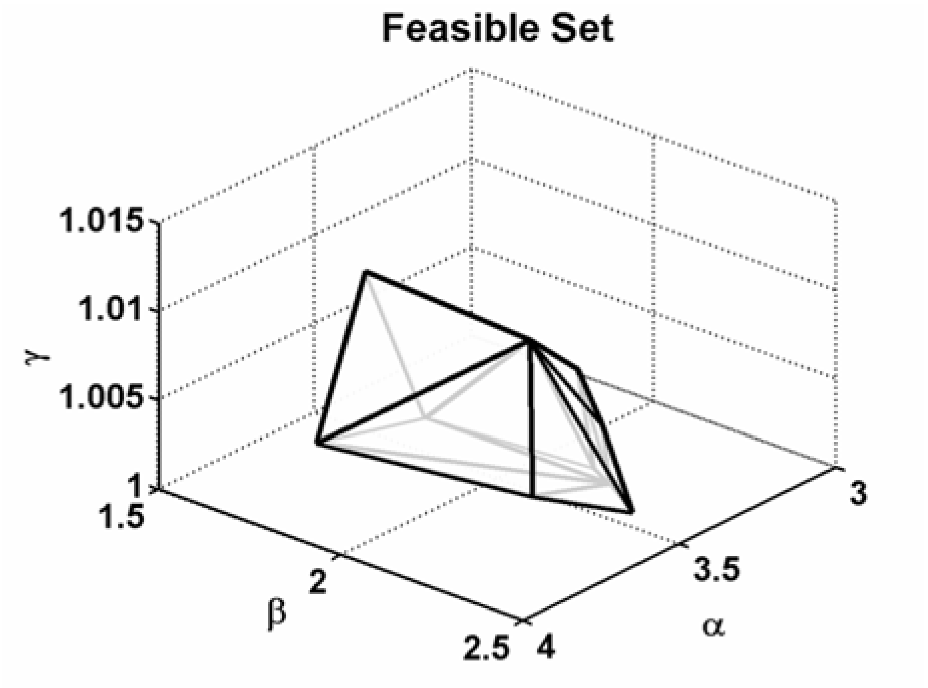
- Obtain input image.
- Compute gamut from image.



Slide credit: Theo Gevers

Gamut mapping algorithm:

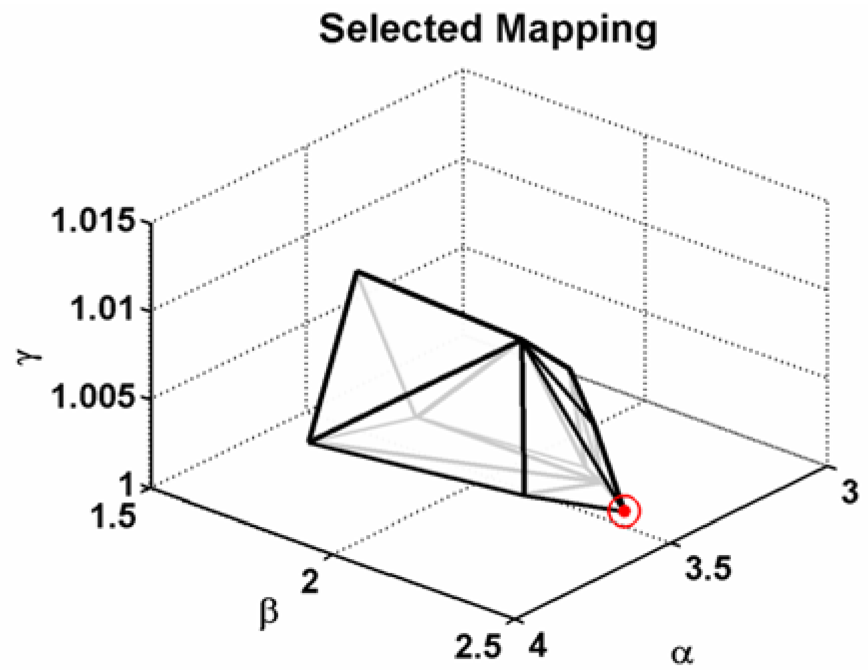
- Obtain input image.
- Compute gamut from image.
- Determine feasible set of mappings from input gamut to canonical gamut.



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.



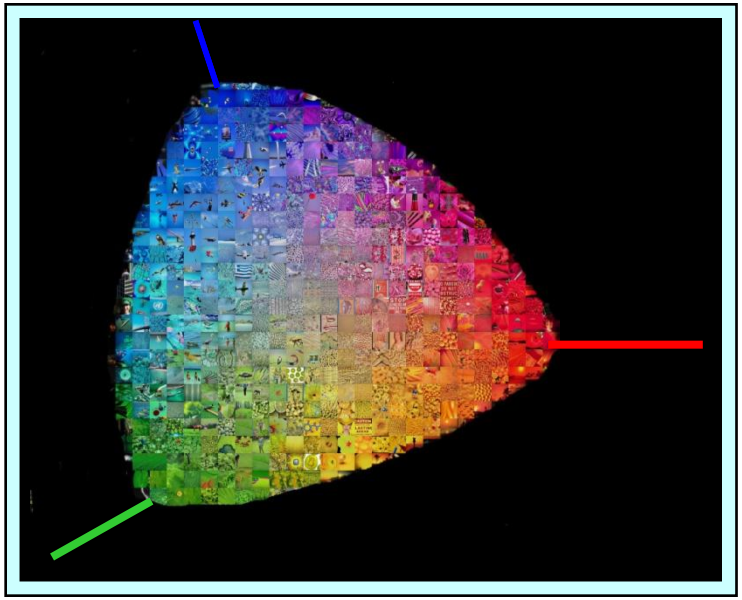
Slide credit: Theo Gevers

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.

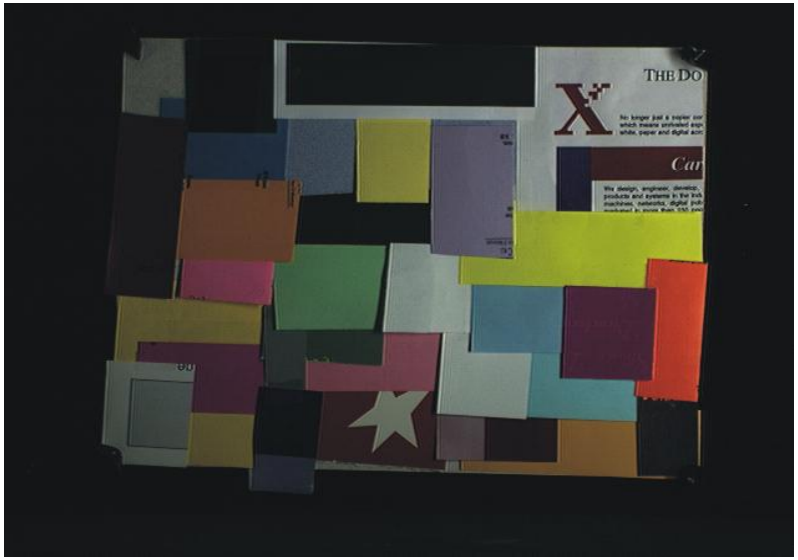
Grey-world: $$\sum_{m=1}^{M} \mathbf{f}_i(\mathbf{x}) \propto \mathbf{c}$$

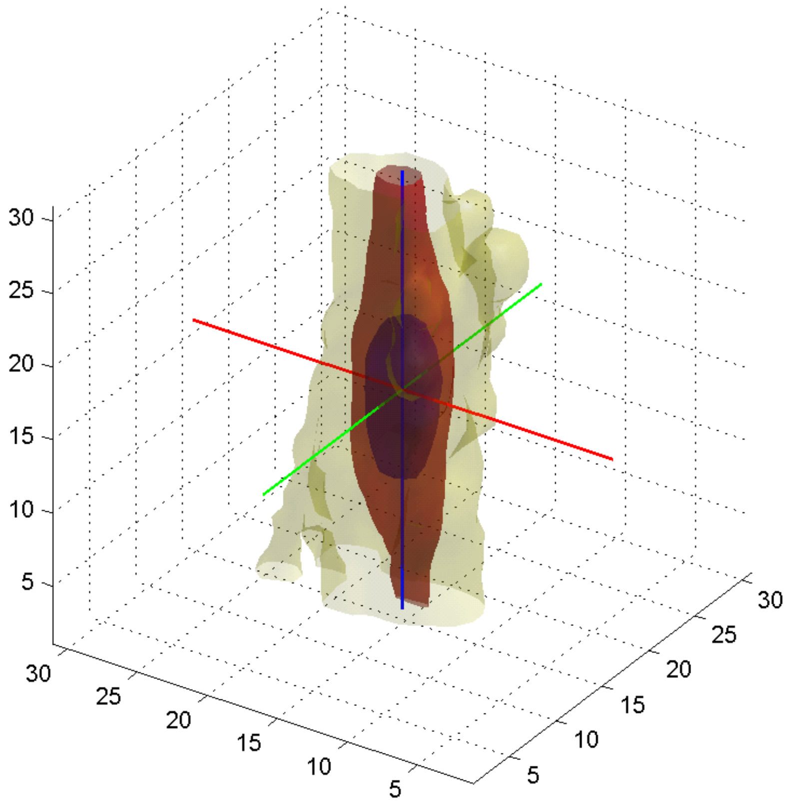
white-patch: $$\left(\sum_{m=1}^{M} \left(\mathbf{f}_i(\mathbf{x}) \right)^{\infty} \right)^{\frac{1}{\infty}} \propto \mathbf{c}$$

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

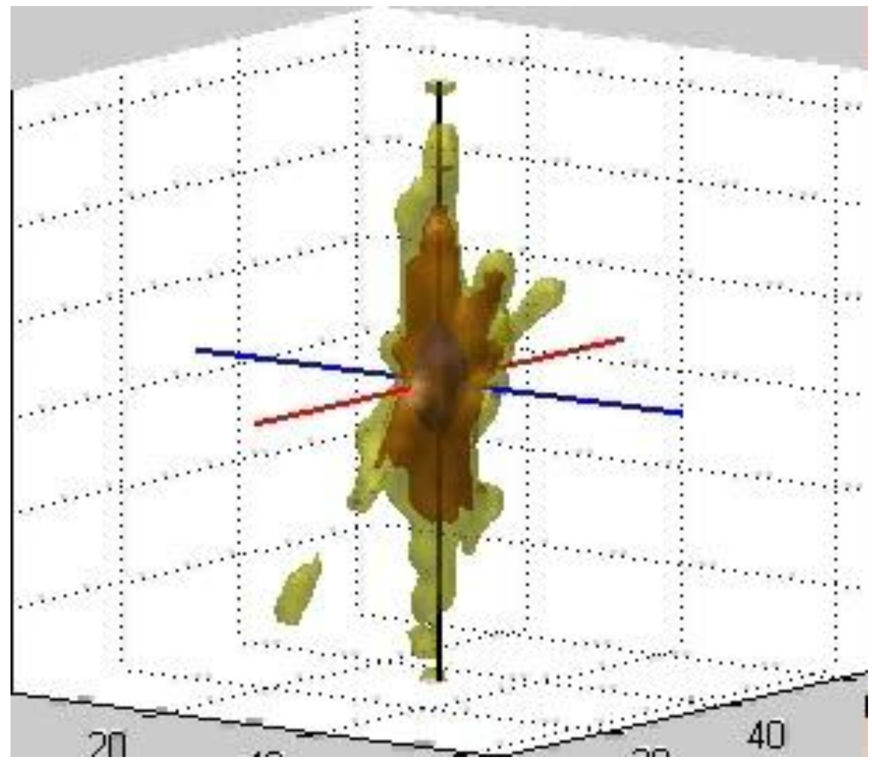
- unifies Grey-World and White Patch : $e^p \approx \sqrt[p]{\int |\mathbf{f}(\mathbf{x})|^p d\mathbf{x}}$

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:

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

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

generalization II: L-norm + differentiation order:

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

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:

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

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

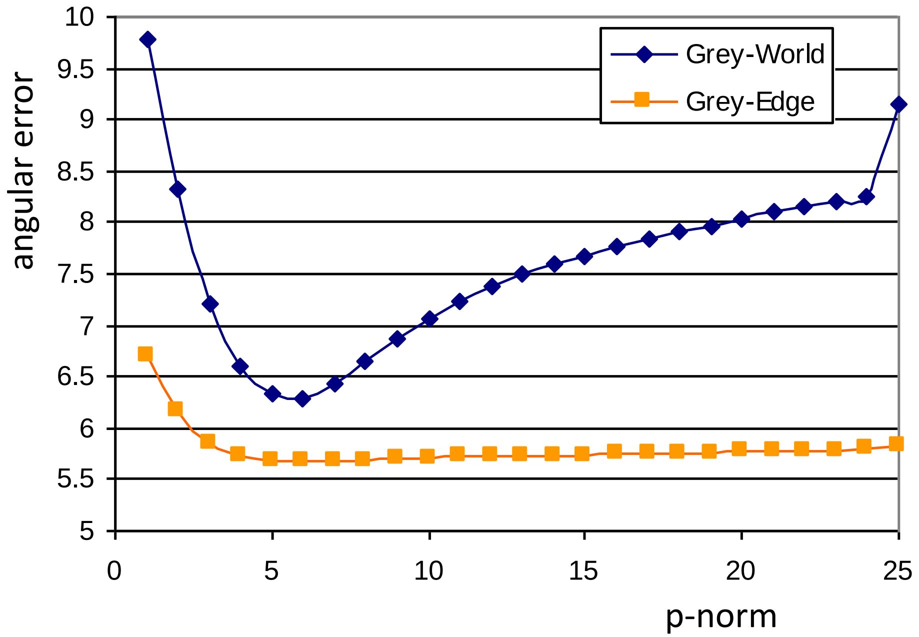
G. Finlayson, E. Trezzi, “Shades of gray and colour constancy”, *CIC 2004*
J. van de Weijer, T. Gevers “Edge-Based Color Constancy”, *IEEE IP 2007*

Color Constancy: experiment

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

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

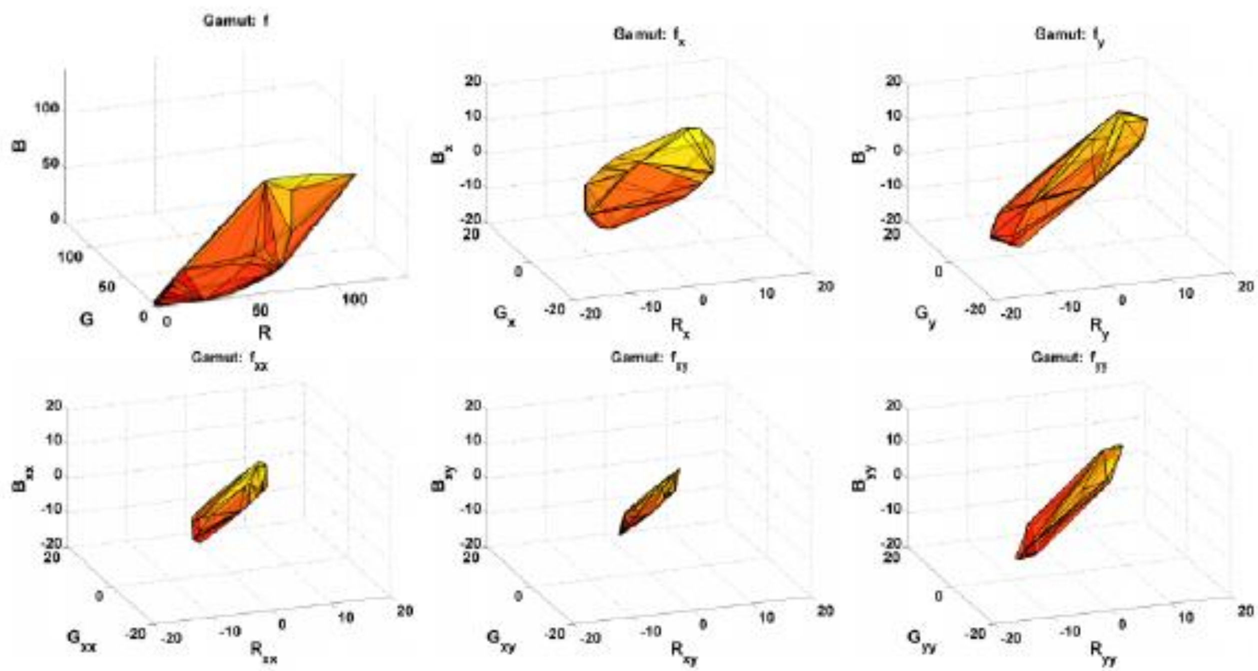
Color Constancy: experiment



	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, 87 Lights	5,3

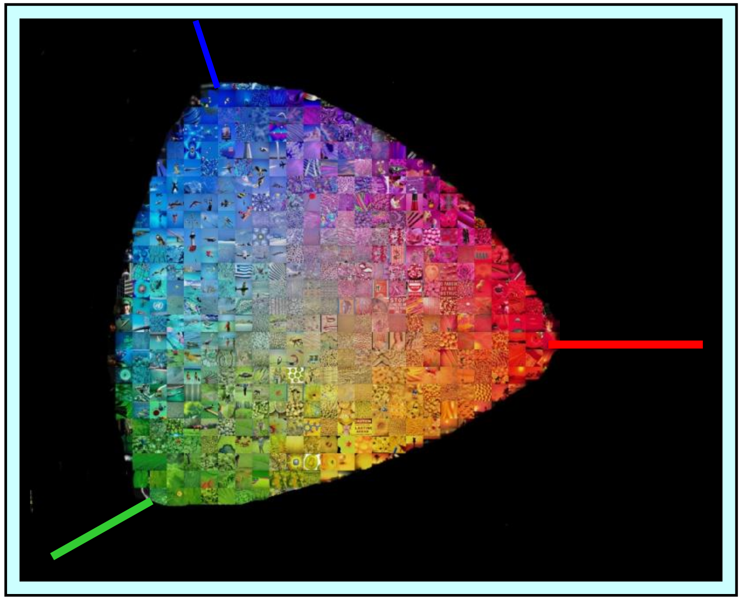
derivative-based gamut mapping

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



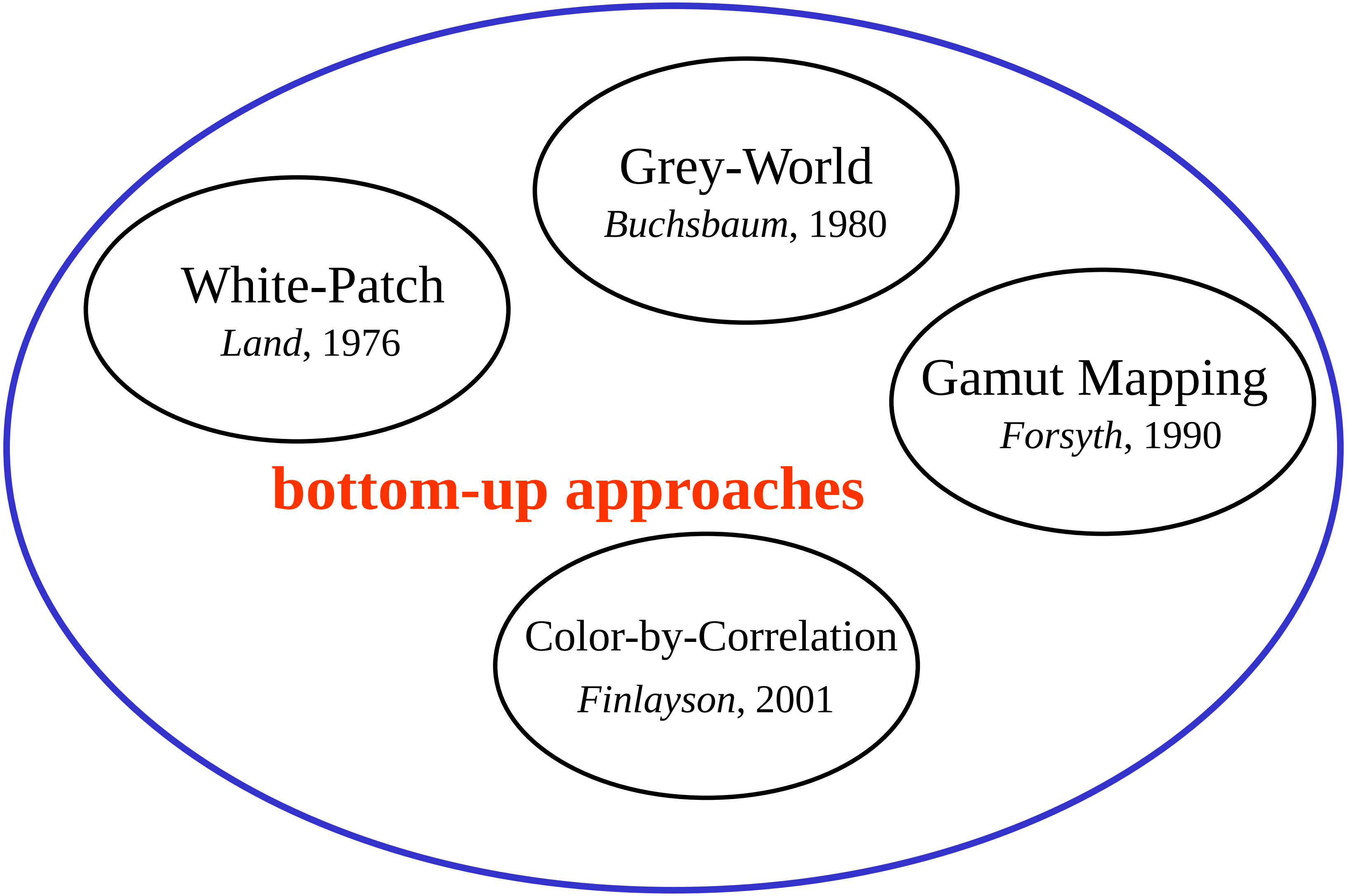
A. Gijsenij, T. Gevers, J. van de Weijer, "Generalized Gamut Mapping using Image Derivative Structures for Color Constancy ", *IJCV 2010*

Color Constancy from High-Level Visual Information



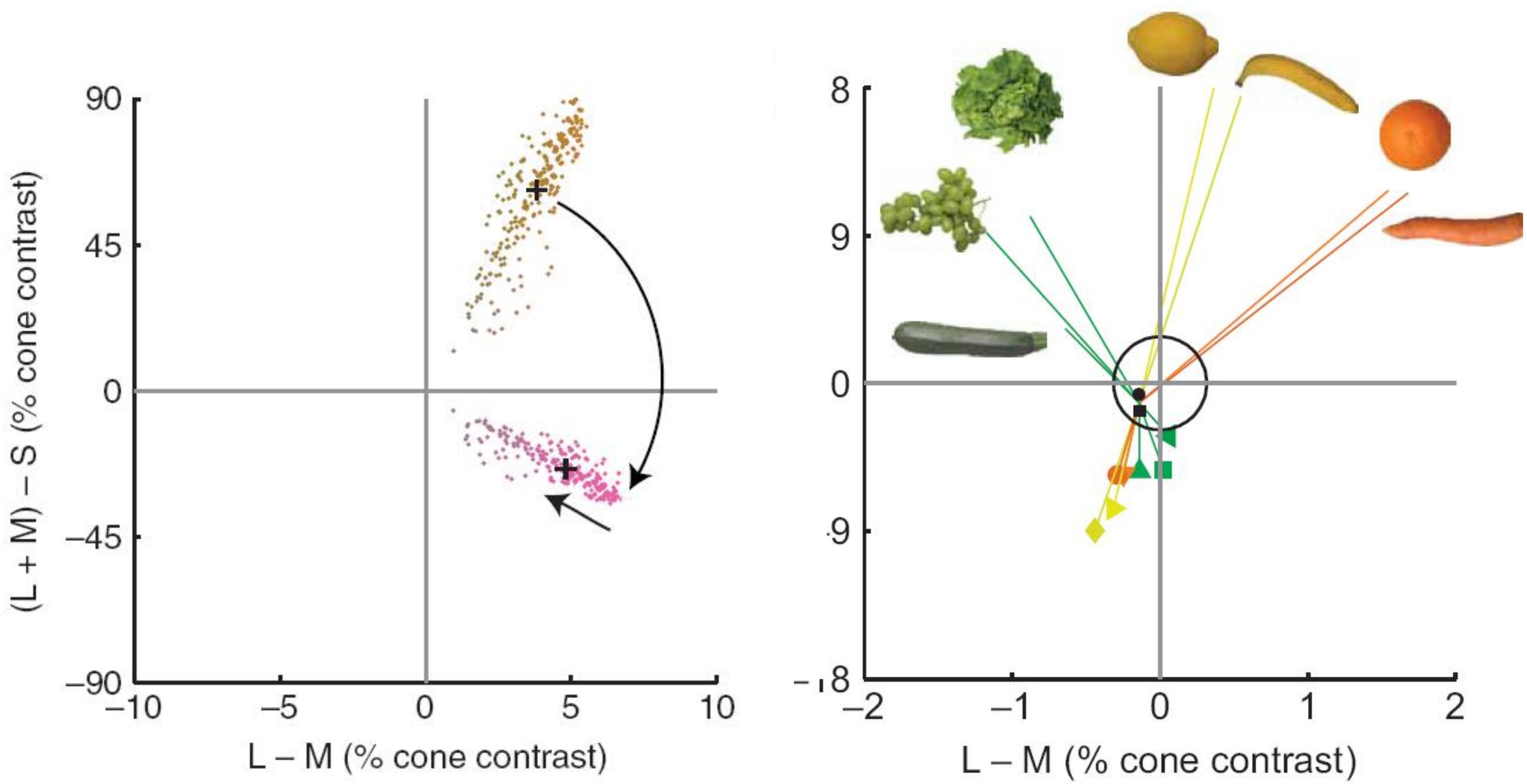
ICCV 2007

computational color constancy



top-down color constancy

psychophysical motivation:



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

problem statement

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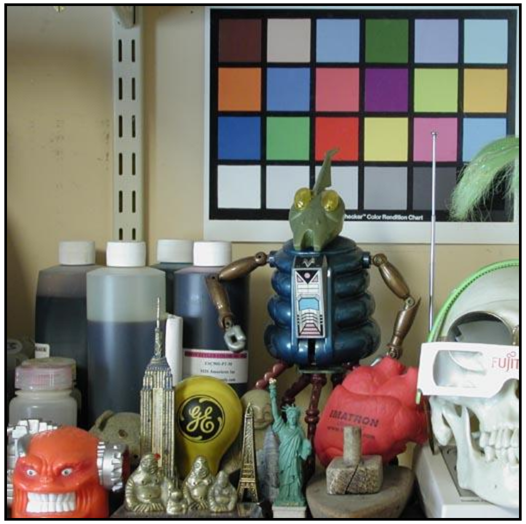
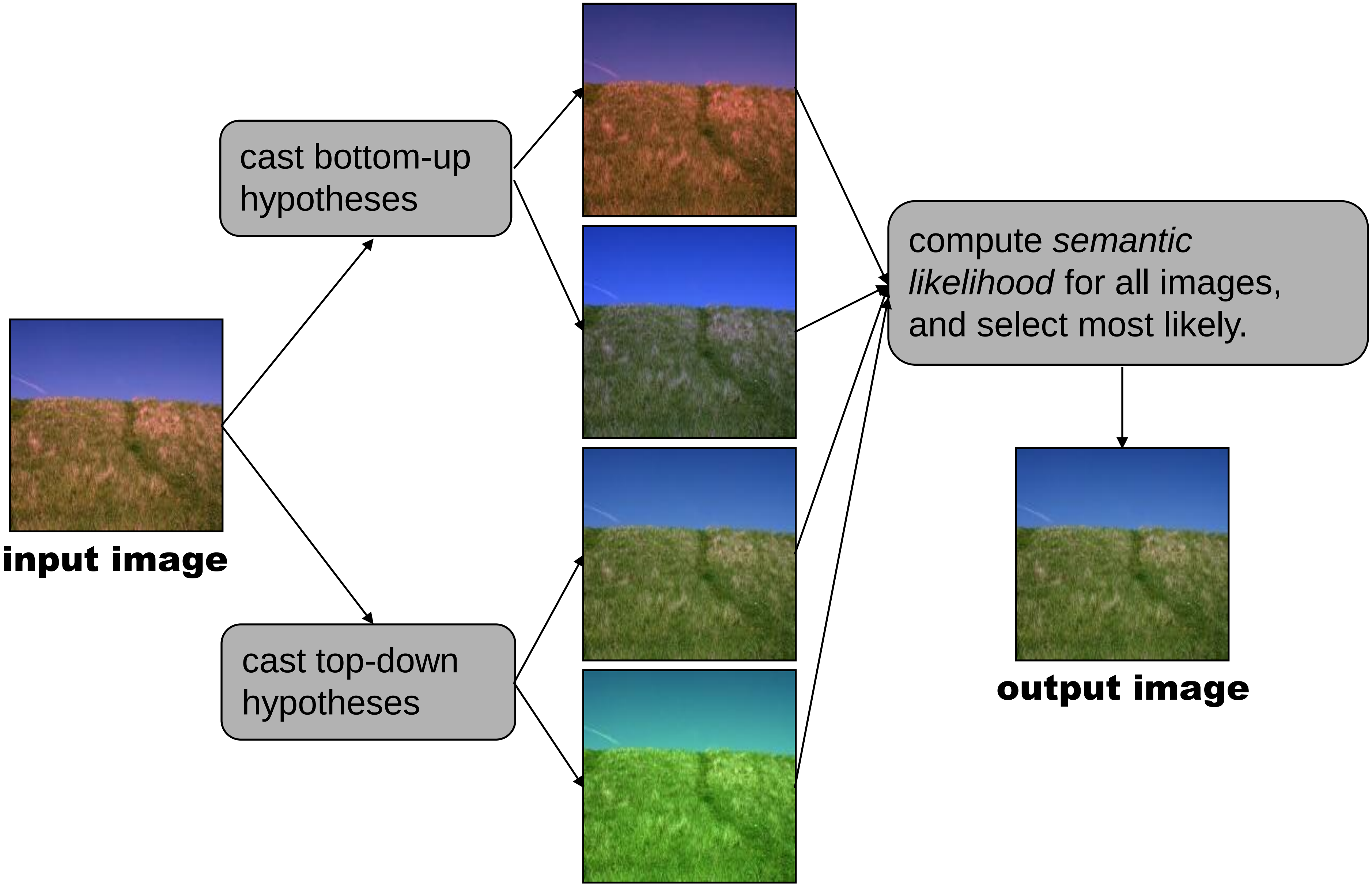


color constancy : the ability to recognize colors of objects invariant of the color of the light source.

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

overview our approach



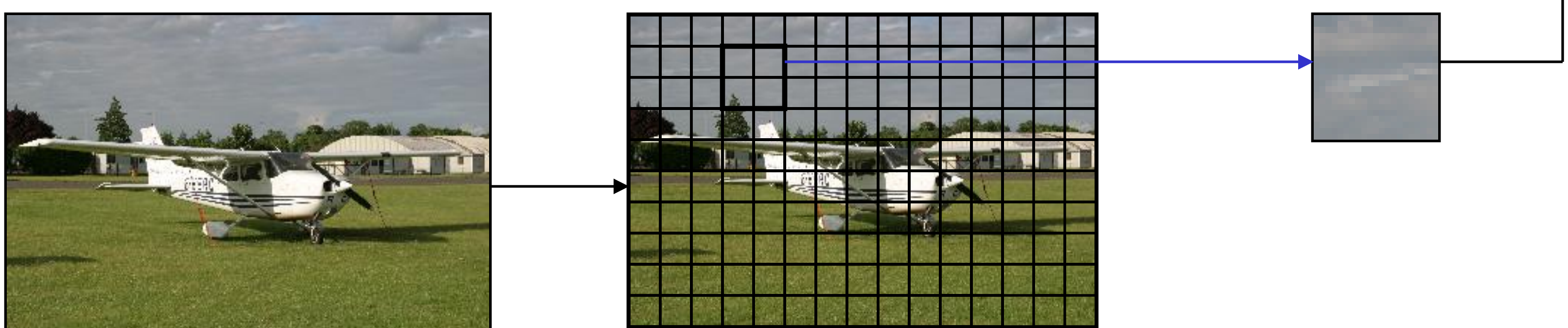
plsa-based image segmentation

- 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



grid **visual words**

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:

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

visual word **image** **semantic topics** **image-specific mixture proportions**

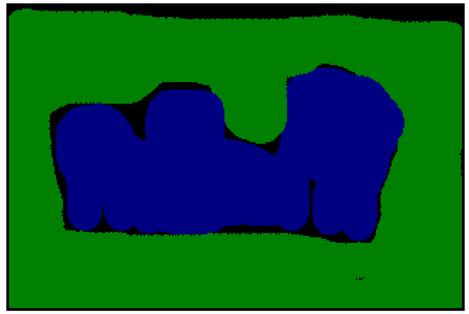
$$p(w|z) = \prod_{m=1}^{M} p(w^m|z)$$

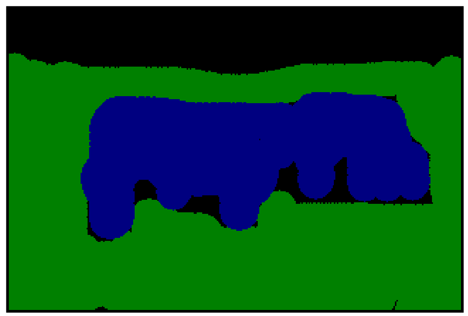
The $p(w^m|z)$ can either be learned supervised or unsupervised.
We assume them to be learned from images taken under a white illuminant.

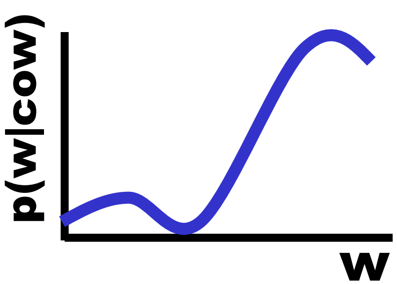
likelihood image $p(d) = \prod_w p(w|d)$

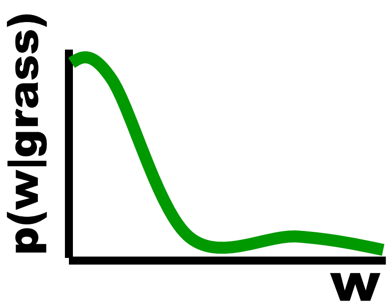
plsa-based image segmentation

supervised learning

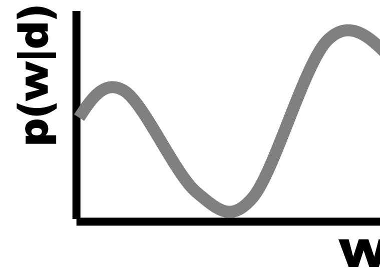







p(w|z)

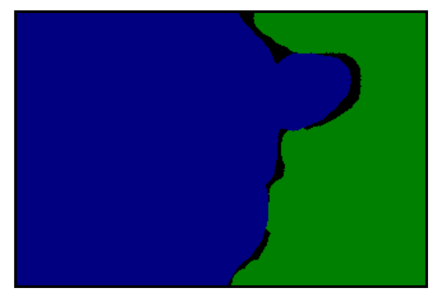
test image



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

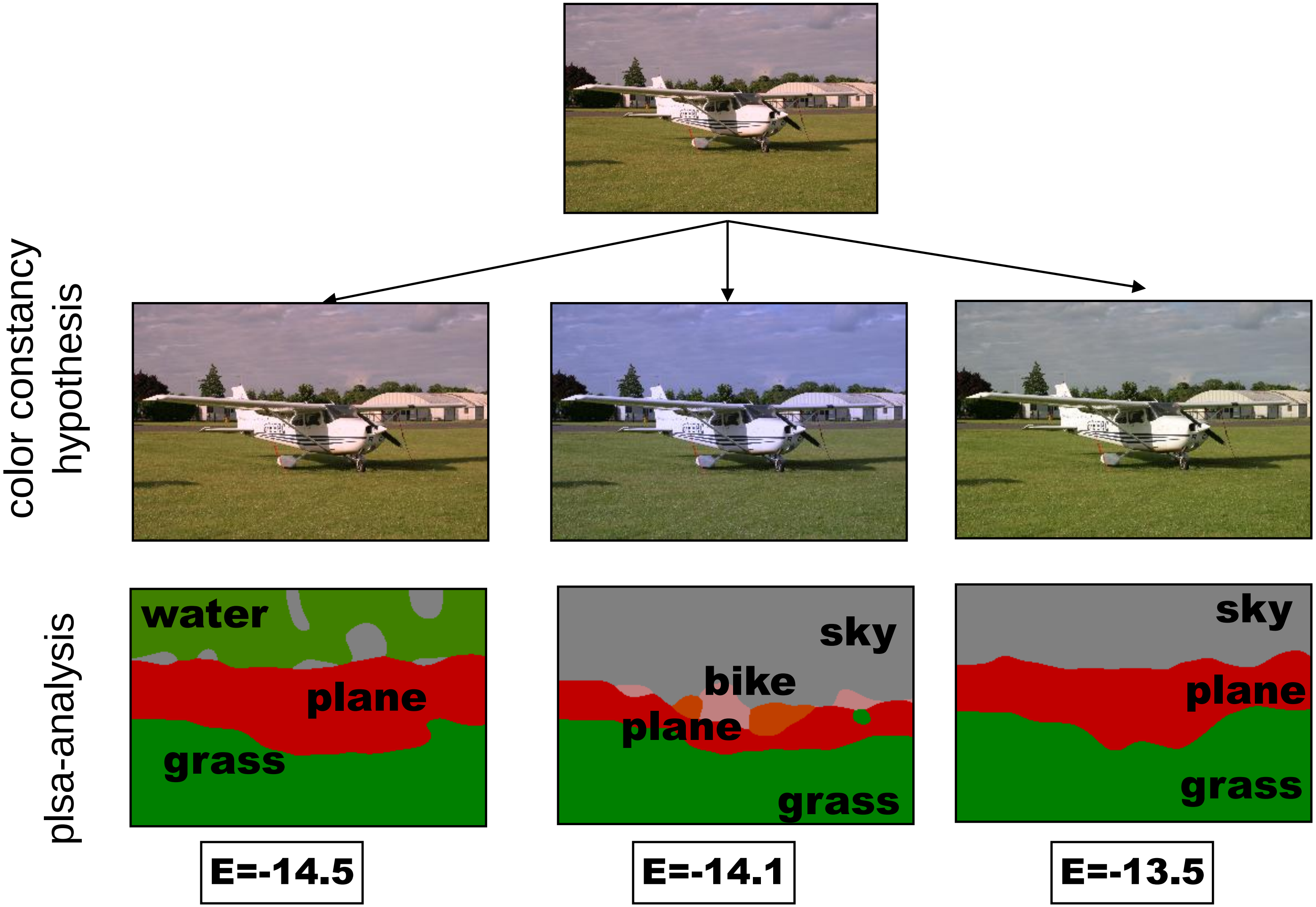
unknown

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



semantic image segmentation

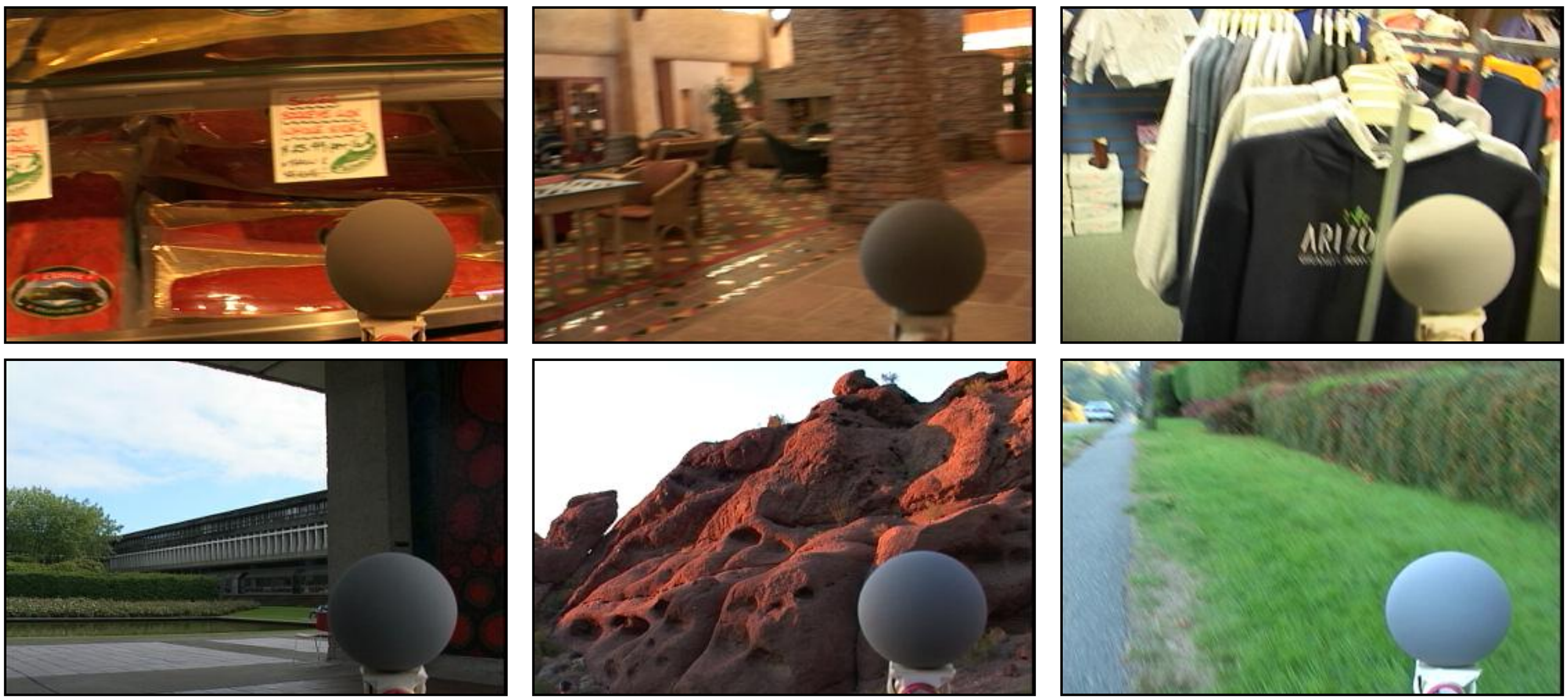
semantic likelihood image



experiment: illuminant estimation

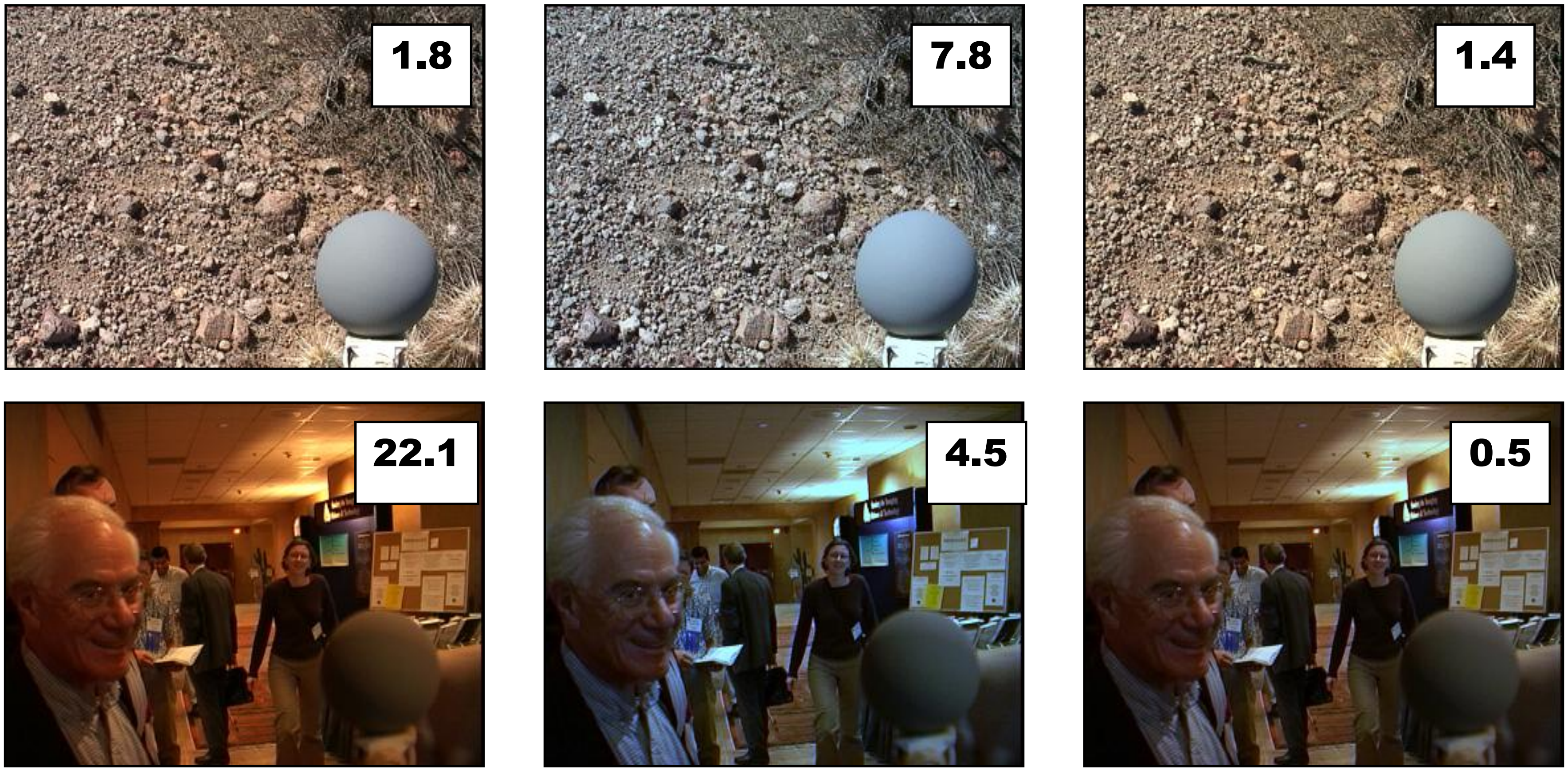
Data Set contains both indoor and outdoor scenes from a wide variety of locations (150 training, 150 testing)

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



input image | bottom-up | top-down

experiment: illuminant estimation

results in angular error:

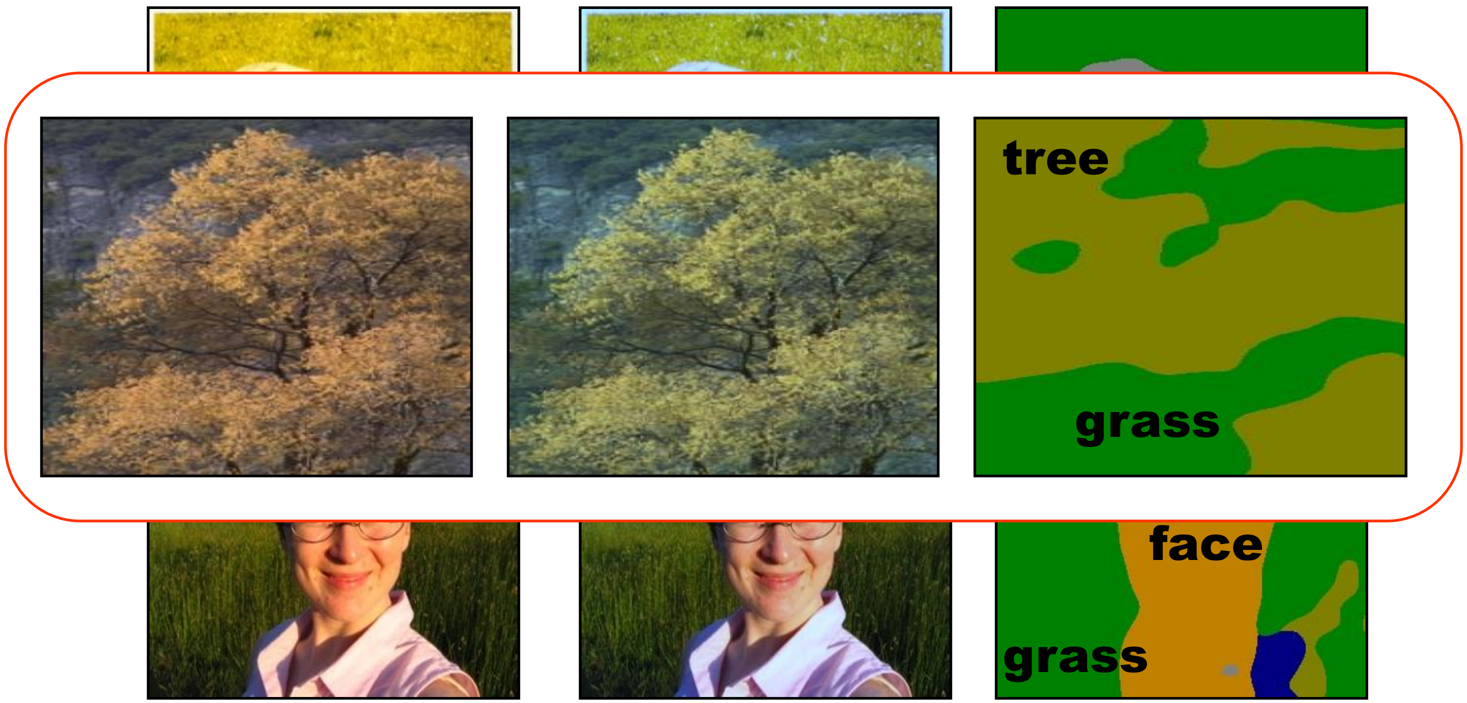
Method	Mean μ	Median	Trimean
Do Nothing	15.6°	14.0°	14.6°
White-Patch ($\mathbf{e}^{0,\infty,0}$)	12.7°	10.5°	11.3°
Grey-World ($\mathbf{e}^{0,1,0}$)	13.0°	11.0°	11.5°
general Grey-World ($\mathbf{e}^{0,p,\sigma}$)	12.6°	11.1°	11.6°
$1^{\text{st}}-$order Grey-Edge ($\mathbf{e}^{1,p,\sigma}$)	11.1°	9.5°	9.8°
$2^{\text{nd}}-$order Grey-Edge ($\mathbf{e}^{2,p,\sigma}$)	11.2°	9.6°	10.0°
Spatial Correlations (without reg.)	12.7°	10.8°	11.5°
Spatial Correlations (with reg.)	12.7°	5.3°	5.7°
Using Inverse Intensity Chromaticity Space	14.7°	11.0°	11.6°
Pixel-based Gamut Mapping	11.8°	8.9°	10.0°
Edge-based Gamut Mapping	13.7°	11.9°	12.3°
Intersection: Complete 1-jet	11.8°	8.9°	10.0°
Regression (SVR)	13.1°	11.2°	11.8°
Statistical Combination (No$-N-$Max)	10.3°	8.2°	8.8°
Using High-level Visual Information	9.7°	7.7°	8.2°
Using Natural Image Statistics	9.9°	7.7°	8.3°

Computational Color Constancy: Survey and Experiments. TIP 2011.

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



overview

PART I:
Color Image Acquisition

Keigo Hirakawa

• Color Image Sensor.

• Chrominance/luminance decompositions and demosaicking algorithms.

• Denoising before, during, and after demosaicking.

• Color fidelity issues due to noise and crosstalk.

PART II:
Color Image Processing fundamentals
Joost van de Weijer

• Dichromatic Reflection model.

• Photometric Invariance Color Features.

• Color constancy.

• Color Saliency.

PART III:
Applications

Theo Gevers

• Color Feature Detection.

• Color in Motion and Tracking.

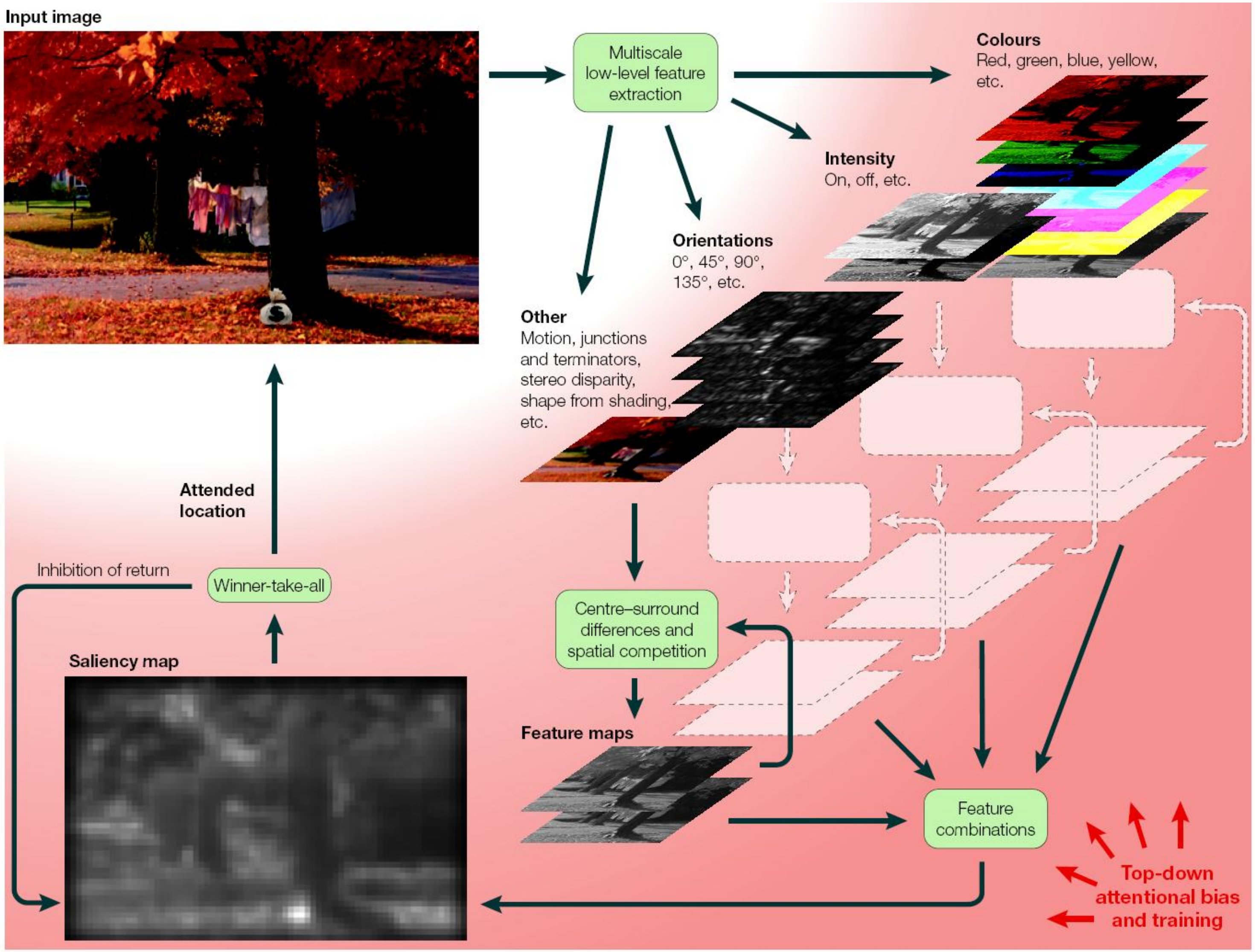
• Color for Object Recognition.

• Color in Image/video Classification.

Saliency Detection

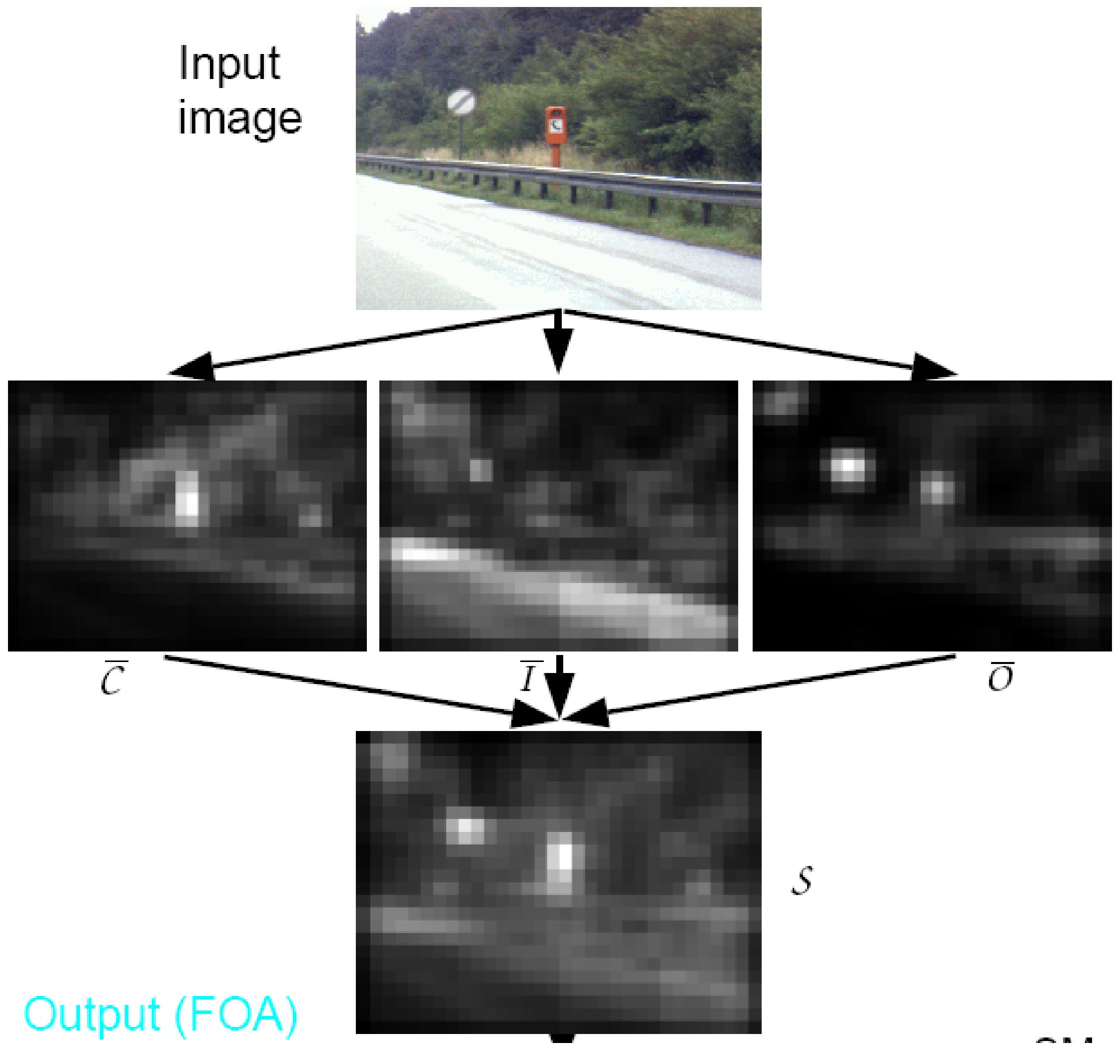
- Goal: direct our gaze rapidly towards objects of interest in our environment.
- Visual attention is know to be driven by both *bottom up* (image based) and *top-down* (task based) cues.
- Bottom-up saliency uses simple visual attributes such as *intensity*, *contrast*, *color opponency*, *orientation* , *direction* and *velocity* of *motion*.
- What matters is *feature contrast* rather than absolute feature strength (as in center surround systems).

Saliency Detection



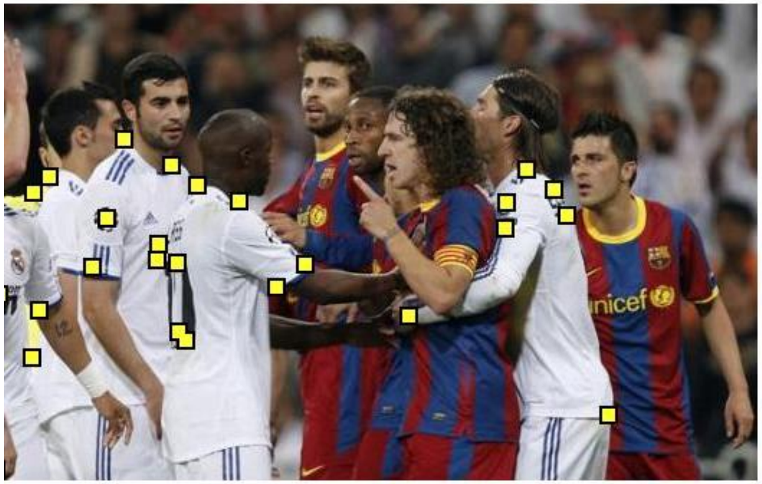
L.Itty, C. Koch “Computational Modelling of Visual Attention”, Nature Reviews Neurosciende, 2001.

Saliency Detection

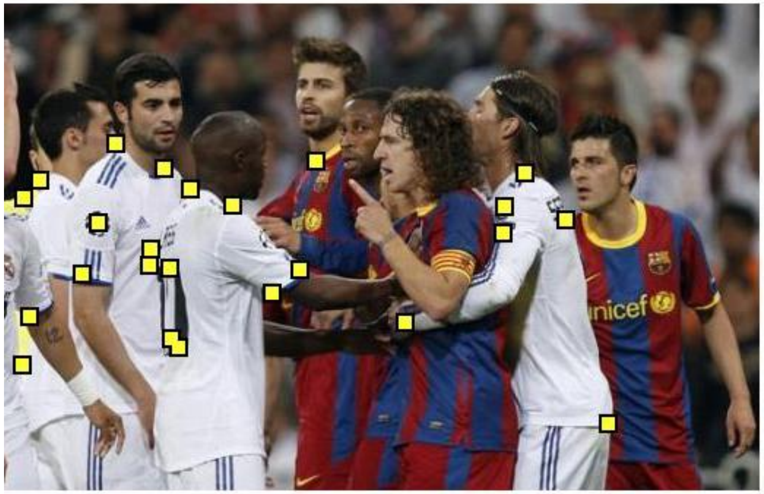


L.Itty, C. Koch "Computational Modelling of Visual Attention", Nature Reviews Neurosciende, 2001.

black-white focus of detectors



luminance



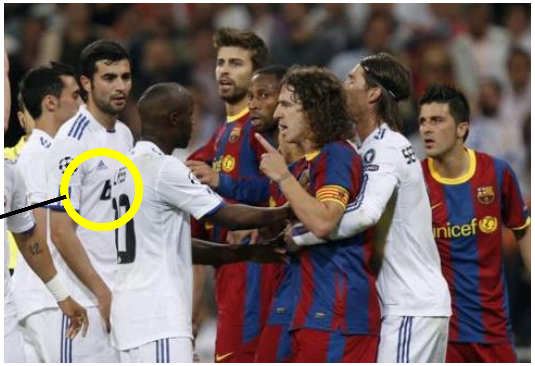
RGB

color distinctiveness

- color Harris *detector*:

$$H\left(\mathbf{f}_x,\mathbf{f}_y\right)=\overline{\mathbf{f}_x\cdot\mathbf{f}_x}\,\overline{\mathbf{f}_y\cdot\mathbf{f}_y}-\overline{\mathbf{f}_x\cdot\mathbf{f}_y}^{\,2}-k\left(\overline{\mathbf{f}_x\cdot\mathbf{f}_x}+\overline{\mathbf{f}_y\cdot\mathbf{f}_y}\right)^2$$

- many detectors can be written as: $H\left(\mathbf{f}_x,\mathbf{f}_y\right)$
  - Laplace
  - Curvature detectors
  - symmetry detectors
  - optical flow



- the local patch can be described by:

$$v=\begin{pmatrix}R & G & B & R_x & G_x & B_x & R_y & G_y & B_y\end{pmatrix}$$

- the information content of an event, *v*, is equal to :

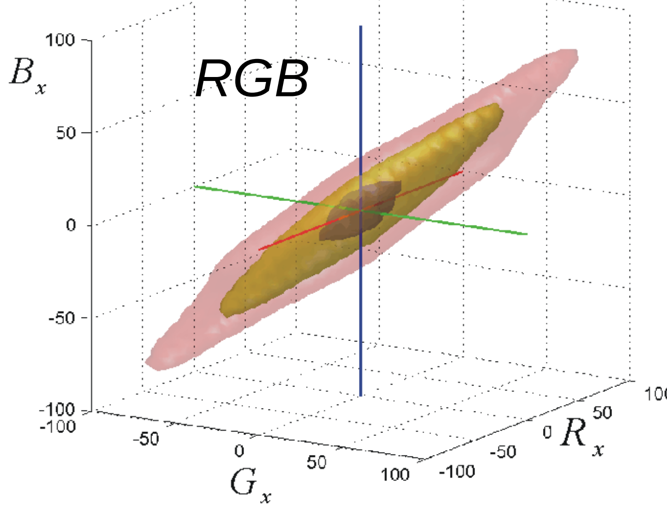
$$I(v)=-\log\left(p(v)\right)=-\log\left(p(\mathbf{f})\,p(\mathbf{f}_x)\,p(\mathbf{f}_y)\right)$$

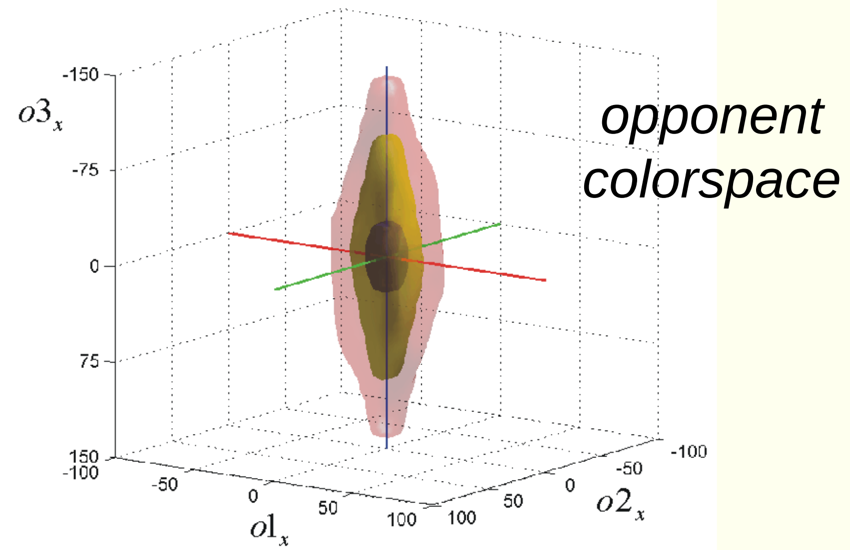
- equation differential-based salient point detectors :

Color Boosting Saliency: $p\left(\mathbf{f}_x\right)=p\left(\mathbf{f}'_x\right)\leftrightarrow\left|g\left(\mathbf{f}_x\right)\right|=\left|g\left(\mathbf{f}'_x\right)\right|$

statistics of color images

- The statistics of $\mathbf{f}_x$ is computed by looking of the 40.000 images of the Corel database.





- Isosalient surfaces can be approximated by aligned ellipsoids in decorrelated color spaces.

statistics of color images

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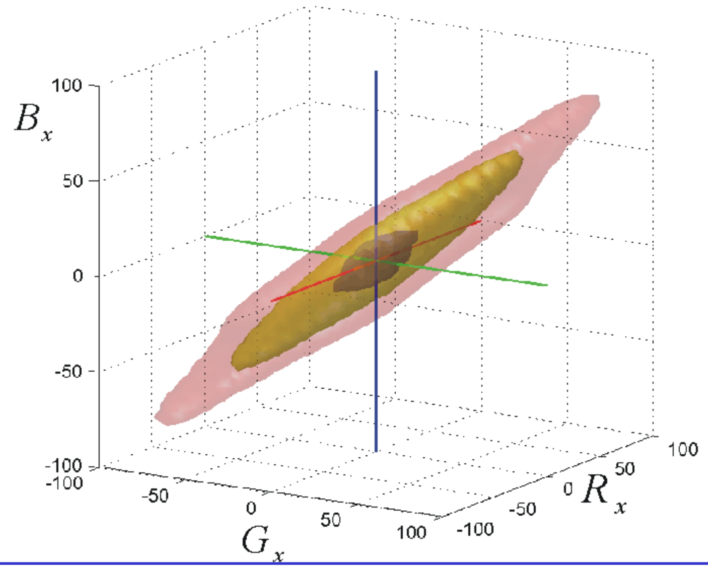


color boosting:

$$\mathrm{N} = \overline{\mathrm{f_x}\left(\mathrm{f_x}\right)^{\mathrm{t}}} = \begin{pmatrix} \overline{R_{\mathrm{x}}R_{\mathrm{x}}} & \overline{R_{\mathrm{x}}G_{\mathrm{x}}} & \overline{R_{\mathrm{x}}B_{\mathrm{x}}} \\ \overline{R_{\mathrm{x}}G_{\mathrm{x}}} & \overline{G_{\mathrm{x}}G_{\mathrm{x}}} & \overline{G_{\mathrm{x}}B_{\mathrm{x}}} \\ \overline{R_{\mathrm{x}}B_{\mathrm{x}}} & \overline{G_{\mathrm{x}}B_{\mathrm{x}}} & \overline{B_{\mathrm{x}}B_{\mathrm{x}}} \end{pmatrix}$$

$$\mathbf{N} = \mathbf{U}\mathbf{\Lambda}\mathbf{\Lambda}\mathbf{U}^{\mathbf{t}}$$

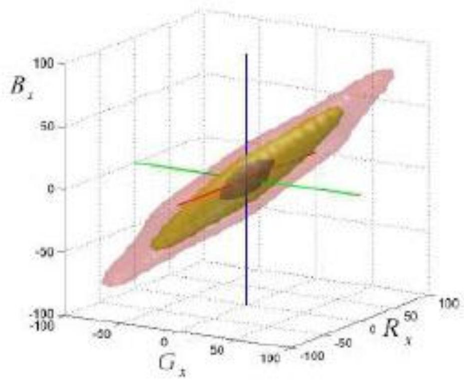
$$\overline{R_{\mathrm{x}}R_{\mathrm{x}}} = \sum_{\mathbf{x}\in X^i} R_{\mathrm{x}}\left(\mathbf{x}\right) R_{\mathrm{x}}\left(\mathbf{x}\right),$$

$$\mathbf{g}\left(\mathbf{f_x}\right) = \mathbf{\Lambda}^{-1}\mathbf{U}^{\mathbf{t}}\mathbf{f_x}$$

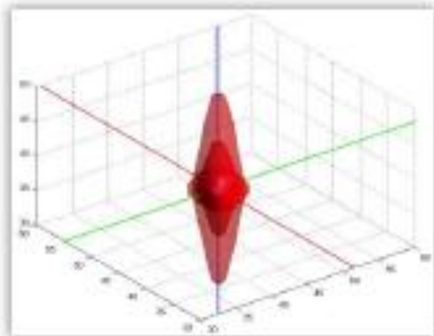
J. van de Weijer, Th. Gevers, A. Bagdanov, Boosting color saliency in image feature detection, IEEE PAMI 2006.

statistics of color images:

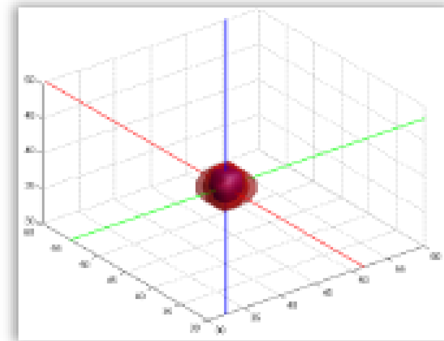
decorrelation whitening



derivatives
RGB color space



derivatives
opponent color space



derivatives
color boosted space

color boosting:

$$\mathbf{N} = \overline{\mathbf{f_x}\left(\mathbf{f_x}\right)^{\mathbf{t}}} = \begin{pmatrix} \overline{R_{\mathbf{x}}R_{\mathbf{x}}} & \overline{R_{\mathbf{x}}G_{\mathbf{x}}} & \overline{R_{\mathbf{x}}B_{\mathbf{x}}} \\ \overline{R_{\mathbf{x}}G_{\mathbf{x}}} & \overline{G_{\mathbf{x}}G_{\mathbf{x}}} & \overline{G_{\mathbf{x}}B_{\mathbf{x}}} \\ \overline{R_{\mathbf{x}}B_{\mathbf{x}}} & \overline{G_{\mathbf{x}}B_{\mathbf{x}}} & \overline{B_{\mathbf{x}}B_{\mathbf{x}}} \end{pmatrix}$$

$$\mathbf{N} = \mathbf{U}\mathbf{\Lambda}\mathbf{\Lambda}\mathbf{U}^{\mathbf{t}}$$

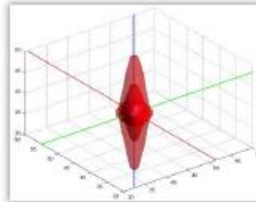
$$\overline{R_{\mathbf{x}}R_{\mathbf{x}}} = \sum_{\mathbf{x}\in X^i} R_{\mathbf{x}}\left(\mathbf{x}\right) R_{\mathbf{x}}\left(\mathbf{x}\right),$$

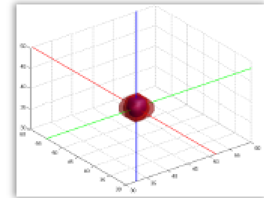
$$\mathbf{g}\left(\mathbf{f_x}\right) = \mathbf{\Lambda}^{-1}\mathbf{U}^{\mathbf{t}}\mathbf{f_x}$$

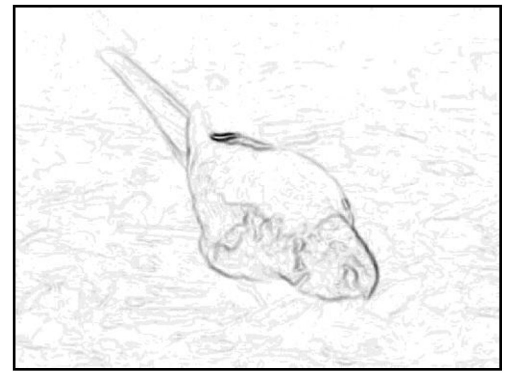
J. van de Weijer, Th. Gevers, A. Bagdanov, Boosting color saliency in image feature detection, IEEE PAMI 2006.

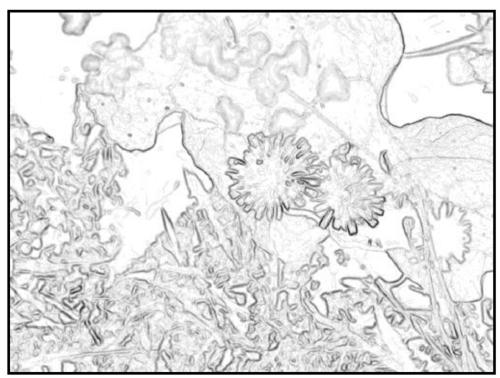
examples color boosting

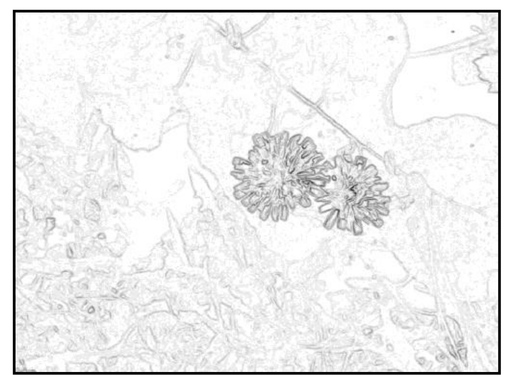
examples:









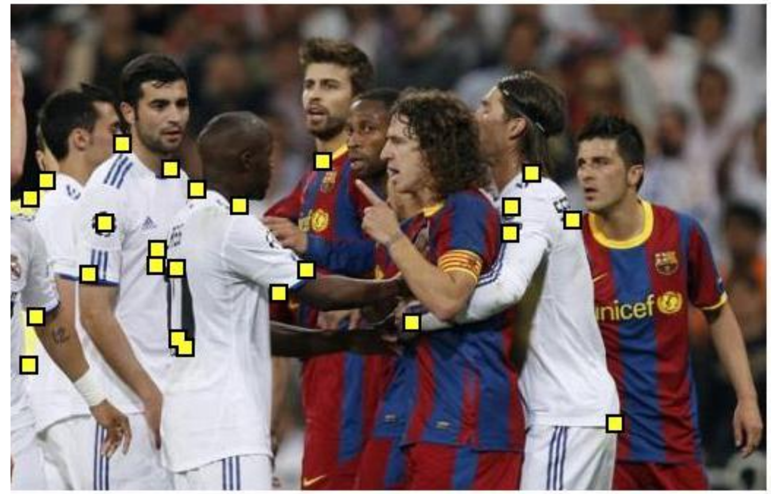


input image

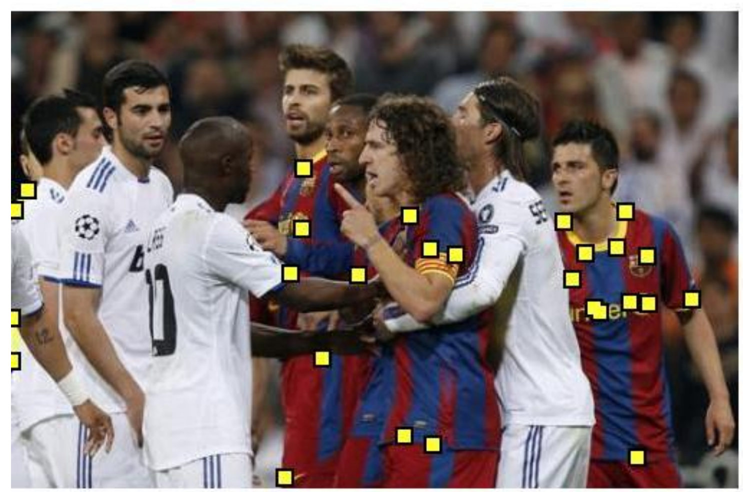
color edges

color boosted edges

examples color boosting



RGB



color boosting

examples color boosting

luminance

color boosted

Laplacian-of-Gaussian

Harris Laplace based on luminance.

Object recoloring

Extensions of dichromatic reflection model:

- multiple illuminants
- interreflections

Shida Beigpour, Joost van de Weijer, Recoloring based on intrinsic Image estimation, ICCV 2011

State-of-the-Art (Hue & Saturation Offset)

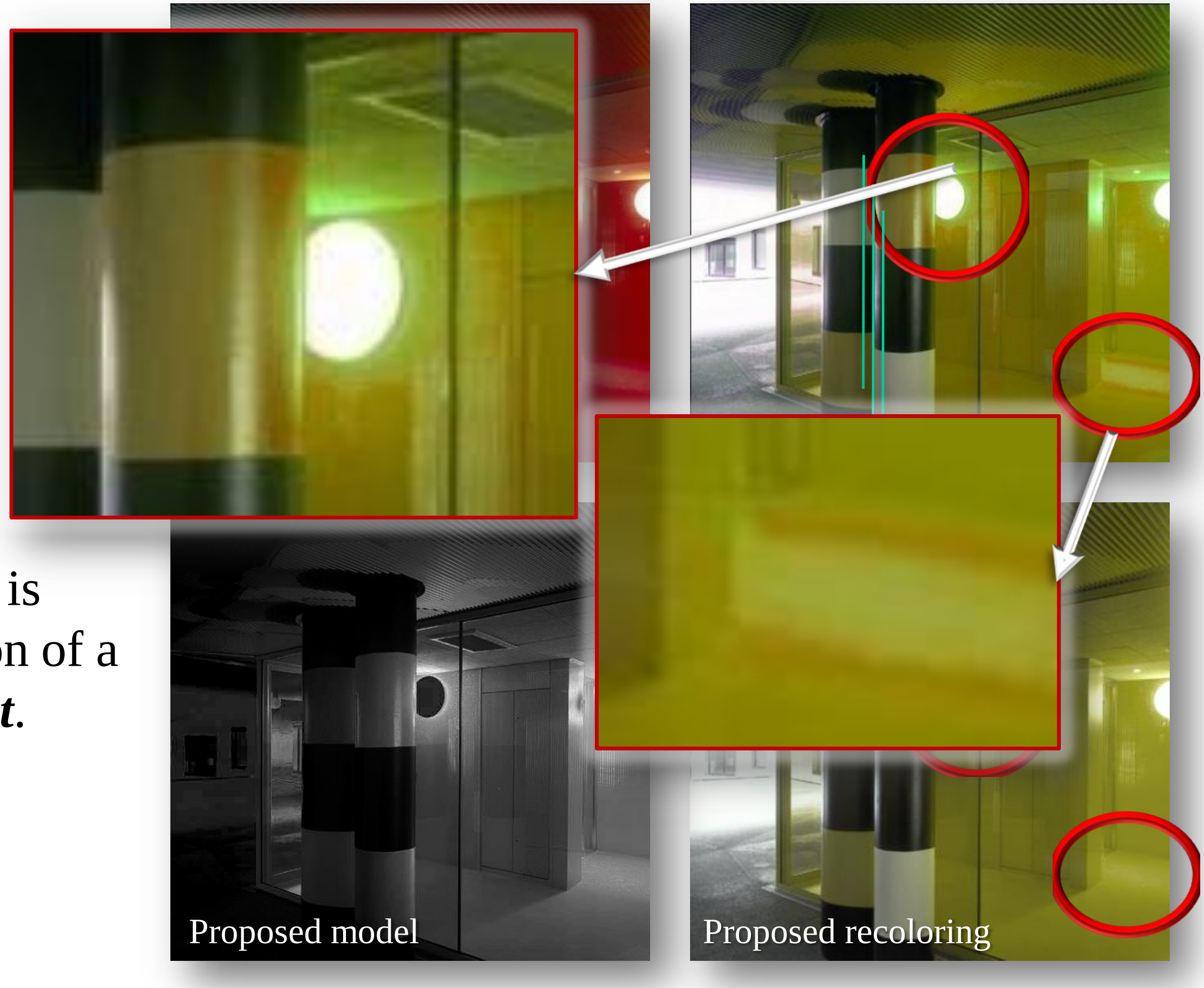


Photo-editing software is based on the assumption of a ***single white illuminant***.

Phyiscs-based Recoloring

Geometry of surface

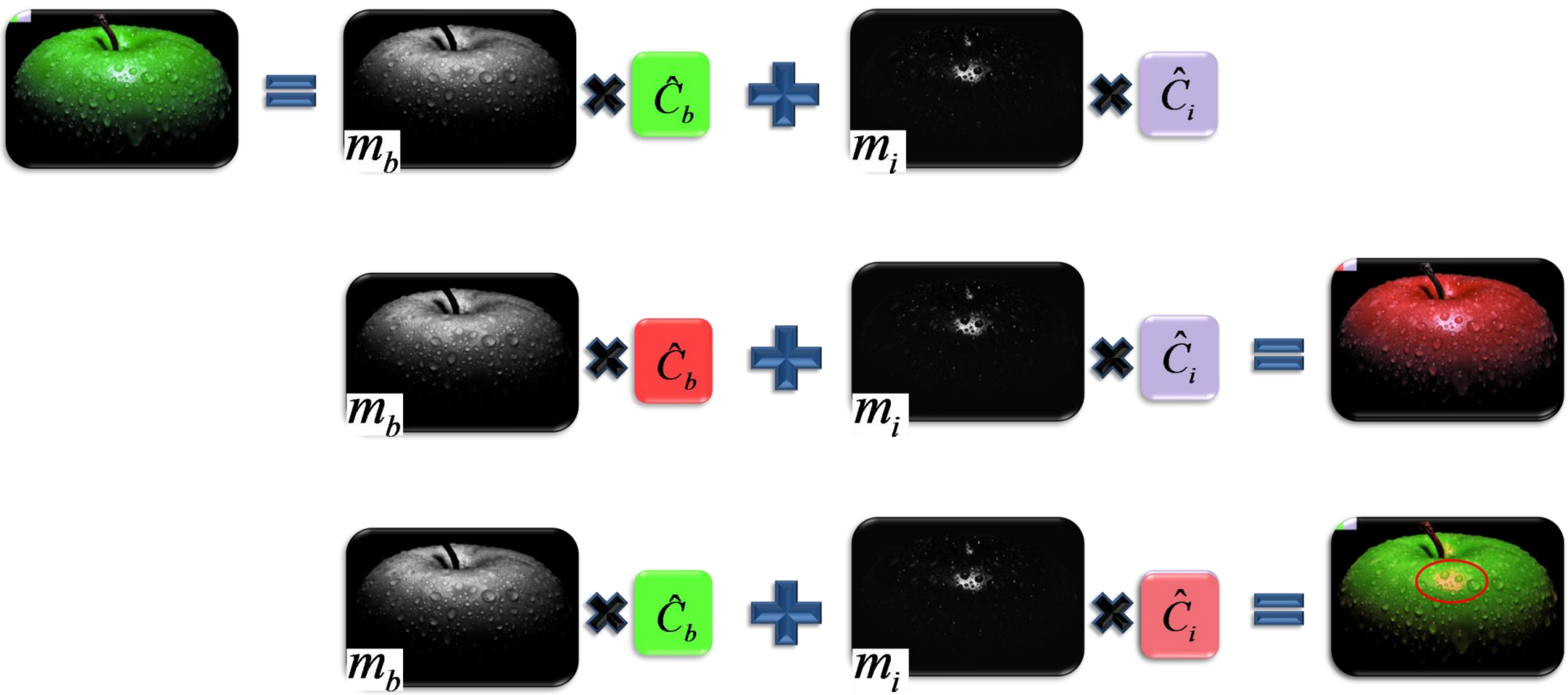
Geometry of incident light

$$f = m_b \times \hat{C}_b + m_i \times \hat{C}_i$$

Pixel's RGB value

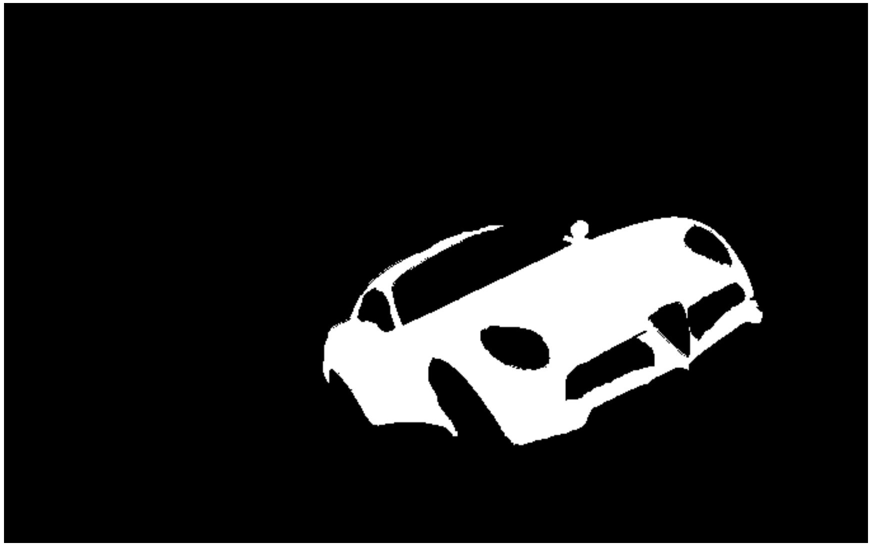
Reflectance color

Illuminant Color



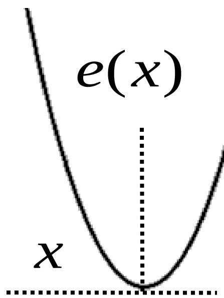
Reflectance estimation

- to constrain the problem of reflectance estimation we restrict ourselves to **single colored pre-segmented objects**.



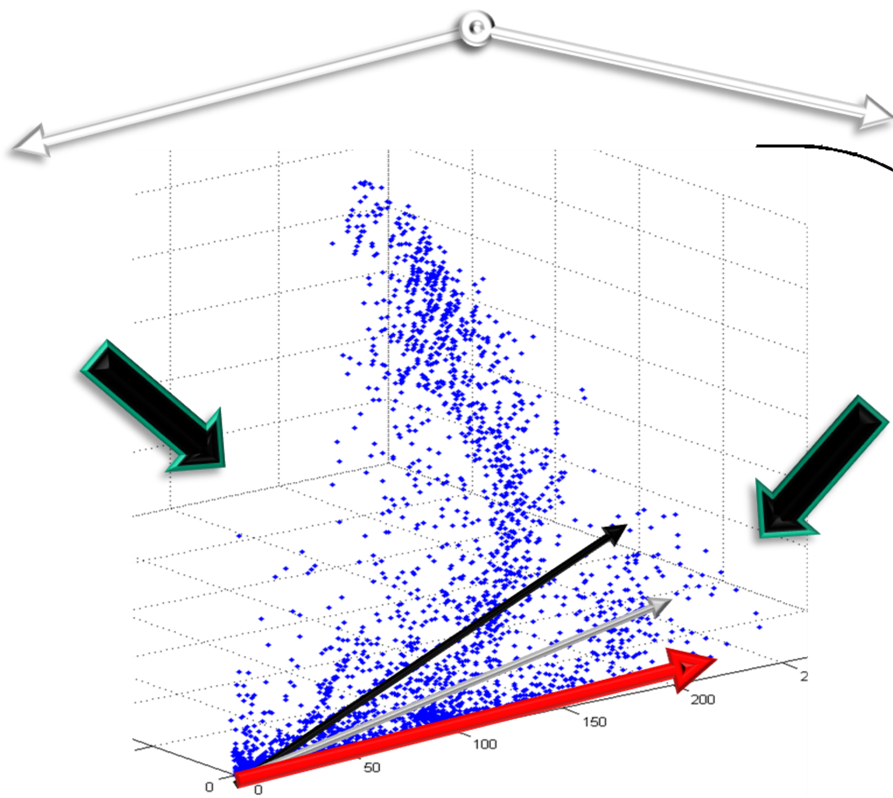
Robust body reflectance estimation

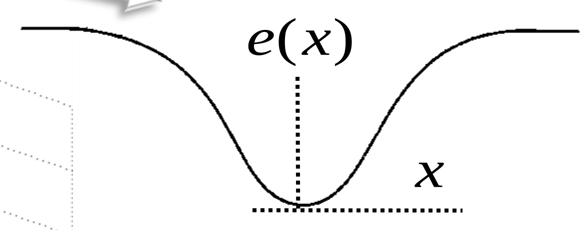
$$e(x) = \left\| f(x) - ((f(x))^T \hat{v}')\hat{v} \right\|$$



$$\int e(x)^2$$

Least Squares



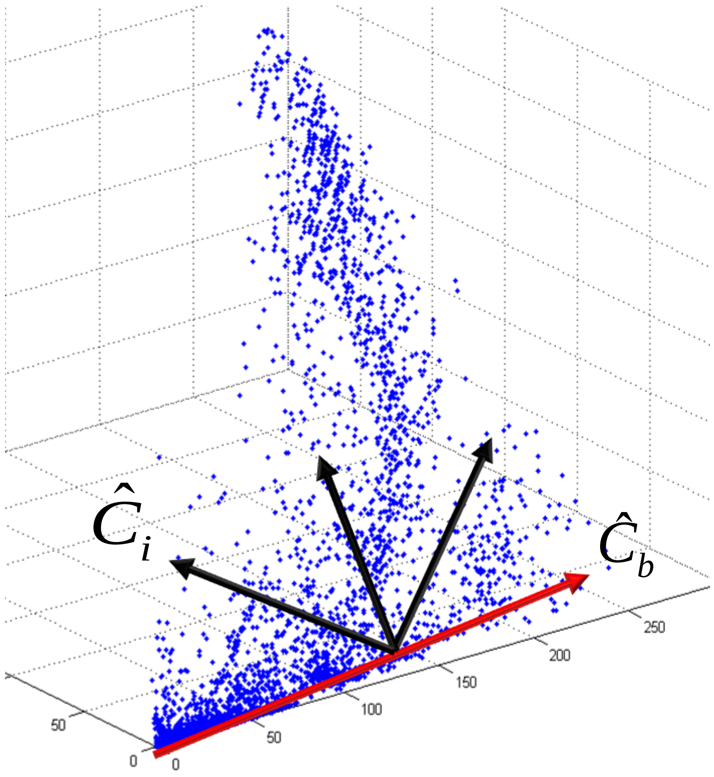


$$\int \rho(e(x))$$

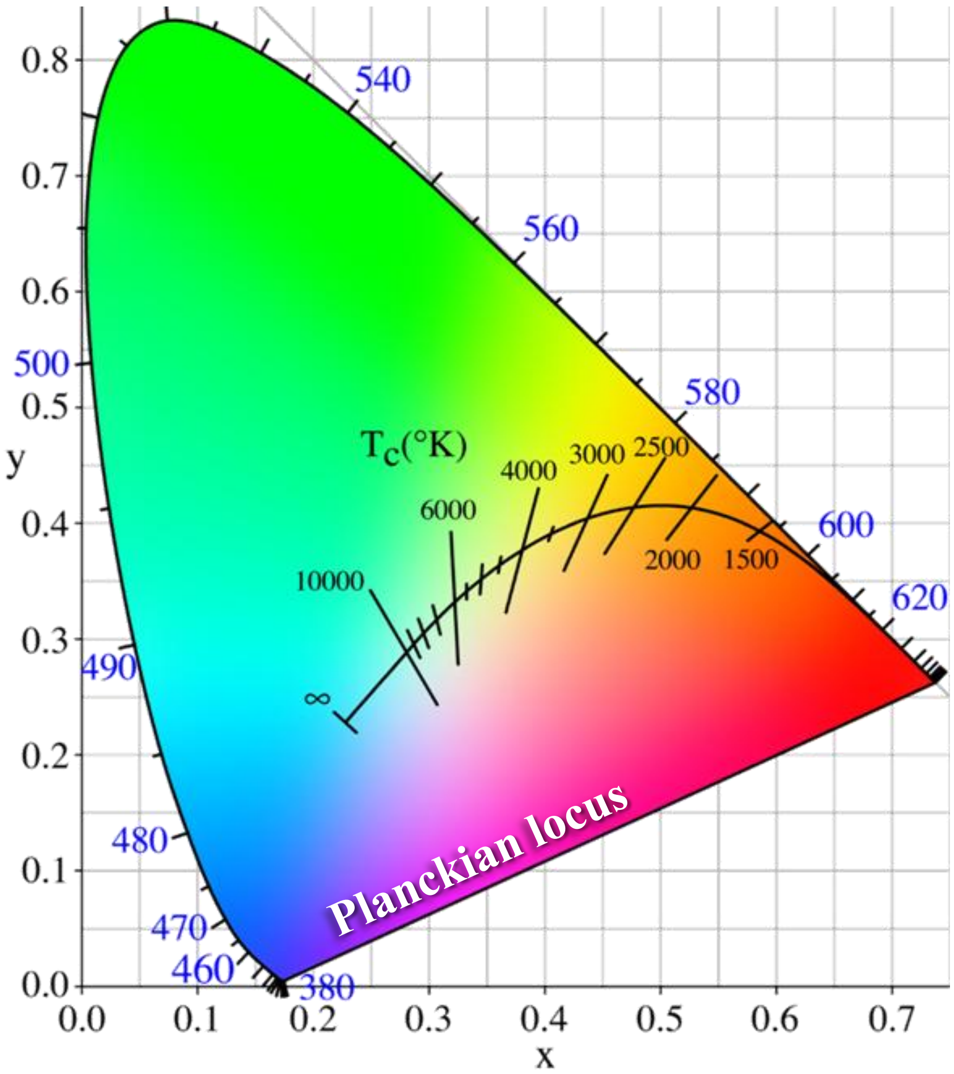
Gaussian

Illuminant estimation

• the problem of illuminant estimation underconstrained.



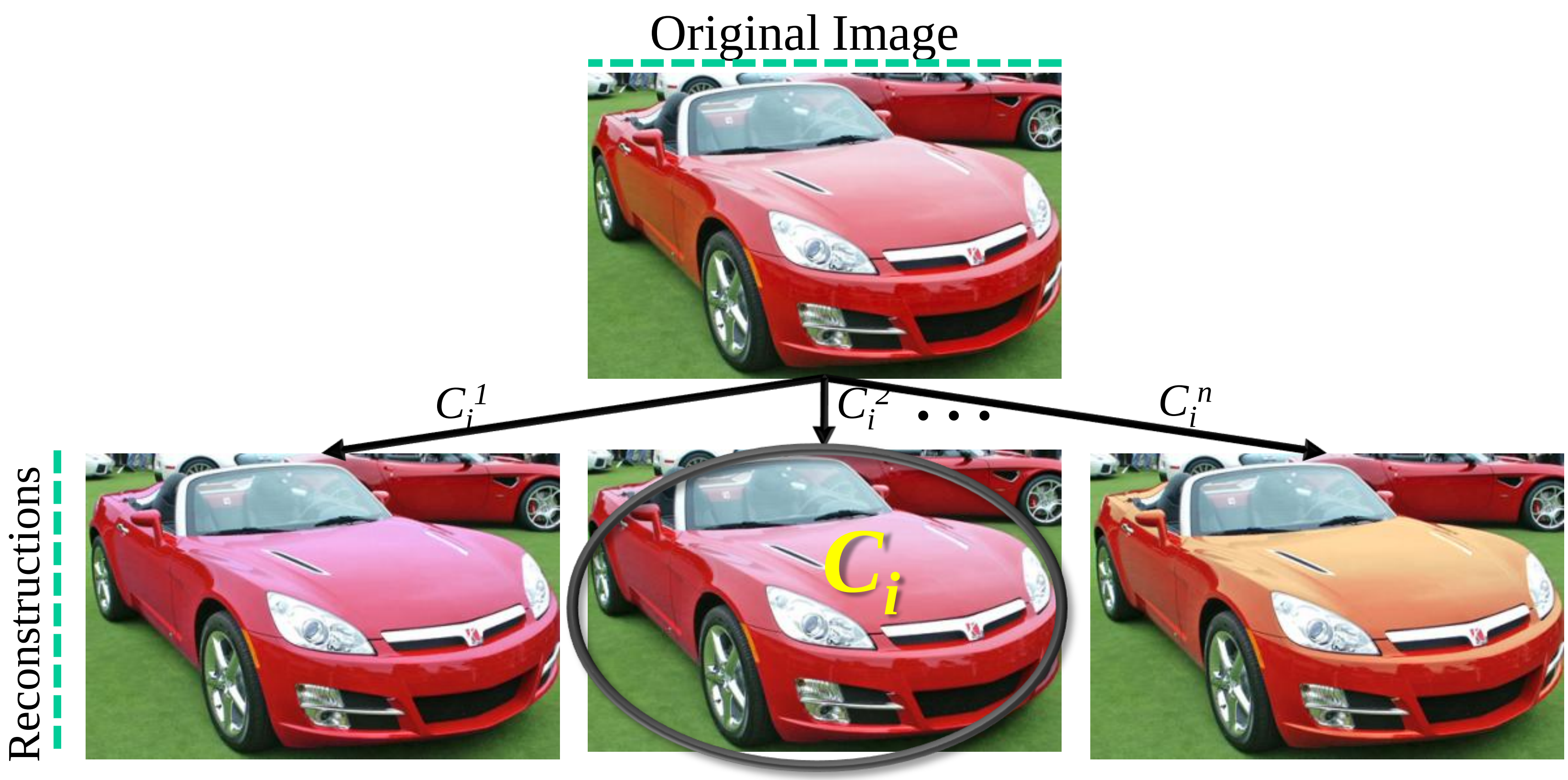
Illuminant estimation



Chromaticity of natural lights follows closely the **Planckian locus**.

Illuminant estimation

- Choose the Planckian illuminant which minimizes the reconstruction error.



$$reconstructionError = \sqrt{\sum_{forAllPixels} (original - reconstructed)^2}$$

Illuminant estimation

We extend the dichromatic model to include a second illuminant . This allows us to handle:

- outdoor shadows
- single-color interreflections.

$$\boxed{\mathbf{f} = m_b^1 \mathbf{c}\,\mathbf{L}^1 + m_s^1 \mathbf{l}^1 + m_b^2 \mathbf{c}\,\mathbf{L}^2}$$

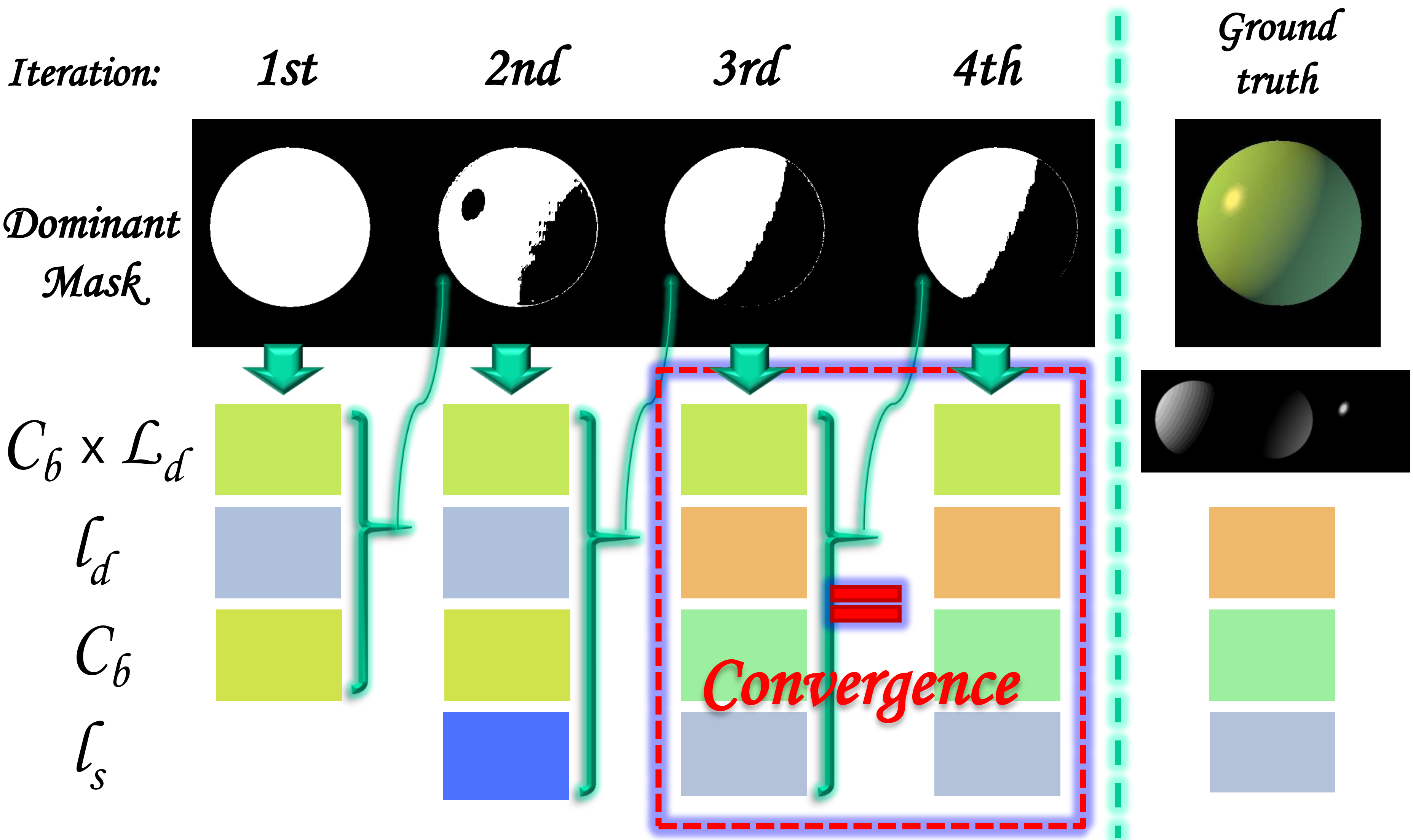
second Lambertian

second Lambertian

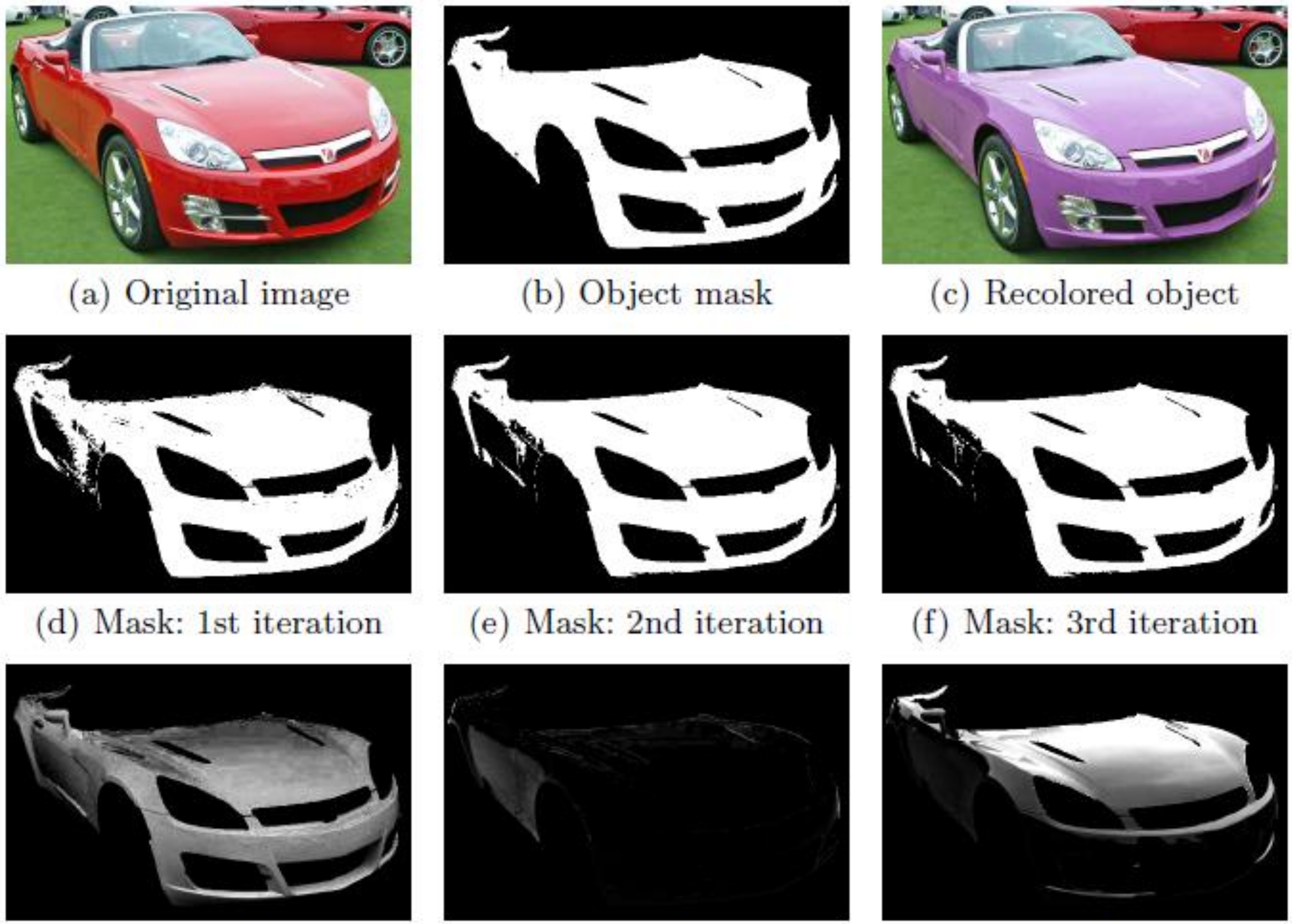
speculrities first illuminant

$$\mathbf{L} = diag\left(\mathbf{l}\right)$$

Two illuminant estimation



Experimental results



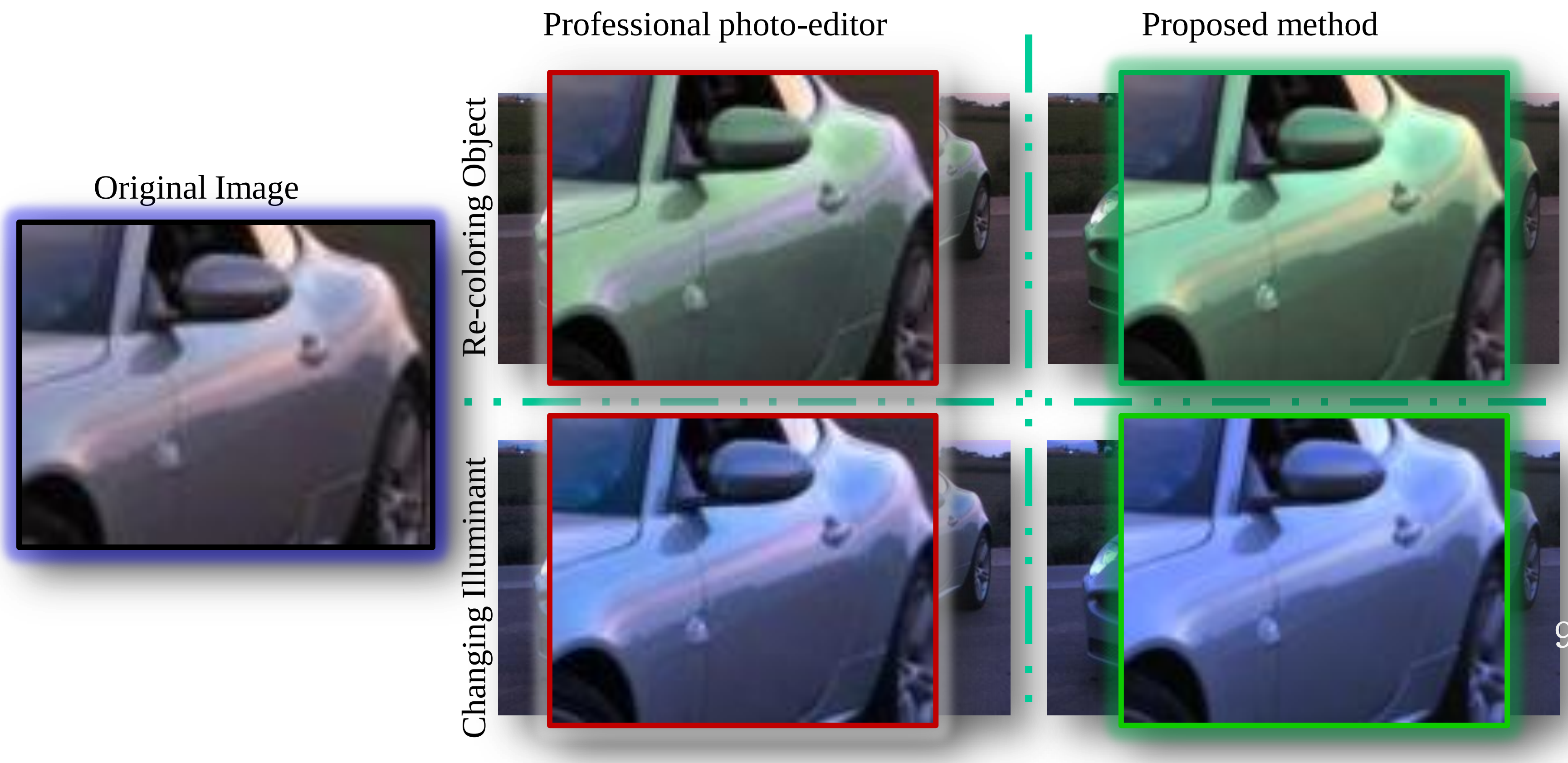
(a) Original image (b) Object mask (c) Recolored object

(d) Mask: 1st iteration (e) Mask: 2nd iteration (f) Mask: 3rd iteration

(g) m_b^1 (h) m_b^2 (i) m_s^1

State-of-the-Art (Hue & Saturation Offset)

Re-coloring both the *illuminant* and the *object* colors can be achieved through same method.



Experimental results

Re-coloring examples on natural scenes

Experimental results

Re-coloring examples on natural scenes with green interreflections of the grass.

Original-Image

Professional photo-editor

MIDR-based method

Experimental results

Photo-montage: here the greenish reflection of grass is replaced by reddish reflection of the carpet to match the scene.

The do's and dont's of Color Features

1. Take care in combining different channels:
   Tensor-based features solve the opposing vector problem.
2. Look at what kind of photometric invariance your problem needs:

   Do not take derivatives of circular color spaces.

   Compute first derivatives, then color space transform.

   Quasi-invariants are more stable for feature detection.
3. When working with invariance take instabilities into account.
   Use error analysis to find certainty measures for your invariants.
4. When considering photometric invariance always also take discriminative power into account.
5. From information theory an optimal color space for salient feature detection can be derived.
6. Color information is highly corrupted in compressed data. In compression (jpeg, mpeg) chrominance is subsampled.

Questions ?

Acknowledgements

- Theo Gevers
- Cordelia Schmid
- Maria Vanrell
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- Arjan Gijsenij
- Eduard Vazquez
- Fahad Shahbaz
- Shida Beigpour
- David Rojas

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