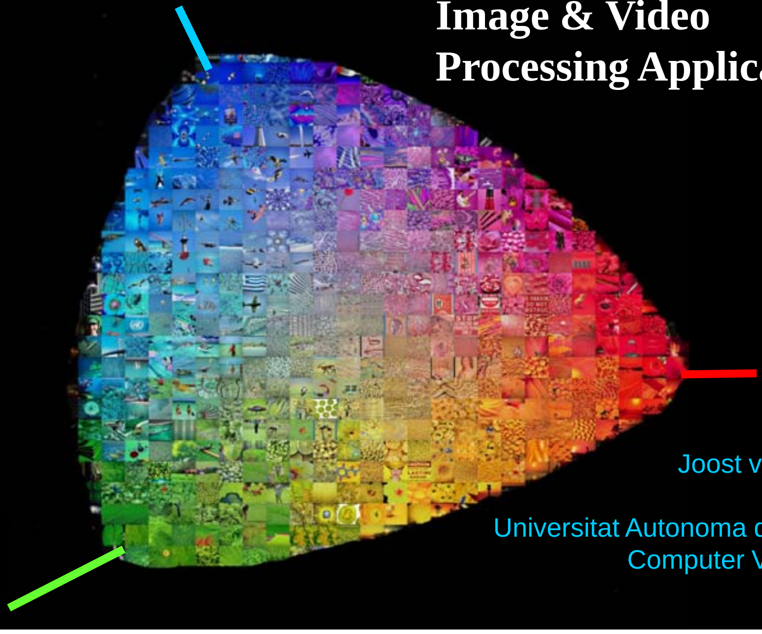
Color in Image & Video Processing Applications



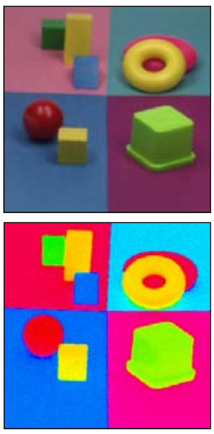
DAGM 2010
Darmstadt

Joost van de Weijer

Universitat Autonoma de Barcelona
Computer Vision Center

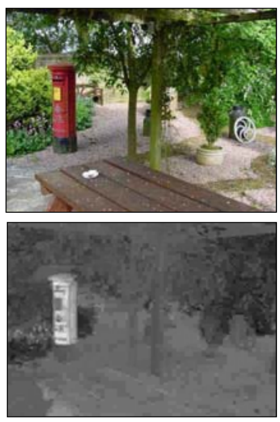
Why use Color ?

photometric invariance

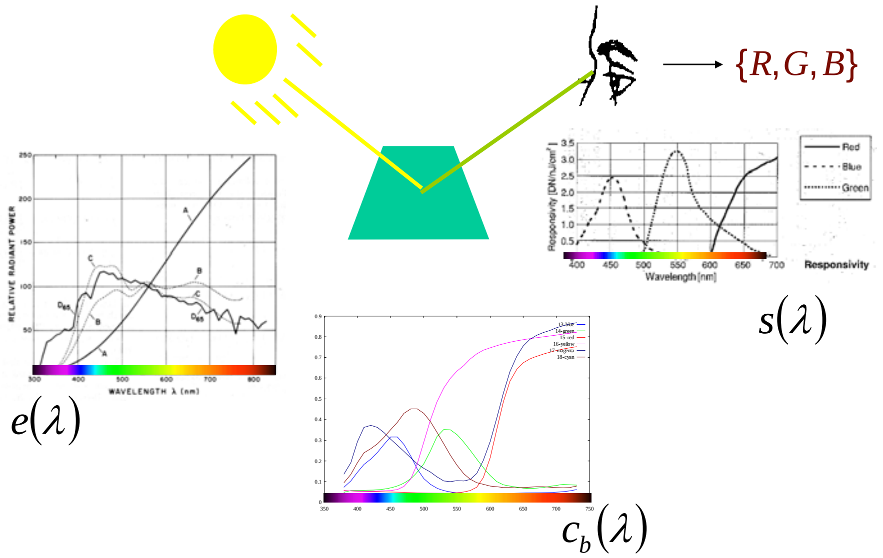


discriminative power

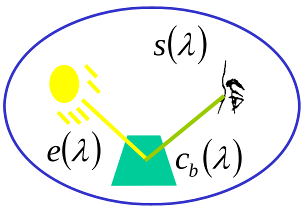
saliency detection



Physics approach to color



overview



THEORY

PART I: features
- color spaces
- color feature extraction
- saliency detection.

PART II: color constancy
- bottom-up color constancy
- top-down color constancy
- color constant features

APPLICATIONS

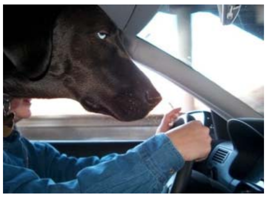
IMAGE CLASSIFICATION
- combining color and shape

IMAGE SEGMENTATION
- deviations from the reflection model

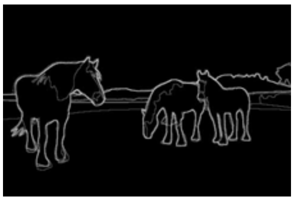
OBJECT RECOLORING
- complex reflection models

Applications

classification



segmentation



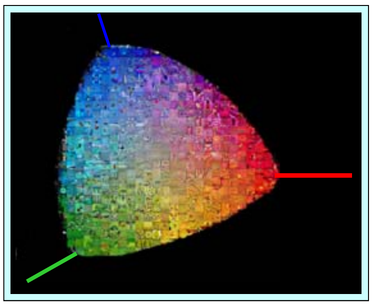
human segmentation

Object recoloring

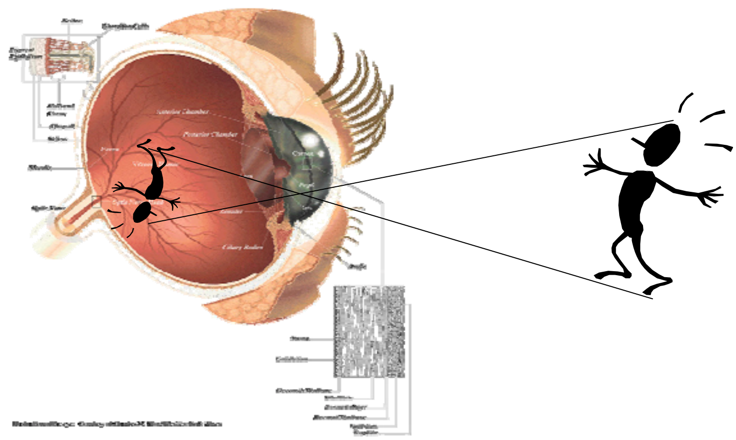
2

Color Basics

- human vision
- physics–based reflection model



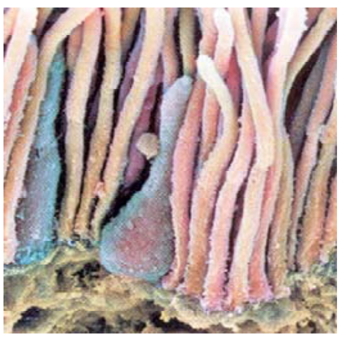
Human vision

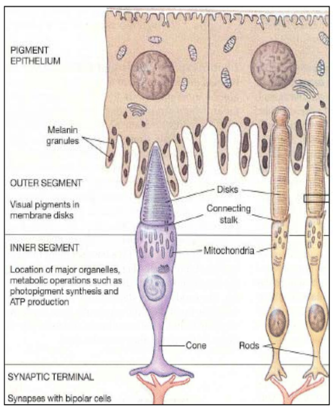


Human vision

Humans have two types of photoreceptors:

- **rods:** achromatic night time vision when light levels are low.
- **cones:** color vision during day time when light levels are high.





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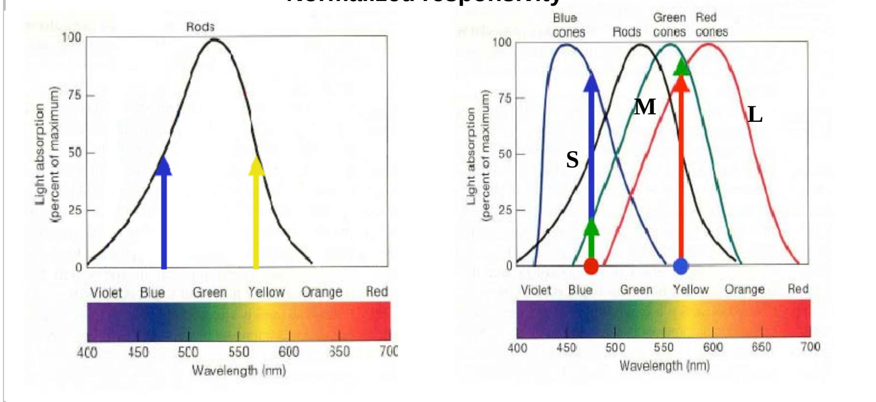
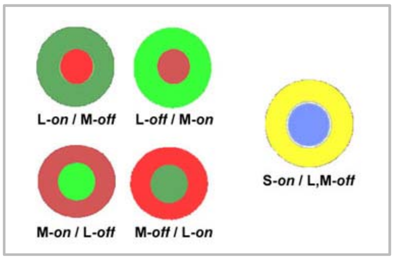
Normalized responsivity



opponent color system

The information from these receptors is combined in the retina as colour opponent signals through the optic nerve.

Retinal neurons appear to encode both achromatic contrast systems and chromatic contrast systems.



$$R = r - \frac{g+b}{2} \qquad G = g - \frac{r+b}{2}$$

$$B = b - \frac{r-g}{2} \qquad Y = \frac{r+g}{2} - \frac{|r-g|}{2} - b$$

$$RG = R - G \qquad BY = B - Y$$

((r,g,b) normalized RGB)

Opponent mechanism **[Itti PAMI 95]**

opponent color system

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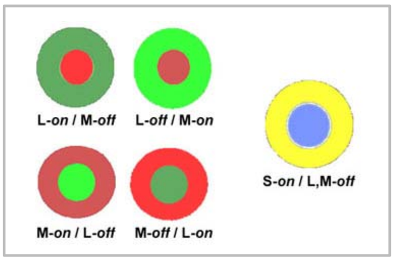
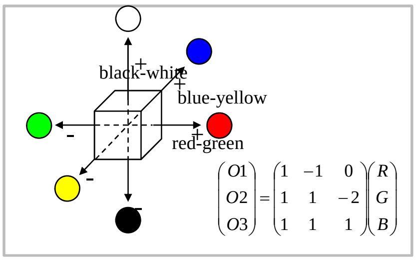


Opponent mechanism



Linear combination of RGB

CIE 1931 standard observer

- computing the matching function for humans

- *primary stimuli:*
  R=700nm
  G=546.1nm
  B=435.8nm

Projected illuminants at sub-intervals = 5nm

Image courtesy Bill Freeman

CIE 1931 standard observer

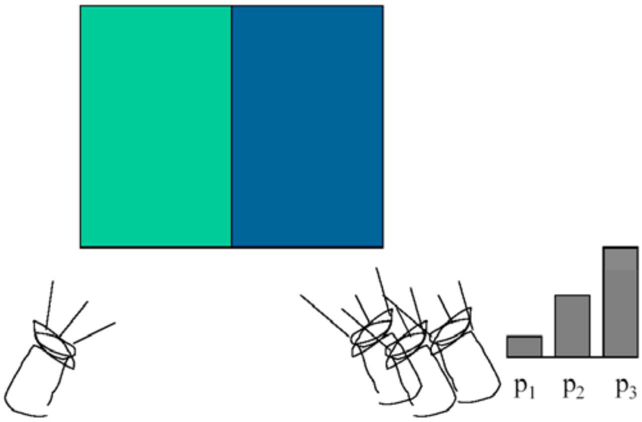


Image courtesy Bill Freeman

CIE 1931 standard observer

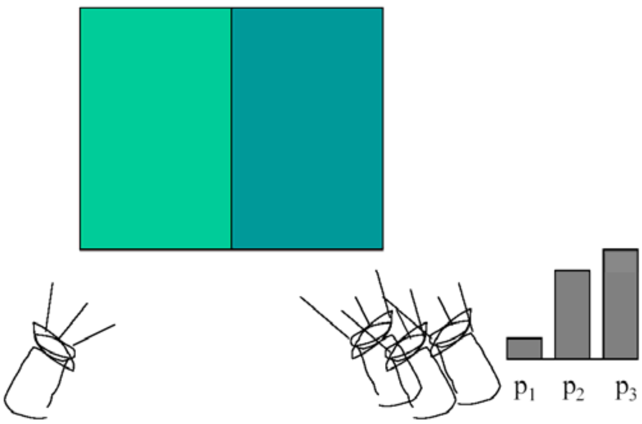


Image courtesy Bill Freeman

CIE 1931 standard observer

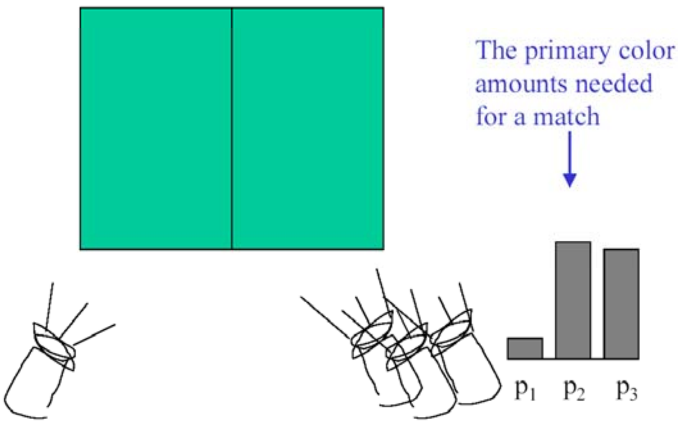


Image courtesy Bill Freeman

CIE 1931 standard observer

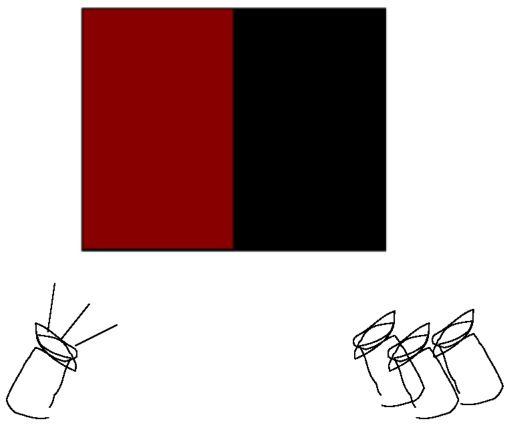


Image courtesy Bill Freeman

CIE 1931 standard observer

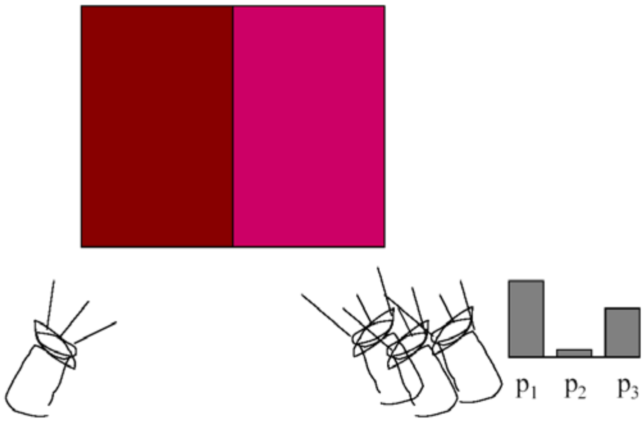


Image courtesy Bill Freeman

CIE 1931 standard observer

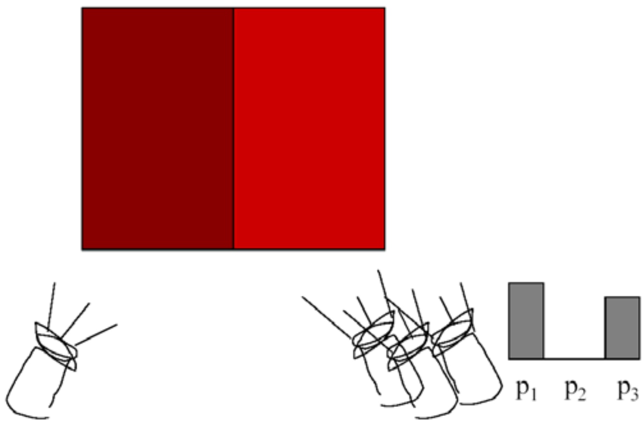


Image courtesy Bill Freeman

CIE 1931 standard observer

We say a "negative" amount of p_2 was needed to make the match, because we added it to the test color's side.

The primary color amounts needed for a match:

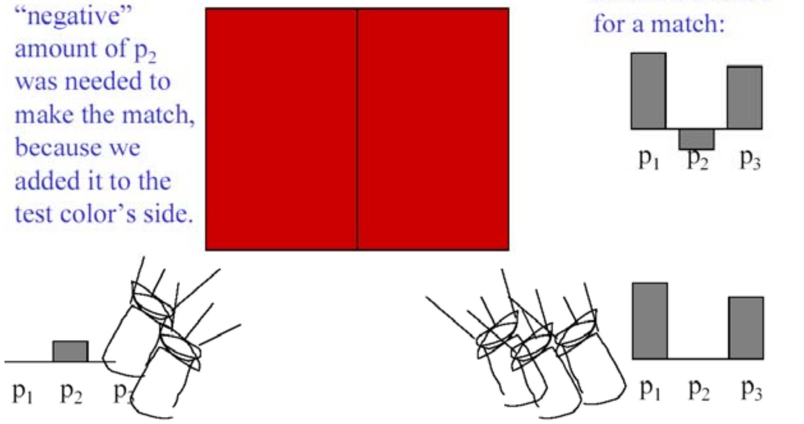
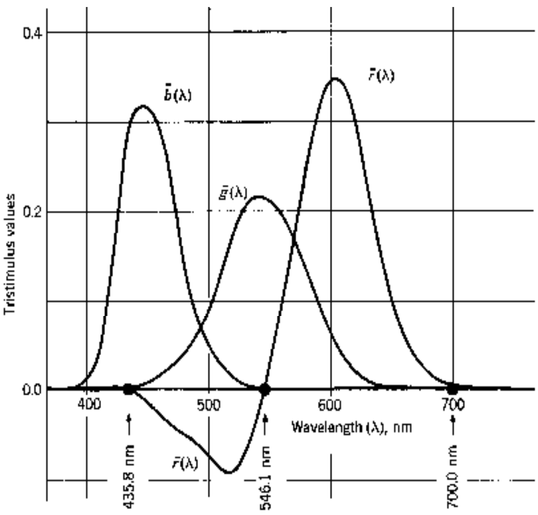


Image courtesy Bill Freeman

CIE 1931 standard observer

Experiment result
(*Commission International de l'Eclairage*)



- *Visuall field = 2 degrees*
- *Interval = [380,780]*
- *Sub-intervals = 5nm.*
- *primary stimuli:*
  R=700nm
  G=546.1nm
  B=435.8nm
- *Every position gives the mixing weights for the primary stimuli.*
- *The resulting functions are the color* ***matching functions***

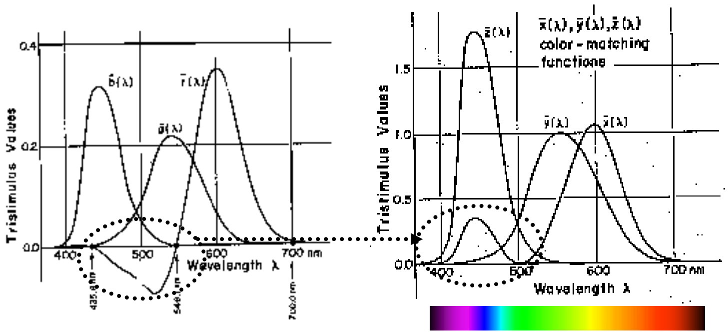
$$\bar{r}(\lambda), \bar{g}(\lambda), \bar{b}(\lambda)$$

XYZ color space

Imaginary space: XYZ (Standard colorimètric Observer (CIE 1931)**)**

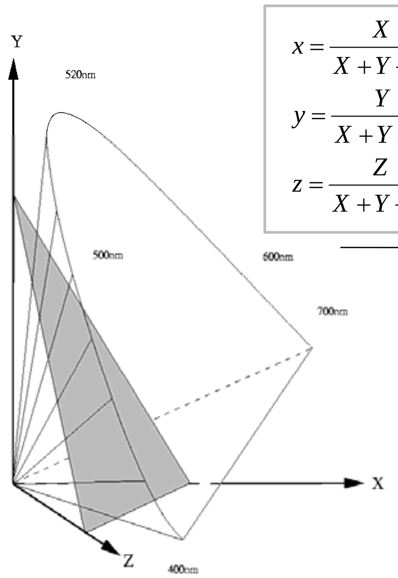
Goal:

- Avoid negative values in the color matching functions. This simplifies the constructions of color measurement devices.
- Correlate one of the functions to the intensity.



Chromaticity.exe

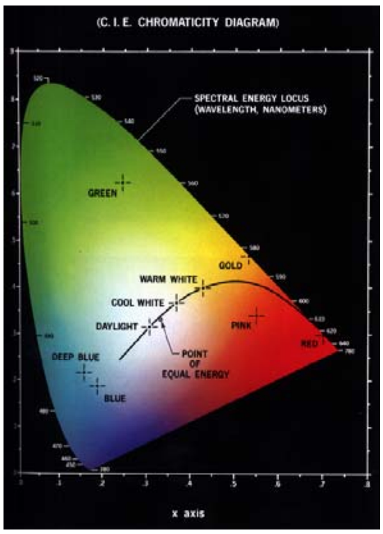
CIE diagram



$$x = \frac{X}{X+Y+Z}$$

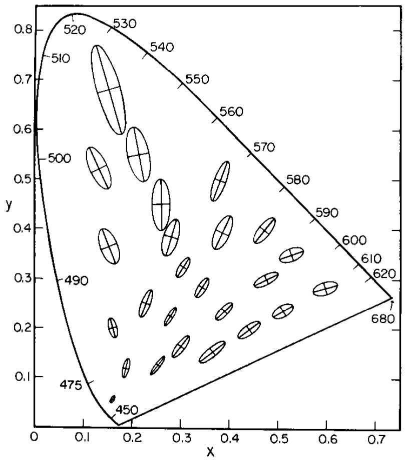
$$y = \frac{Y}{X+Y+Z}$$

$$z = \frac{Z}{X+Y+Z}$$



$$white:(x,y,z)=\left(\tfrac{1}{3},\tfrac{1}{3},\tfrac{1}{3}\right)$$

MacAdam Ellipses



- If two stimuli are presented, one of them at the center of the ellipse, and the other one inside the ellipse, there is not a perceived difference.
- The space is not perceptually uniform (then the ellipses would be circles).

Perceptually uniform space

- CIELUV and CIELAB are examples of perceptually uniform color spaces.

$$L^* = \begin{cases} 116\left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16 & \text{if } \frac{Y}{Y_n} > k \\ 903.3\frac{Y}{Y_n} & \text{if } \frac{Y}{Y_n} \le k \end{cases}$$

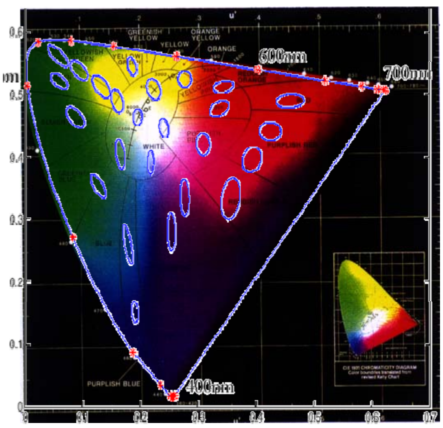
$$a^* = 500\left(f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right)$$

$$b^* = 200\left(f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right)$$

$$f(x) = \begin{cases} \sqrt[3]{x} & \text{if x > k} \\ 7.787\text{x} + \frac{16}{116} & \text{if x} \le \text{k} \end{cases}$$

$$k = 0.008856$$

CIELUV



$$\Delta E^*_{ab} = \sqrt{\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2}}$$

sRGB

- sRGB: standard RGB color space (HP, Microsoft, Pantone,Corel etc).

•Linear relation with XYZ space:

$$\begin{pmatrix} R_{linear} \\ G_{linear} \\ B_{linear} \end{pmatrix} = \begin{pmatrix} 3.2406 & -1.5372 & -0.4986 \\ -0.9689 & 1.8758 & 0.0415 \\ 0.0557 & -0.2040 & 1.057 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$$

- sRGB images are assumed to have a gamma=2.2.

- In case of unknown origin people often assume sRGB. For example in the case of data sets collected from the internet.

Device dependent color spaces

- **RGB**: output of majority of cameras and is dependent on the camera sensitivity response.
- **CMY(K)**: Is the standard generally applied for printing devices.

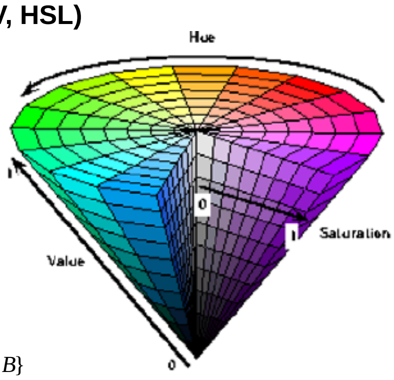
HSI: human perception (others HSV, HSL)

$$H = \begin{cases} \frac{\pi}{3}\left(\frac{G-B}{\Delta_2}\right) & si \quad R = max\{R,G,B\} \\ \frac{\pi}{3}\left(2.0+\frac{B-R}{\Delta_2}\right) & si \quad G = max\{R,G,B\} \\ \frac{\pi}{3}\left(4.0+\frac{R-G}{\Delta_2}\right) & si \quad B = max\{R,G,B\} \end{cases}$$

$$S = \begin{cases} \frac{\Delta_2}{\Delta_1} & si \quad L \leq 0.5 \\ \frac{\Delta_2}{2-\Delta_1} & si \quad L > 0.5 \end{cases}$$

$$I = \frac{1}{3}(R+G+B) \qquad \Delta_1 = max\{R,G,B\} + min\{R,G,B\}$$

$$\Delta_2 = max\{R,G,B\} - min\{R,G,B\}$$



Device dependent color spaces

- **RGB**: output of majority of cameras and is dependent on the camera sensitivity response.
- **CMY(K)**: Es the standard generally applied for printing devices.

HSI: often used in computer vision

Orthonormal opponent space:

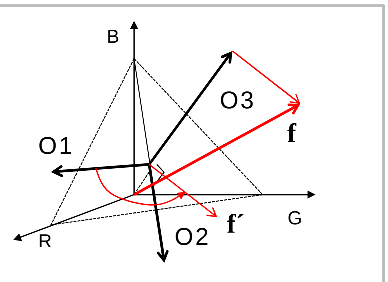
$$\begin{pmatrix} O1 \\ O2 \\ O3 \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & -\frac{2}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

$$H = \arctan\left(\frac{O1}{O2}\right)$$

$$S = \sqrt{O1^2 + O2^2}$$

$$I = O3$$

S is not normalized with intensity !



Projection of **f** on **O3** is the *intensity*. Let **f**´ the projection on the plane O1-O2, its length is the *satutation* and its angle the *hue*.

Guidelines application of color spaces

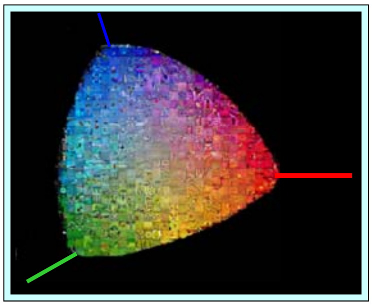
- be aware that many color spaces are devise dependent (industrial applications).
- apply CIELAB or CIELUV only when perceptually uniformity of the color space is relevant.

√ Learning color names ✗ tracking

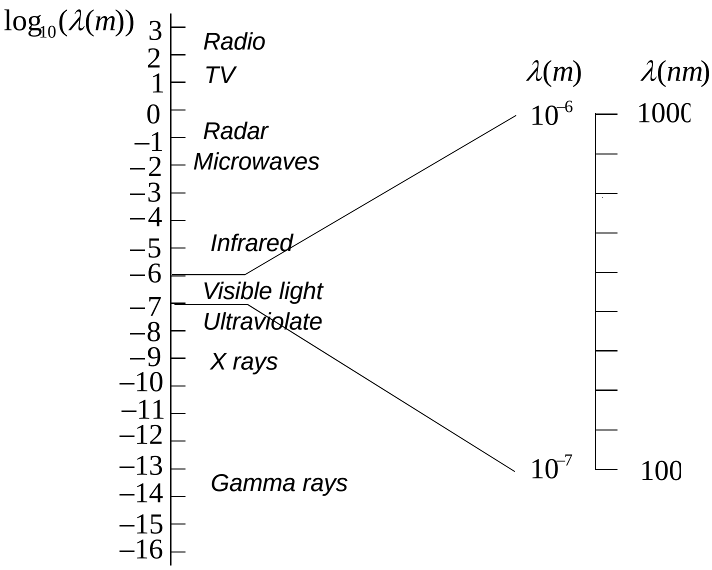
- when you want to decorrelate only luminance use opponent color space. HSI spaces introduces non-linearities.
- Choose the color space which fits the photometric invariants your application requires.

2

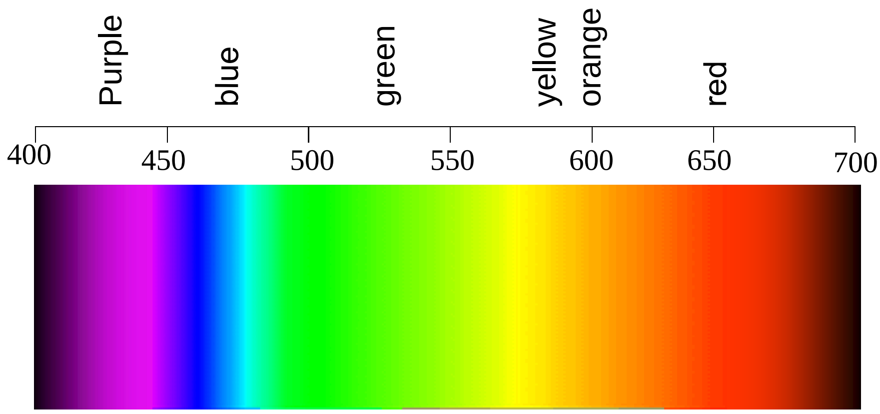
Reflection Models



Electromagnetic radiation spectrum



visible light spectrum



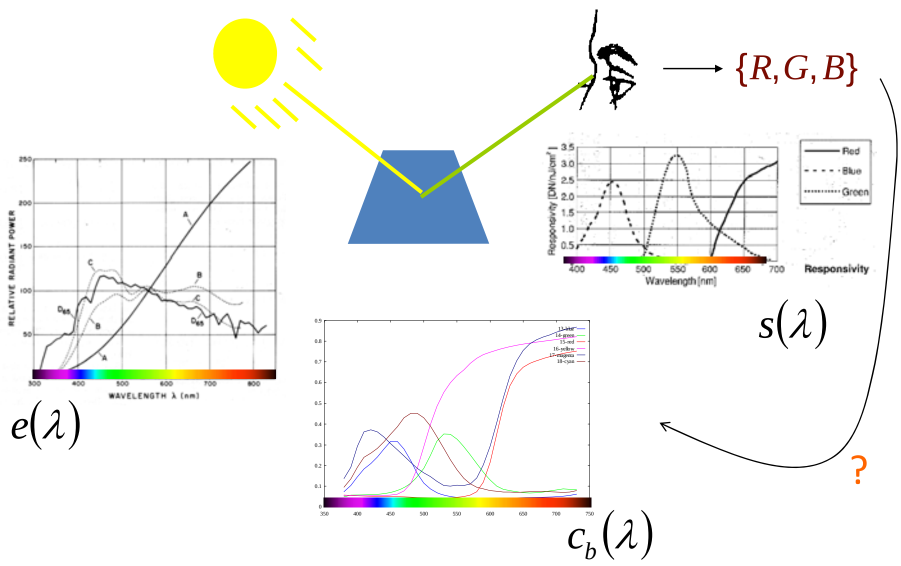
nanometers ⇨ $1nm = 10^{-9} m$

Spectra.exe

http://askabiologist.asu.edu/research/seecolor/atable.html

slide credit: R. Baldrich

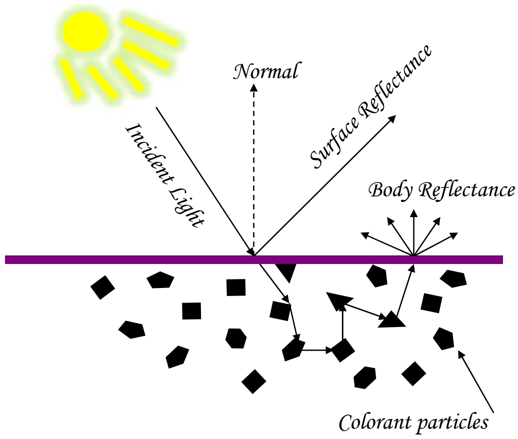
Surface reflectance



Dichromatic reflection model

Two types of reflection:

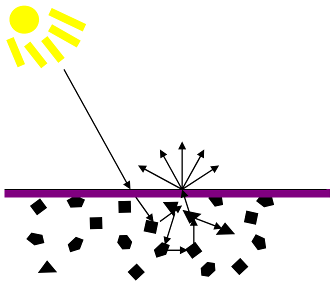
- Body reflection
- Surface reflection

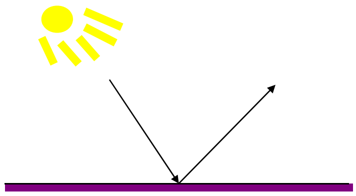


Metals: mainly specular reflection.

Dielectric: specular and diffuse reflection. It includes materials that are coloured using pigments: paints, plastic, ceramic, fabric, paper, etc.

Reflecting materials





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

$$f_b(\lambda,\Theta) = m_b(\Theta)c_b(\lambda)$$

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

$$f_s(\lambda,\Theta) = m_s(\Theta)c_s(\lambda) \approx m_s(\Theta)h$$

slide credit: R. Baldrich

Dichromatic reflection model:

$$\boxed{f(\lambda,\Theta) = f_b(\lambda,\Theta) + f_s(\lambda,\Theta)}$$

$f_b(\lambda,\Theta)$: Reflected light by the object body. It depends on the pigments used to colour the object and it's the one that makes the object look coloured. (Diffuse reflectance)

$f_s(\lambda,\Theta)$: Reflected light from the surface. It has a SPD nearly the same as the incident light. (Specular or regular reflectance)

Θ: Angles that depend on light source position, observer and surface

The spectral and geometrical terms can be separated:

$$f(\lambda,\Theta) = m_b(\Theta)c_b(\lambda) + m_s(\Theta)c_s(\lambda)$$

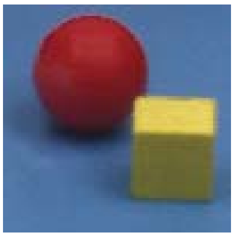
$$\mathbf{f} = m_b\mathbf{c_b} + m_s\mathbf{c_s}$$

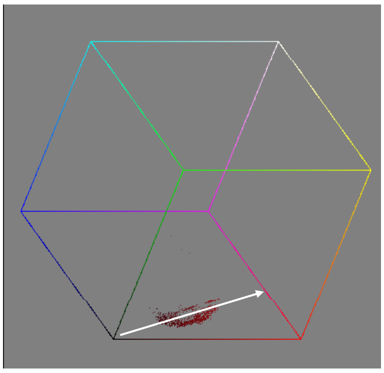
slide credit: R. Baldrich

Dichromatic Reflection Model

dichromatic model for matte surfaces:

$$\mathbf{f} = m_b\mathbf{c_b}$$



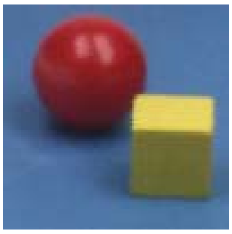


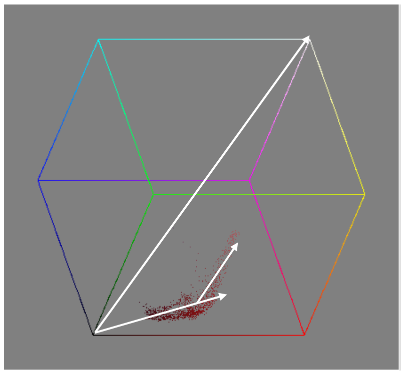
RGB-histogram

Dichromatic Reflection Model

dichromatic model for specular surfaces:

$$\mathbf{f} = m_b \mathbf{c_b} + m_s \mathbf{c_s}$$





RGB-histogram

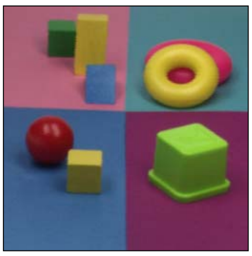
color spaces: normalized RGB

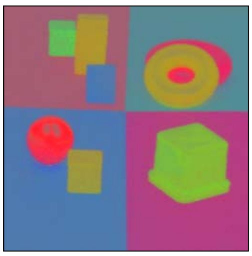
- normalized RGB is given by:

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

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

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





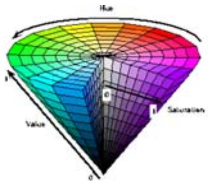
normalized RGB

color spaces: hue-saturation-intensity

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

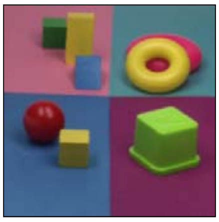
$$sat = \sqrt{\tfrac{2}{3}\left(R^2+G^2+B^2-RG-RB-GB\right)}$$

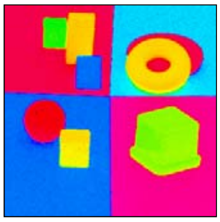
$$i = \frac{R+G+B}{\sqrt{3}}$$



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

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

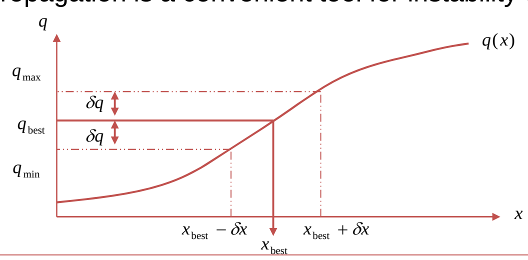




hue

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 $u,...,w$ are measured with corresponding uncertainties $\sigma_u,...,\sigma_w$ to compute function $q(u,...,w)$.
The predicted uncertainty is defined by :

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

Take care of instabilities

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

• Error propagation is a convenient tool for instability evaluation:

Ex. 1

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

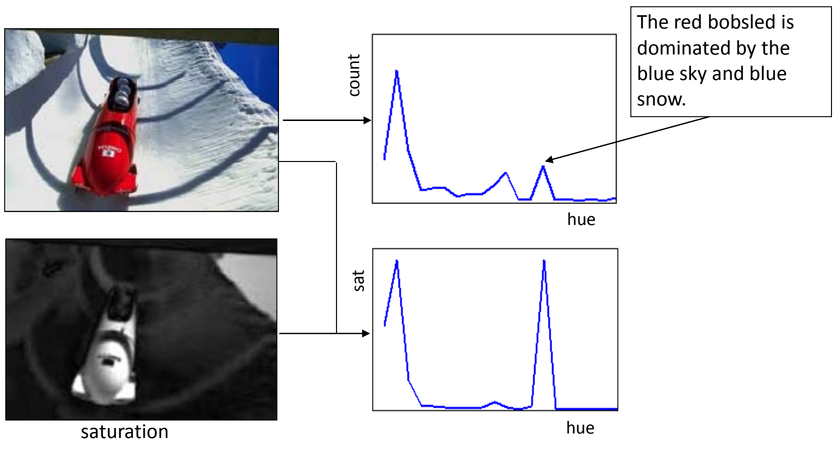
$$(\partial hue)^2 = \left(\frac{\partial hue}{\partial R}\right)^2 \partial^2 R + \left(\frac{\partial hue}{\partial G}\right)^2 \partial^2 G + \left(\frac{\partial hue}{\partial B}\right)^2 \partial^2 B$$

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

Take care of instabilities

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

• Error analysis is a convenient tool for instability evaluation:



References: photometric invariants

- S.A. Shafer. *Using color to separate reflection components*. Color research and applications, 1985.
- G.J. Klinker et al.. *A physical approach to color image understanding.* IJCV, 1990.
- M.J. Swain, D.H. Ballard . *Color indexing*. IJCV, 1991
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- J. van de Weijer, C. Schmid. Coloring local feature extraction. ECCV, 2006
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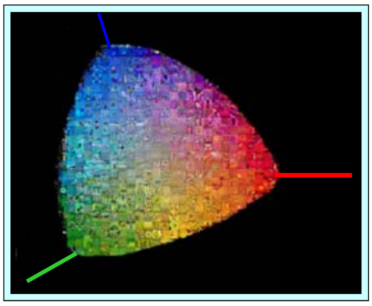
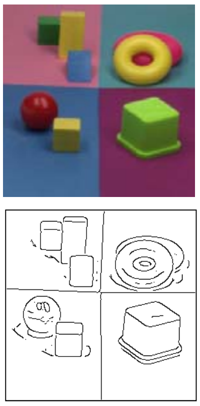
10

Color Differential Structure



differential-based computer vision

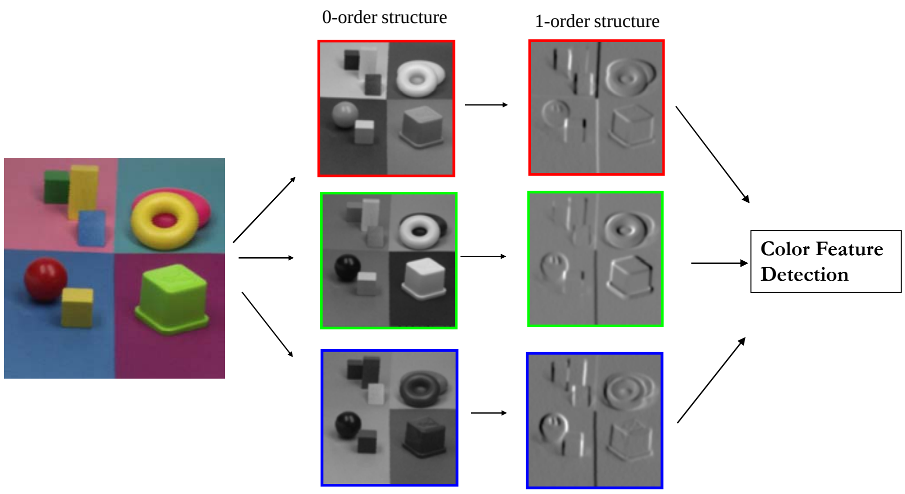


1. How do we combine the differential structure of the various color channels ?
2. How do we incorporate color invariance theory into the measurements of the differential structure while maintaining robustness ?

isoluminance

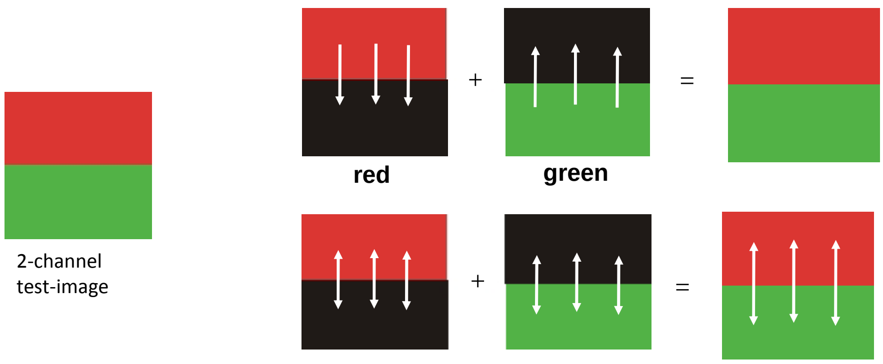
luminance gradient: isoluminant edges are not detected.

Color Feature Detection



from luminance to color

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

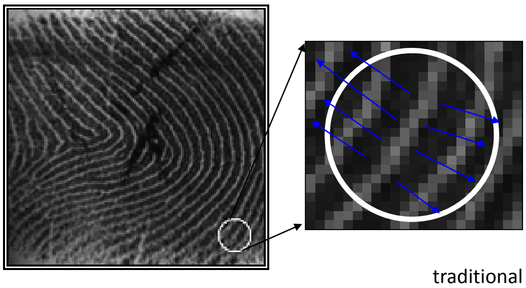


2-channel
test-image

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

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
- ...

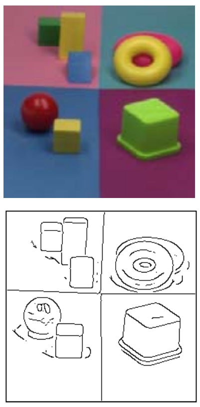
traditional orientation estimation:

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

tensor-based orientation estimation:

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

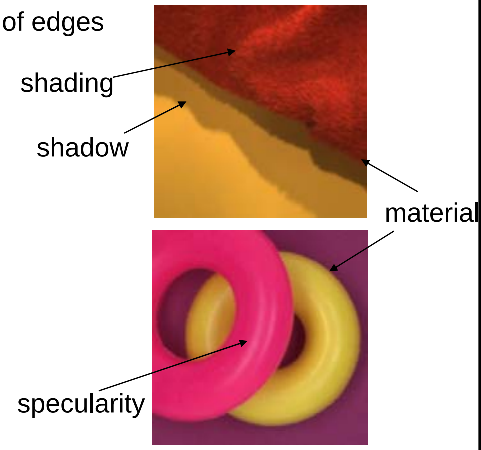
differential-based computer vision



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

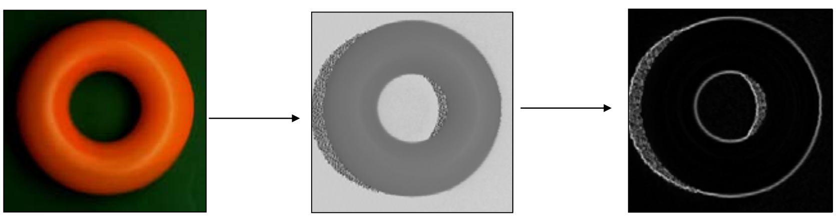
- we differ between three types of edges
  1. material edge
  2. shadow/shading edge
  3. specular edge
- assumptions:
  1. white illumination
  2. neutral interface reflection
  3. shadows are not colored.



Computation of quasi-invariance

IMAGE → (nonlinear transformation) → FULL INVARIANT → FULL INVARIANT DERIVATIVE

IMAGE → (linear operation) → DERIVATIVES → QUASI- INVARIANT DERIVATIVE



hue

hue$_x$

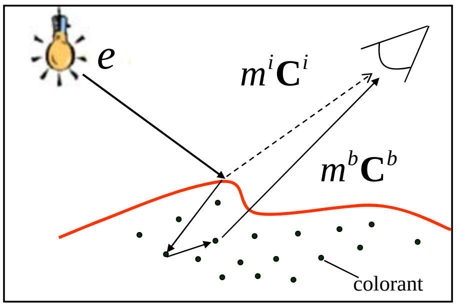
Dichromatic Model

• dichromatic model:

$$\mathbf{F} = e(m^b\mathbf{C}^b + m^s\mathbf{C}^s)$$

body + specular

intensity illuminant

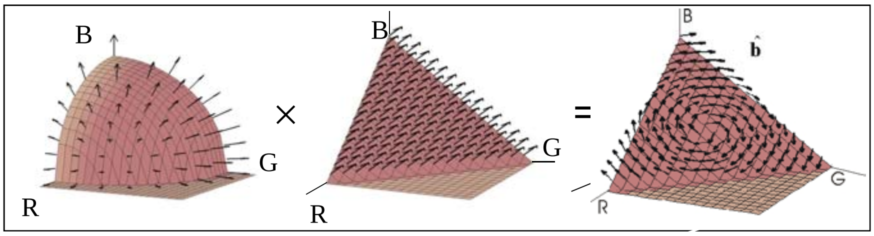


• first order photometric structure:

$$\mathbf{F}_x = \{R_x, G_x, B_x\} = m^b\mathbf{C}^b_x + \left(e_x m^b + e m^b_x\right)\mathbf{C}^b + e m^i_x \mathbf{C}^i$$

material + (shadow+shading) + specular

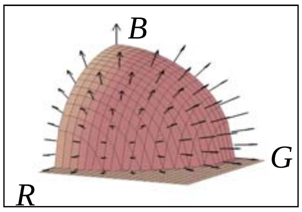
Shadow-Shading-Specular Quasi-Invariant



spherical coordinates	*opponent colors*	*hue-saturation-intensity*
shading variant	specular variant	shading-specular variant
shading invariant	specular invariant	shading-specular invariant

spherical coordinates

- For matte surfaces : $\mathbf{f} = m^b \mathbf{c}^b$
- all shadow-shading variation is in the radial direction



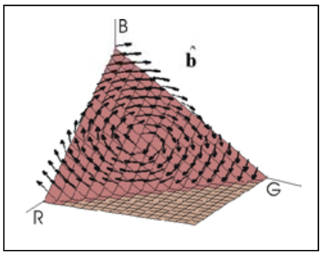
shadow/shading direction

uncertainty of c_x

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

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

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

invariant edge detection applications

~~Colo Feature Extraction~~

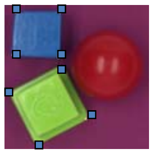
~~Multi Image Applications~~ ~~• image retrieval~~

Color Feature Detection

Single Image Applications

- snakes

- feature extraction



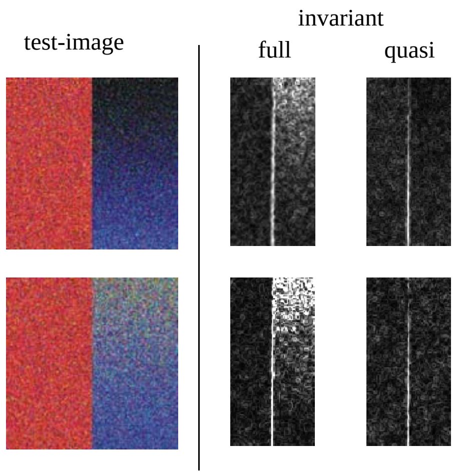
Instabilities

shadow-shading invariance:

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

specular-shadow-shading invariance:

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

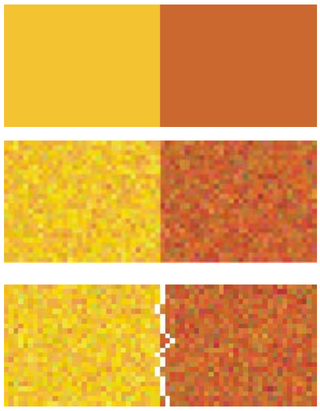


Edge Detection

• experiments conducted on pantone colorset (1012) which is used to compose 500.000 edges.

• edge detection is based on the maximum response path of the derivative energy.

• edges are tested on
- edge displacement.
- percentage of missed edges.



Edge Detection

• experiments conducted on pantone color set (1012) which is used to compose 500.000 edges.

• edge detection is based on the maximum response path of the derivative energy.

• edges are tested on
- edge displacement.
- percentage of missed edges.

shadow-shading:

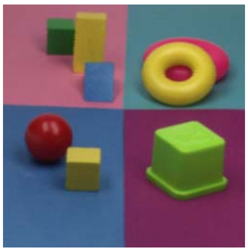
	Δ	ε
full	0.21	2.0
quasi	0.043	0.99

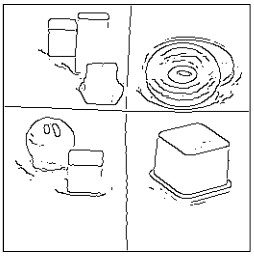
specular-shadow-shading:

	Δ	ε
full	0.85	9.8
quasi	0.35	5.8

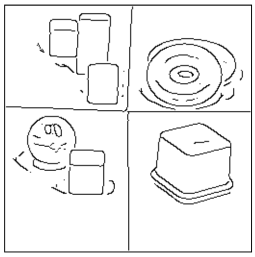
• Conclusion: Quasi invariants more than half the edge displacement, and have higher discriminative power.

experiments : canny edge detection



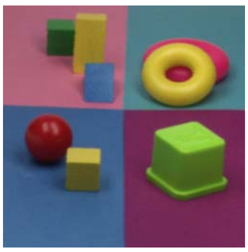


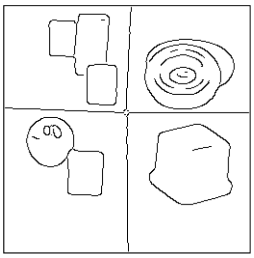
luminance-gradient



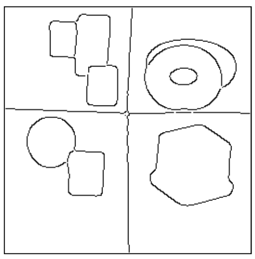
RGB-gradient

experiments : canny edge detection



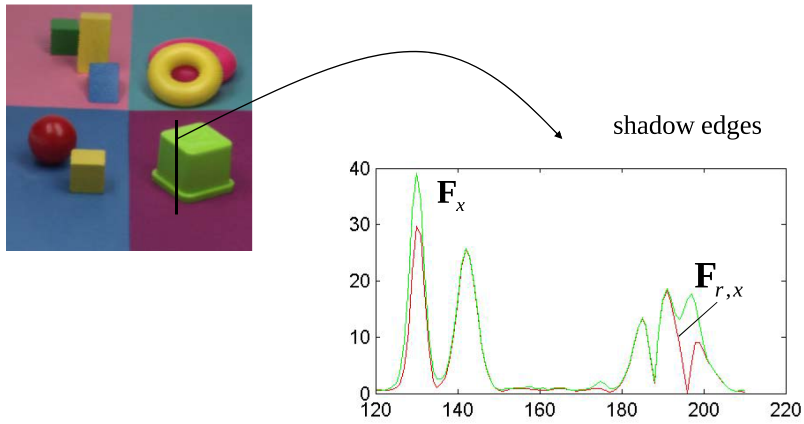


shadow-shading quasi-invariant

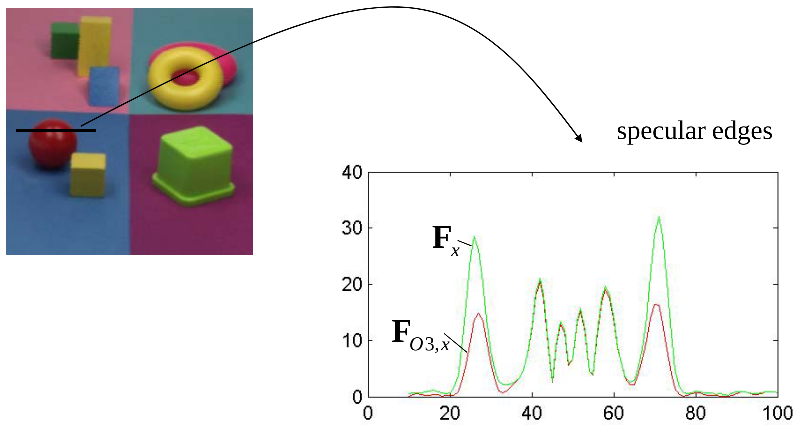


shadow-shading-specular quasi-invariant

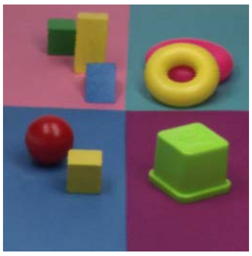
Edge Classification



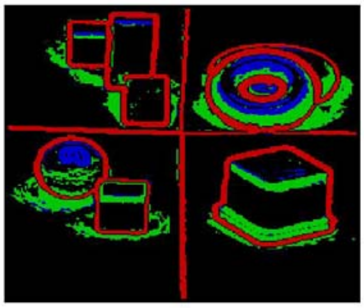
Edge Classification



Edge Classification

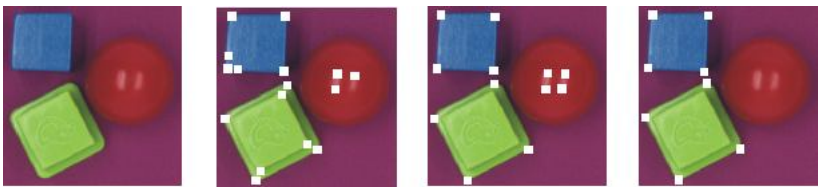


red - object edge
green-shading/shadow edge
Blue – specular edge



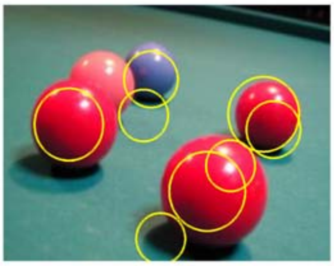
Photometric Invariant Corner Detection

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



RGB | shadow-shading | specular-shadow-shading

experiments : Hough transform



RGB-gradient

shadow-shading-specular quasi-invariant

references: color differential structure

- S. DiZenzo. *A note on the gradient of a multi-image.* Computer Vision, Graphics, and Image Processing, 1986.
- G. Sapiro and D. Ringach. *Anisotropic diffusion of multivalued images with applications to color filtering.* IEEE Image Processing, 1996.
- J.M. Geusebroek et al. *Color Invariance.* IEEE Trans. Pattern Analysis and Machine Intelligence, 2001.
- J. van de Weijer, Th. Gevers, J-M Geusebroek. *Quasi-invariant edge and corner detection*, IEEE Trans. Pattern Analysis and Machine Intelligence, 2006.
- J. van de Weijer, Th. Gevers, A.W.M. Smeulders, *Robust Photometrical Invariant Features from the Color Tensor*, IEEE T. Image Processing, 2006.

Color Salient Features

Saliency Detection

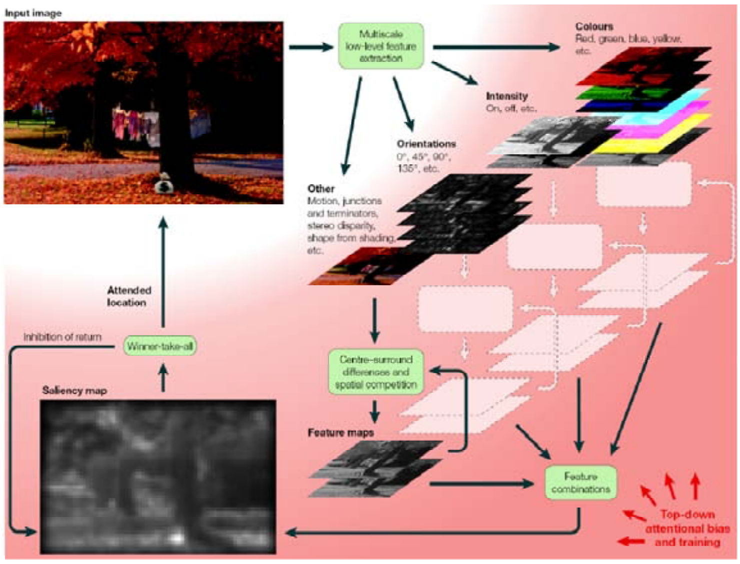
• Goal: direct our gaze rapidly towards objects of interest in our environment.

• 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*.

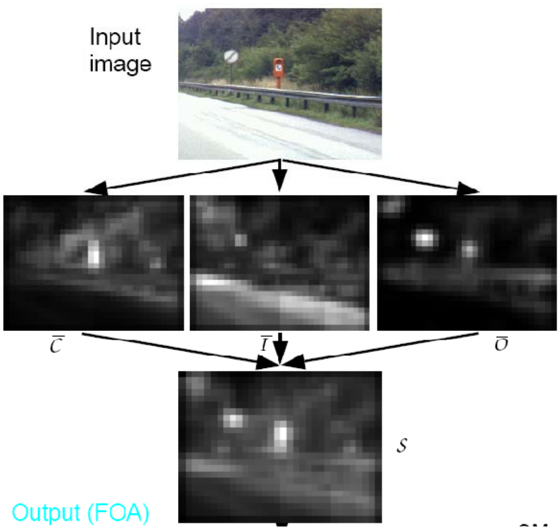
• What matters is *feature contrast* rather than absolute feature strength (as in center surround systems).

overview approach



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

Computational Modeling of Visual Attention



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

black-white focus of detectors

luminance-based points

color-based points

color distinctiveness

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

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

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

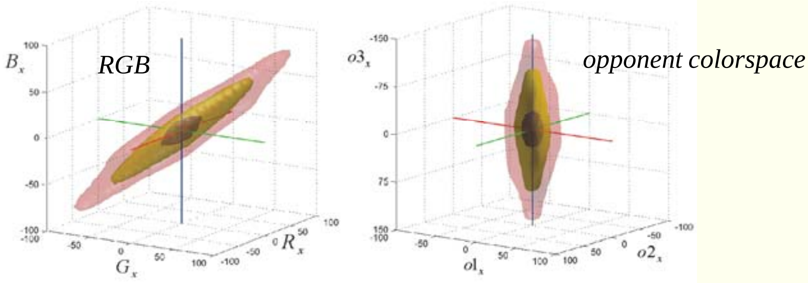
- equation differential-based salient point detectors : $H(\mathbf{f}_x, \mathbf{f}_y)$

To change from strength to information content of edges:

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

statistics of color images:

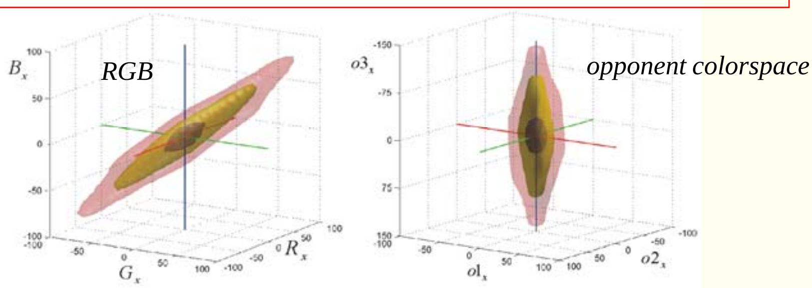
• The statistics of $\mathbf{f}_x$ is computed by looking of the 40.000 images of the Corel database.



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

statistics of color images:

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



color boosting:

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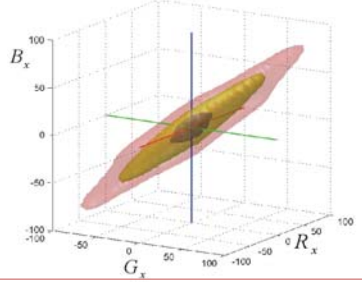


color boosting:

$$\mathrm{N} = \overline{\mathrm{f_x}\,(\mathrm{f_x})^{\mathrm{t}}} = \begin{pmatrix} \overline{R_x R_x} & \overline{R_x G_x} & \overline{R_x B_x} \\ \overline{R_x G_x} & \overline{G_x G_x} & \overline{G_x B_x} \\ \overline{R_x B_x} & \overline{G_x B_x} & \overline{B_x B_x} \end{pmatrix}$$

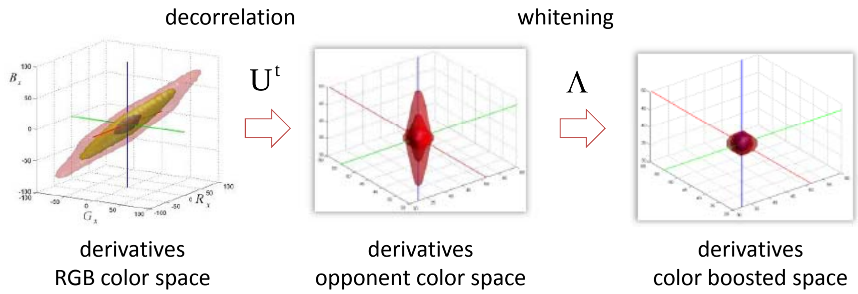
$$\overline{R_x R_x} = \sum_{\mathbf{x} \in X^i} R_x(\mathbf{x})\, R_x(\mathbf{x}),$$

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

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

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

Color boosting:



color boosting:

$$\mathrm{N} = \overline{\mathrm{f_x}\,(\mathrm{f_x})^{\mathrm{t}}} = \begin{pmatrix} \overline{R_x R_x} & \overline{R_x G_x} & \overline{R_x B_x} \\ \overline{R_x G_x} & \overline{G_x G_x} & \overline{G_x B_x} \\ \overline{R_x B_x} & \overline{G_x B_x} & \overline{B_x B_x} \end{pmatrix}$$

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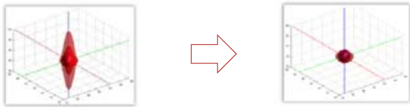
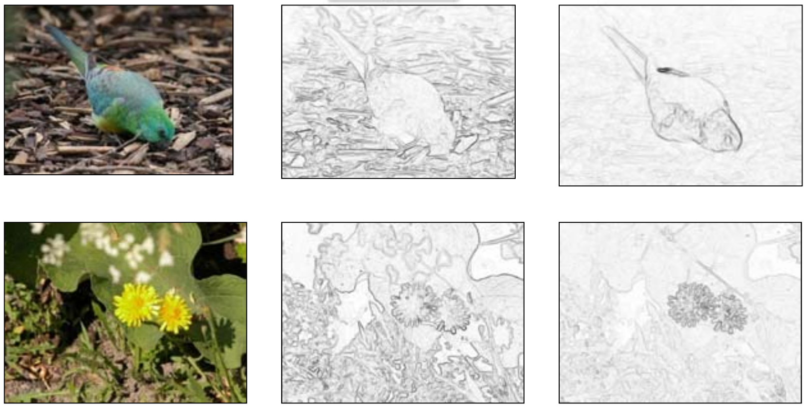
J. van de Weijer, Th. Gevers, A. Bagdanov, Boosting color saliency in image feature detection, IEEE PAMI 2006.

bottom-up color attention:

examples:





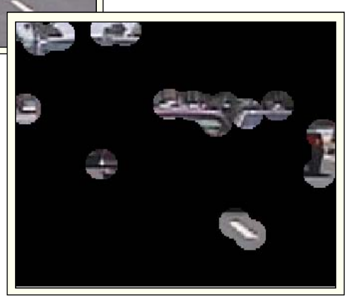
input image

color edges

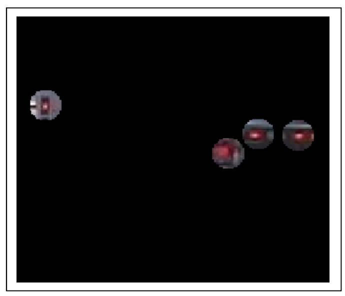
color boosted edges
bottom-up attention

saliency points

input car-image



RGB-based (first 20 points)



saliency boosting (first 4 points)

generality approach: global optimal regions

RGB gradient

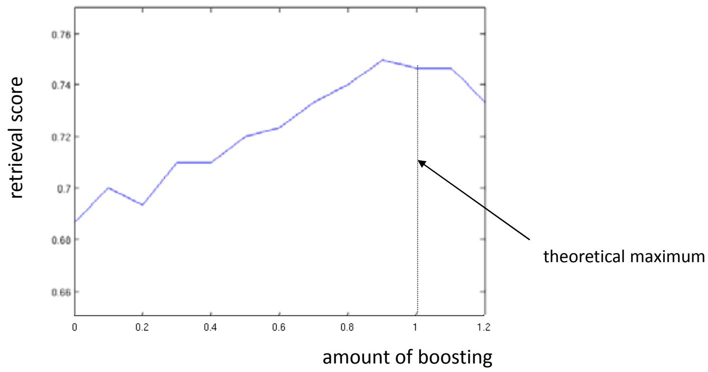
color boosting

experiment: image retrieval

Quantitative evaluation of color boosting on a retrieval experiment.

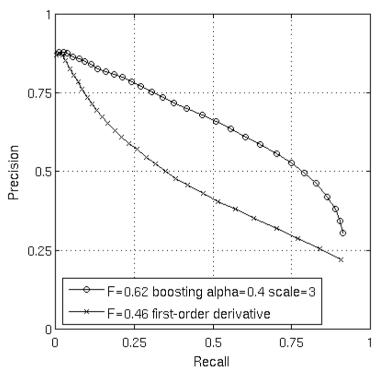
- Nister database: around 10.000 images
- detector: DoG (color boosted)
- descriptor: SIFT+hue

experiment: image retrieval



- color boosting improves results between 5-10 percent
- the obtained maximum score is ‘equal’ to the theoretical maximum.

experiment: edge detection



Berkeley Segmentation Dataset and Benchmar

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 ?