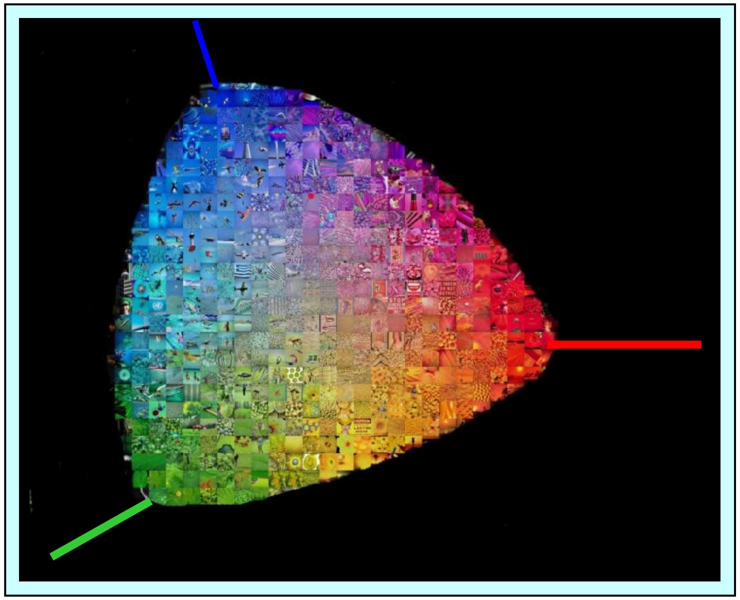
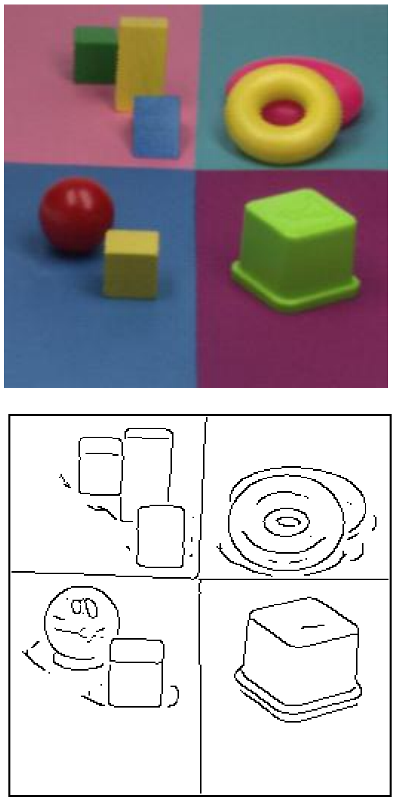
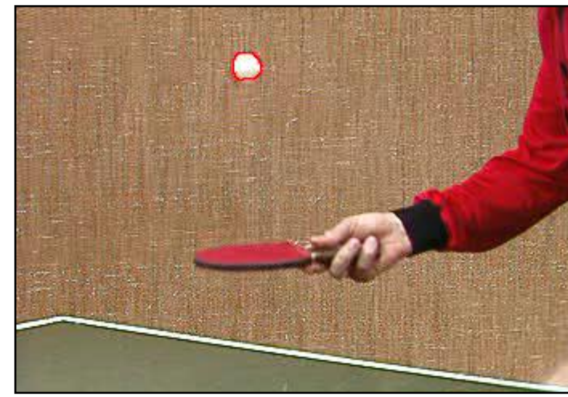
Color Differential Structure



differential-based computer vision



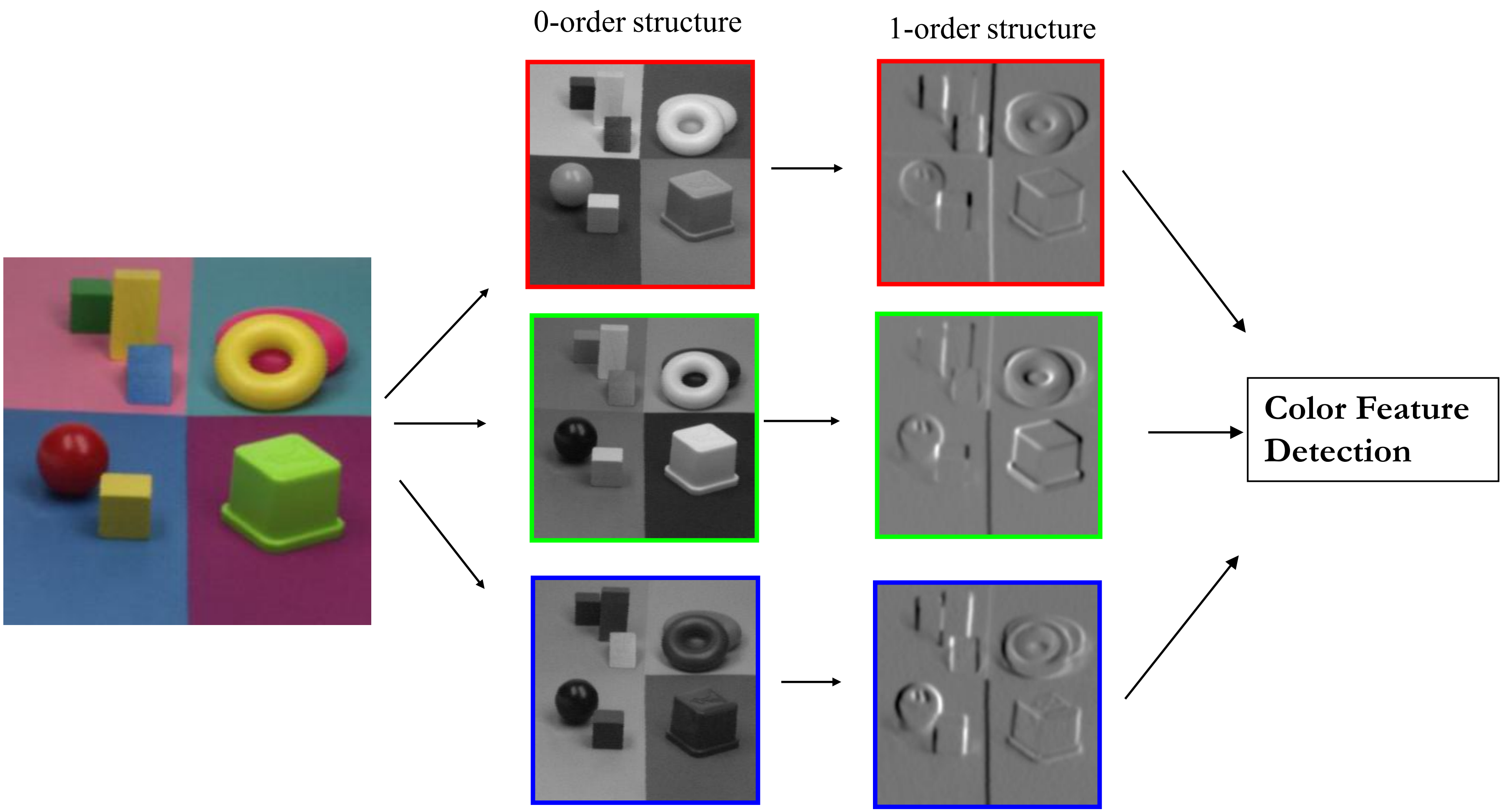


1. How do we combine the differential structure of the various color channels ?
2. How do we incorporate color invariance theory into the measurements of the differential structure while maintaining robustness ?

isoluminance

luminance gradient: isoluminant edges are not detected.

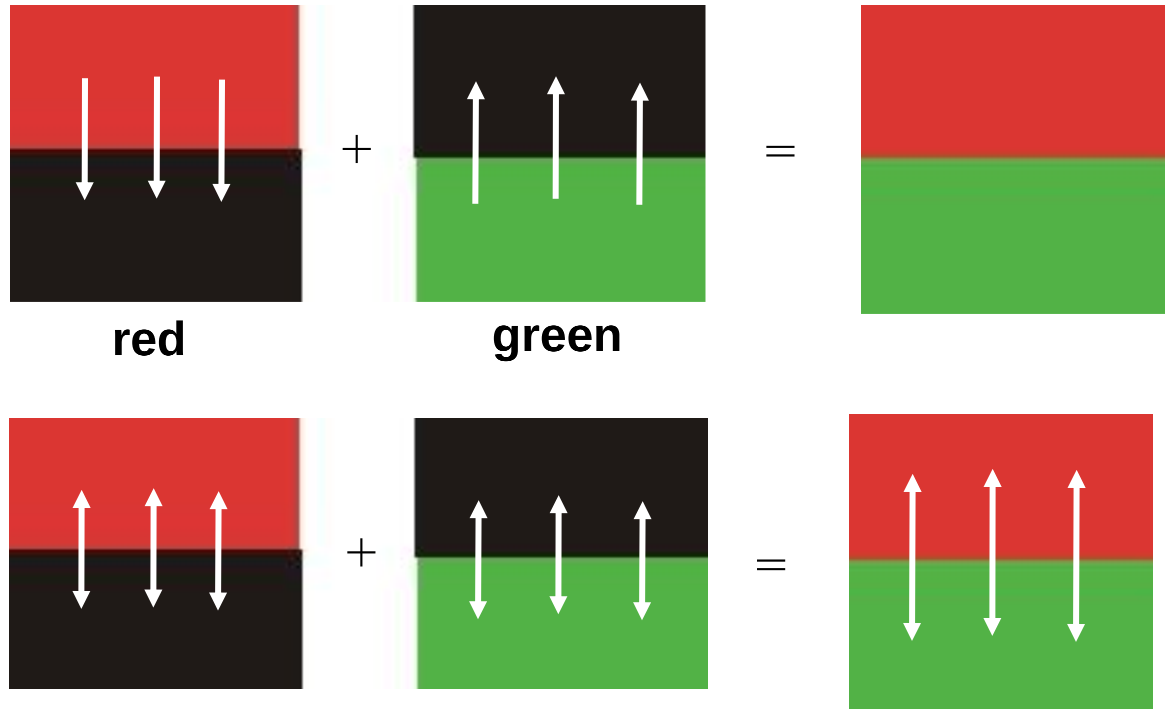
Color Feature Detection



from luminance to color

vector: $R_x + G_x = 0$

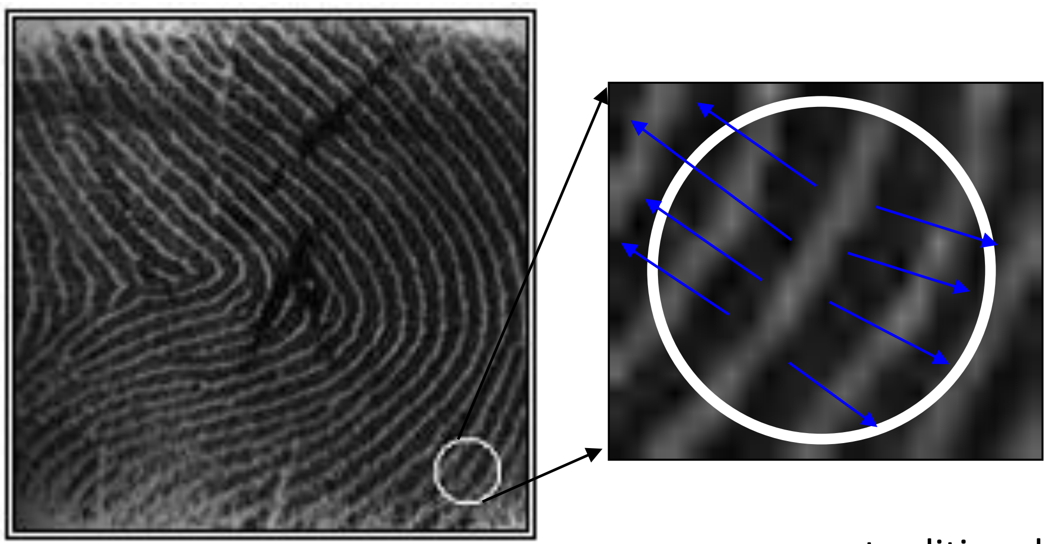
2-channel test-image



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

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
- ...

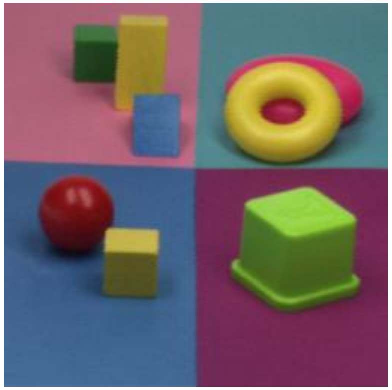
traditional orientation estimation:

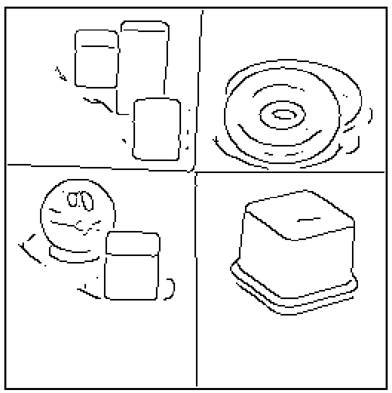
$$\theta = \arctan\left(\frac{f_y}{f_x}\right) \rightarrow \bar{\theta} = \arctan\left(\frac{\overline{f_y}}{\overline{f_x}}\right)$$

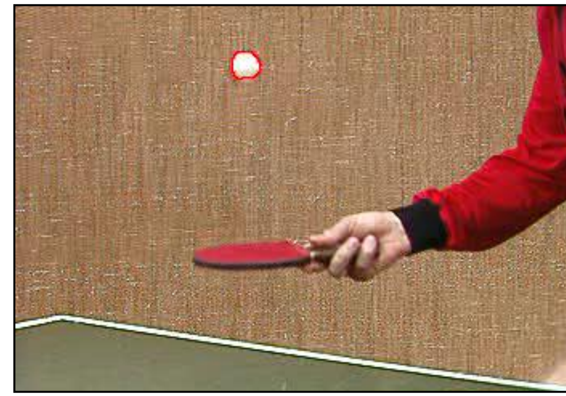
tensor-based orientation estimation:

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

differential-based computer vision





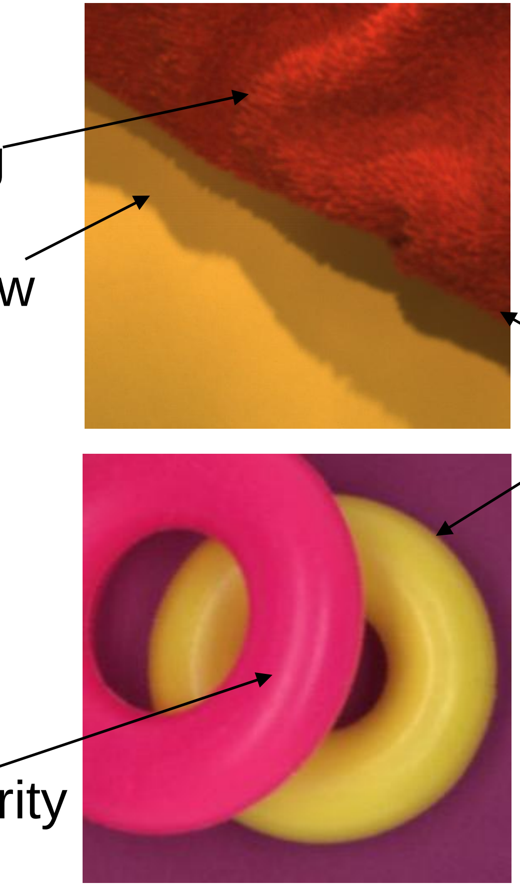


1. How do we combine the differential structure of the various color channels ?
2. How do we incorporate color invariance theory into the measurements of the differential structure while maintaining robustness ?

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.



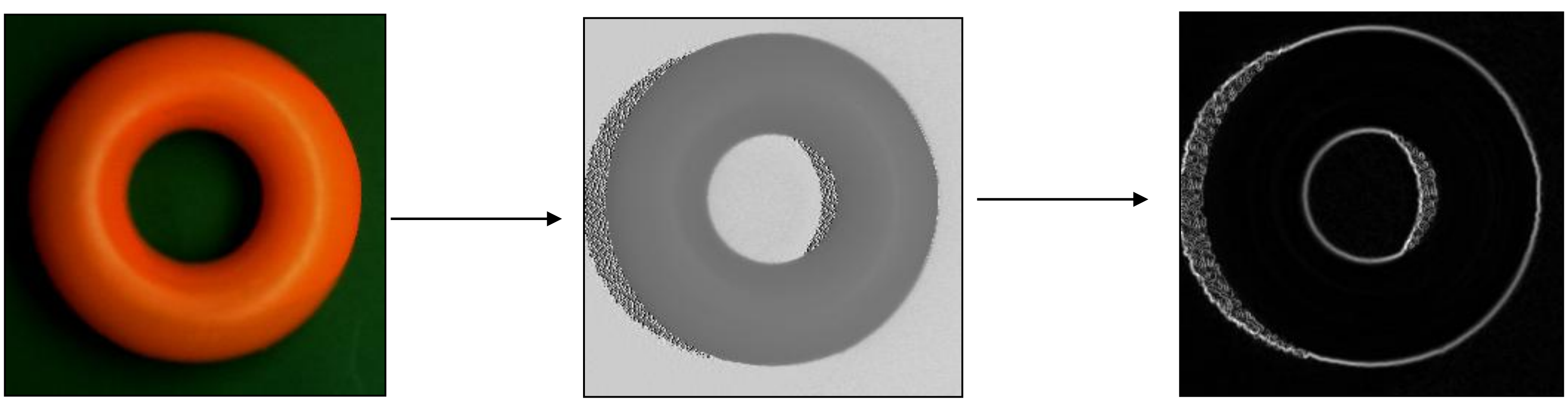
Computation of quasi-invariance

nonlinear transformation

IMAGE → FULL INVARIANT → FULL INVARIANT DERIVATIVE

linear operation

IMAGE → DERIVATIVES → QUASI- INVARIANT DERIVATIVE



hue

hue_x

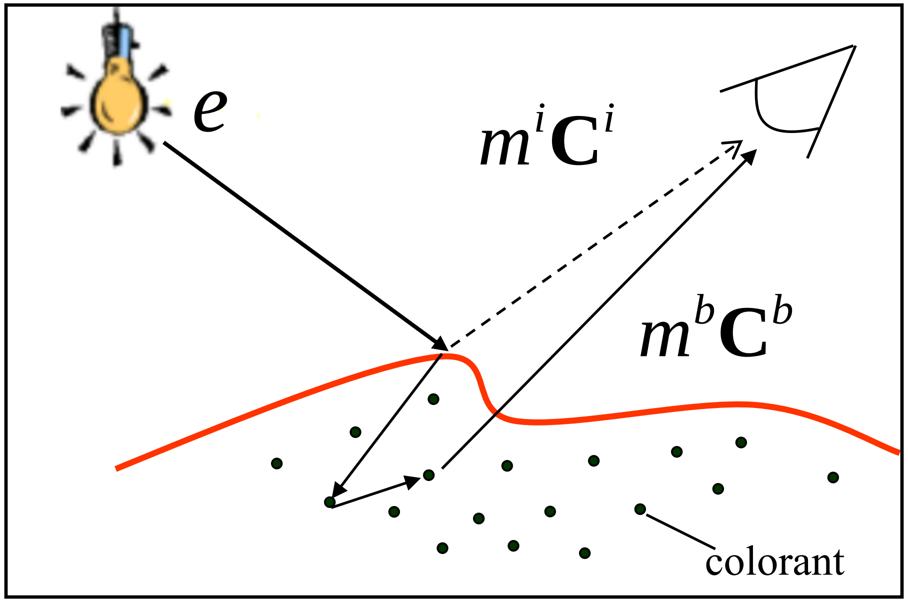
Dichromatic Model

- dichromatic model:

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

body + specular

intensity illuminant

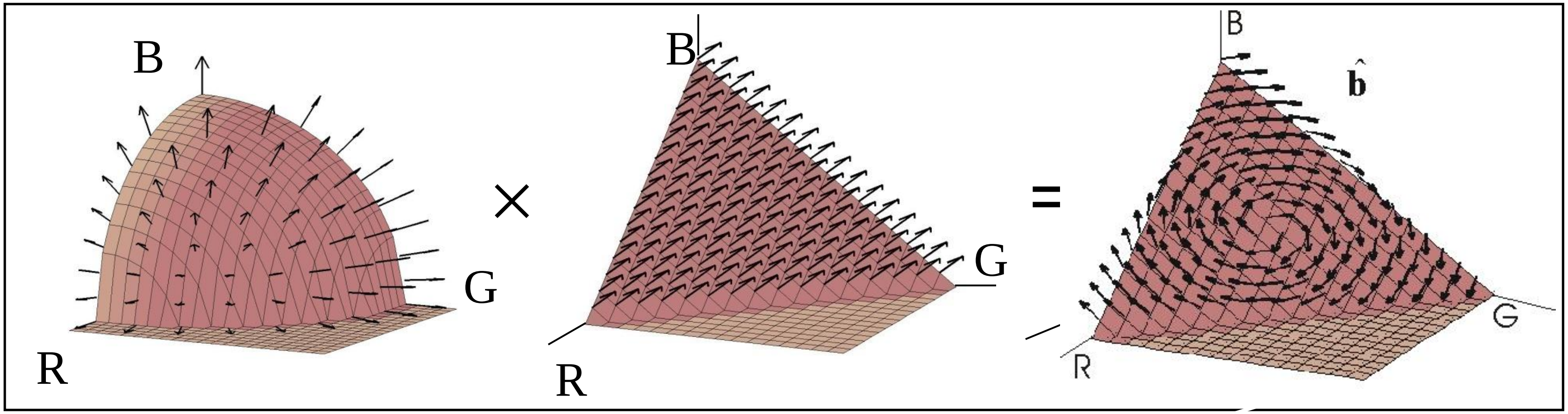


- first order photometric structure:

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

material + (shadow + shading) + specular

Shadow-Shading-Specular Quasi-Invariant

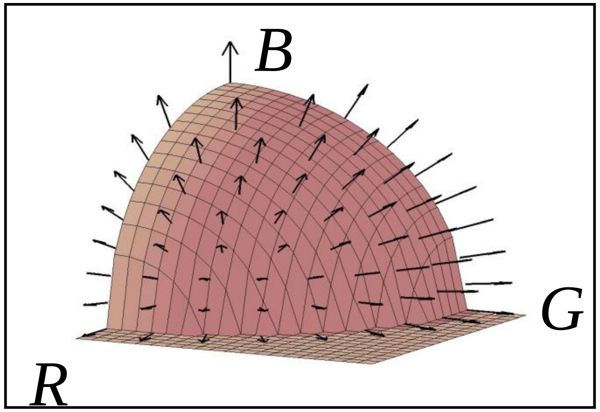


spherical coordinates	*opponent colors*	*hue-saturation-intensity*
shading variant	specular variant	shading-specular variant
shading invariant	specular invariant	shading-specular invariant

spherical coordinates

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

- all shadow-shading variation is in the radial direction



shadow/shading direction

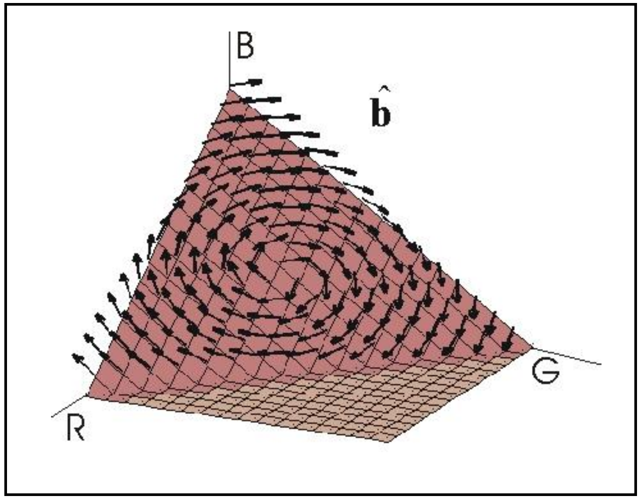
uncertainty of c_x

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

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

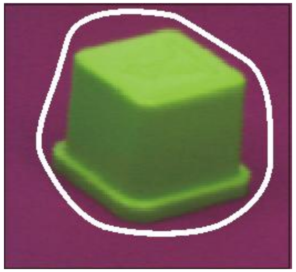
~~Colo Feature Extraction~~

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

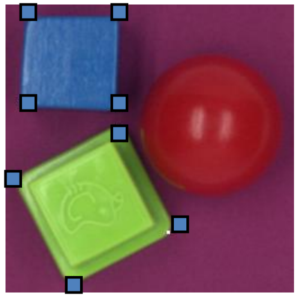
Color Feature Detection

Single Image Applications

- snakes



- feature extraction



Instabilities

test-image

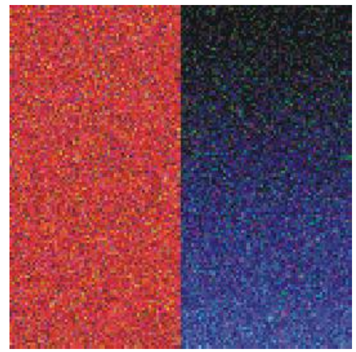
invariant

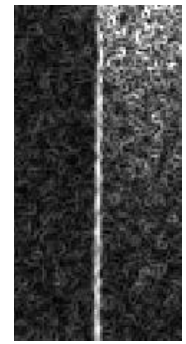
full

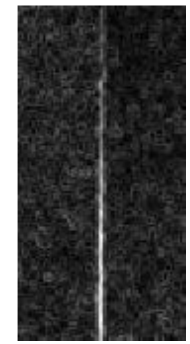
quasi

shadow-shading invariance:

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

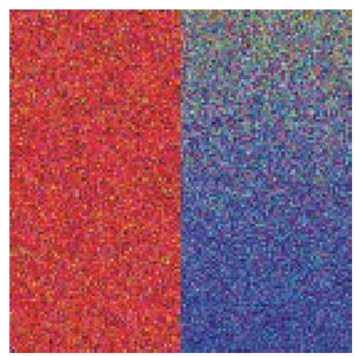


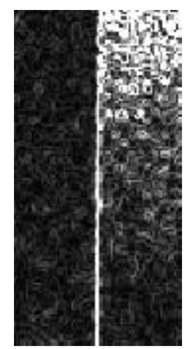


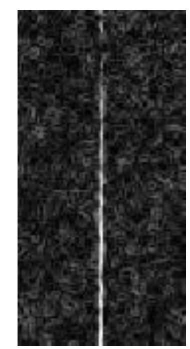


specular-shadow-shading invariance:

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







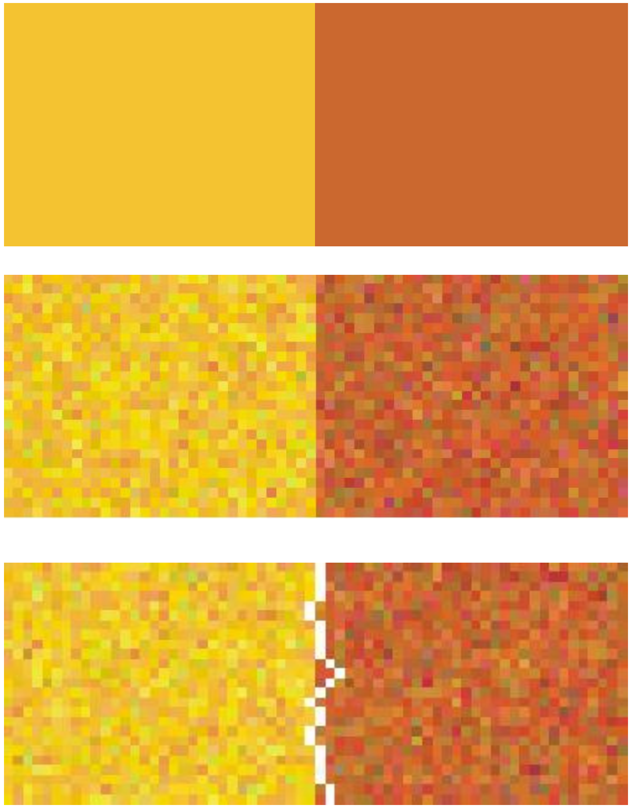
Edge Detection

• 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.



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• 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:

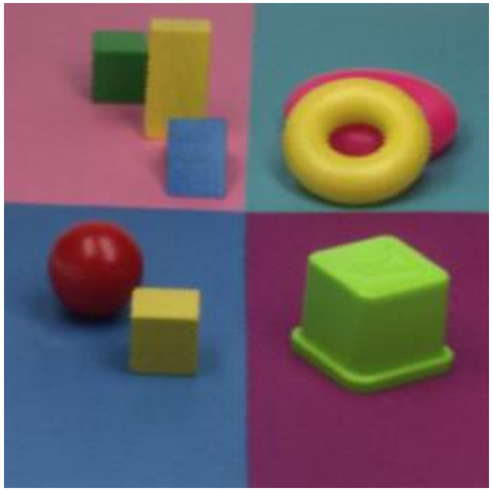
	Δ	ε
full	0.21	2.0
quasi	0.043	0.99

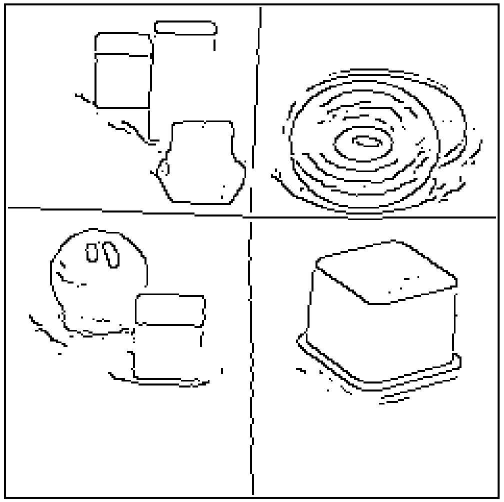
specular-shadow-shading:

	Δ	ε
full	0.85	9.8
quasi	0.35	5.8

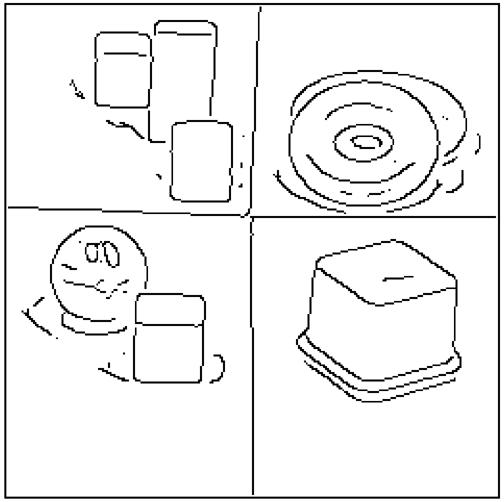
• Conclusion: Quasi invariants more than half the edge displacement, and have higher discriminative power.

experiments : canny edge detection



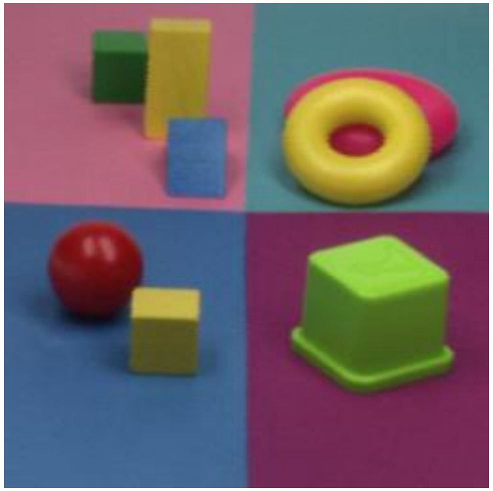


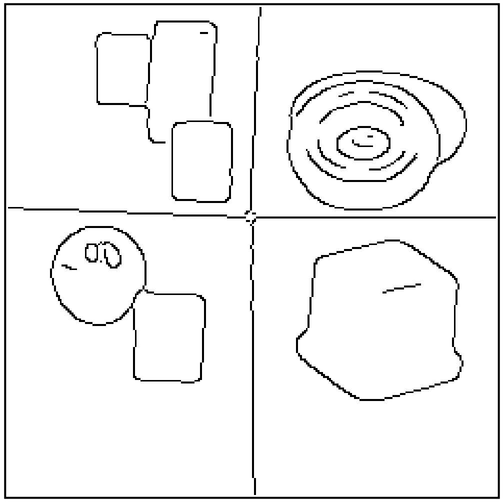
luminance-gradient



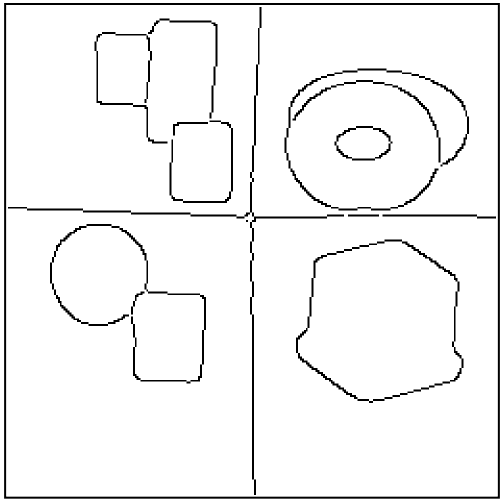
RGB-gradient

experiments : canny edge detection



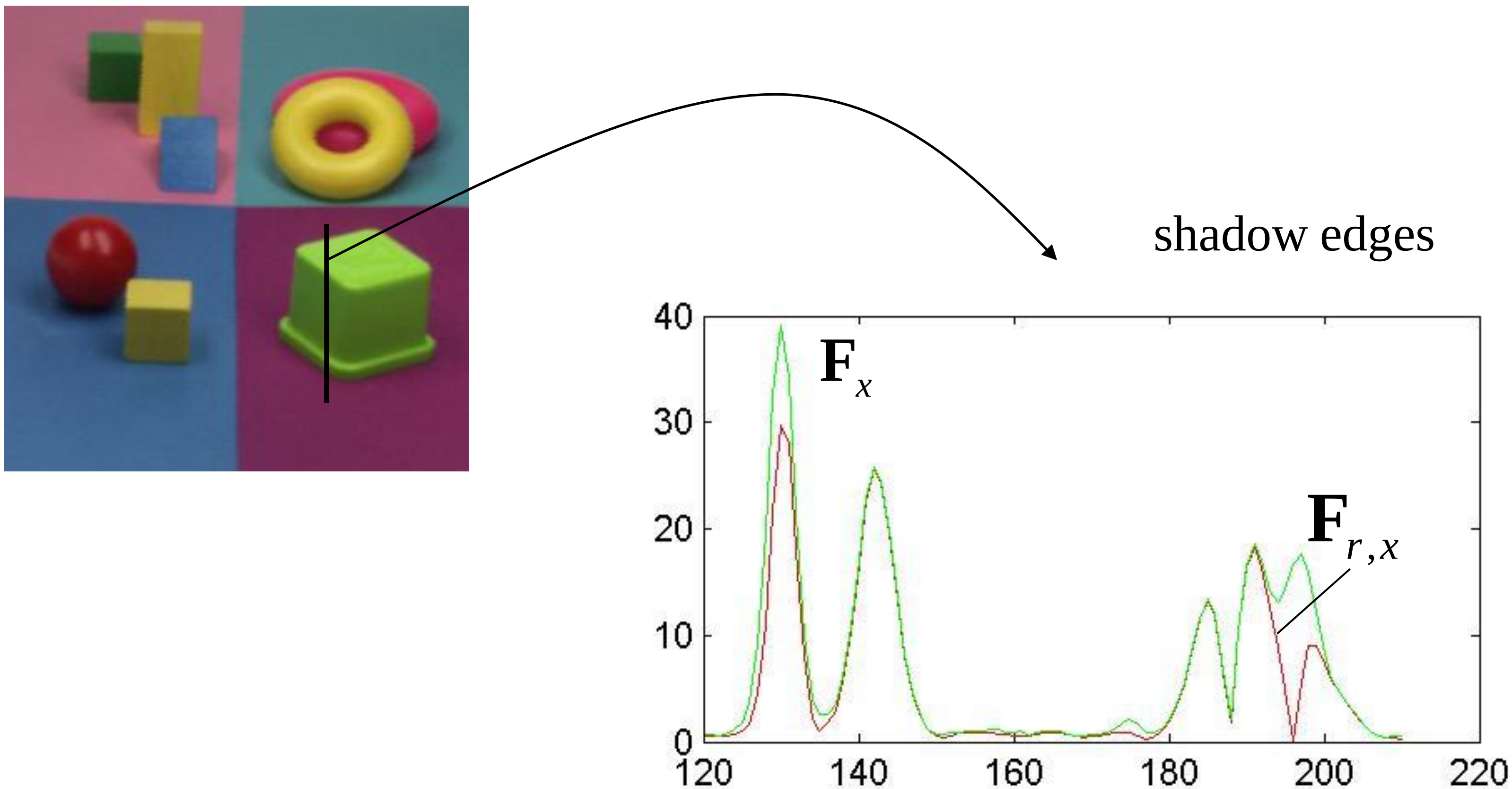


shadow-shading quasi-invariant

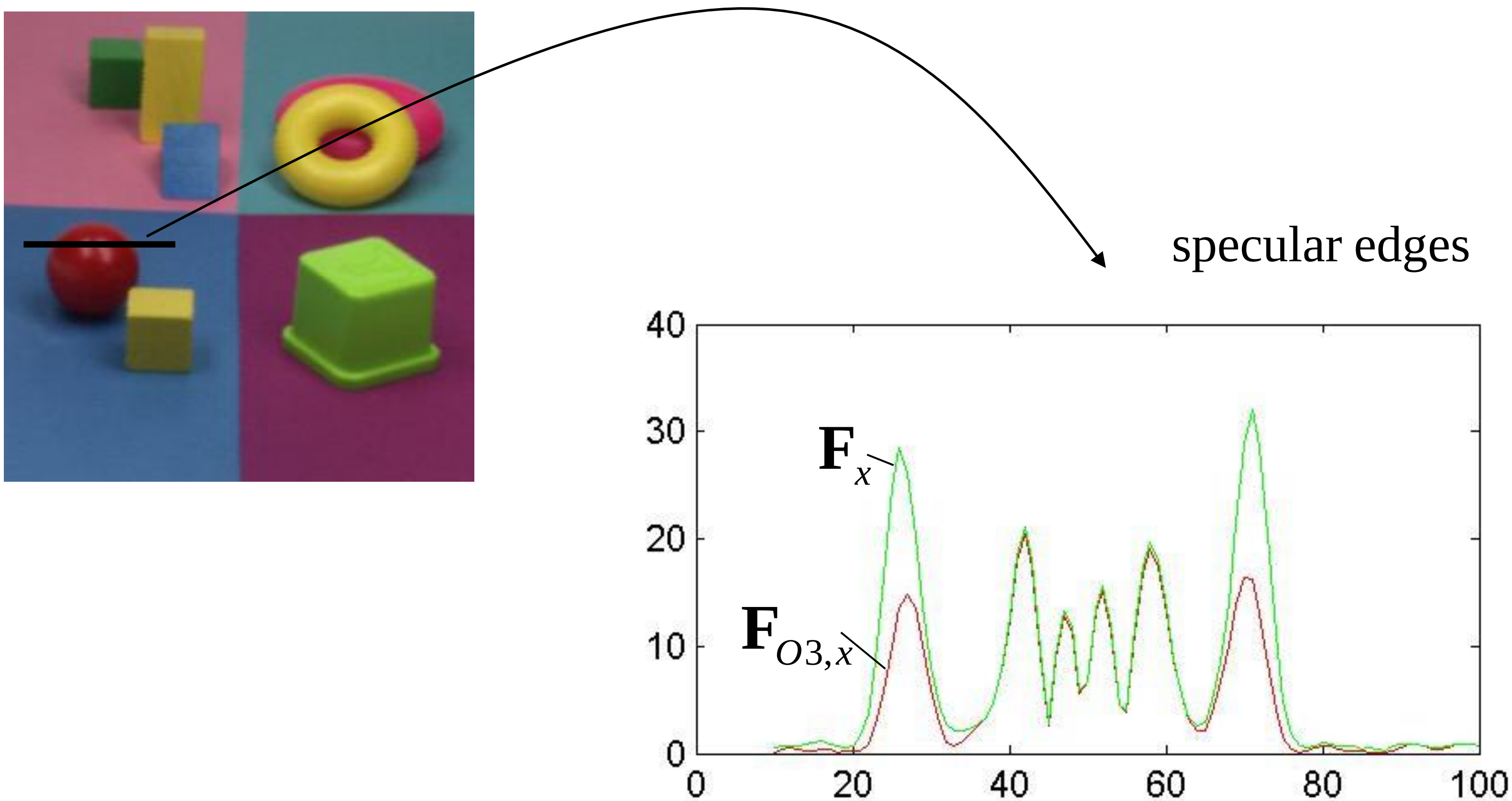


shadow-shading-specular quasi-invariant

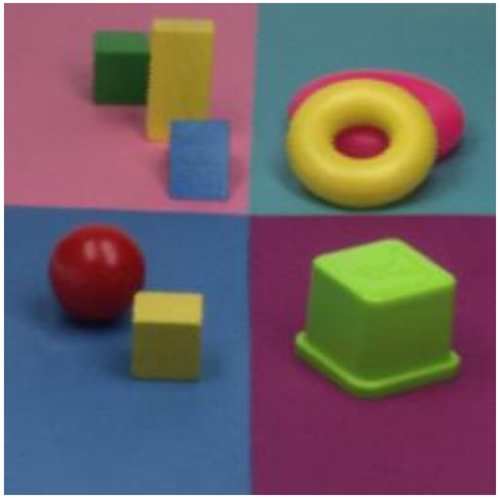
Edge Classification



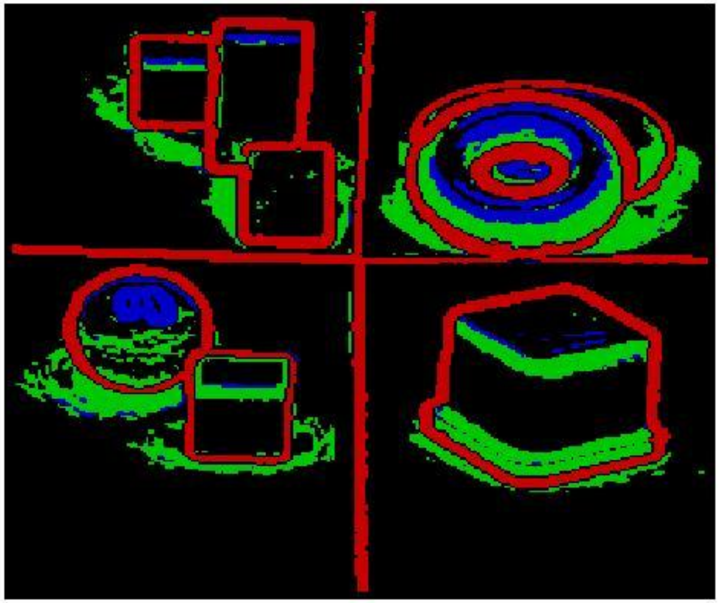
Edge Classification



Edge Classification

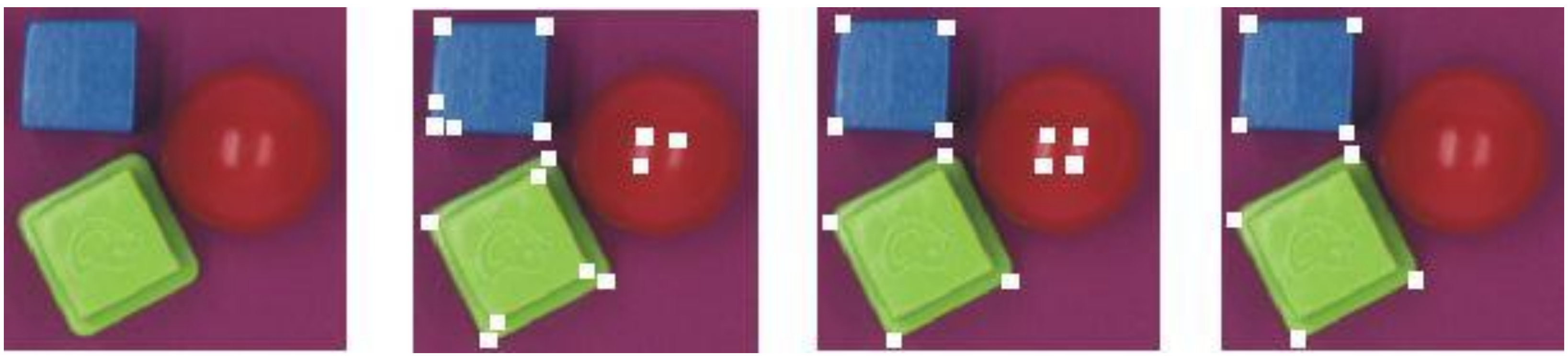


red - object edge
green-shading/shadow edge
Blue – specular edge



Photometric Invariant Corner Detection

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

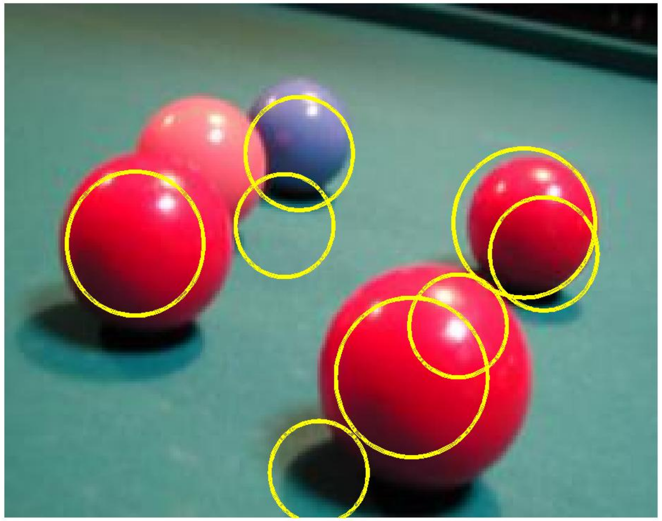


RGB

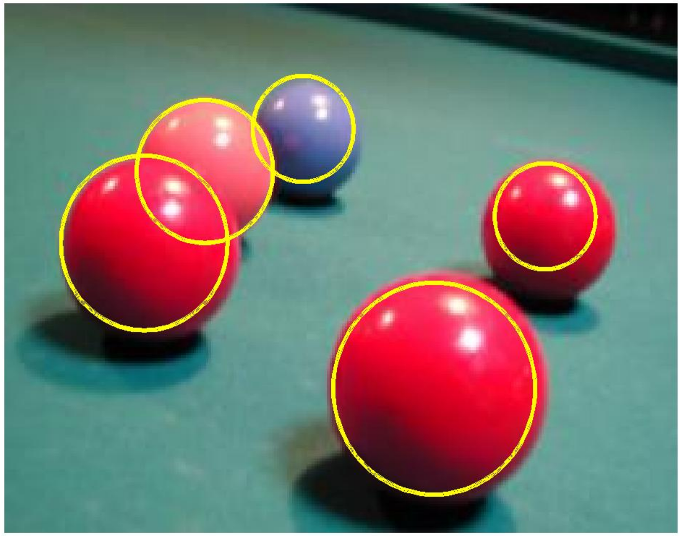
shadow-shading

specular-shadow-shading

experiments : Hough transform



RGB-gradient



shadow-shading-specular quasi-invariant references: color differential structure

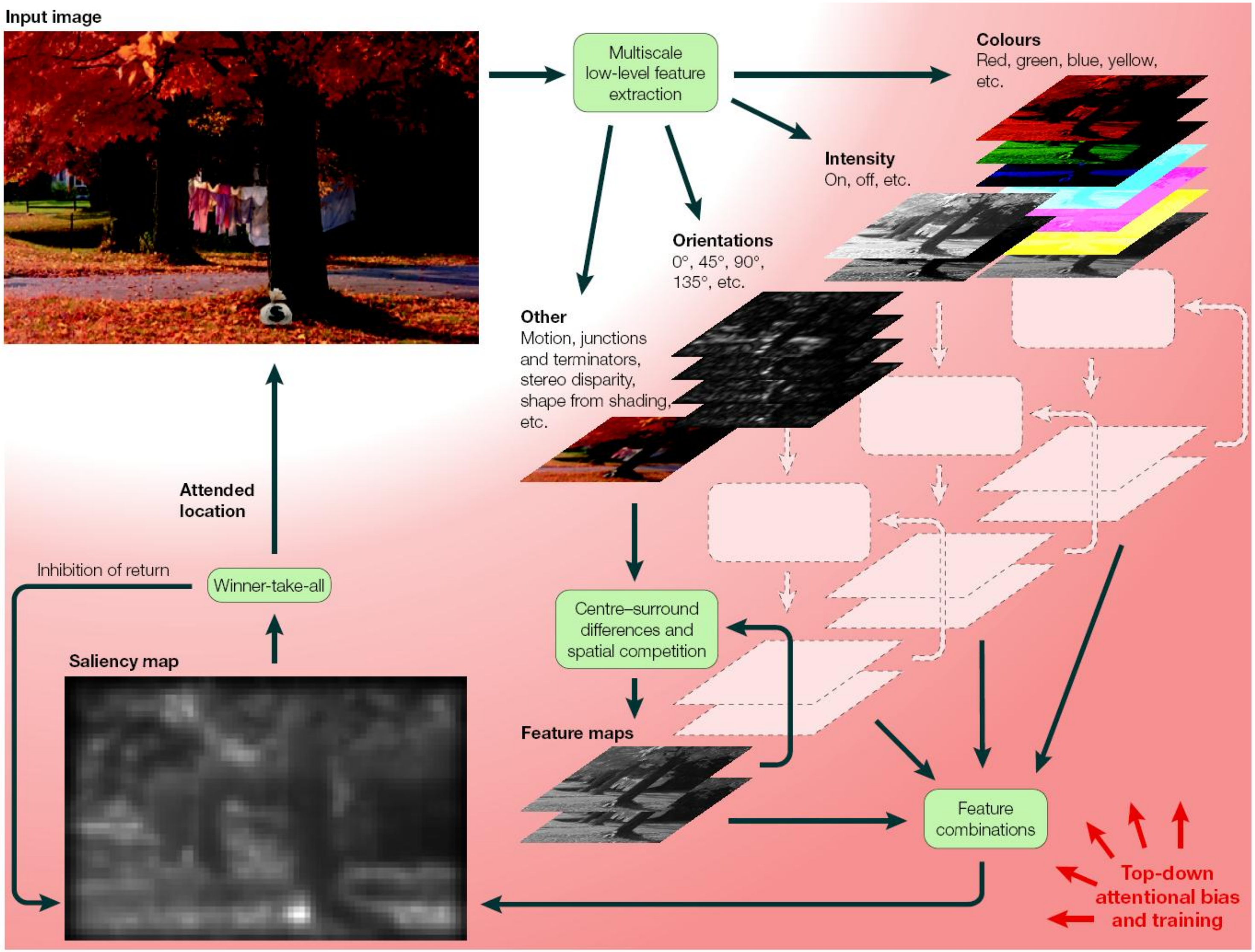
- S. DiZenzo. *A note on the gradient of a multi-image.* Computer Vision, Graphics, and Image Processing, 1986.
- G. Sapiro and D. Ringach. *Anisotropic diffusion of multivalued images with applications to color filtering.* IEEE Image Processing, 1996.
- J.M. Geusebroek et al. *Color Invariance.* IEEE 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

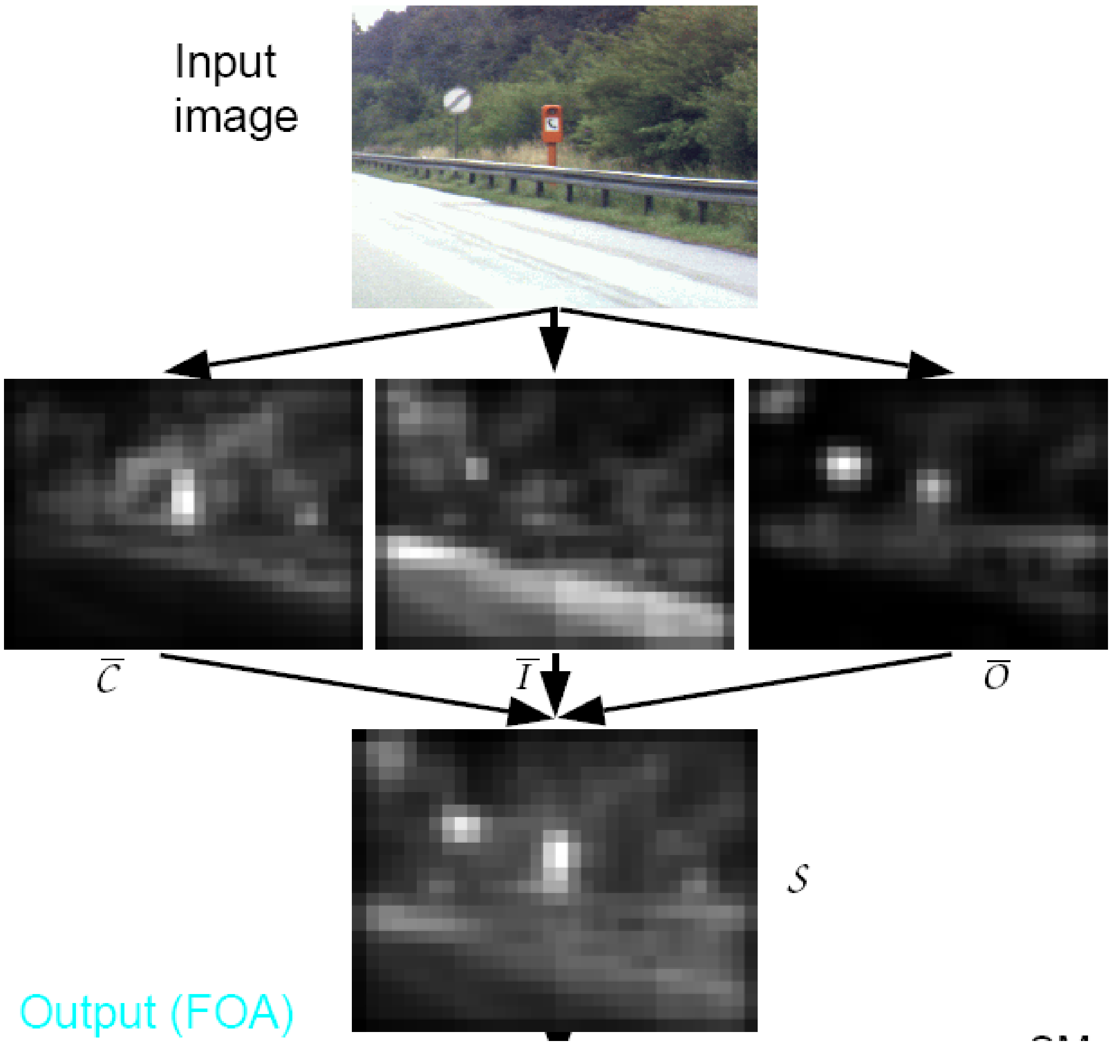
- Goal: direct our gaze rapidly towards objects of interest in our environment.
- Visual attention is know to be driven by both *bottom up* (image based) and *top-down* (task based) cues.
- Bottom-up saliency uses simple visual attributes such as *intensity*, *contrast*, *color opponency*, *orientation* , *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 :

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

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

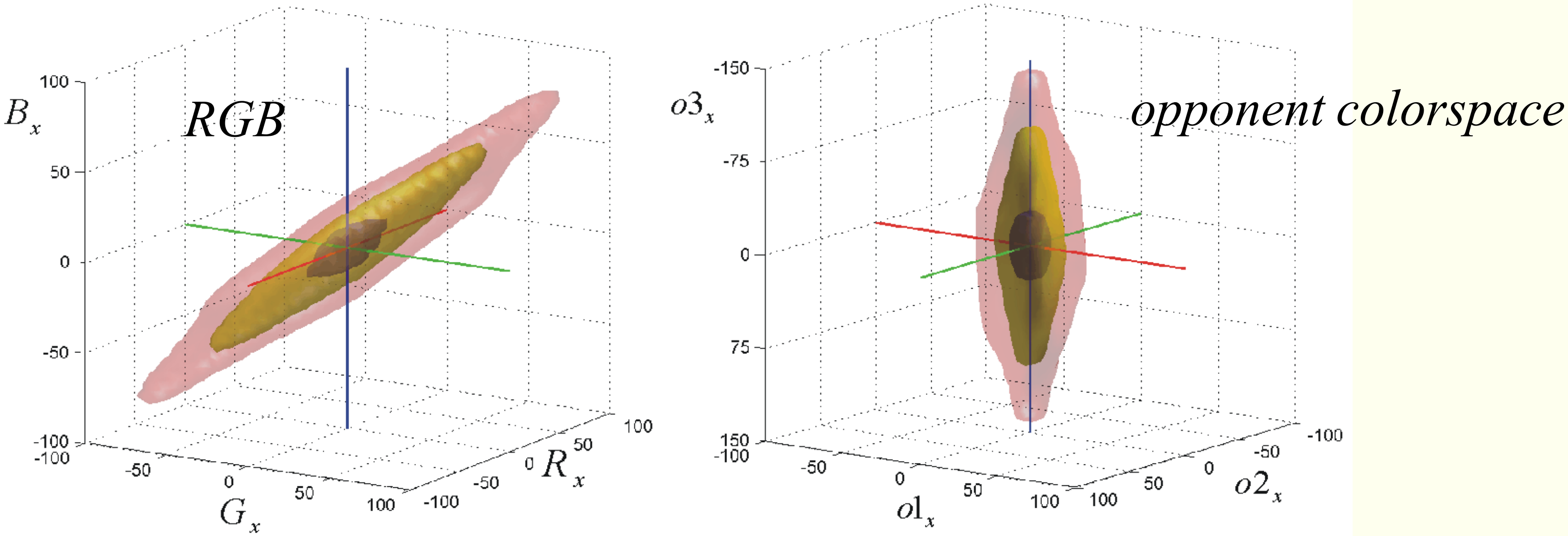
- equation differential-based salient point detectors : $H(\mathbf{f}_x, \mathbf{f}_y)$

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:

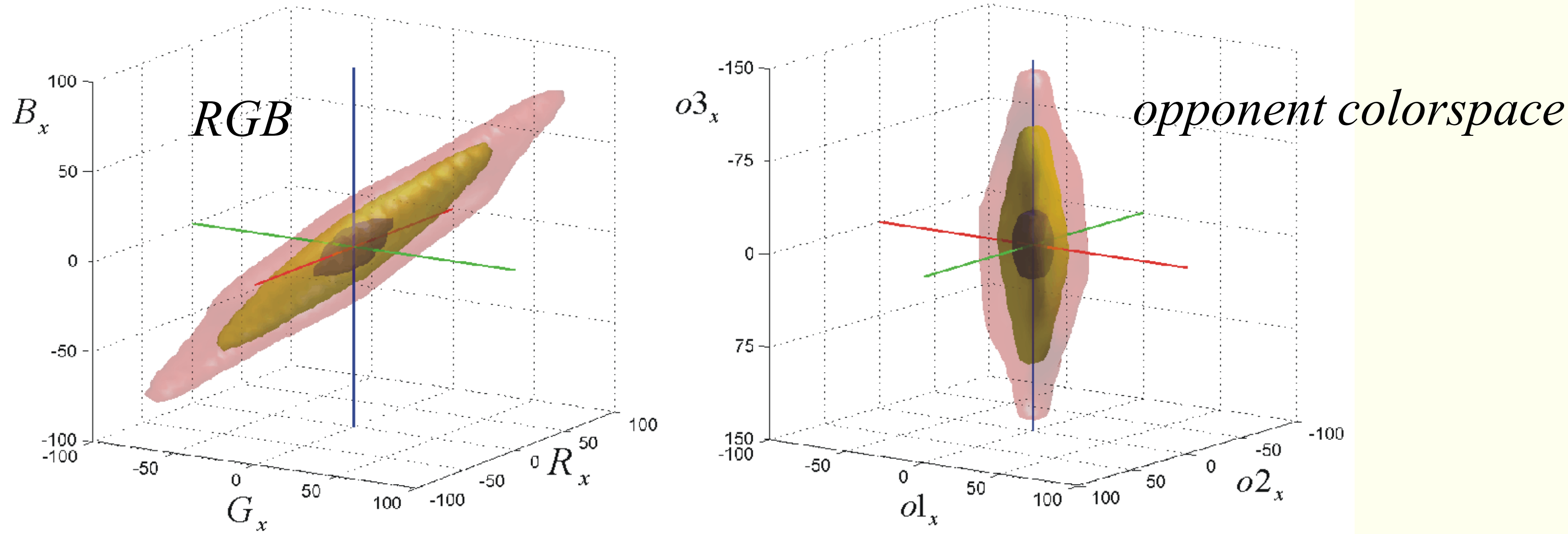
• The statistics of $\mathbf{f}_x$ is computed by looking of the 40.000 images of the Corel database.



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

statistics of color images:

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



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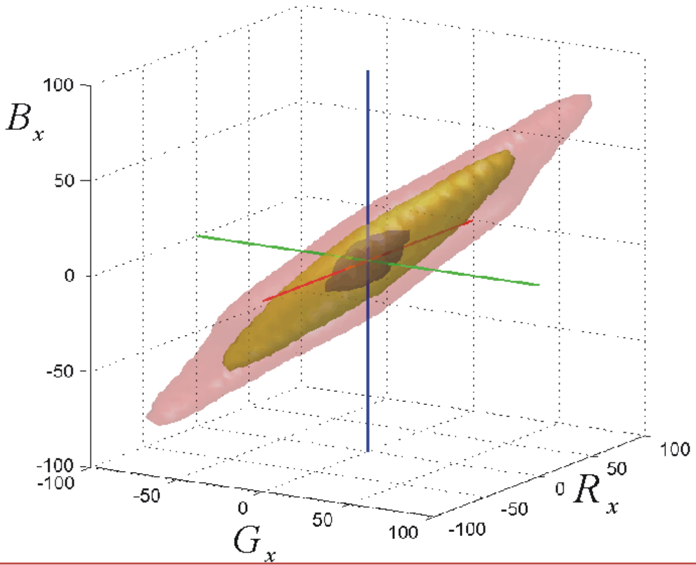


color boosting:

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

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

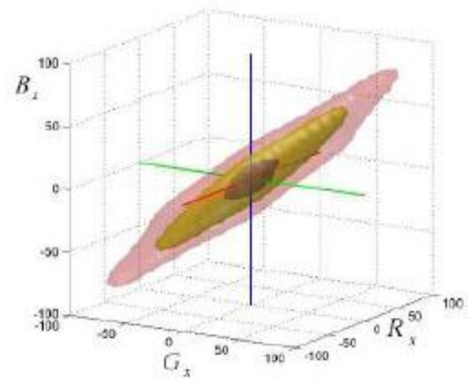
$$\mathbf{N} = \mathbf{U}\mathbf{\Lambda}\mathbf{\Lambda}\mathbf{U}^{\mathbf{t}}$$

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

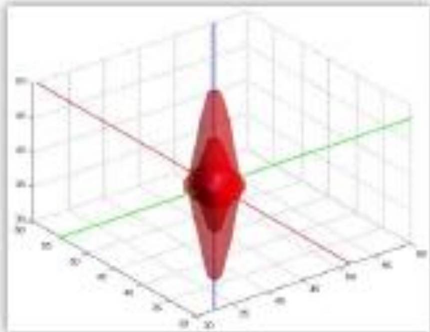
J. van de Weijer, Th. Gevers, A. Bagdanov, Boosting color saliency in image feature detection, IEEE PAMI 2006.

Color boosting:

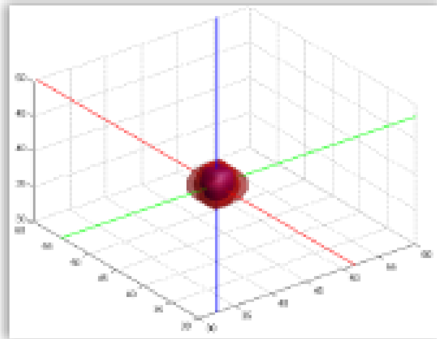
decorrelation whitening



U^{t}



Λ



derivatives
RGB color space

derivatives
opponent color space

derivatives
color boosted space

color boosting:

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

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

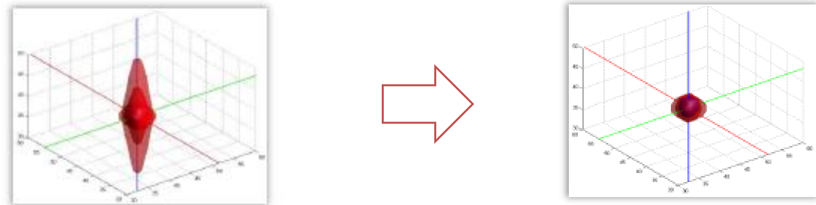
$$\mathbf{N} = \mathbf{U} \mathbf{\Lambda} \mathbf{\Lambda} \mathbf{U}^{\mathbf{t}}$$

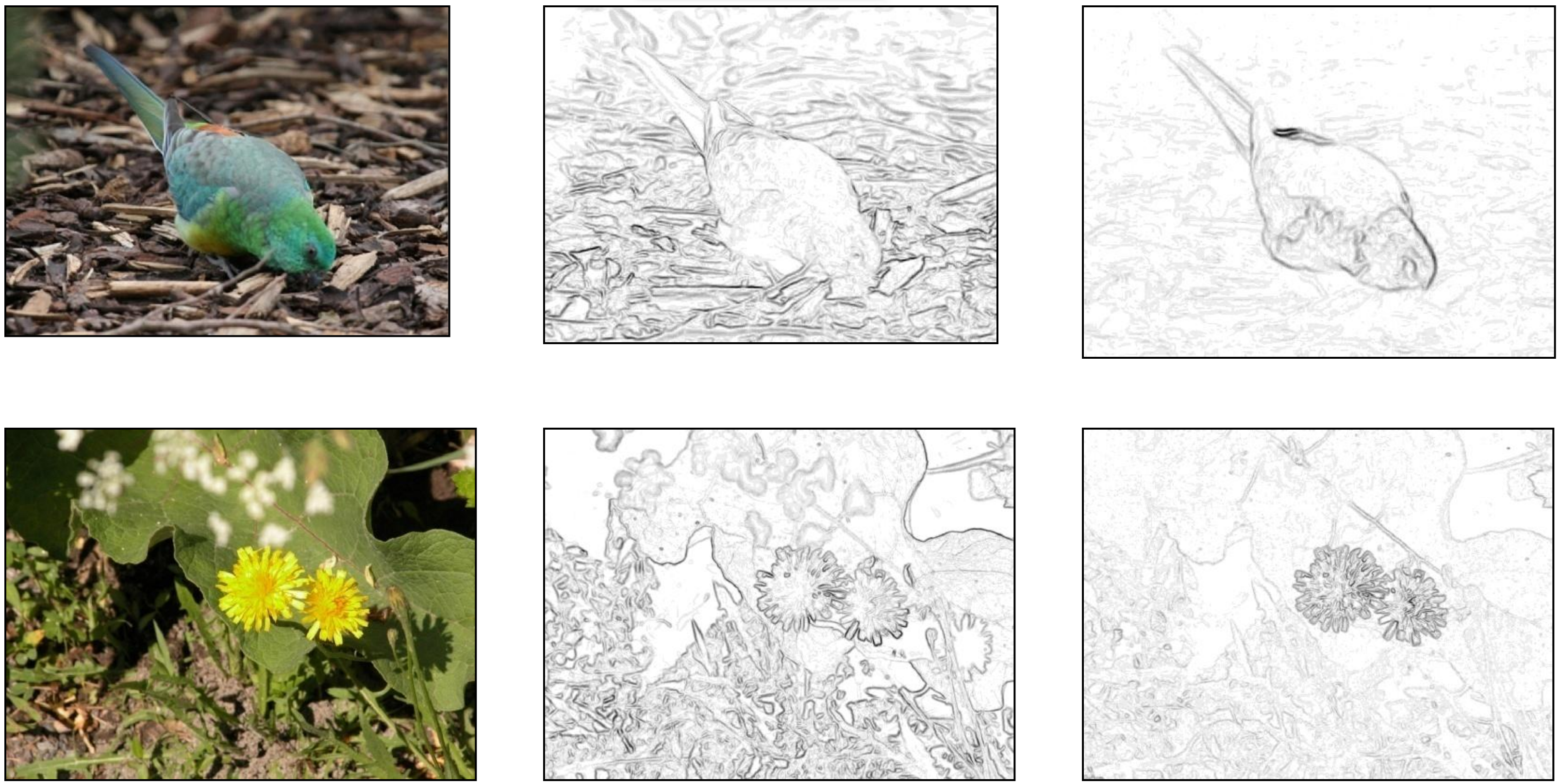
$$\mathbf{g}\left(\mathbf{f_x}\right) = \mathbf{\Lambda}^{-1} \mathbf{U}^{\mathbf{t}} \mathbf{f_x}$$

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

bottom-up color attention:

examples:





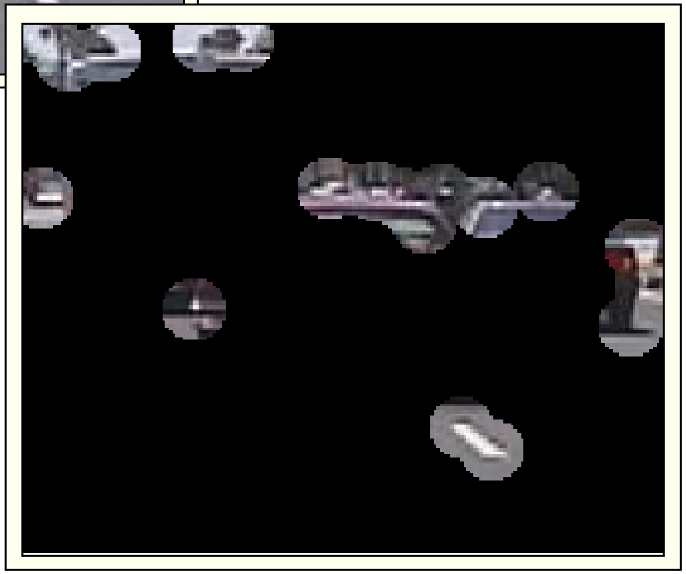
input image

color edges

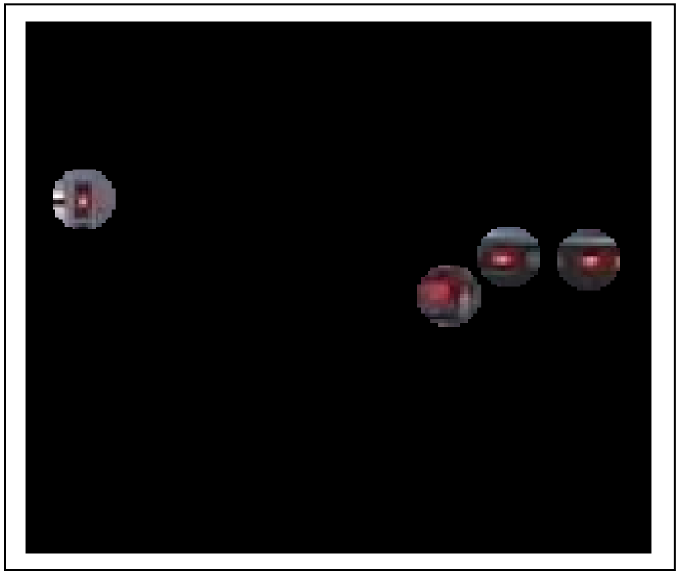
color boosted edges
bottom-up attention

saliency points

input car-image



RGB-based (first 20 points)



saliency boosting (first 4 points)

generality approach: global optimal regions

RGB gradient

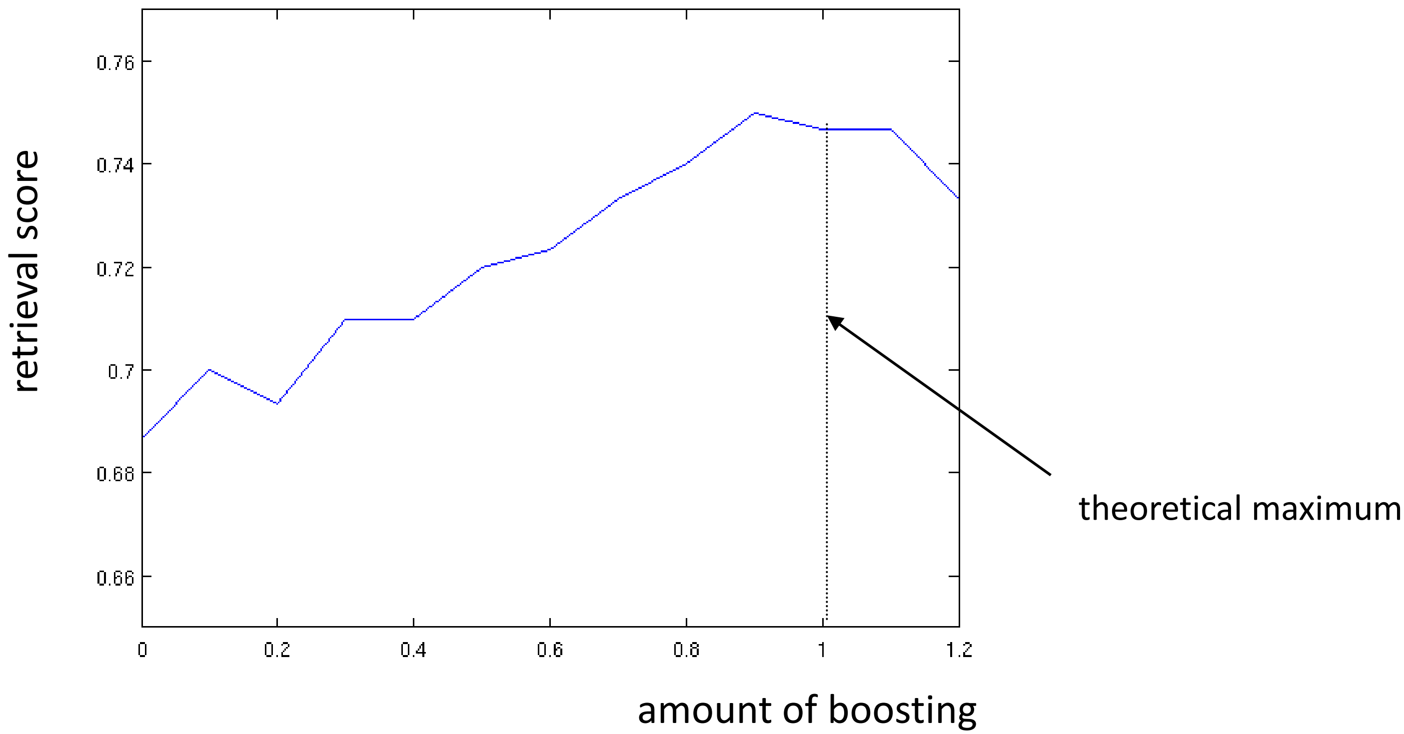
color boosting

experiment: image retrieval

Quantitative evaluation of color boosting on a retrieval experiment.

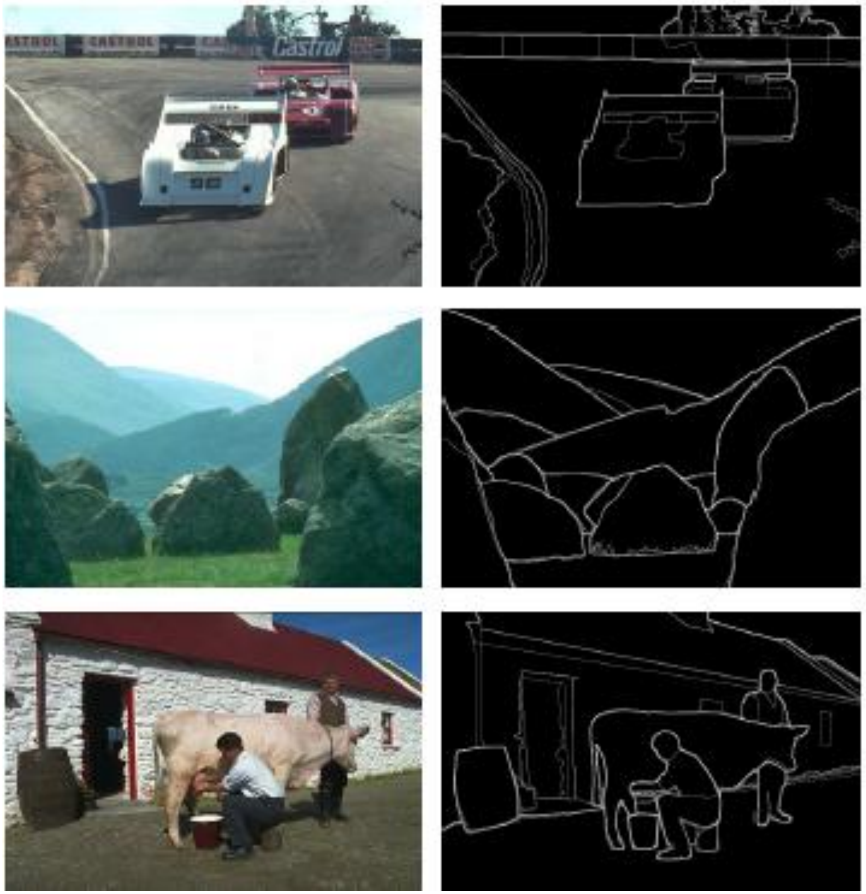
- Nister database: around 10.000 images
- detector: DoG (color boosted)
- descriptor: SIFT+hue

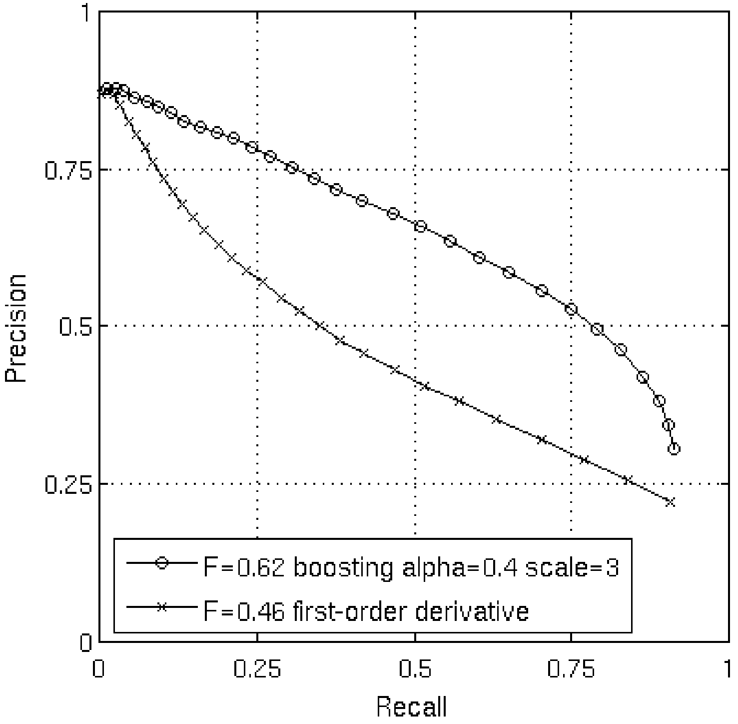
experiment: image retrieval



• 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 Benchmark

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.