Computational Photography and Capture: Intrinsic Images

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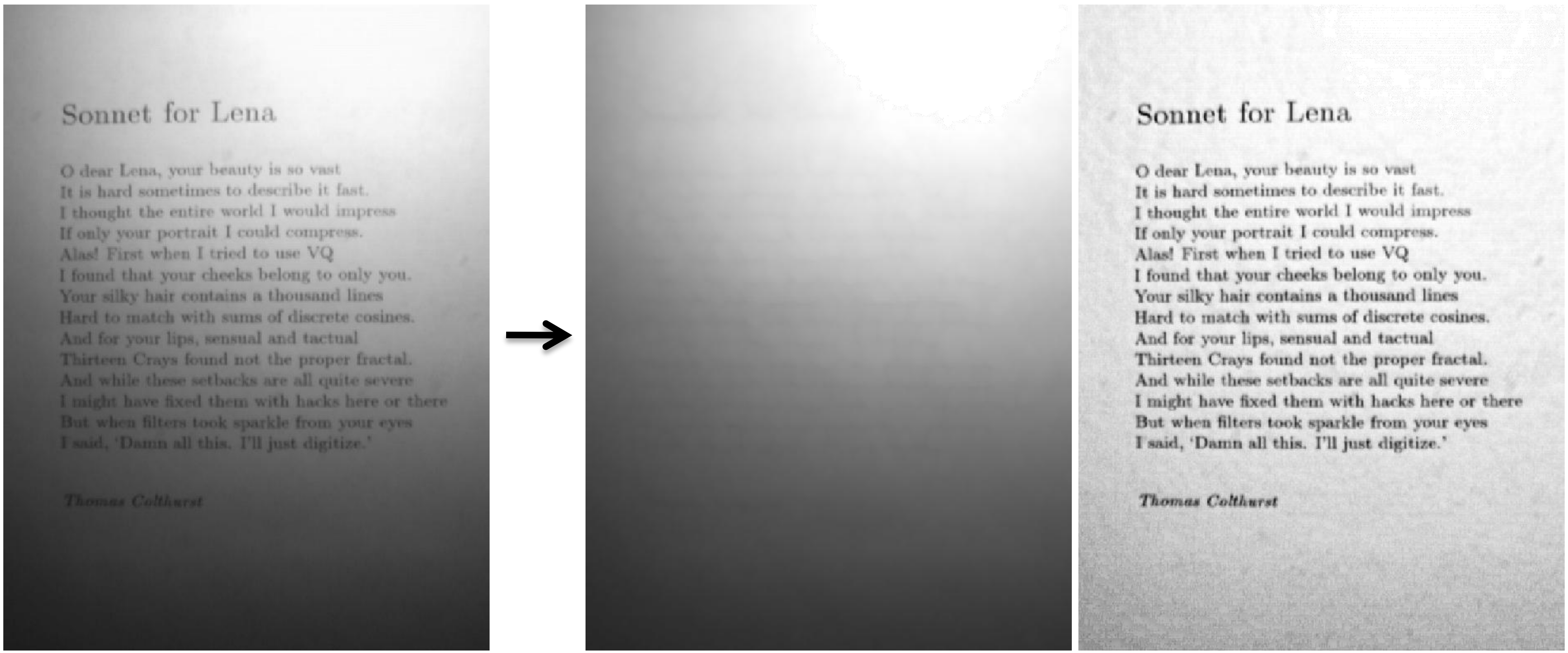
TAs: Clément Godard & Fabrizio Pece

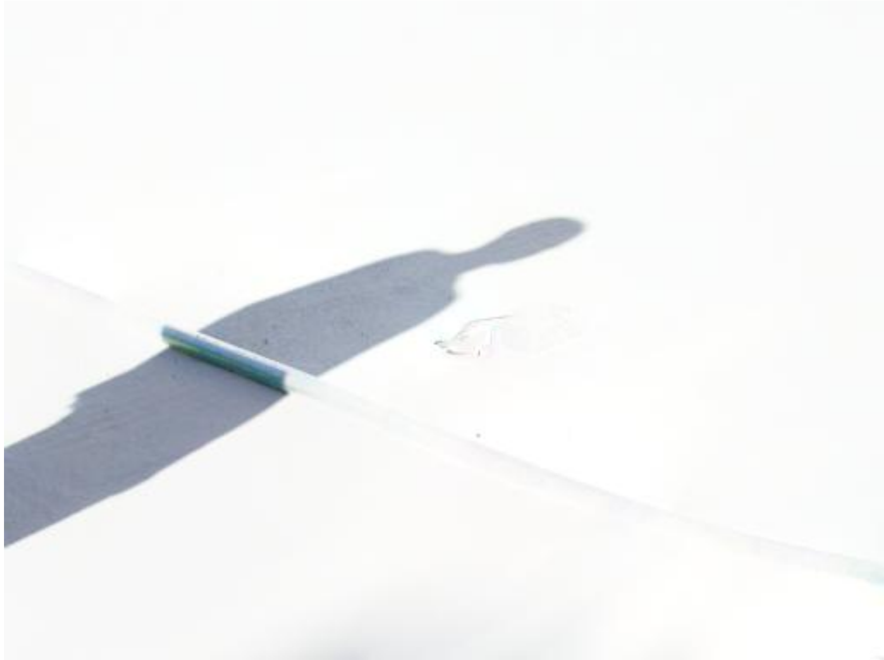
Example Problem: Background Normalization



In a photo, what determines the color of a (Lambertian) surface?

What great things could we do if we could easily separate lighting vs. color?





An Intrinsic Image

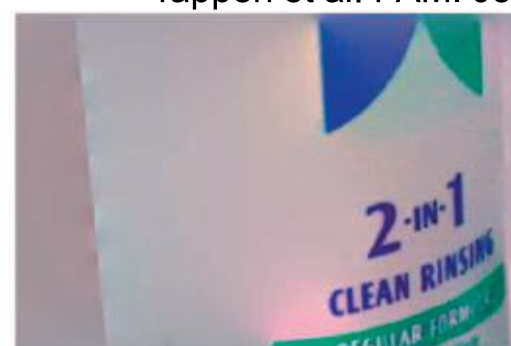
- What effect is the lighting having, irrespective of surface materials?

- What is the surface reflectance, irrespective of lighting?

Tappen et al. PAMI'05

Original

Lighting/Shading

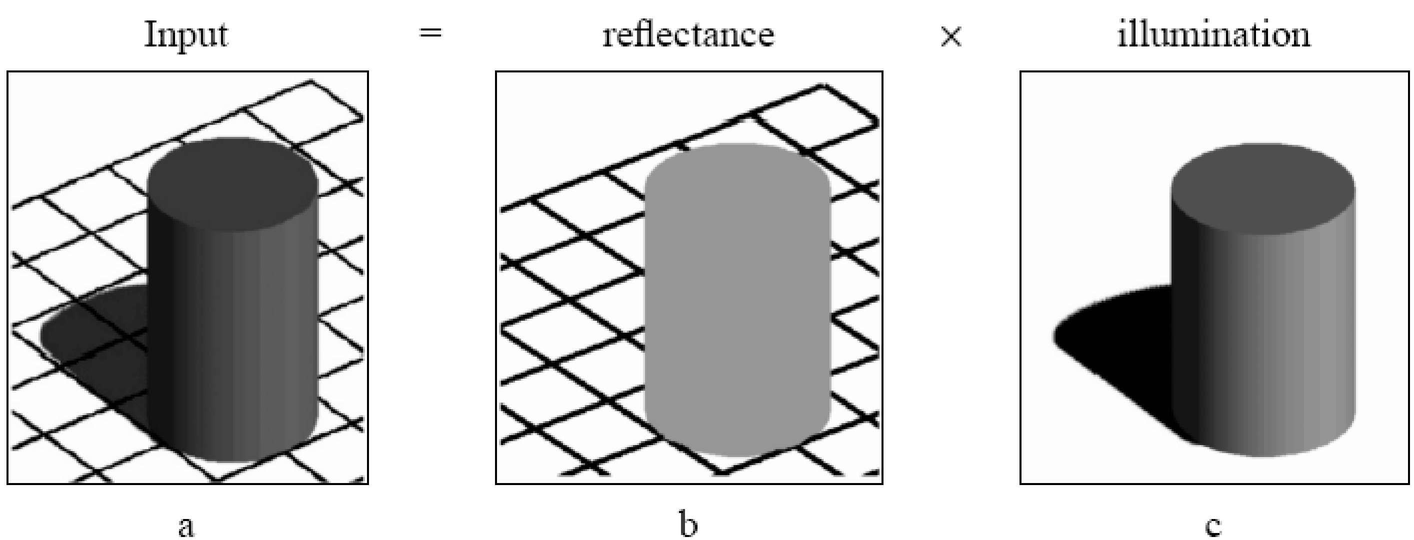


Reflectance

Pursuit of Intrinsic Images (1)

- Lightness and Retinex Theory
  - Land & McCann ’71

- Recovering Intrinsic Scene Characteristics From Images
  - Barrow & Tenenbaum ‘78



Pursuit of Intrinsic Images (2)

- Painted Polyhedra - ICCV'93
- Image Sequences - ICCV'01
- Single Image - NIPS'03
- Entropy Minimization - ECCV'04

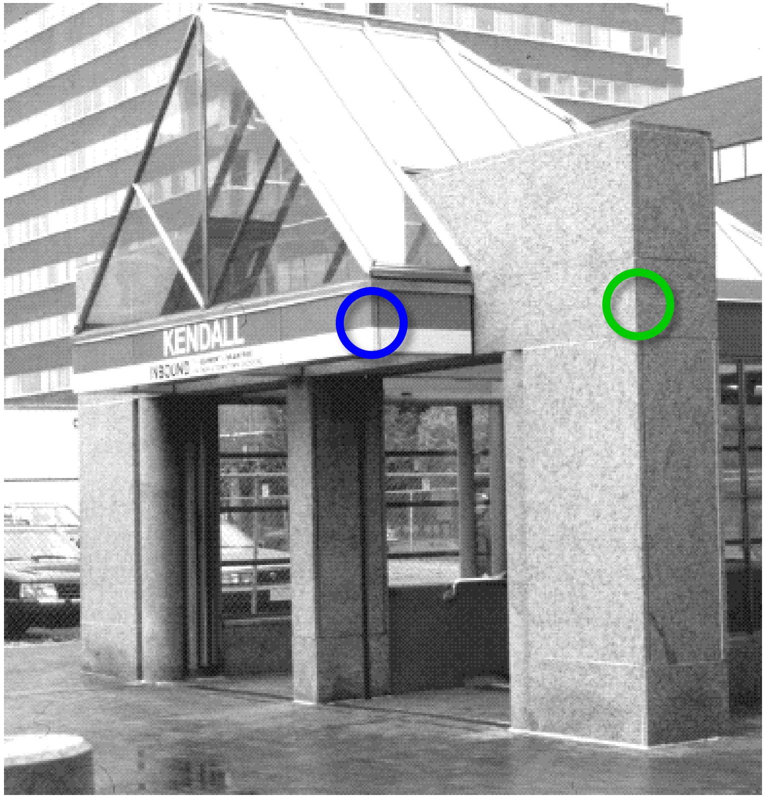
Pursuit of Intrinsic Images (2)

- Painted Polyhedra - ICCV'93 (Generative)
- Image Sequences - ICCV'01 (Discriminative)
- Single Image - NIPS'03 (Discriminative)
- Entropy Minimization - ECCV'04 (Generative)
- User-Assisted Intrinsic Images – Siggraph Asia'09

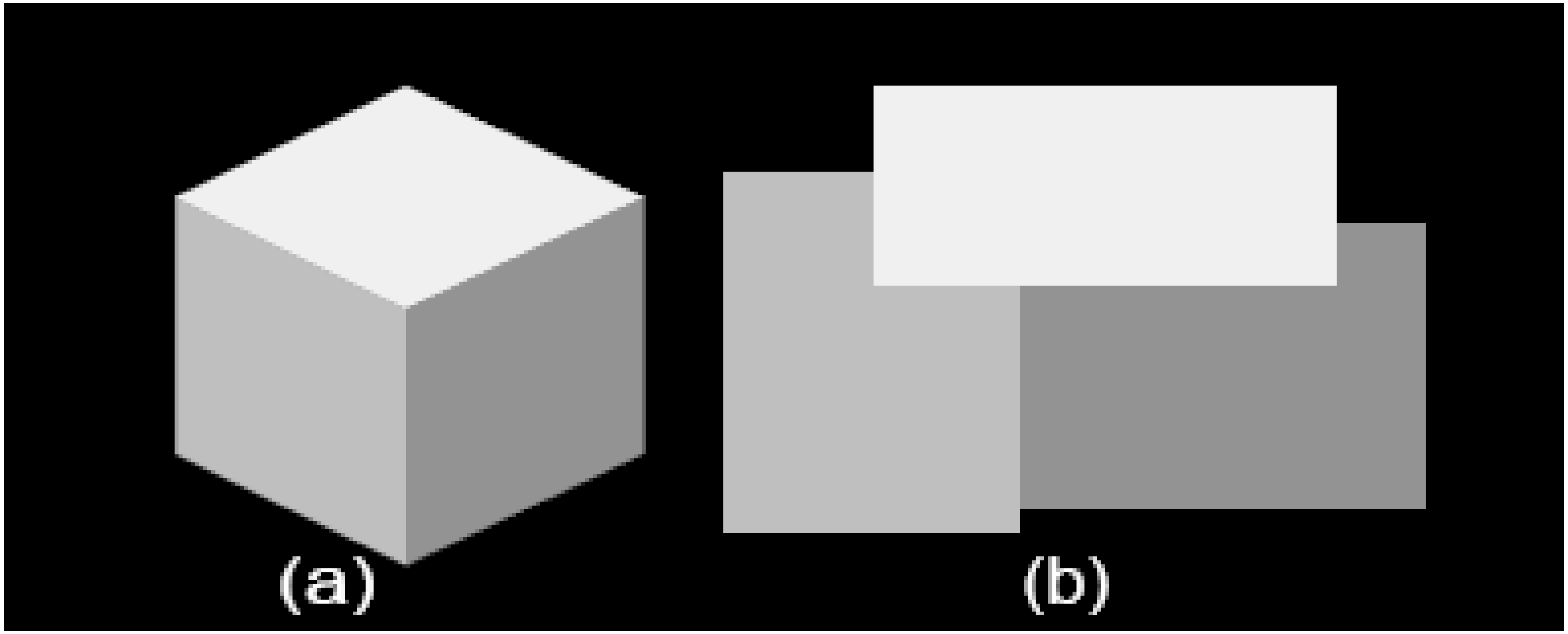
I

Painted Polyhedra

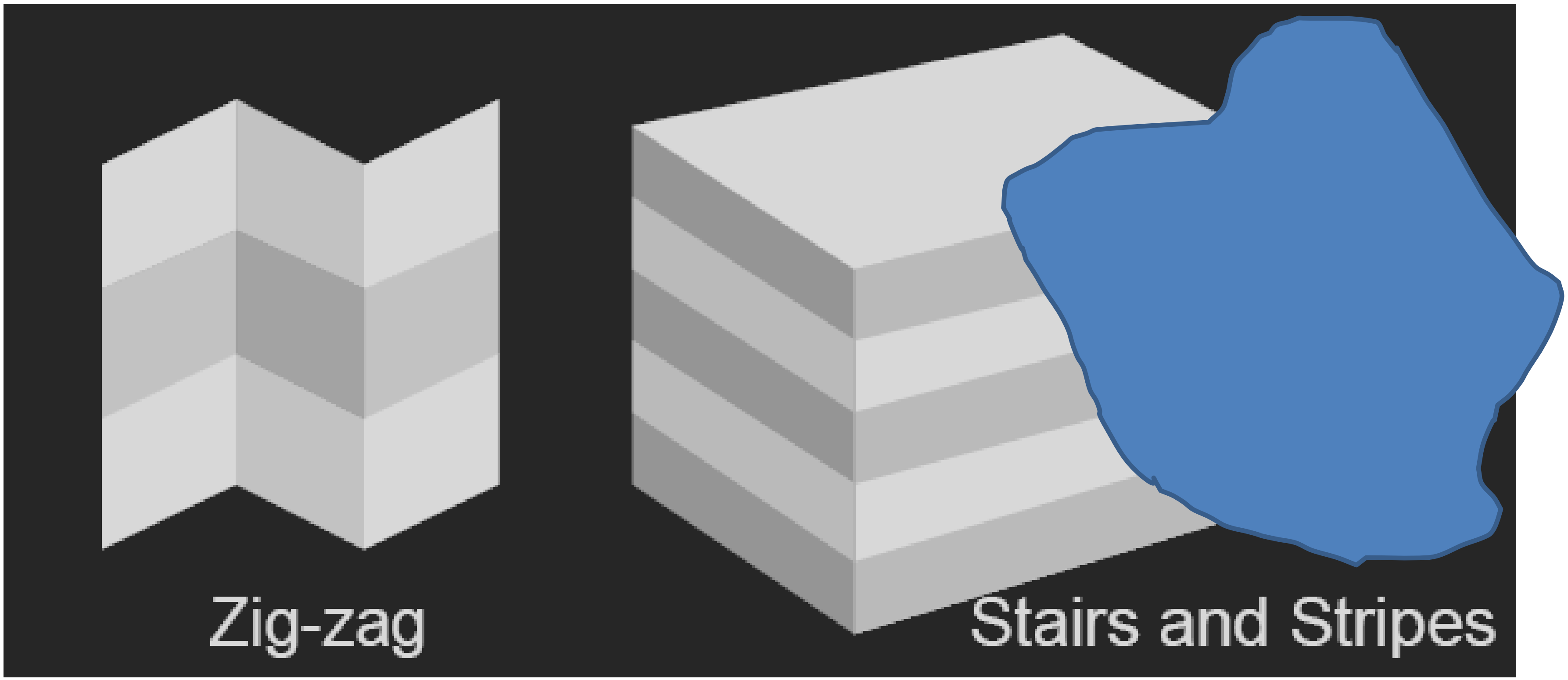
- Recovering Reflectance and Illumination in a World of Painted Polyhedra
  - Sinha & Adelson, ICCV'93



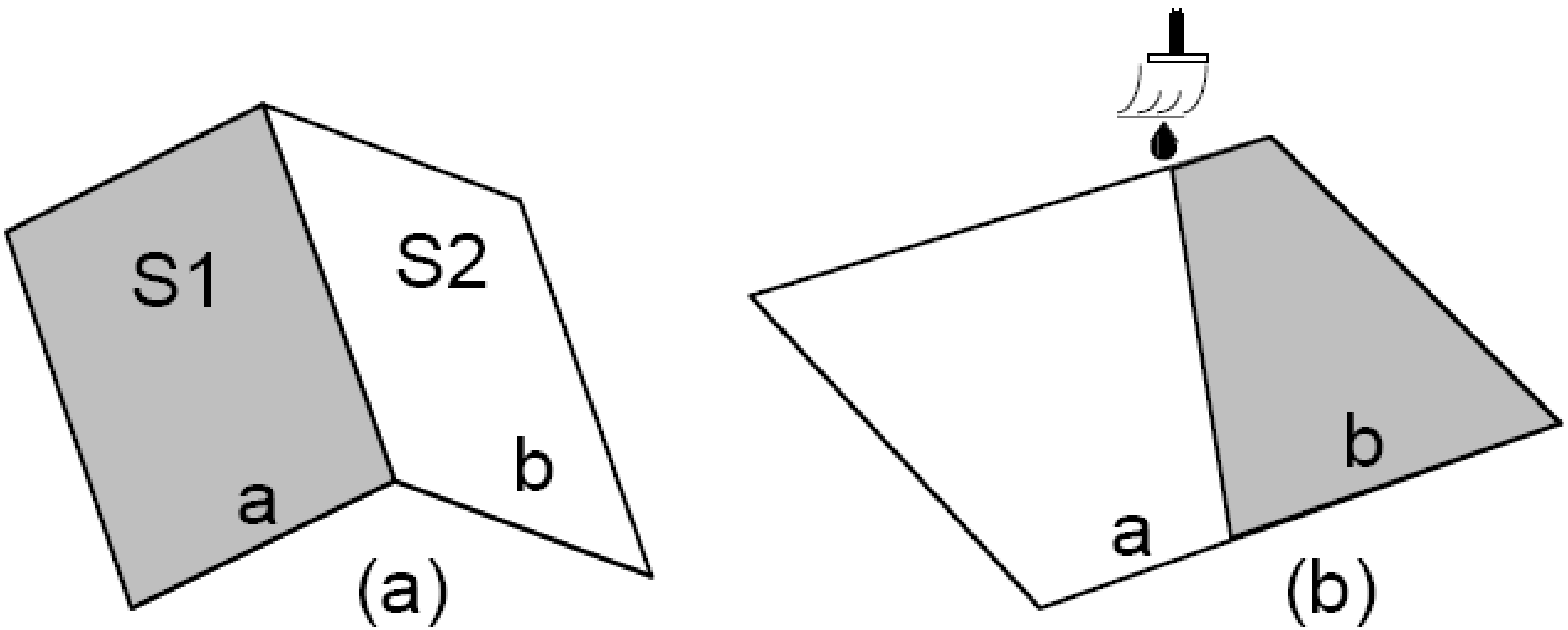
Not All Edges are Equal



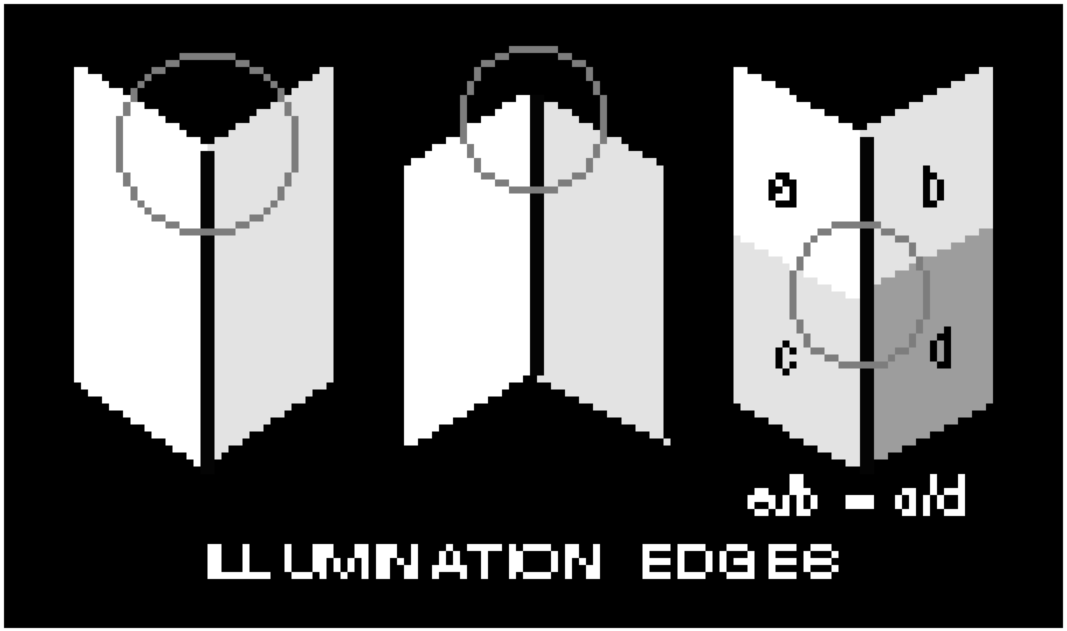
Local Edges are a Hint?

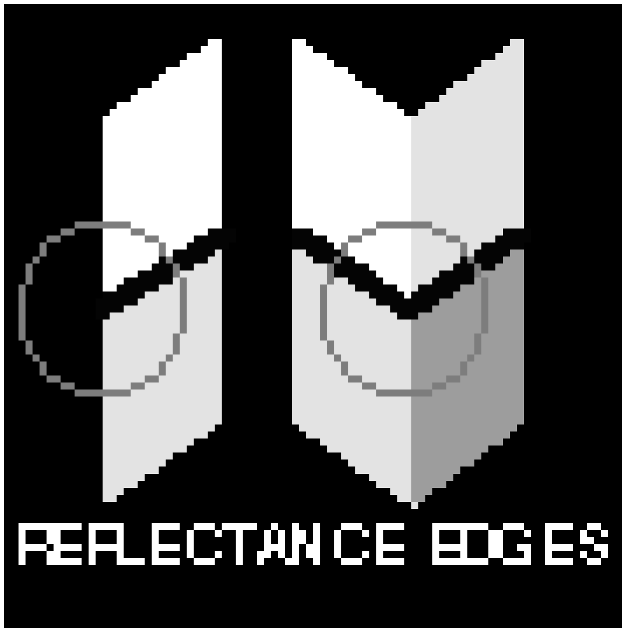


Edge Junctions are Useful



Junction Catalog

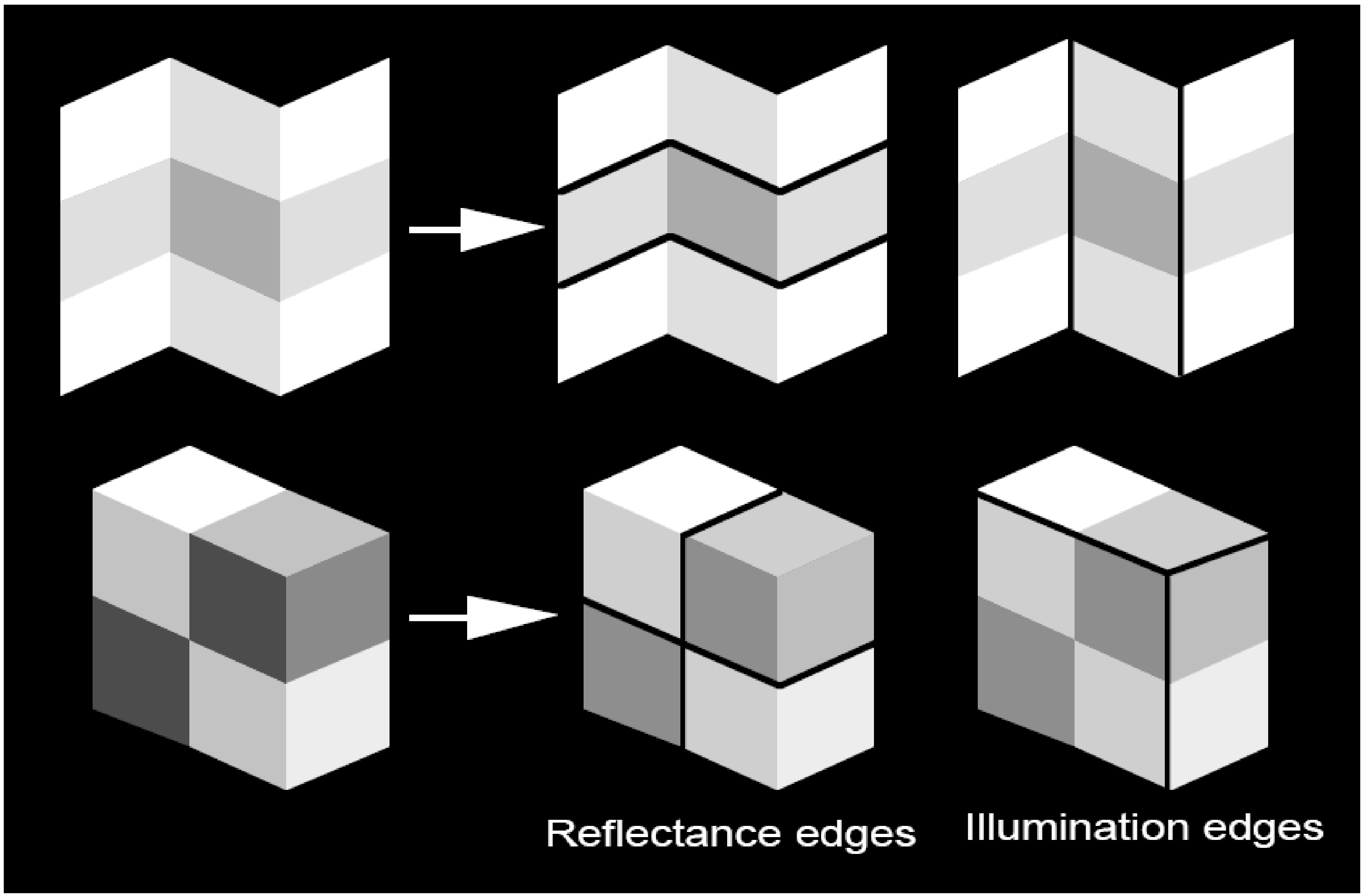




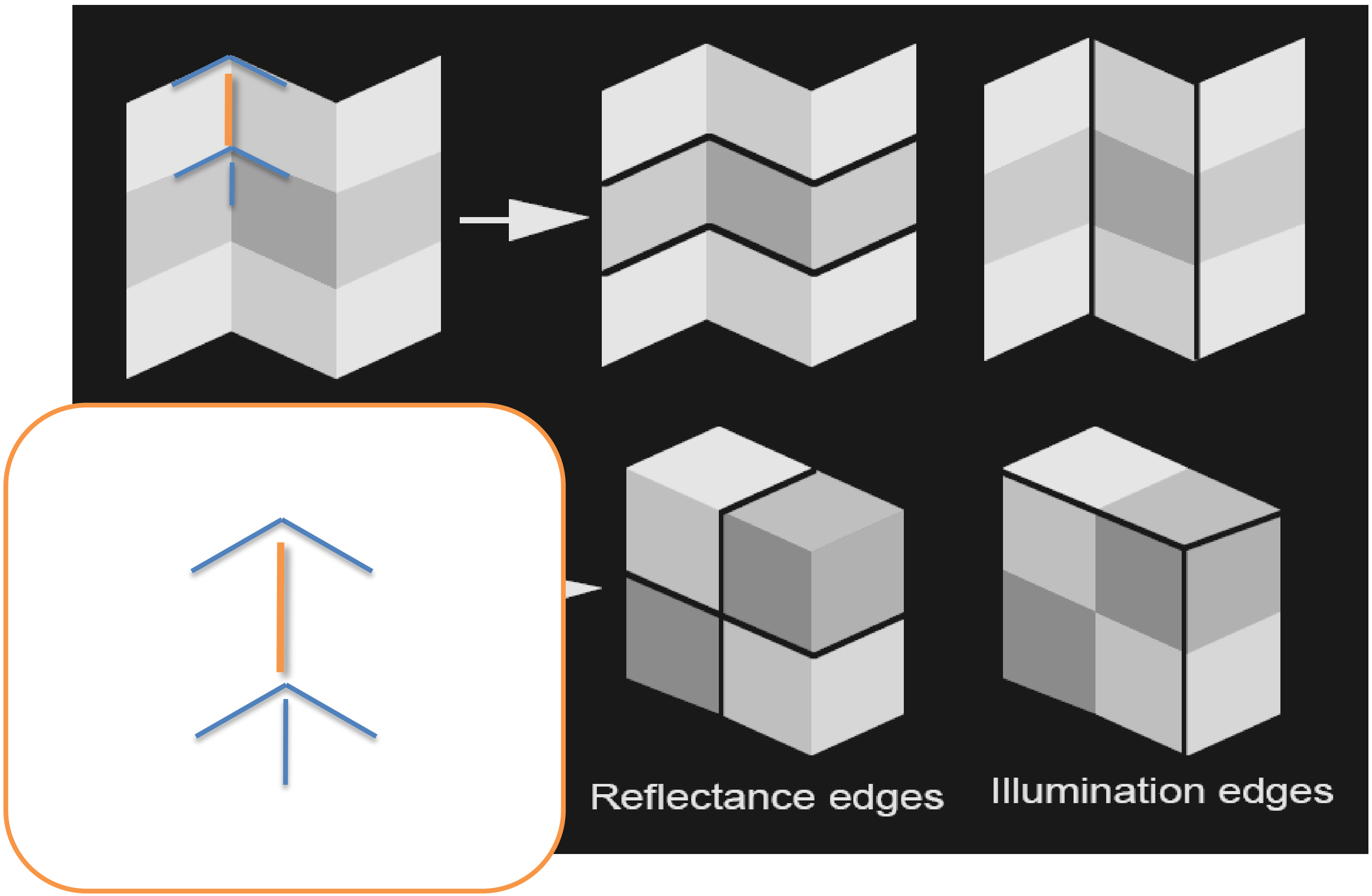
‘Y’, ‘arrow,’ and ‘psi’ junctions

‘T’ junctions

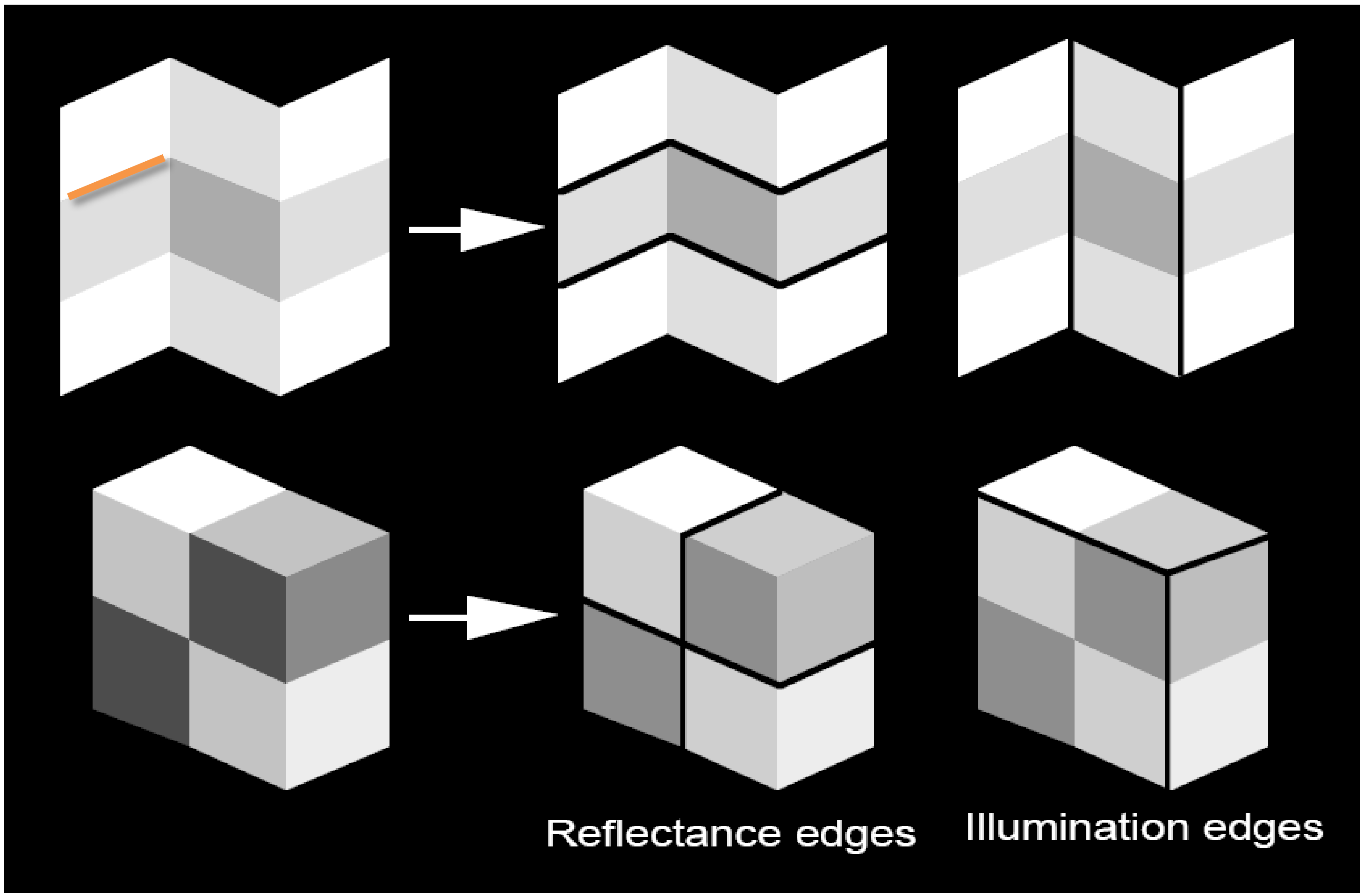
Examples



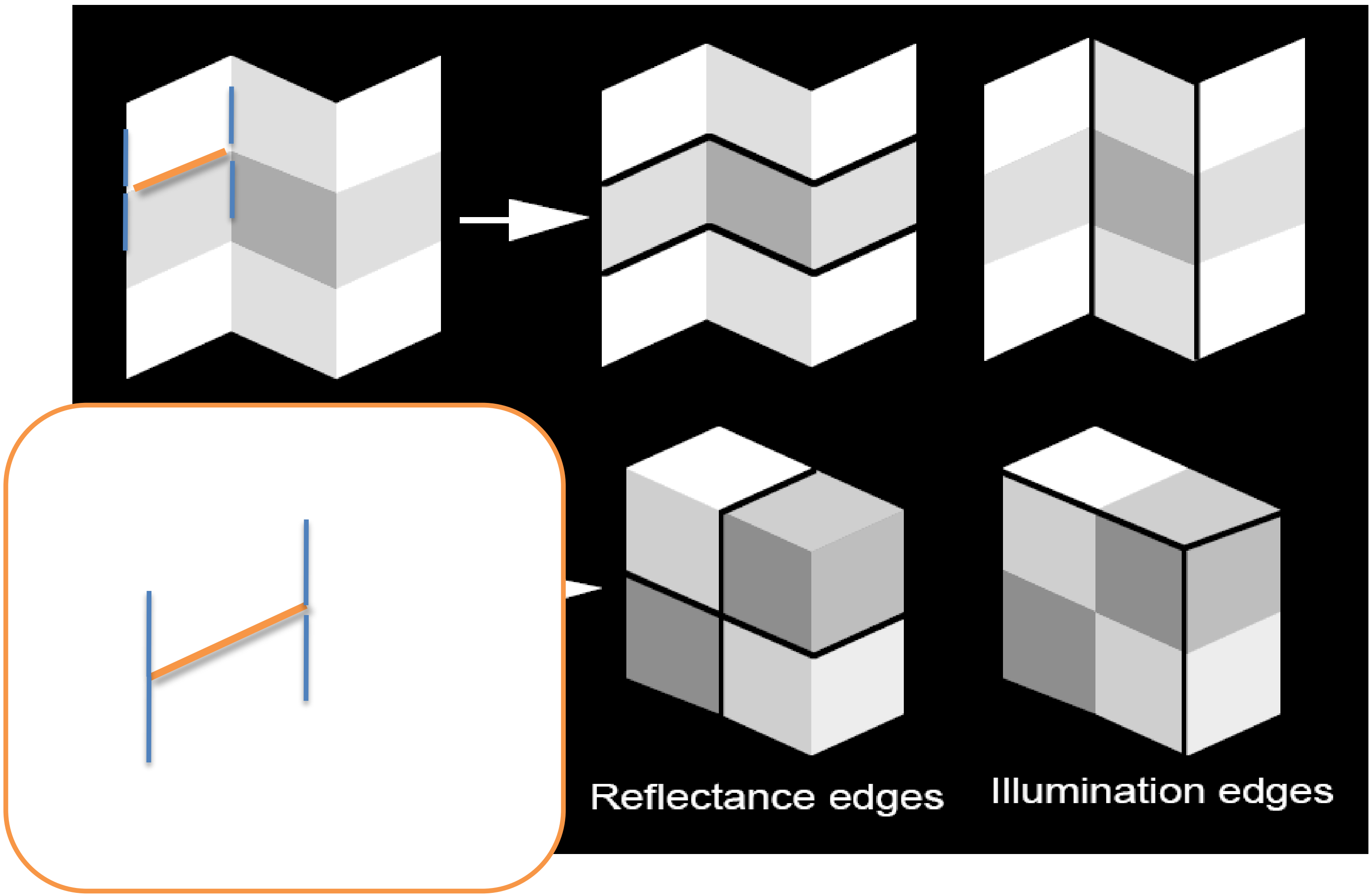
Examples



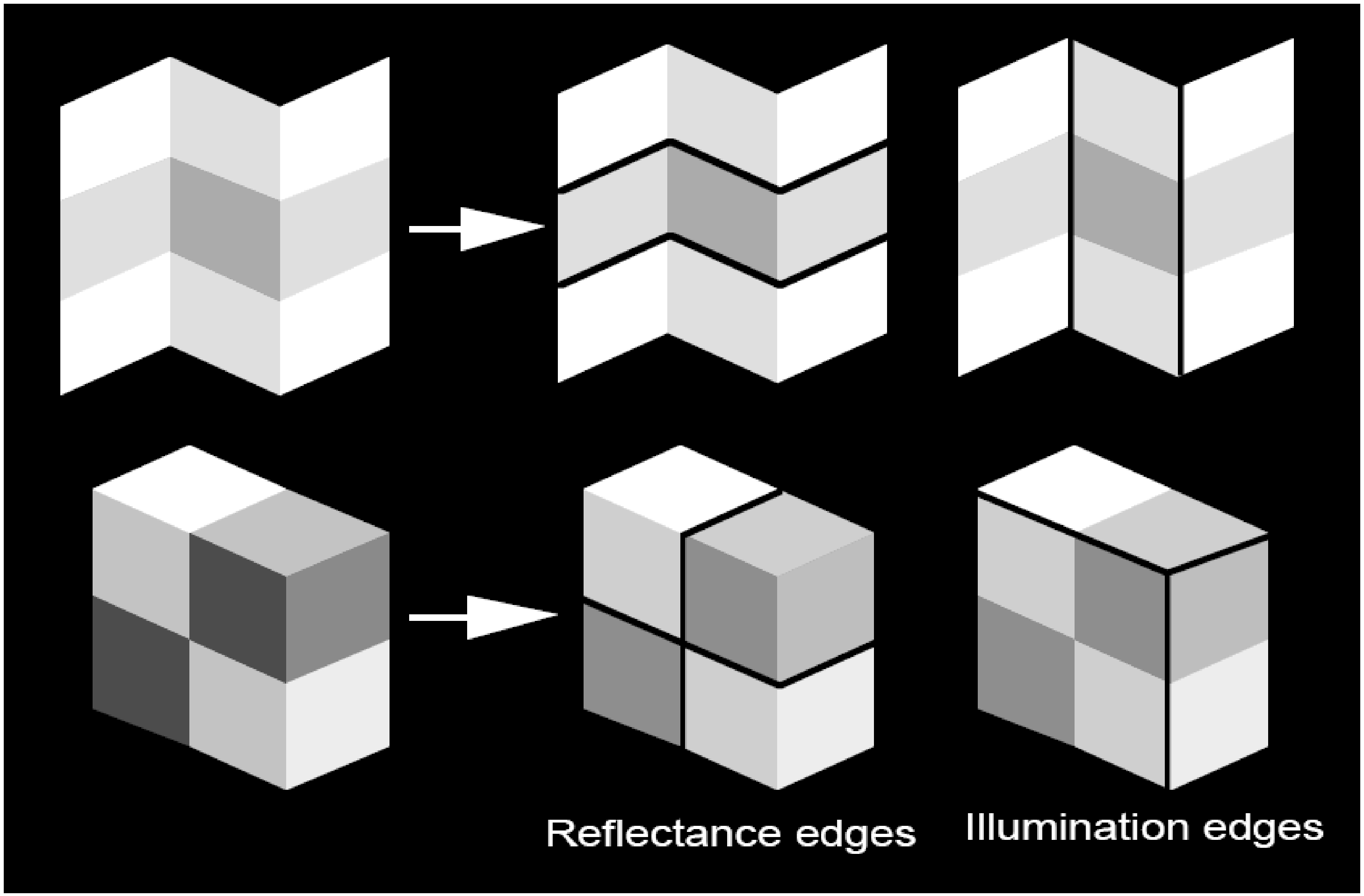
Examples

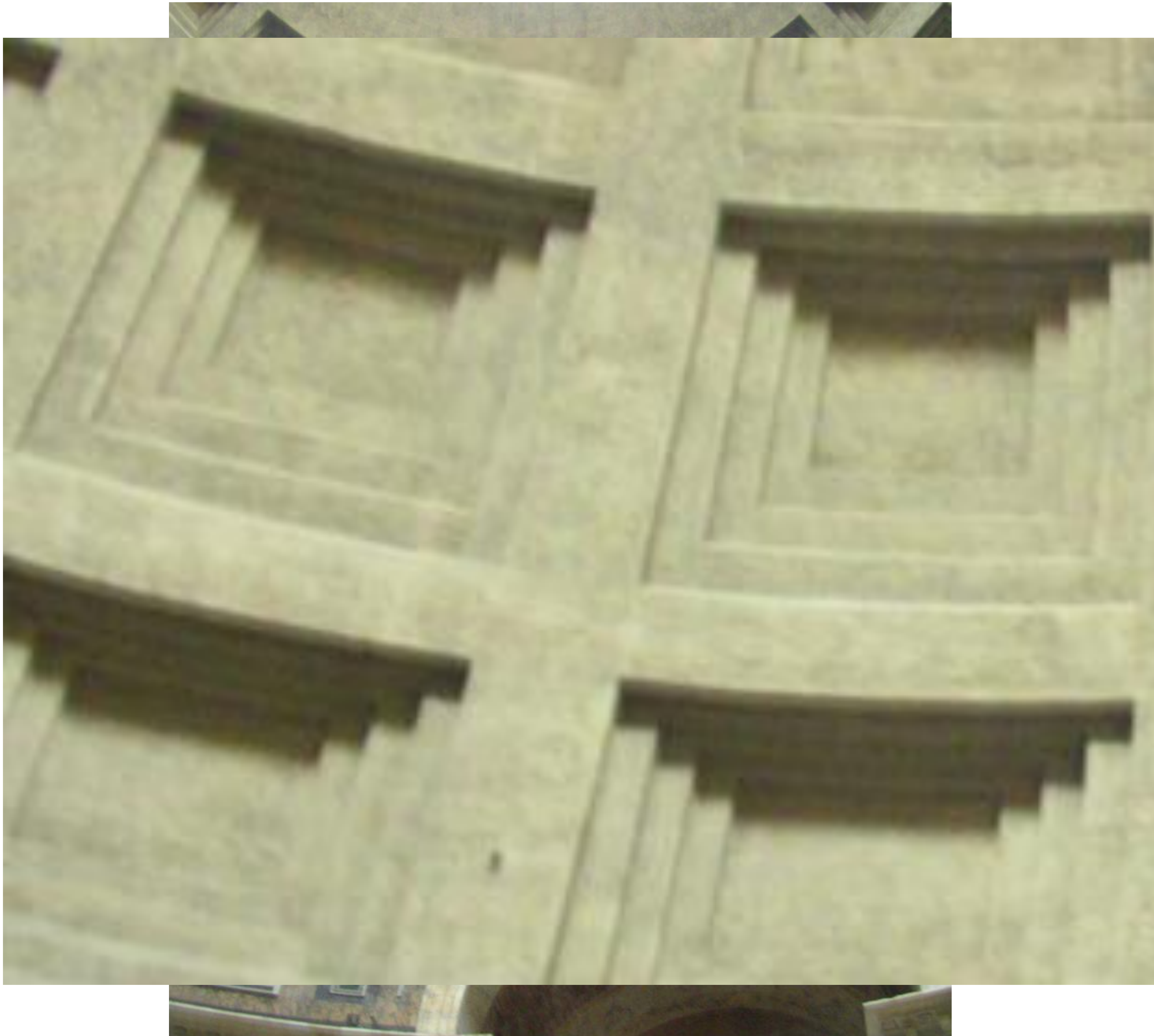


Examples

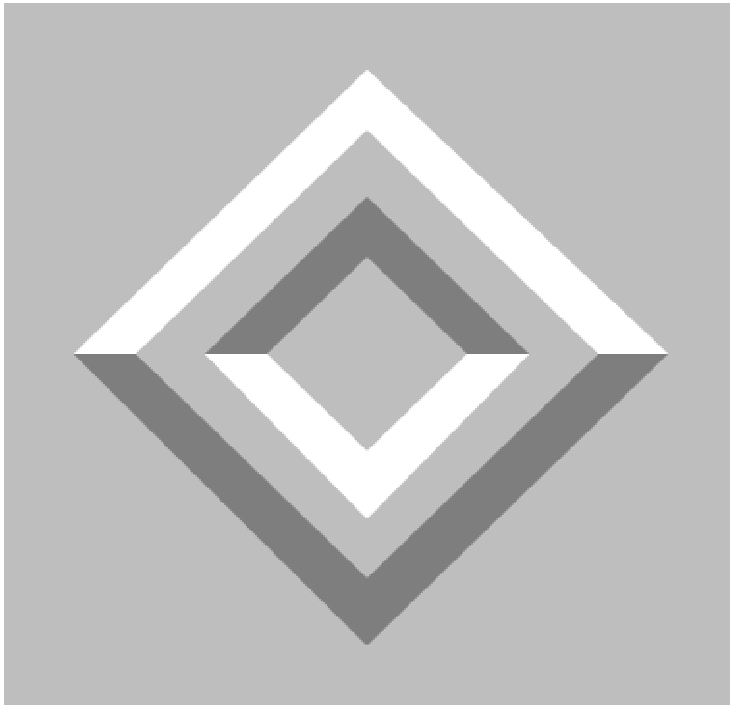


Examples

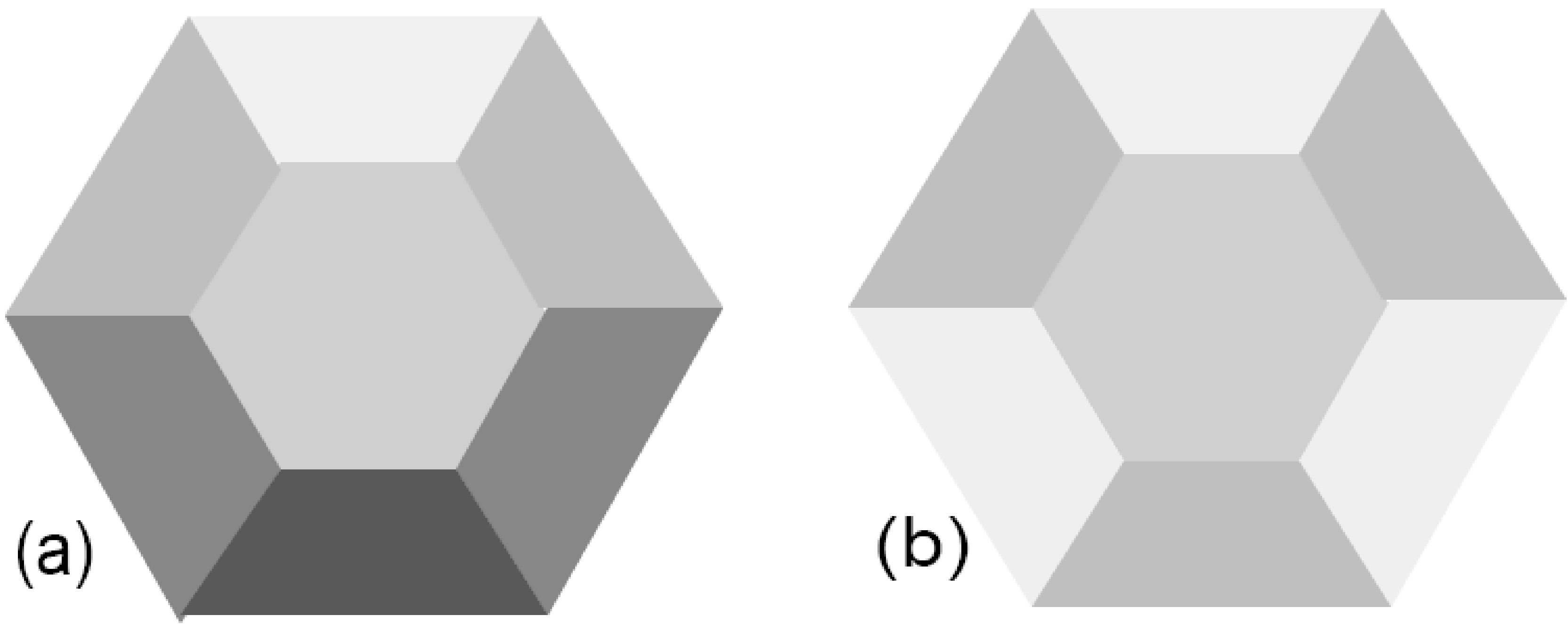




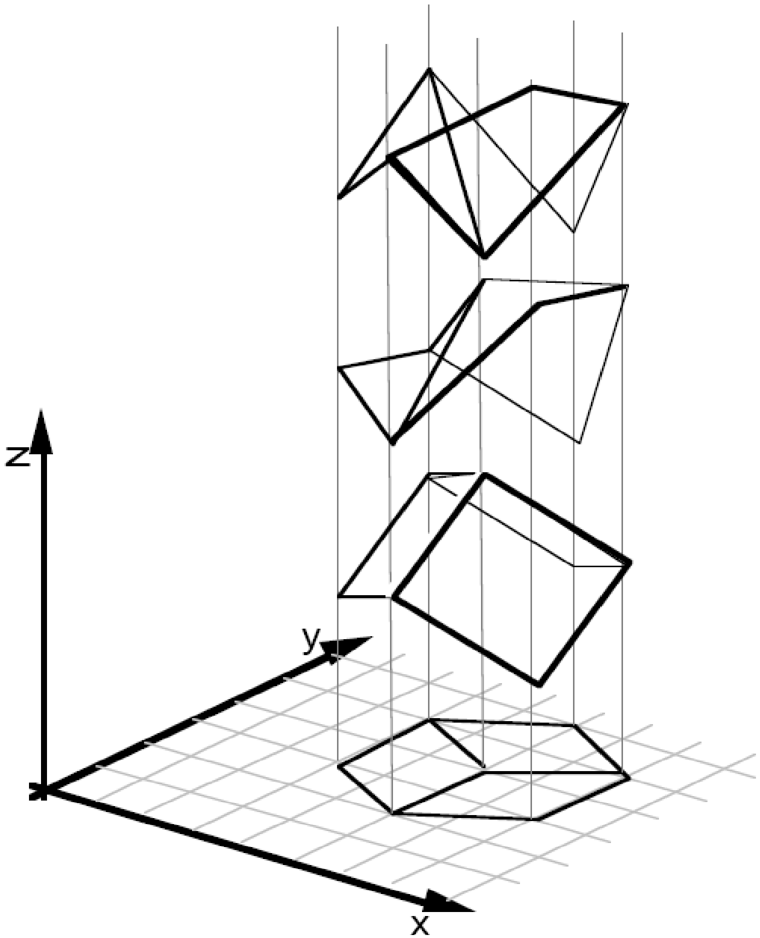
Examples

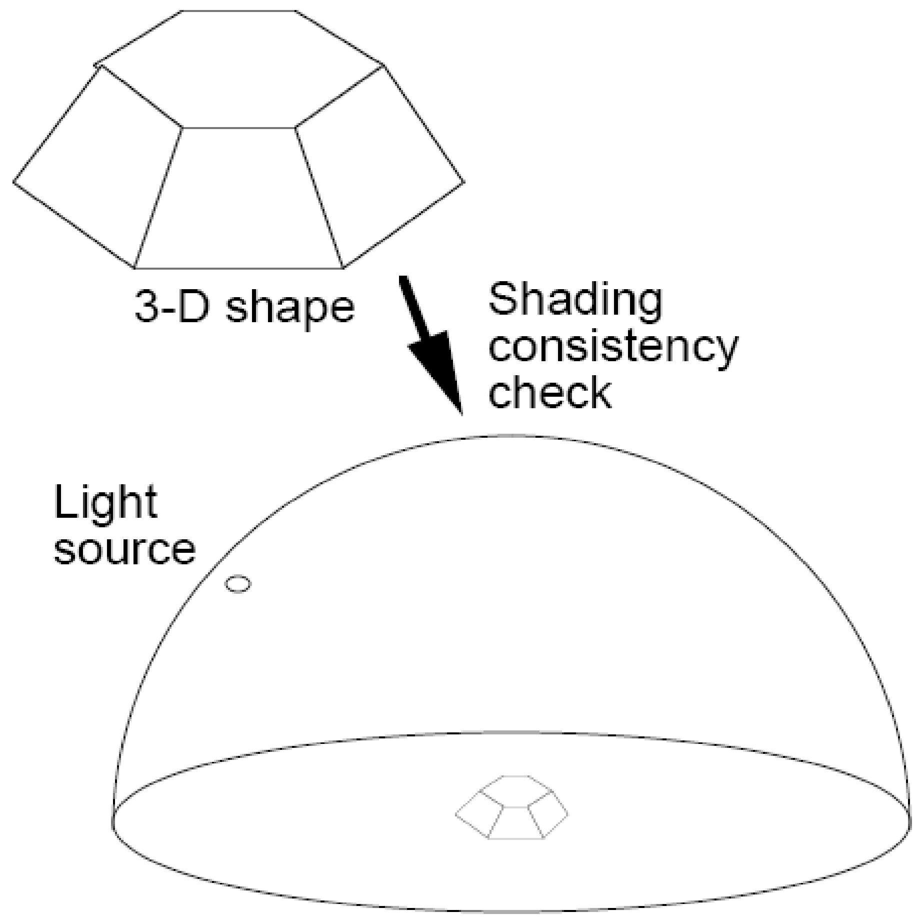


Counter-Example



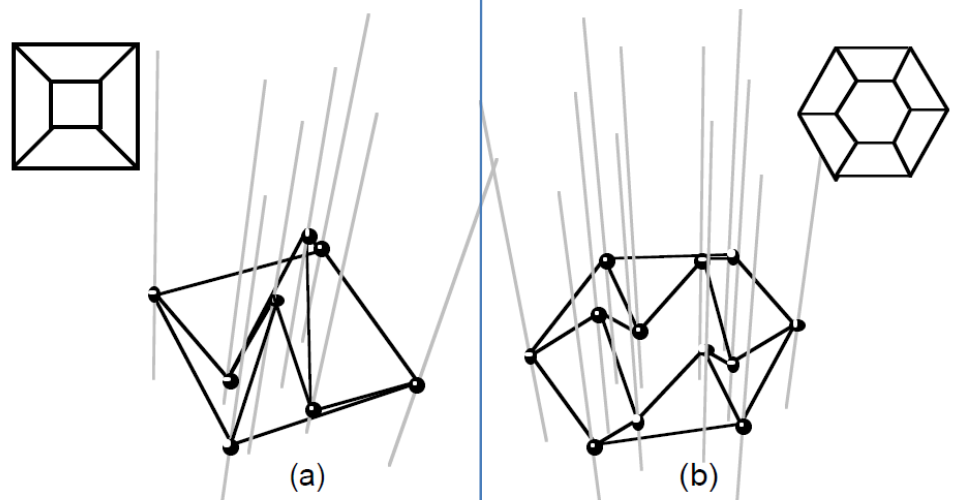
Consistency Check





Global Measures of ‘Correctness’

- Low variance of angles
- Planarity of faces
- Overall compactness
- Consistency with light source



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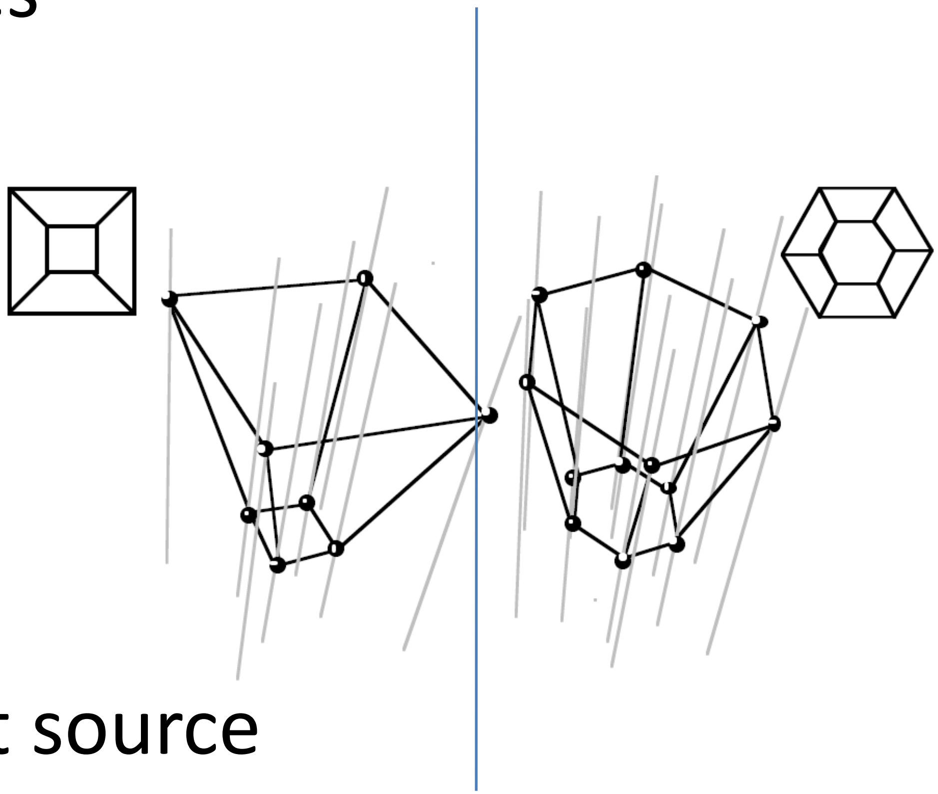
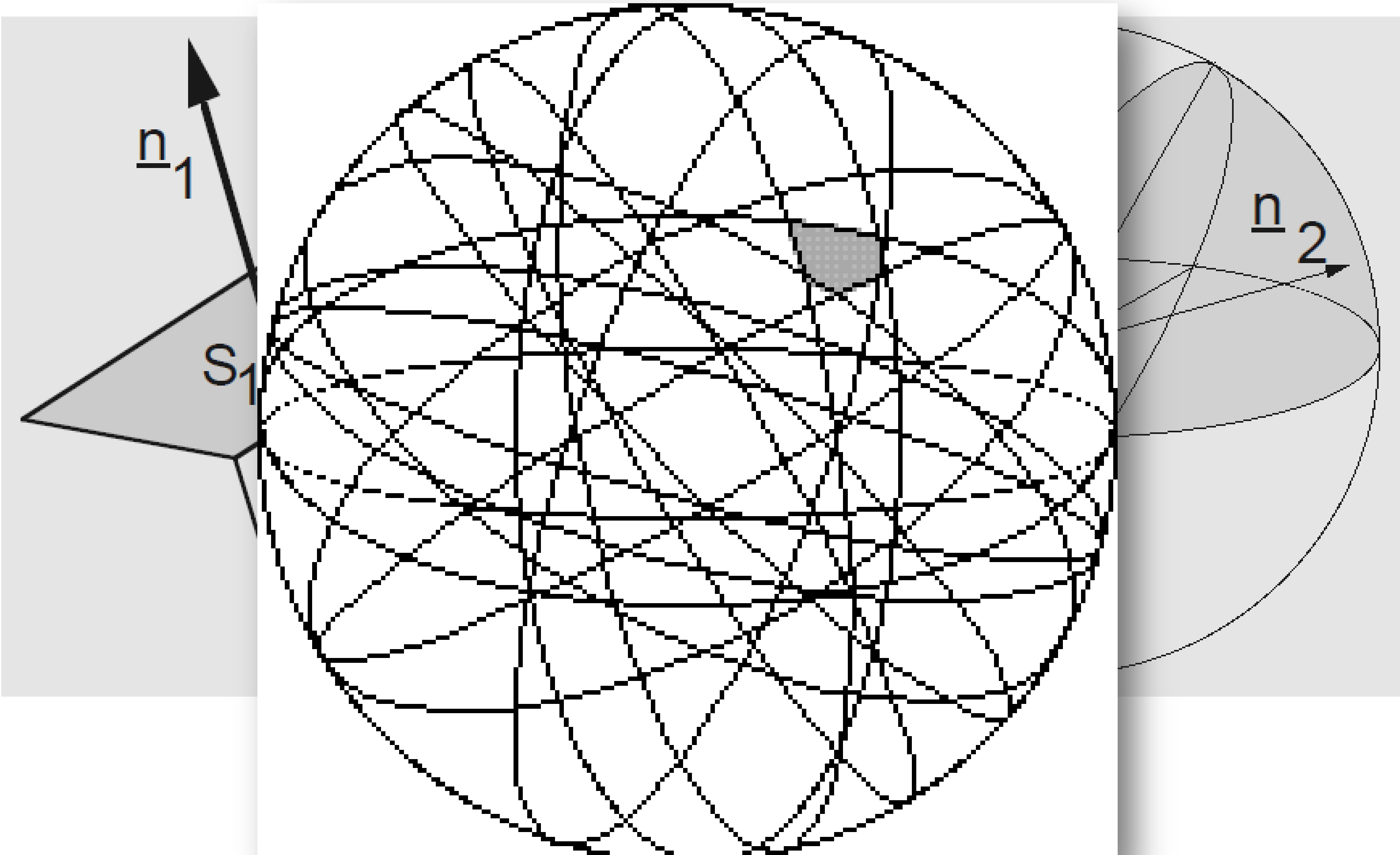
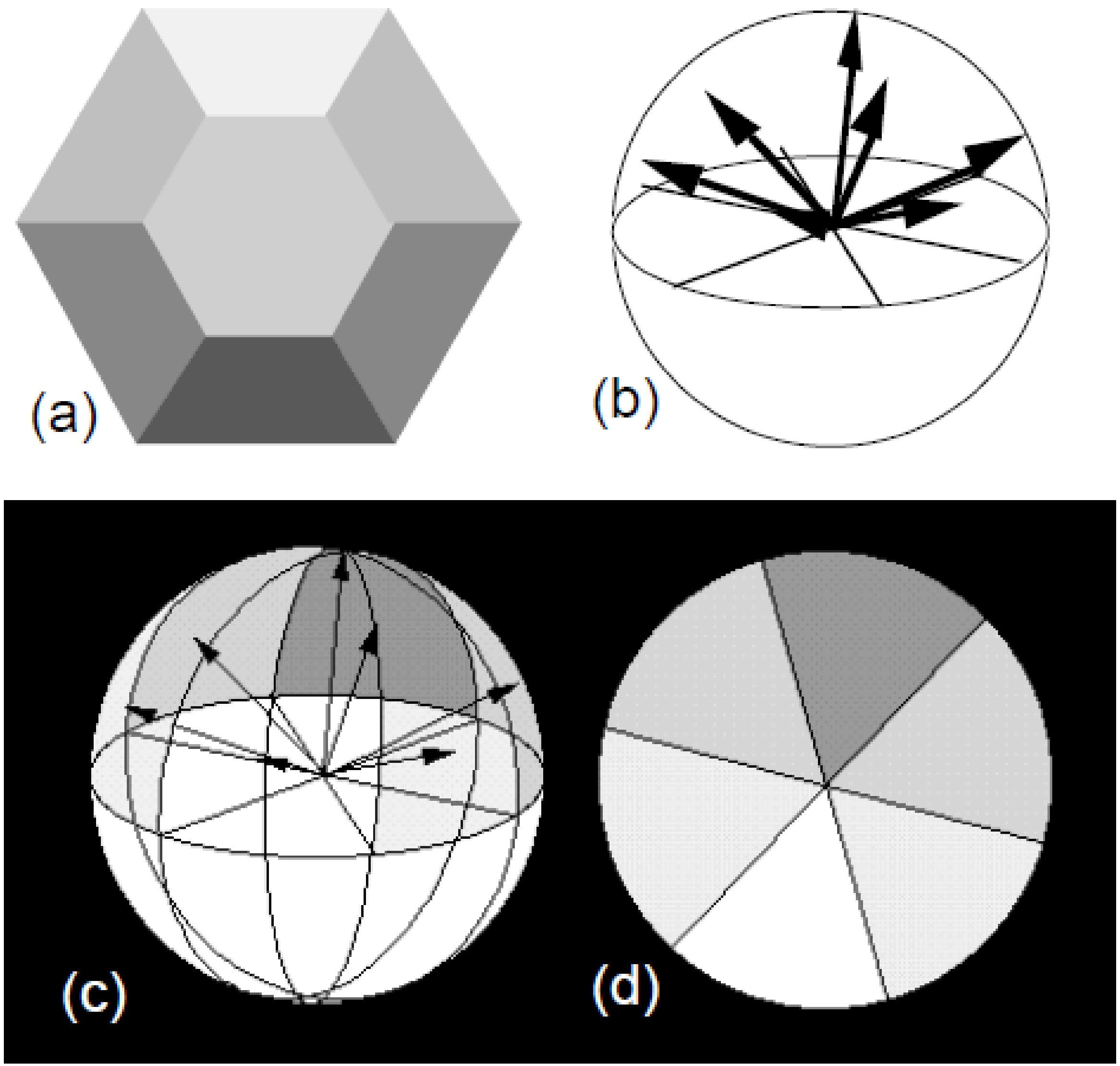


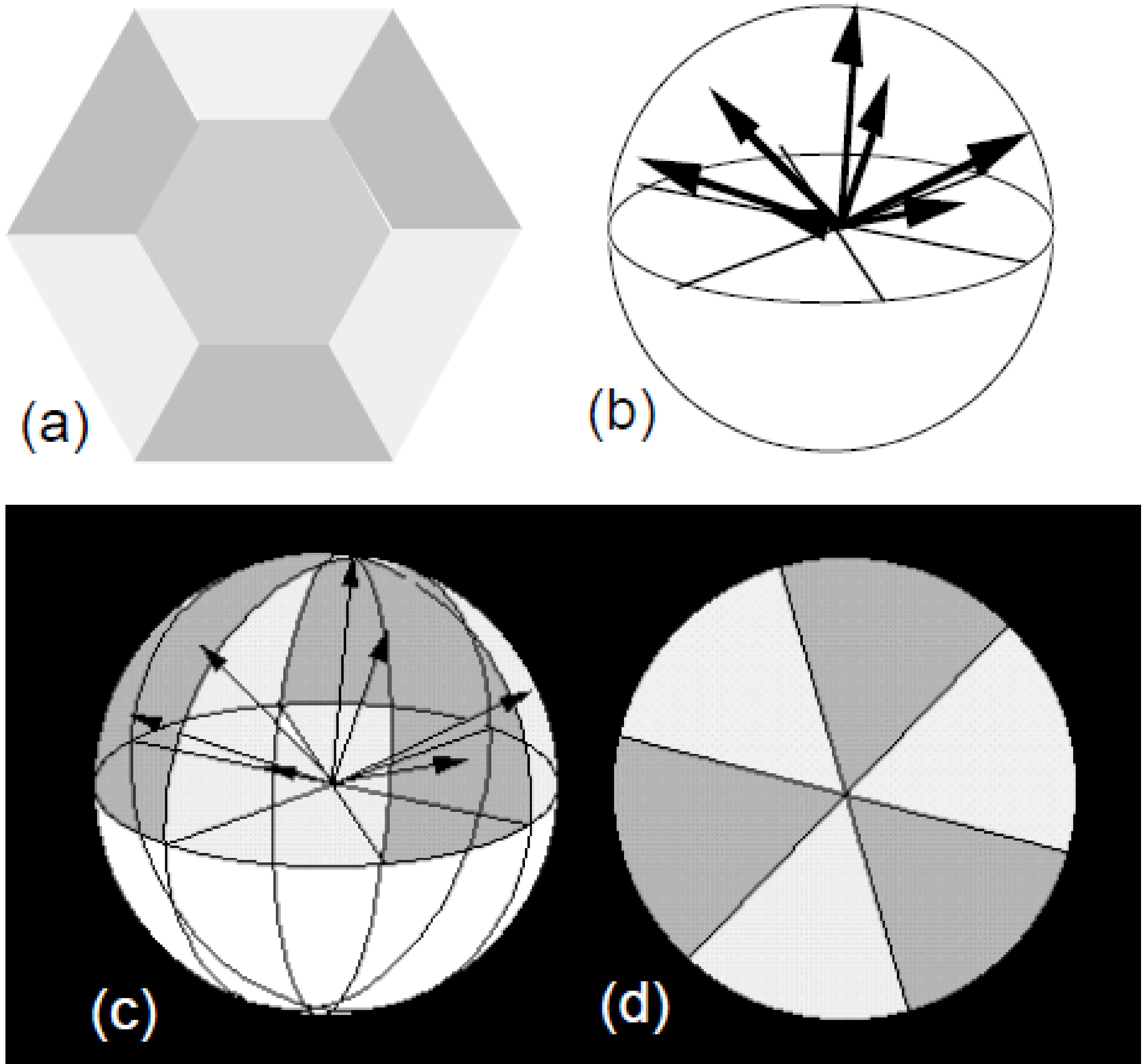
Possibility of Consistent Lighting



Global Analysis Confirms Local Analysis



Global Analysis Trumps Local Analysis



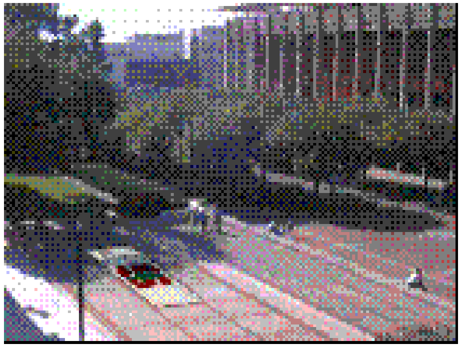
II

Image Sequences

- Deriving Intrinsic Images from Image Sequences
  - Weiss ICCV’01
- For static objects, multiple frames

a

b



c

Problem Formulation

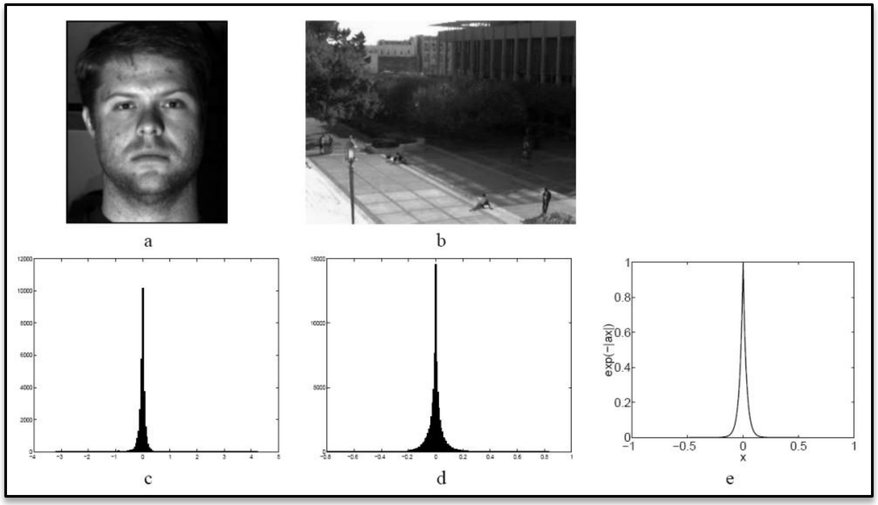
Given a sequence of T images $\{I(x,y,t)\}_{t=1}^{T}$ in which reflectance is constant over time and only the illumination changes, can we solve for a single reflectance image and T illumination images $\{L(x,y,t)\}_{t=1}^{T}$?

$$I(x,y) = L(x,y)R(x,y)$$

$$\Downarrow$$

$$\{I(x,y,t)\}_{t=1}^{T} = \{L(x,y,t)\}_{t=1}^{T} R(x,y)$$

Still completely ill-posed : at every pixel there are T equations and T+1 unknowns.



- Prior based on intuition:
  - derivative-like filter outputs of L tend to be sparse

$$\{I(x,y,t)\}_{t=1}^{T}=\{L(x,y,t)\}_{t=1}^{T}R(x,y)$$

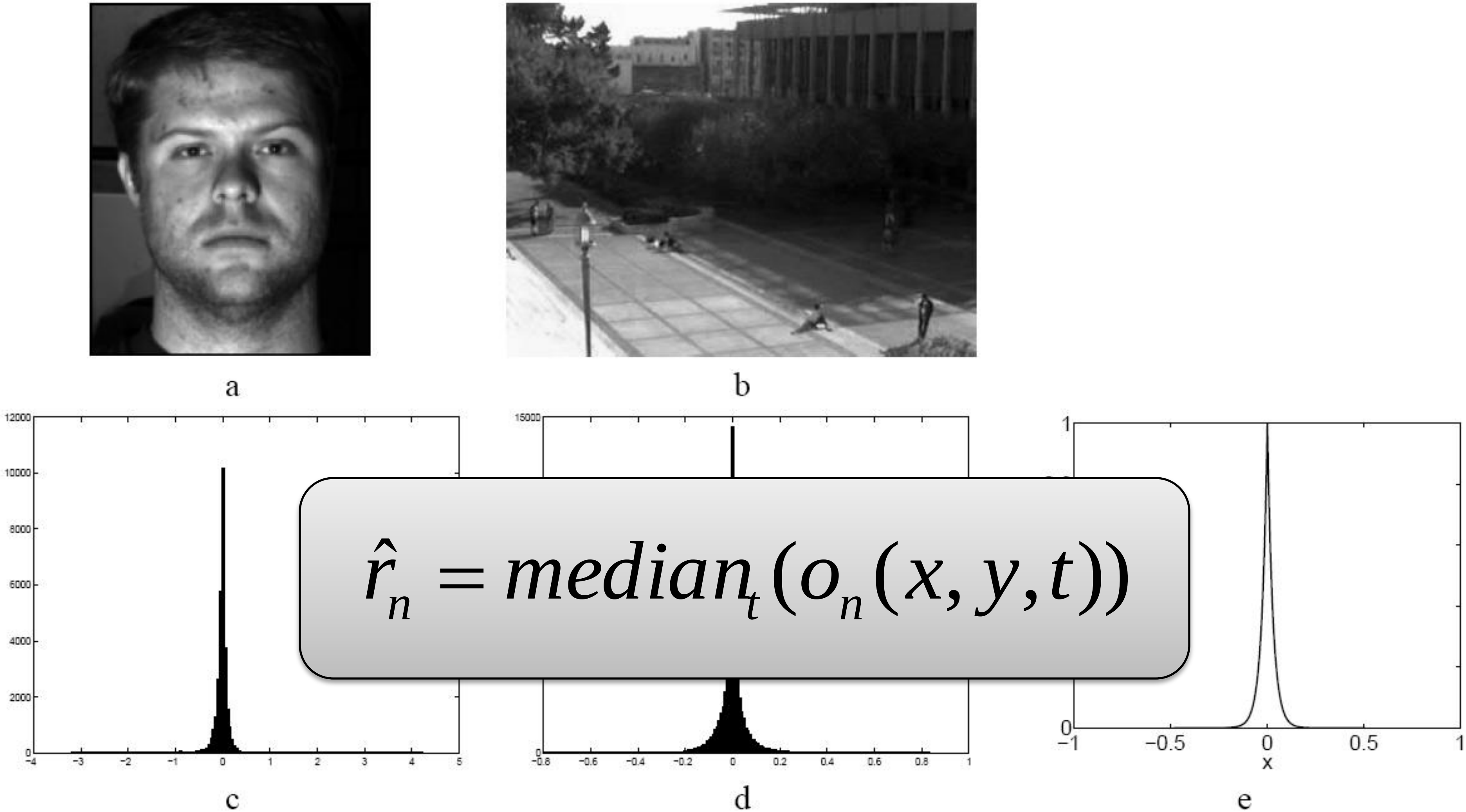
(move to log-space)

$$i(x,y,t)=r(x,y)+l(x,y,t)$$

$$o_n(x,y,t)=i(x,y,t)*f_n$$

f_n = one of N filters like

1	-1

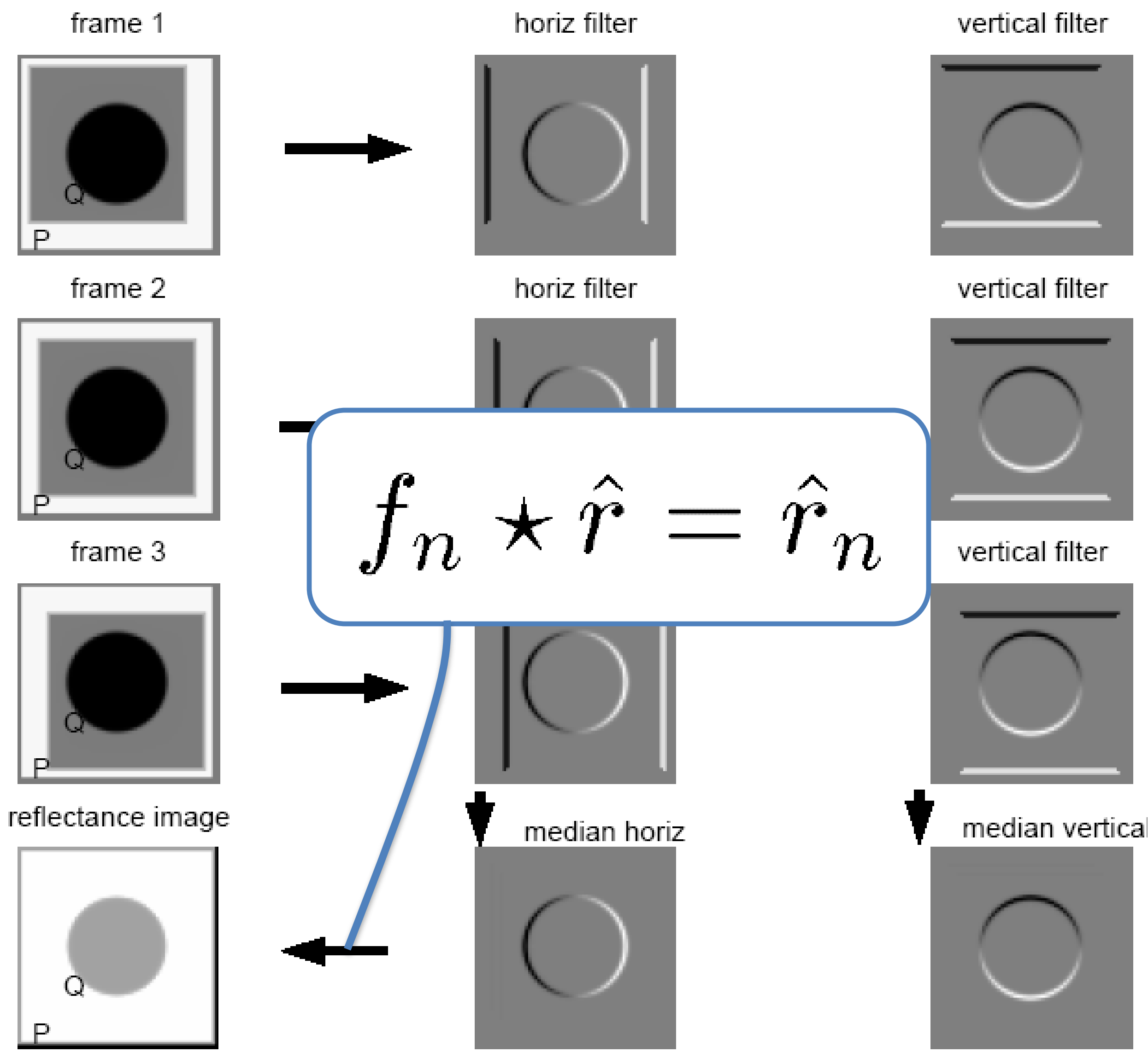


$$\hat{r}_n = median_t(o_n(x, y, t))$$

$$o_n(x, y, t) = i(x, y, t) * f_n$$

- Responses have Laplacian-shaped distribution

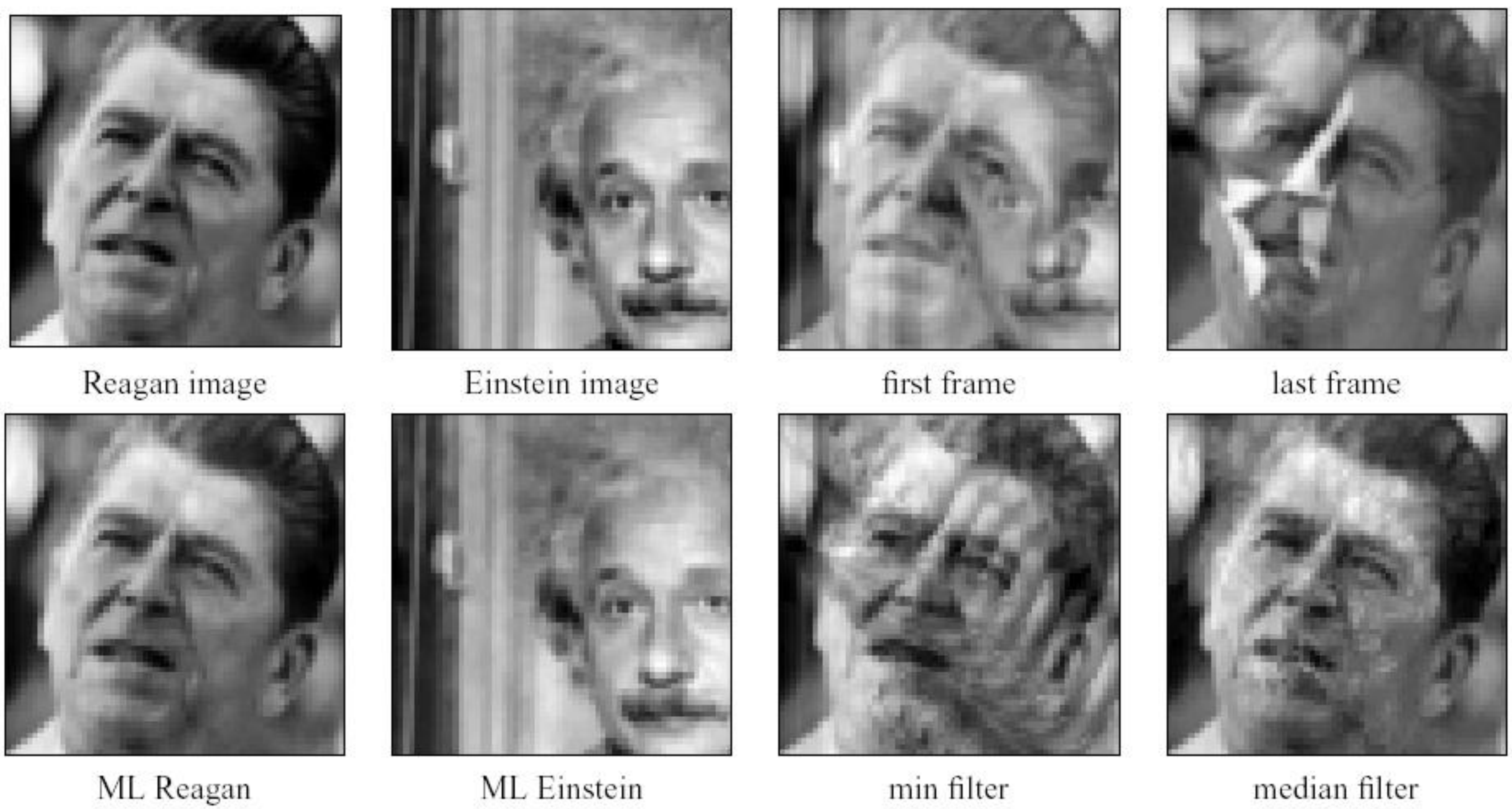
Toy Example



$$f_n \star \hat{r} = \hat{r}_n$$

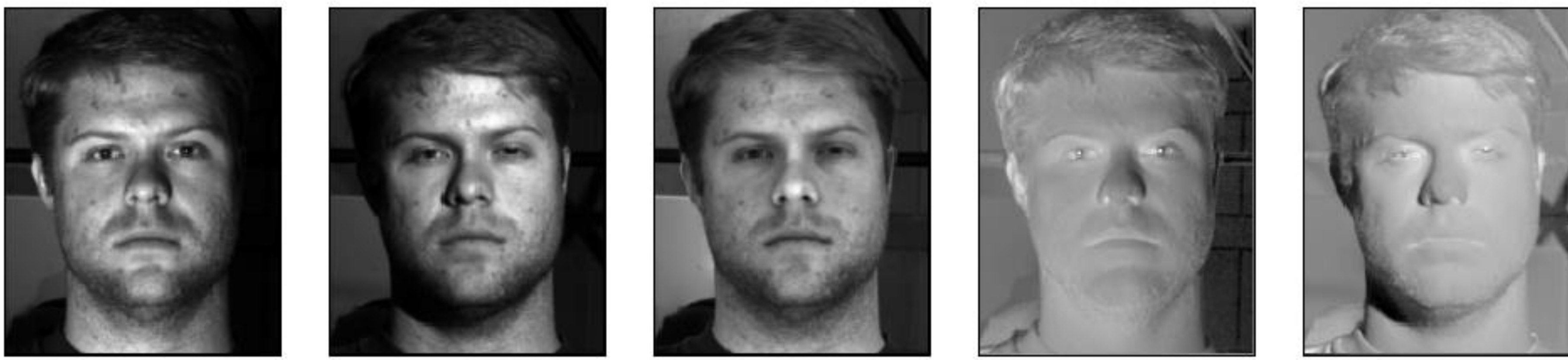
Example Result 1

- Einstein image is translated diagonally 4 pixels per frame



Example Result 2

- 64 images with variable lighting from Yale Face Database

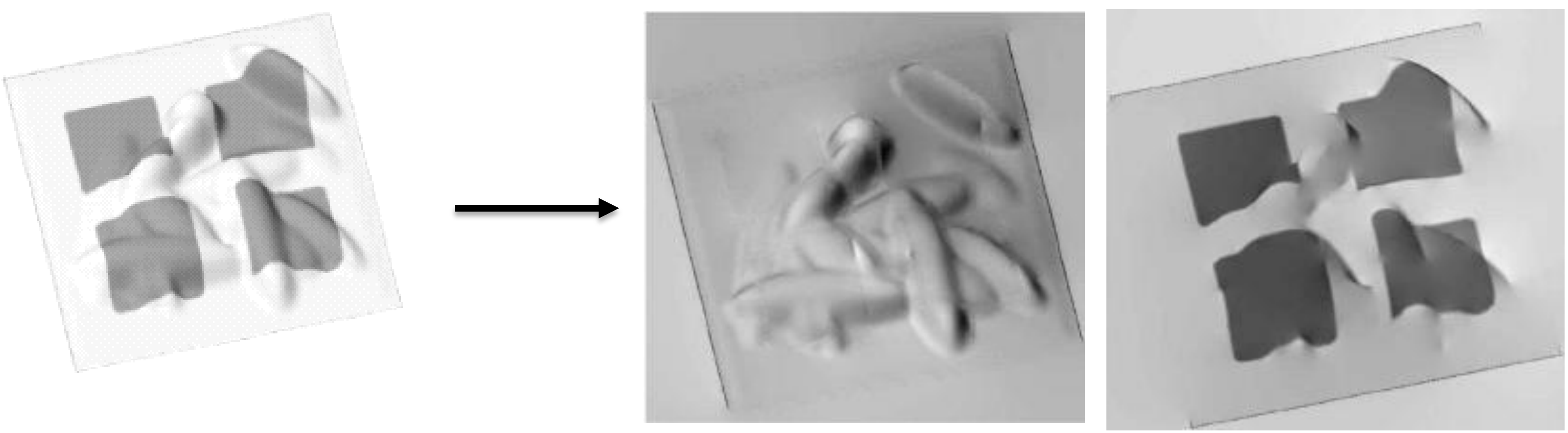


frame 2 | frame 11 | ML reflectance | ML illumination 2 | ML illumination 11

III

Single Image

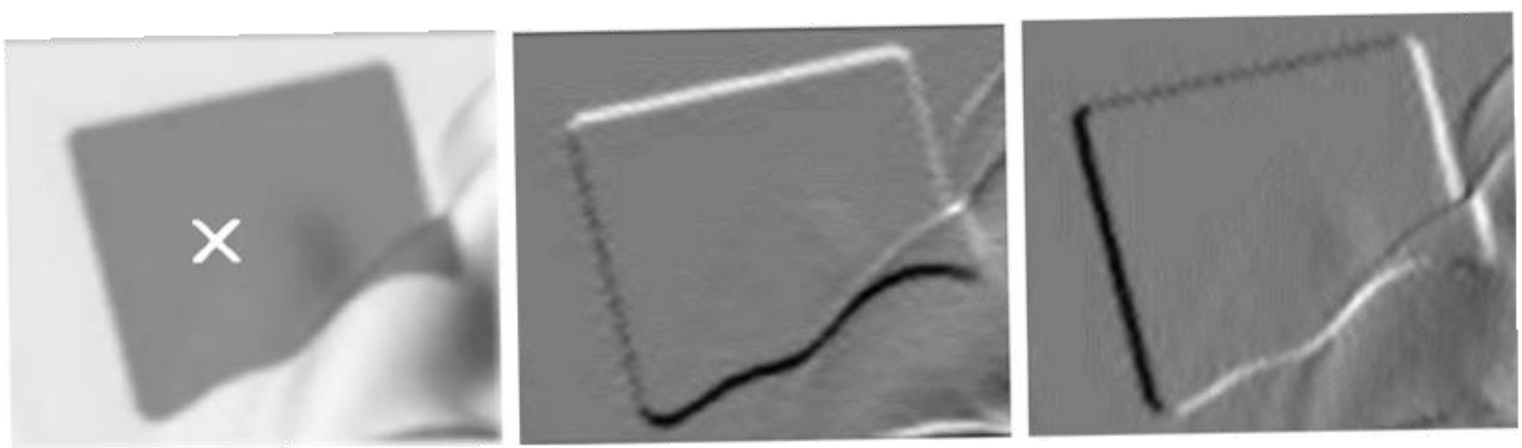
- Recovering Intrinsic Images from a Single Image
  - Tappen, Freeman, Adelson
    - NIPS’03 & PAMI’05



Assumption

- Each derivative is caused either by Shading or Reflectance
- Reduces to a binary classification problem

Image Derivative w.r.t. x and y



Classifying Derivatives

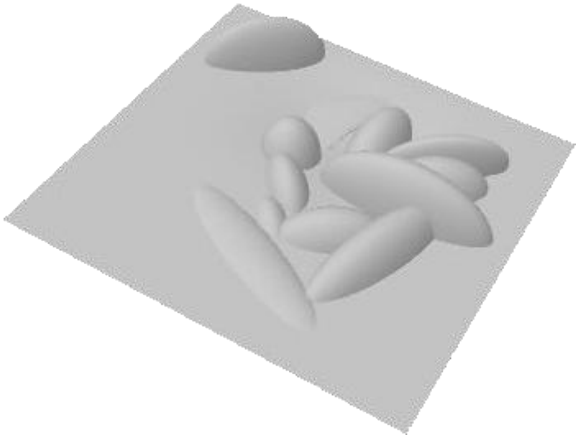
- 4 Basic phases:
  1. Compute image derivatives
  2. Classify each derivative as caused by shading or reflectance
  3. Invert derivatives classified as shading to find shading images
  4. Reflectance image is found the same way

Classification

1. Color information

- changes due to shading should affect R,G and B proportionally

$$C_1 = \alpha \cdot C_2$$

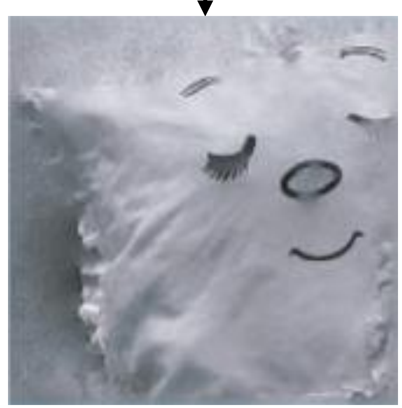


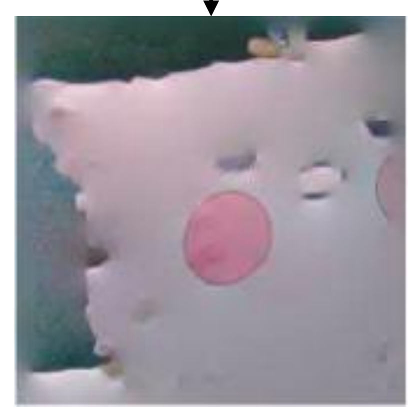
If $C_1 \neq \alpha \cdot C_2$ the changes are caused by reflectance

Color Information - examples

Black on white may be interpreted as intensity change.

Resulting in misclassification





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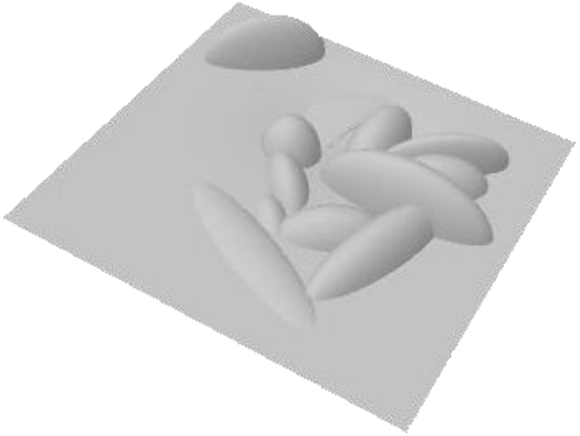

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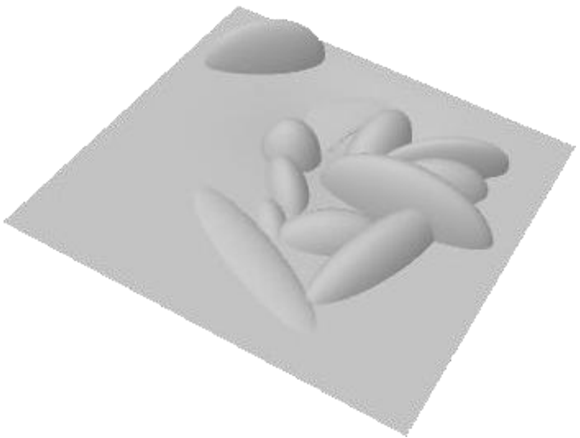
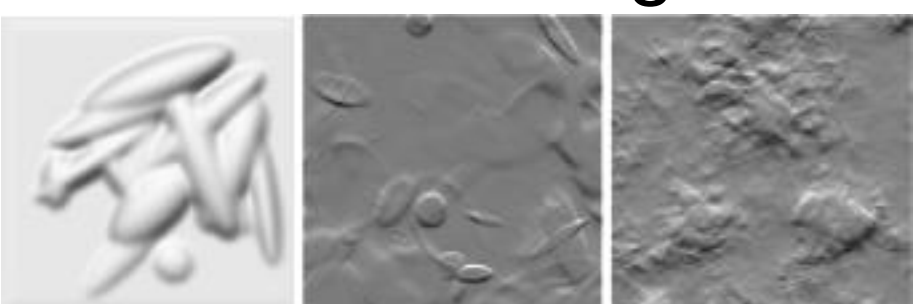
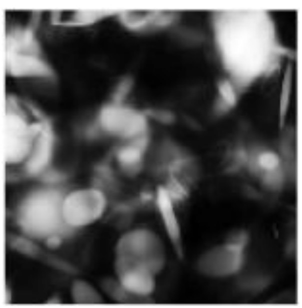


$$C_1 = \alpha \cdot C_2$$

If $C_1 \neq \alpha \cdot C_2$ the changes are caused by reflectance

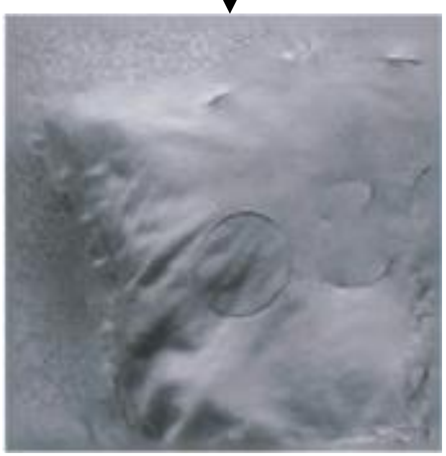
2. Statistical regularities of surfaces

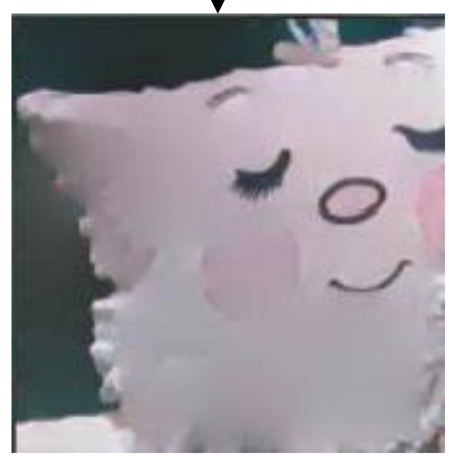




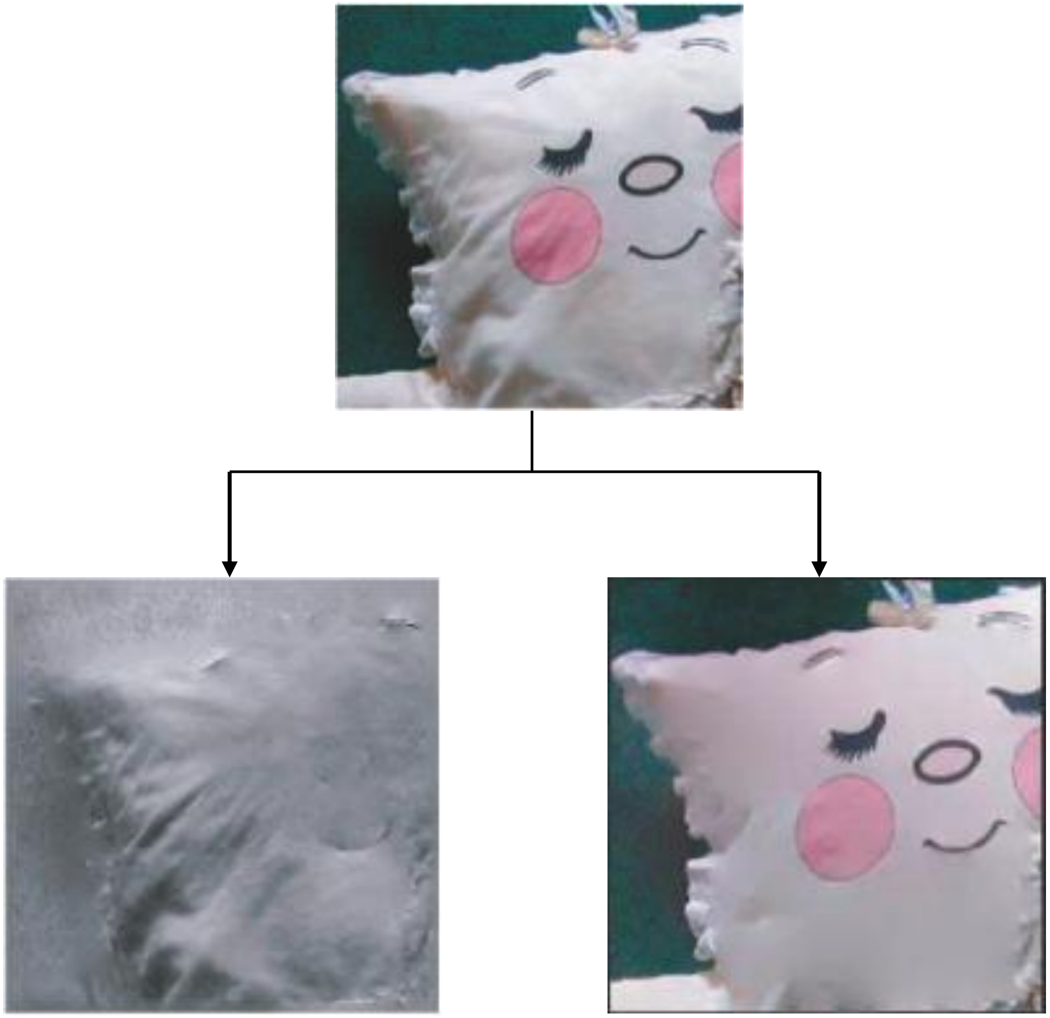
GrayScale Information - examples

Misclassification of the cheeks – due to weak gradients



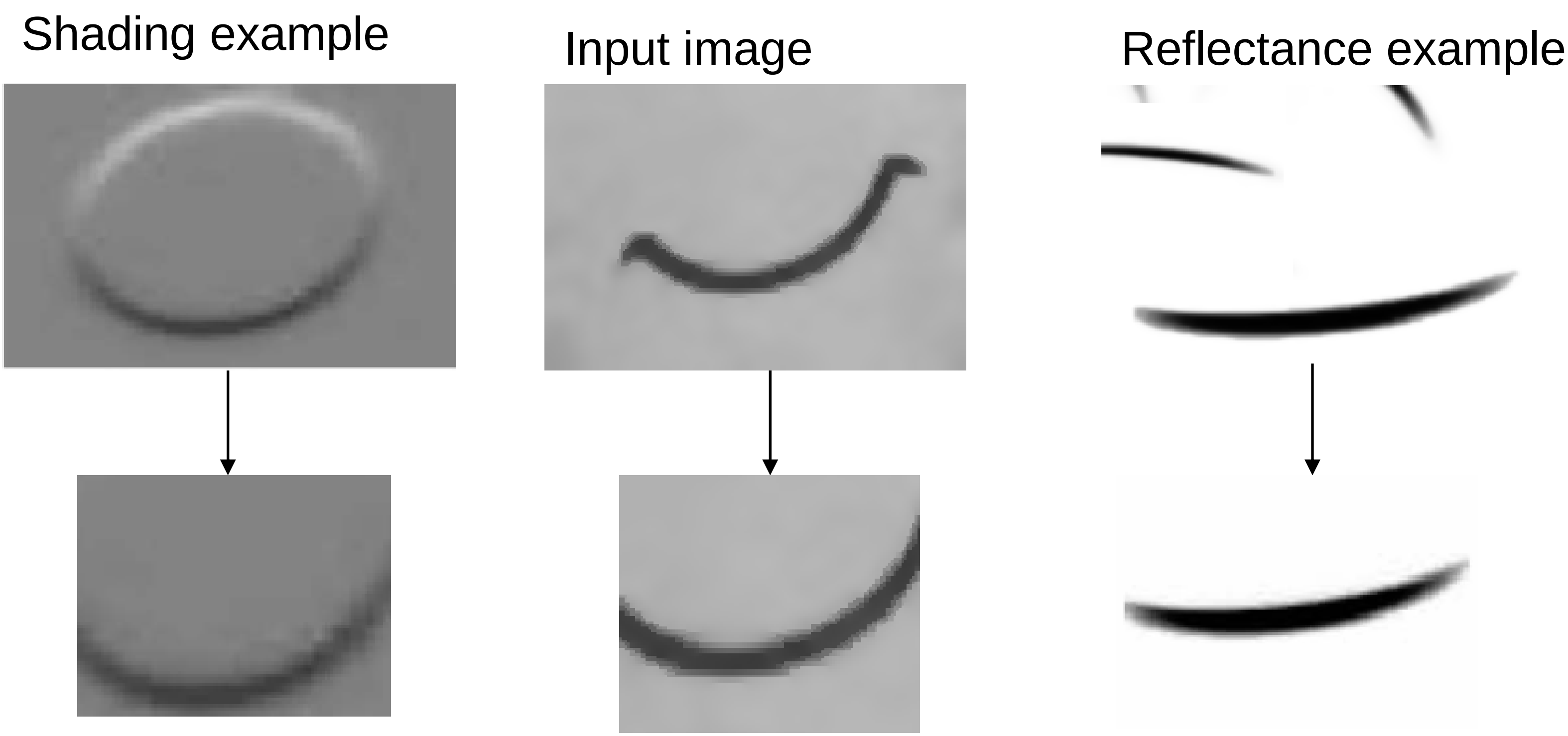


Combining Information (Assuming Statistical Indep.)



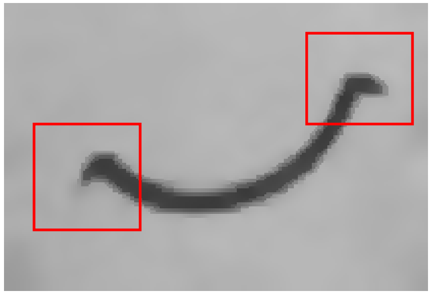
Handling Ambiguities

- Ambiguities - for example – center of the mouth



Handling Ambiguities

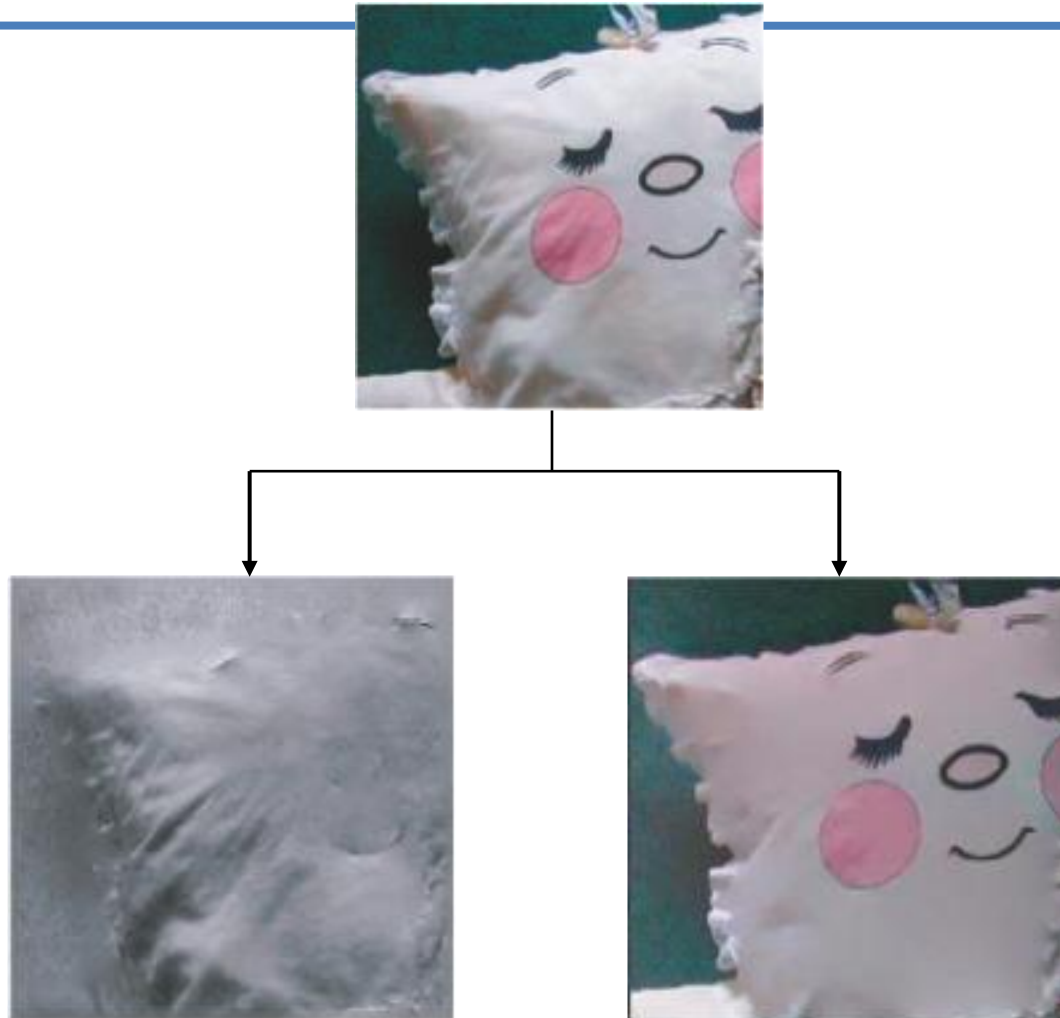
- Derivatives that lie on the same contour should have the same classification



- The mouth corners are well classified as reflectance

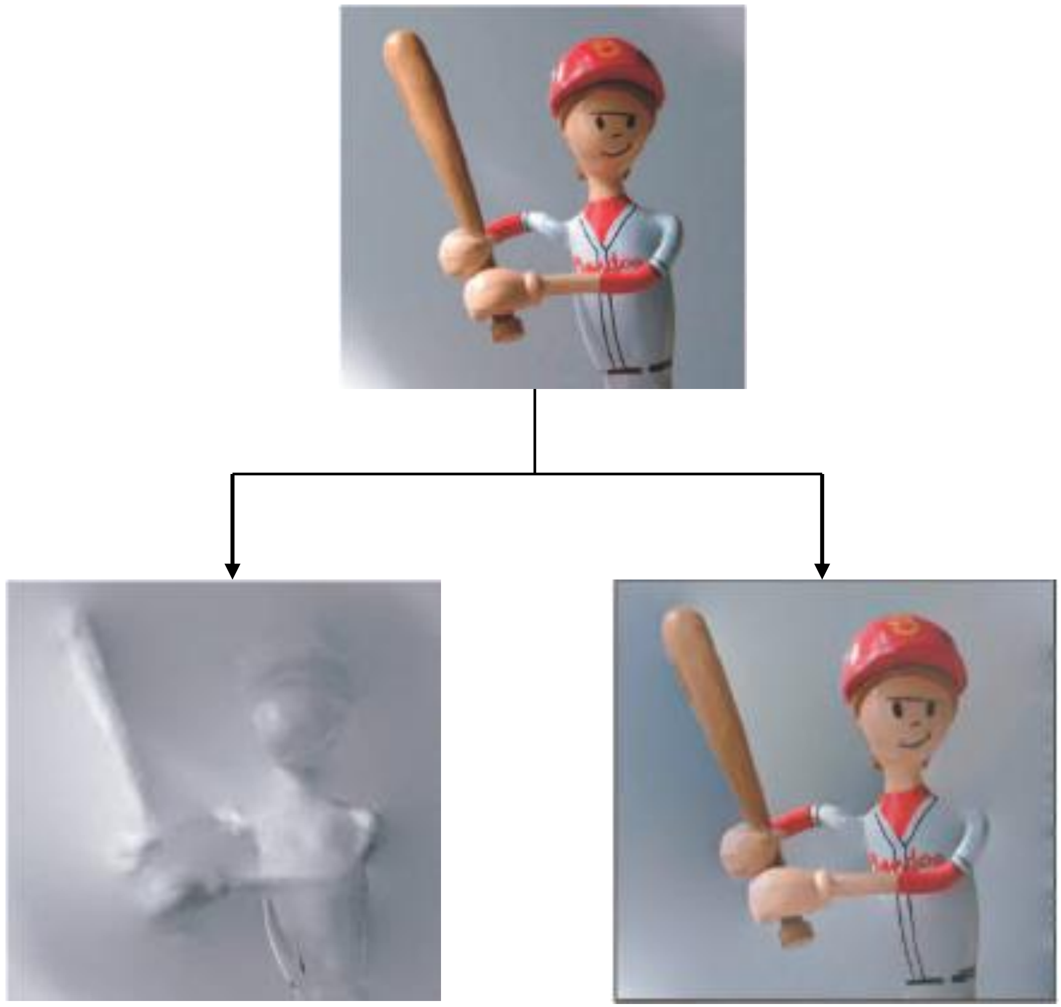
→ Propagate evidence from conclusive areas to ambiguous ones using MRF

Final Results

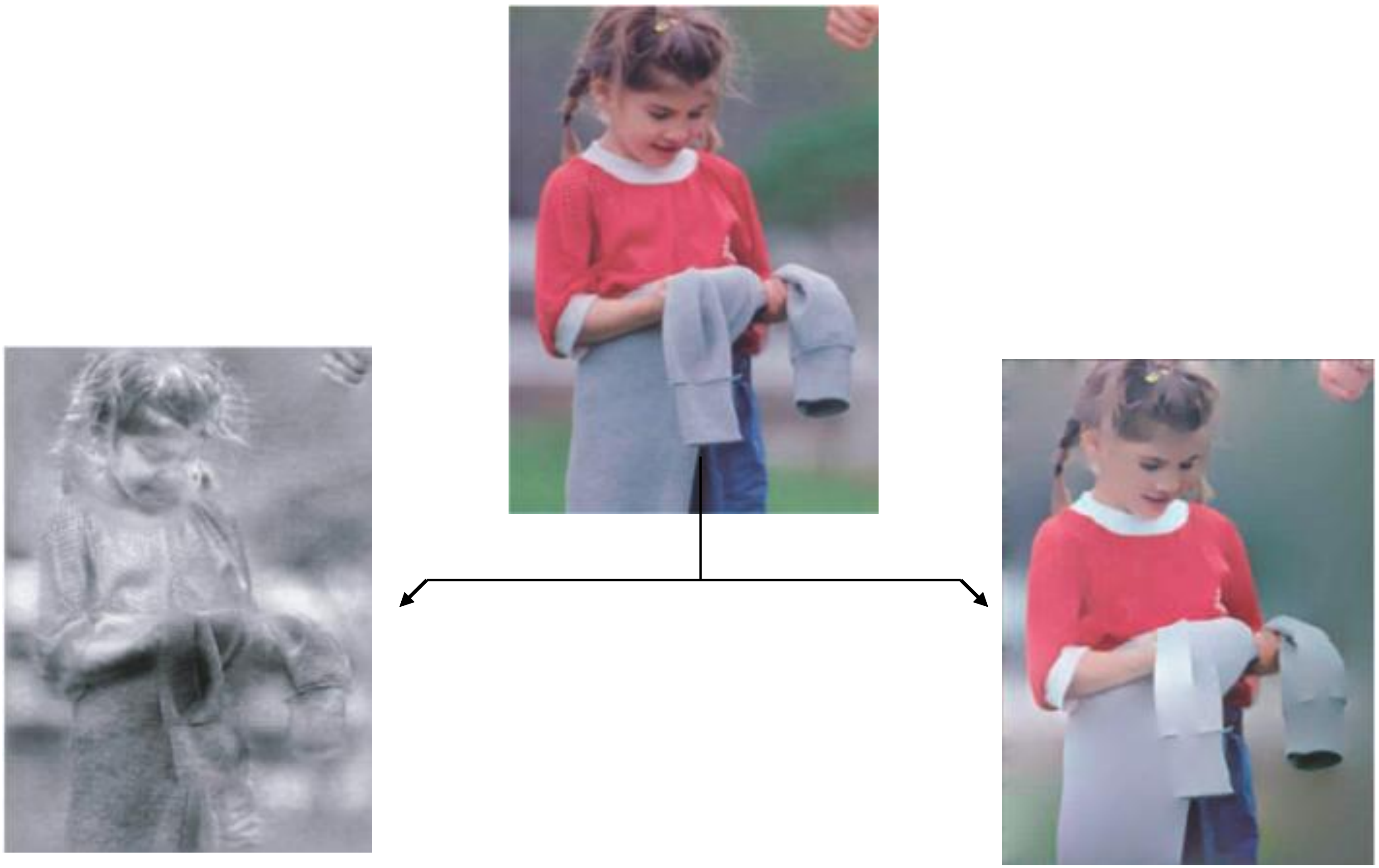


Unpropagated

Final Results



Final Results



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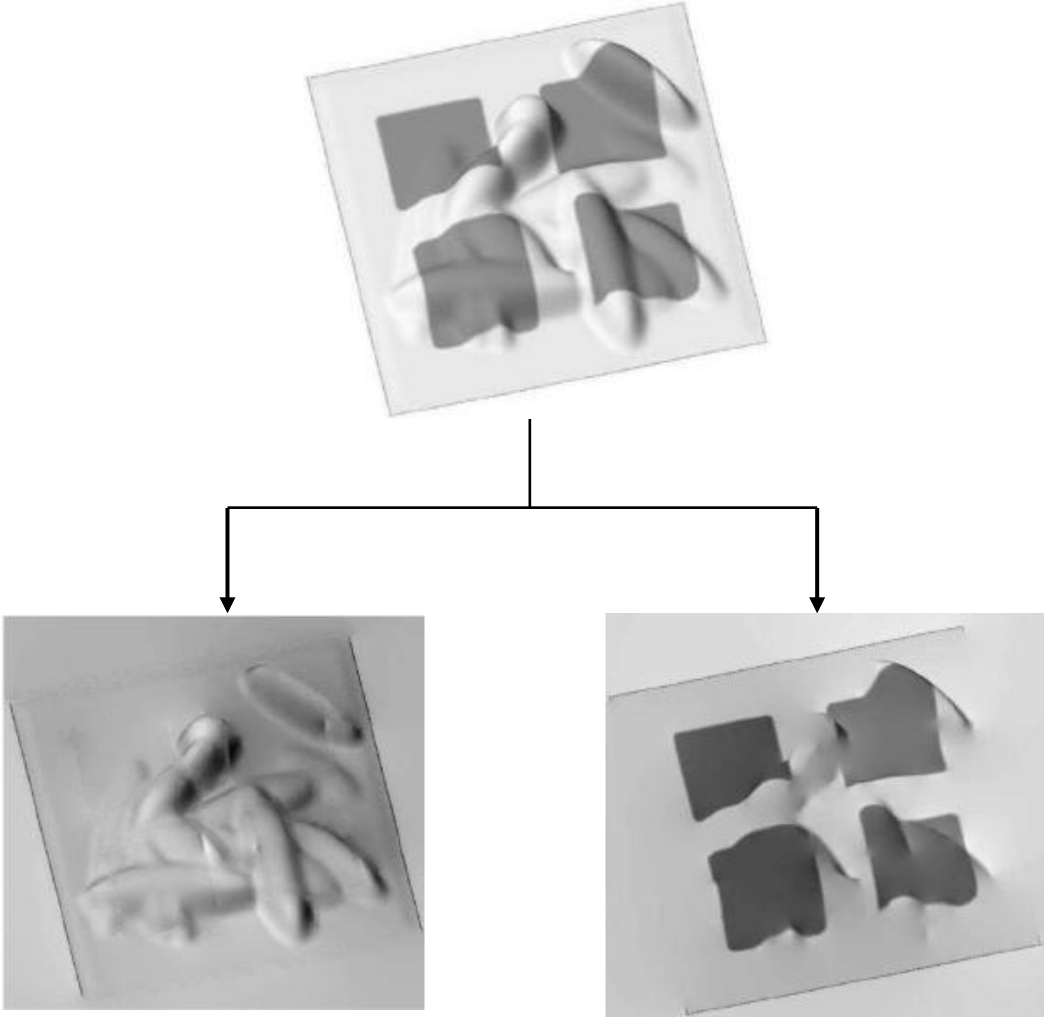


IV

Entropy Minimization

- Intrinsic Images by Entropy Minimization
  - Finlayson, Drew, Lu, ECCV'04

Sensor Response at a Pixel

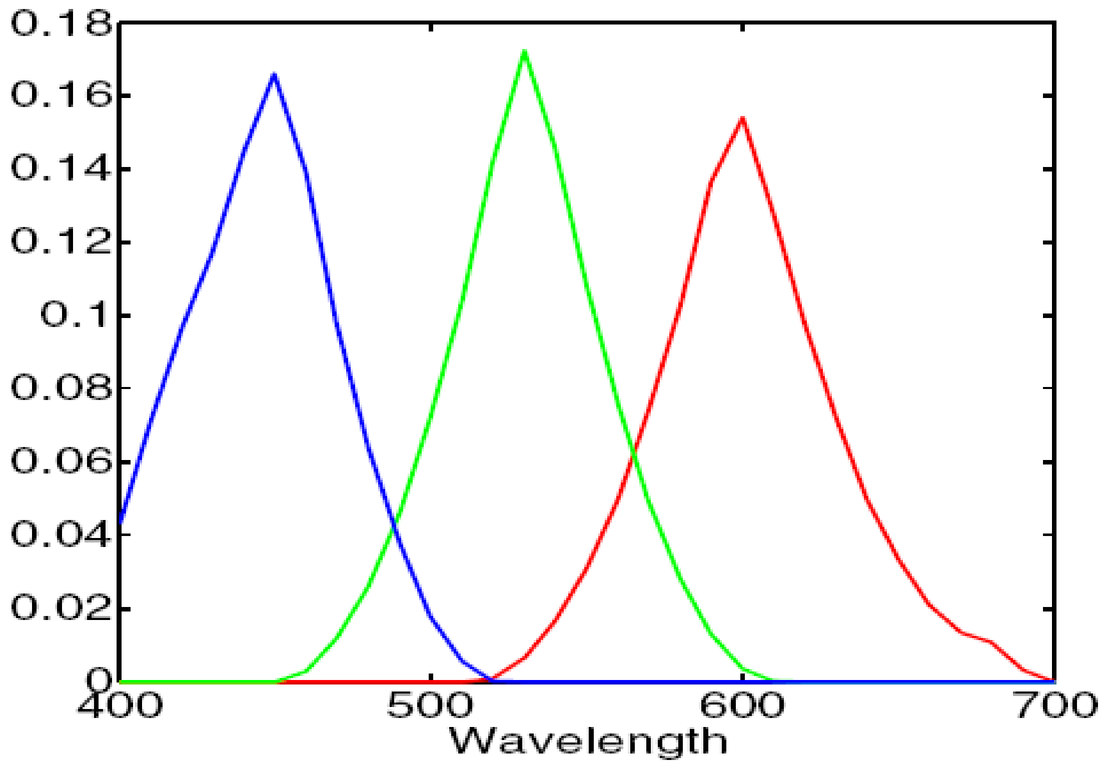
$$\boxed{p_k = \int_\lambda R(\lambda)L(\lambda)S_k(\lambda)d\lambda}$$

R = Reflectance

L = Illumination

S = Sensor Sensitivity

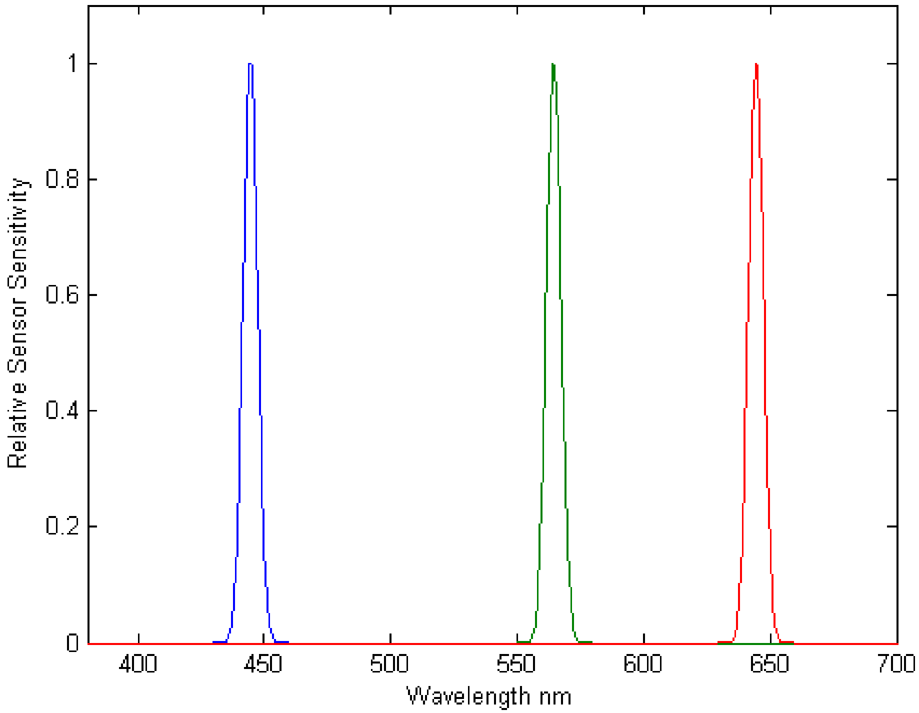
Best When Sensors are Narrow Band



Best When Sensors are Narrow Band

$$S_k(\lambda) = \delta(\lambda - \lambda_k)$$

$$k \in \{R, G, B\}$$



Just Reflectance & Illumination

$$p_k = \int_{\lambda} R(\lambda) L(\lambda) S_k(\lambda) d\lambda$$

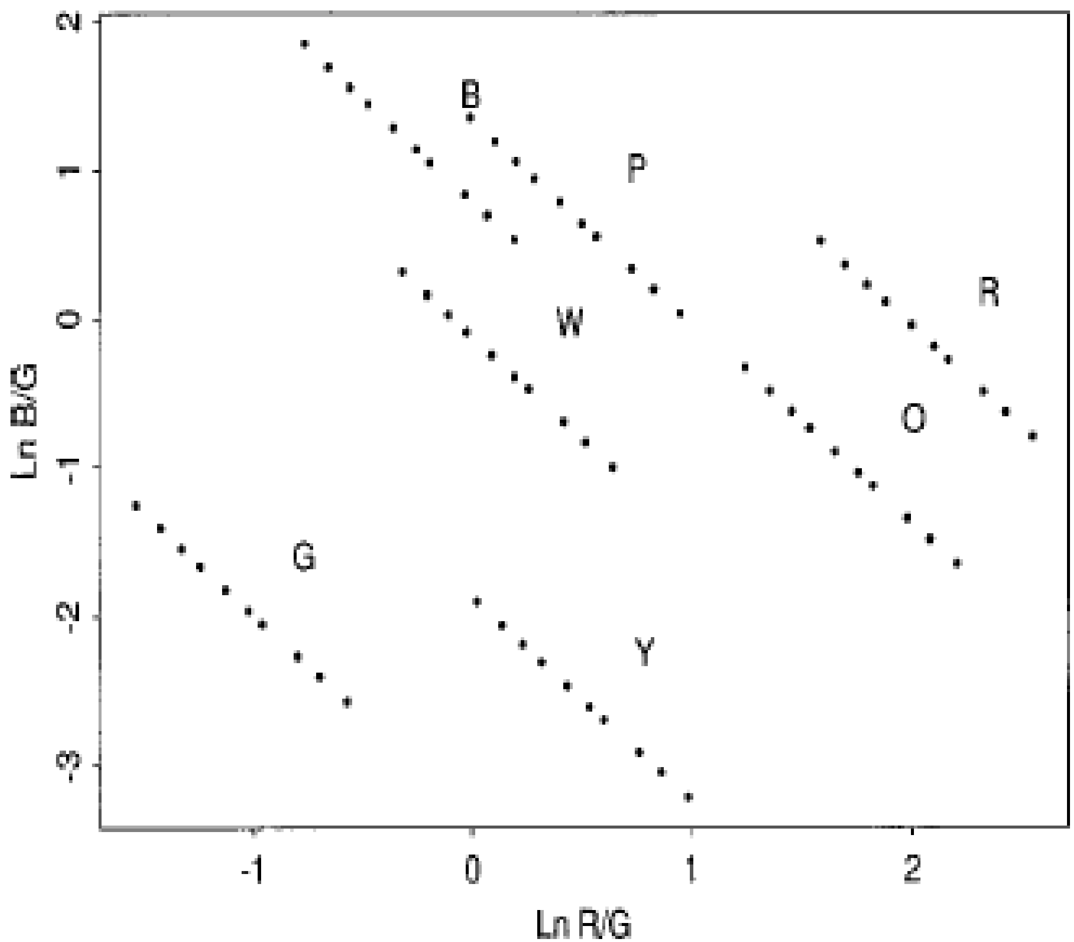
$$\Downarrow$$

$$p_k = \int_{\lambda} R(\lambda) L(\lambda) \delta(\lambda - \lambda_k) d\lambda$$

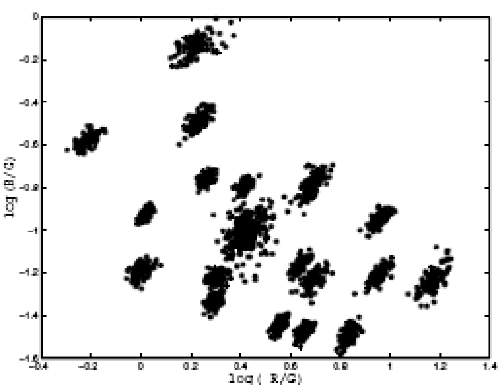
$$\Downarrow$$

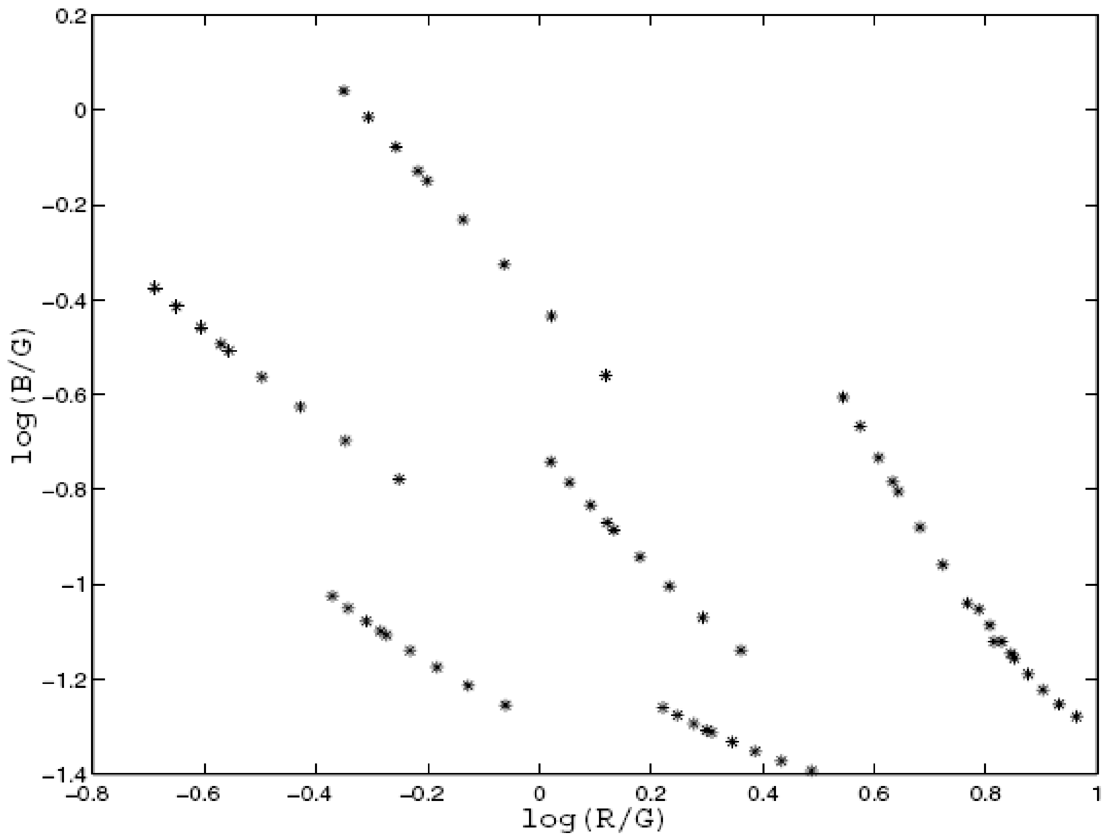
$$p_k = R(\lambda_k) L(\lambda_k)$$

Chromaticity for 7 Surfaces for 10 Illuminants

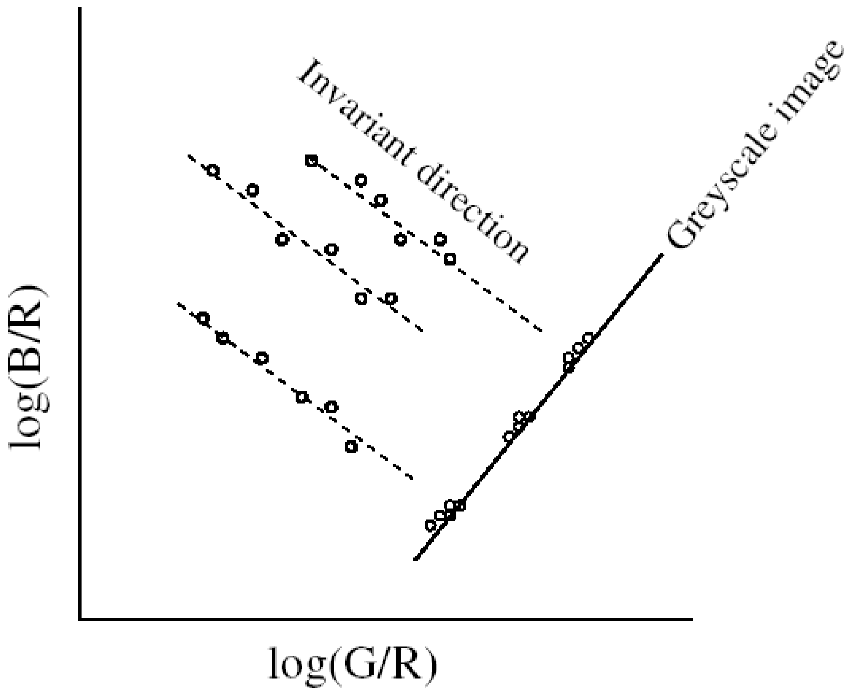


Macbeth Chart Under Changing Illumination

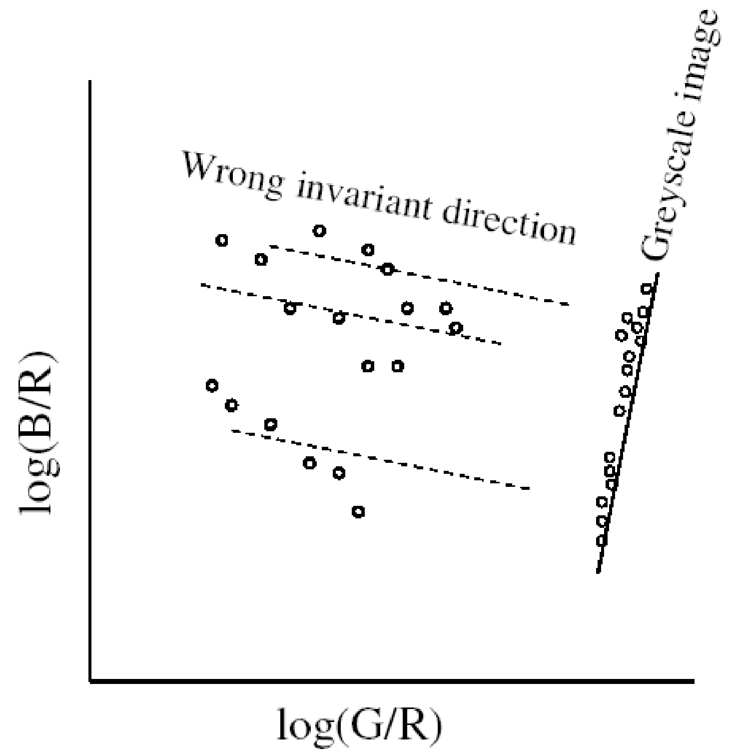




Entropy Minimization

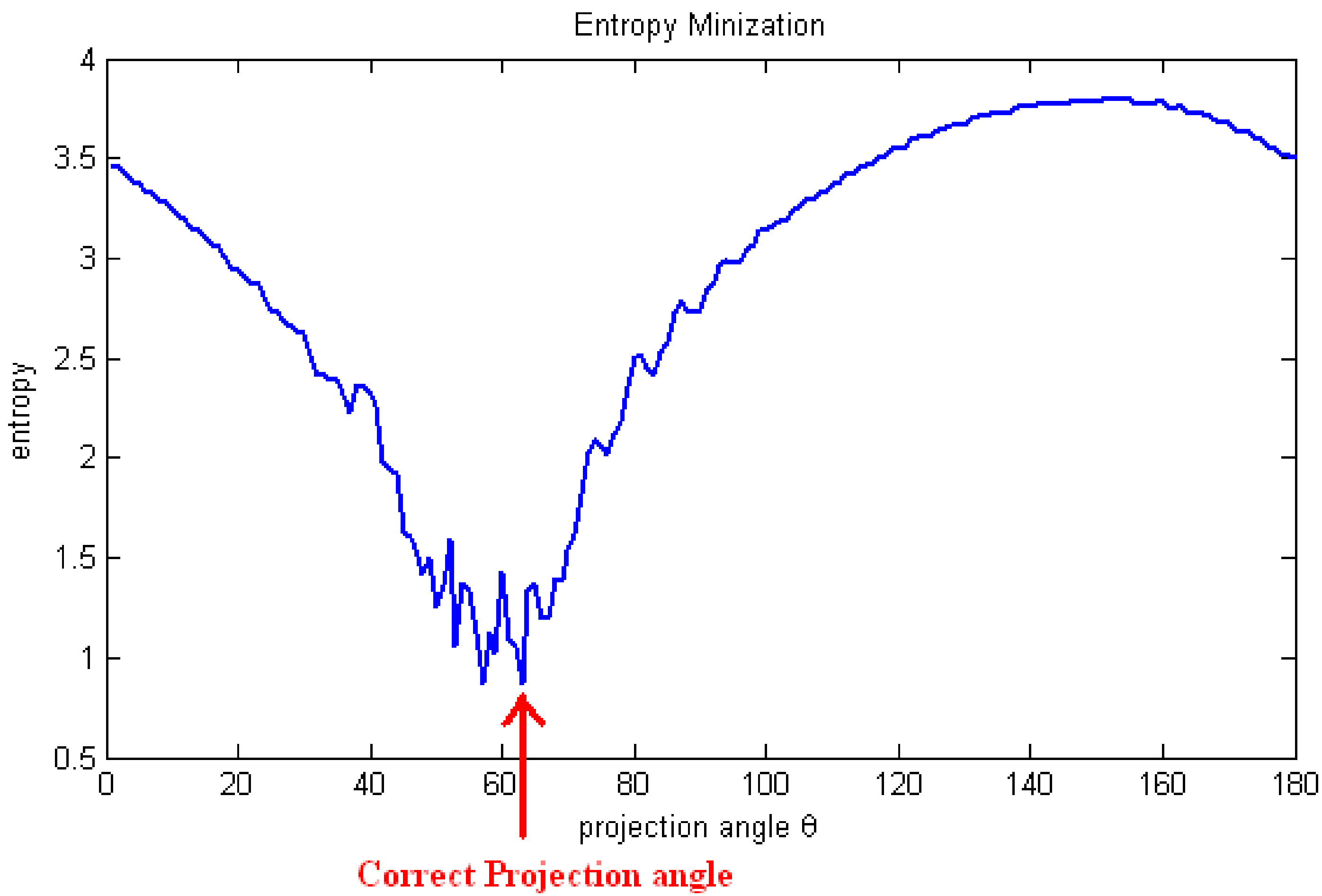


Correct Projection



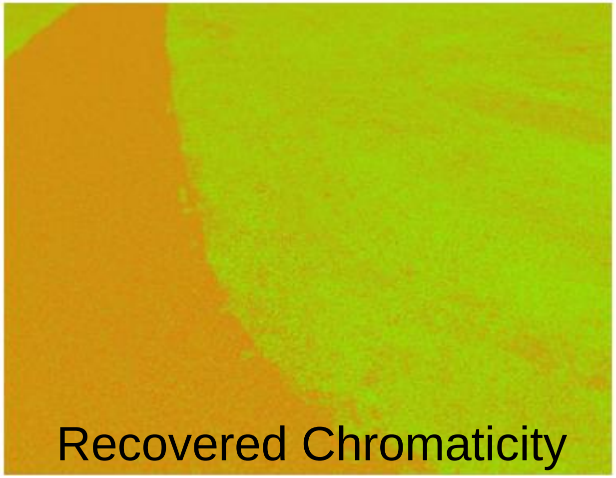
Incorrect Projection

Entropy Minimization

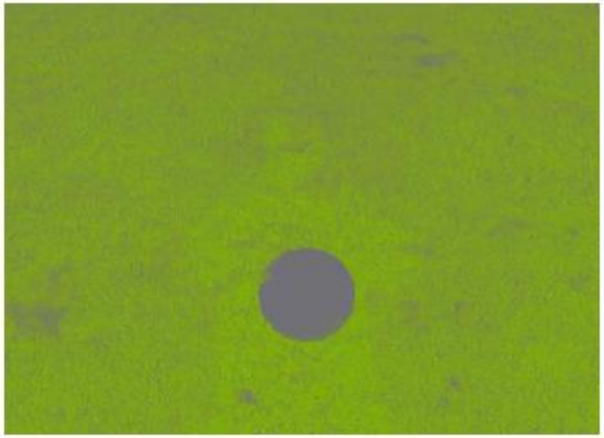


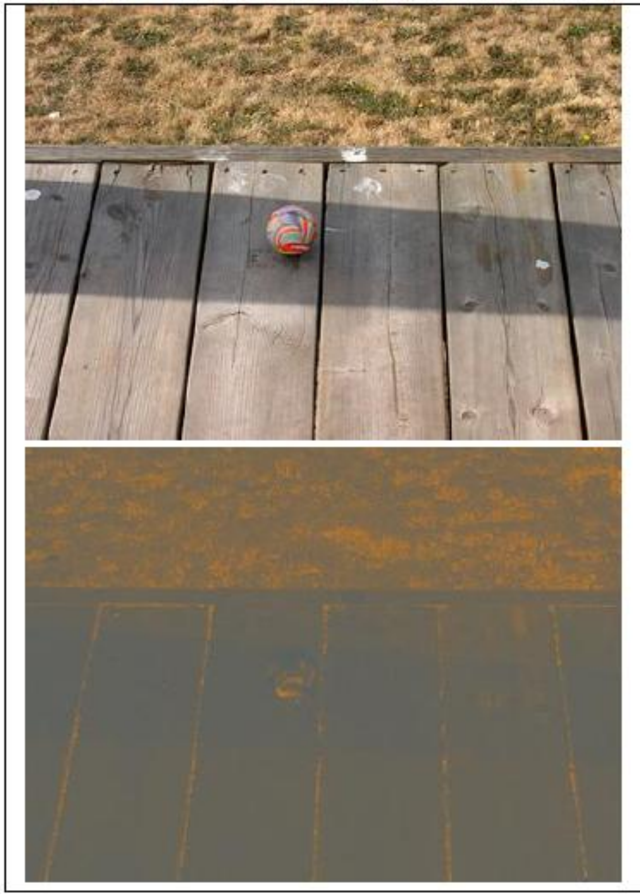
More “spread-out” distribution would produce a larger entropy, hence ***the projection direction that produces the minimum entropy is the correct projection direction***

Sweep Angle of Projection



Recovered Chromaticity






Limitations of Shadow Removal

- Only Hard shadows can be removed
- No overlapping of object and shadow boundaries
- Planckian light sources
- Narrow band cameras are idealized

- Reconstruction methods are texture-dumb

User-Assisted Intrinsic Images

Bousseau et al. 2009

(a) Original photograph (b) User scribbles (c) Reflectance (d) Illumination (e) Re-texturing

Figure 1: *Our system relies on user indications, shown in (b), to extract from a single photograph its reflectance and illumination components (c-d). In (b), white scribbles indicate fully-lit pixels, blue scribbles correspond to pixels sharing a similar reflectance and red scribbles correspond to pixels sharing a similar illumination. This decomposition facilitates advanced image editing such as re-texturing (e).*