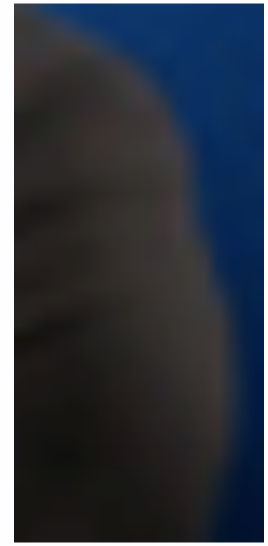
Materials and weather

D.A. Forsyth, UIUC

Key issues

- Physical
  - what makes a pixel take its brightness values?
- Inference
  - what can we recover from the world using those brightness values?
- Human
  - What can people do?
    - which suggests problems we might be able to solve

nickwheeleroz

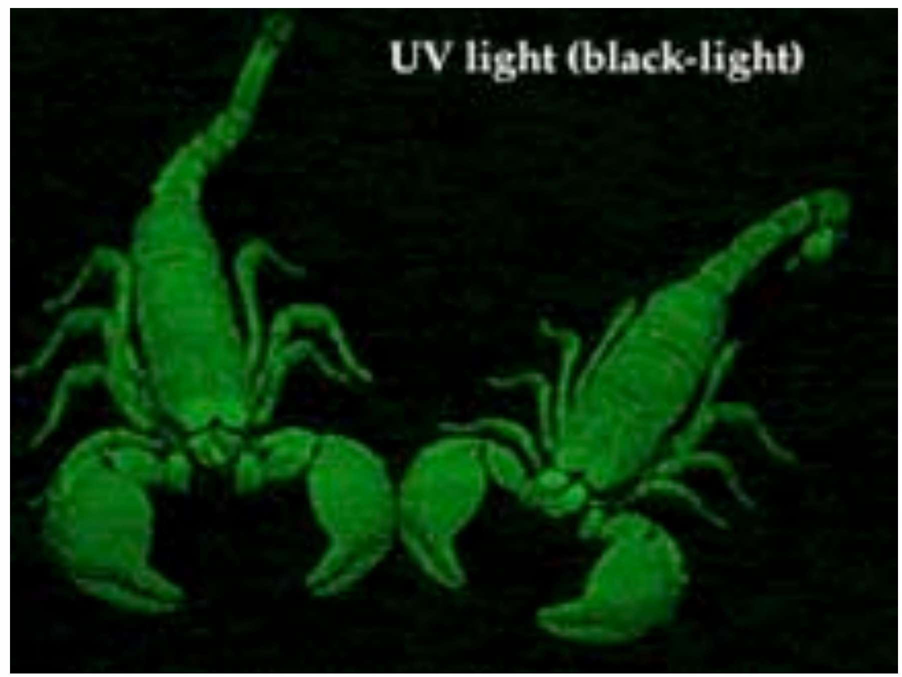


By nickwheeleroz, on Flickr

Processes

- Cameras
  - film: non-linear
  - CCD: linear, with non-linearities made by electronics
- Light
  - is reflected from a surface
  - got there from a source
- Many effects when light strikes a surface -- could be:
  - absorbed; transmitted; reflected; scattered
  - Simplify
    - Assume that
      - surfaces don't fluoresce
      - surfaces don't emit light (i.e. are cool)
      - all the light leaving a point is due to that arriving at that point


White light (indoor)

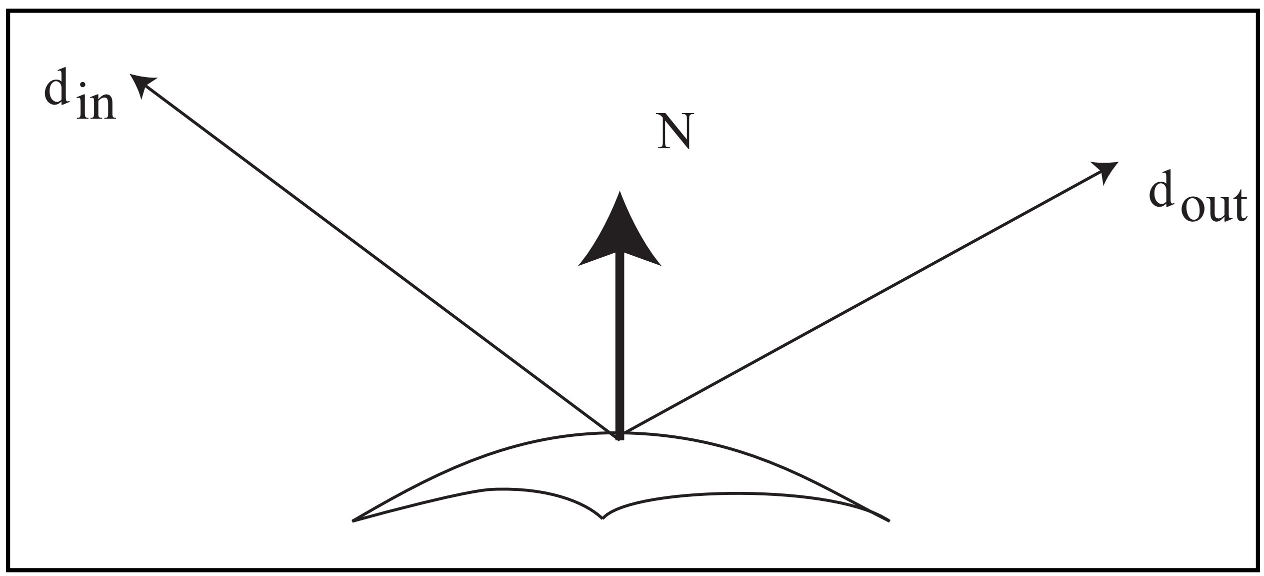

UV light (black-light)

Diffuse reflection

- Light leaves the surface evenly in all directions
  - cotton cloth, carpets, matte paper, matte paints, etc.
  - most “rough” surfaces
  - Parameter: Albedo
    - percentage of light arriving that leaves
    - range 0-1
      - practical range is smaller
- Test:
  - surface has same apparent brightness when viewed from different dir’ns

Specularities

- For some surfaces, reflection depends strongly on angle
  - mirrors (special case)
    - incoming direction, normal and outgoing direction are coplanar
    - angle din, normal and angle dout, normal are the same
  - specular surfaces
    - light reflected in a “lobe” of directions
    - eg slightly battered metal surface
    - can see light sources specularly reflected
      - specularities



Flickr, by suzysputnik

Flickr, by piratejohnny

- Specularities are relatively easy to detect
    - small and bright (usually)

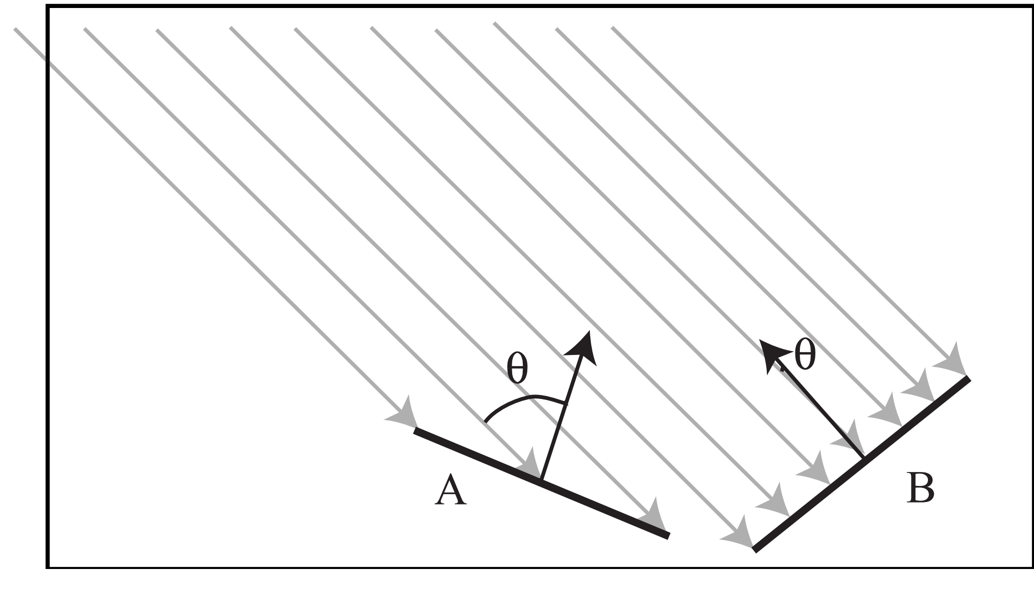
Surfaces and the BRDF

- Many effects when light strikes a surface -- could be:
  - absorbed; transmitted. reflected; scattered
- Assume that
  - surfaces don't fluoresce
  - surfaces don't emit light (i.e. are cool)
  - all the light leaving a point is due to that arriving at that point
- Can model this situation with the Bidirectional Reflectance Distribution Function (BRDF)
- the ratio of the radiance in the outgoing direction to the incident irradiance

$$\rho_{bd}\left(\underline{x},\vartheta_o,\varphi_o,\vartheta_i,\varphi_i,\right)=\frac{L_o\left(\underline{x},\vartheta_o,\varphi_o\right)}{L_i\left(\underline{x},\vartheta_i,\varphi_i\right)\cos\vartheta_i d\omega}$$

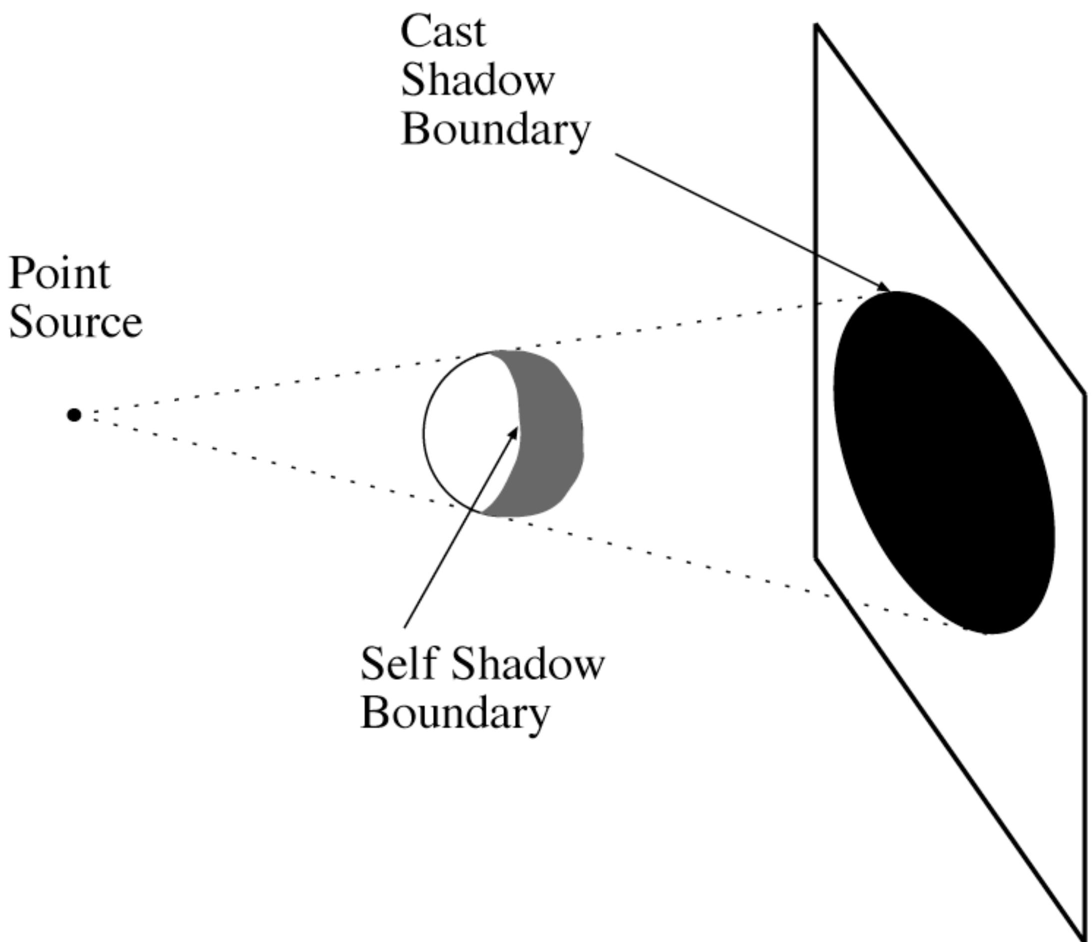
Point source at infinity

- E.g. the sun
  - energy travels in parallel rays
  - energy density received is proportional to cos theta
- Write:
  - p for albedo
  - S for source vector
  - N for normal
  - I for image intensity

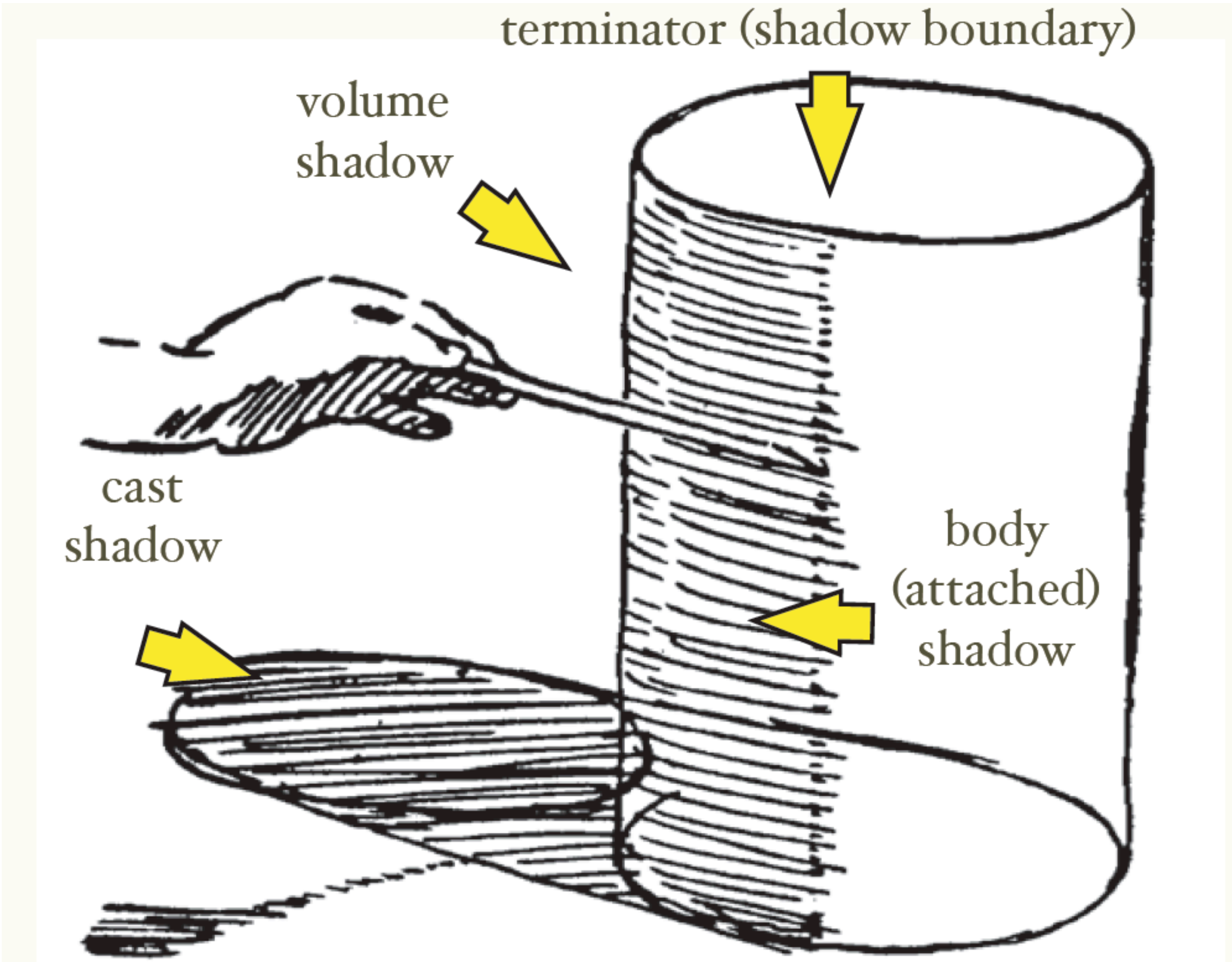


Shadows cast by a point source

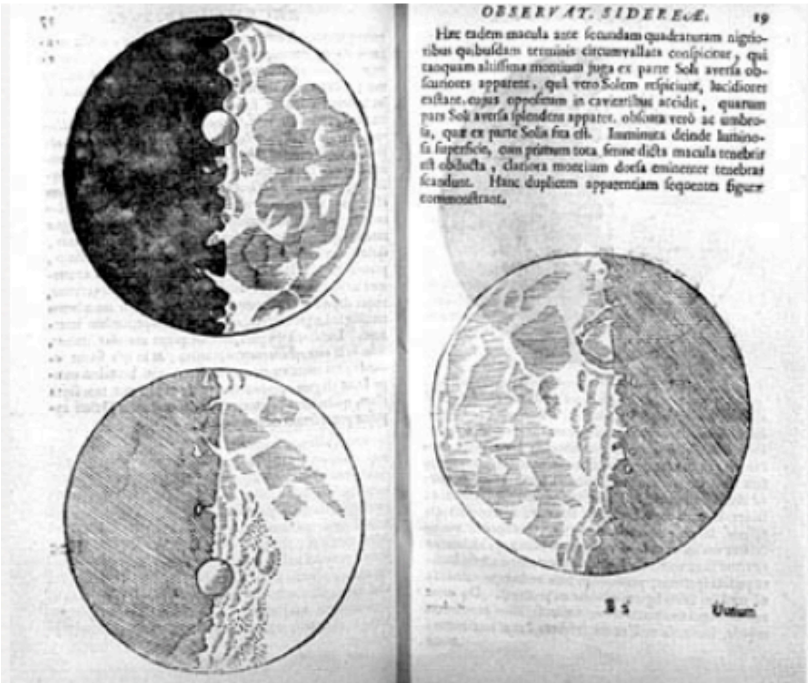
- A point that can’t see the source is in shadow
- For point sources, the geometry is simple



Cues to shape - shadows



From Koenderink slides on image texture and the flow of light



OBSERVAT. SIDEREÆ. 19

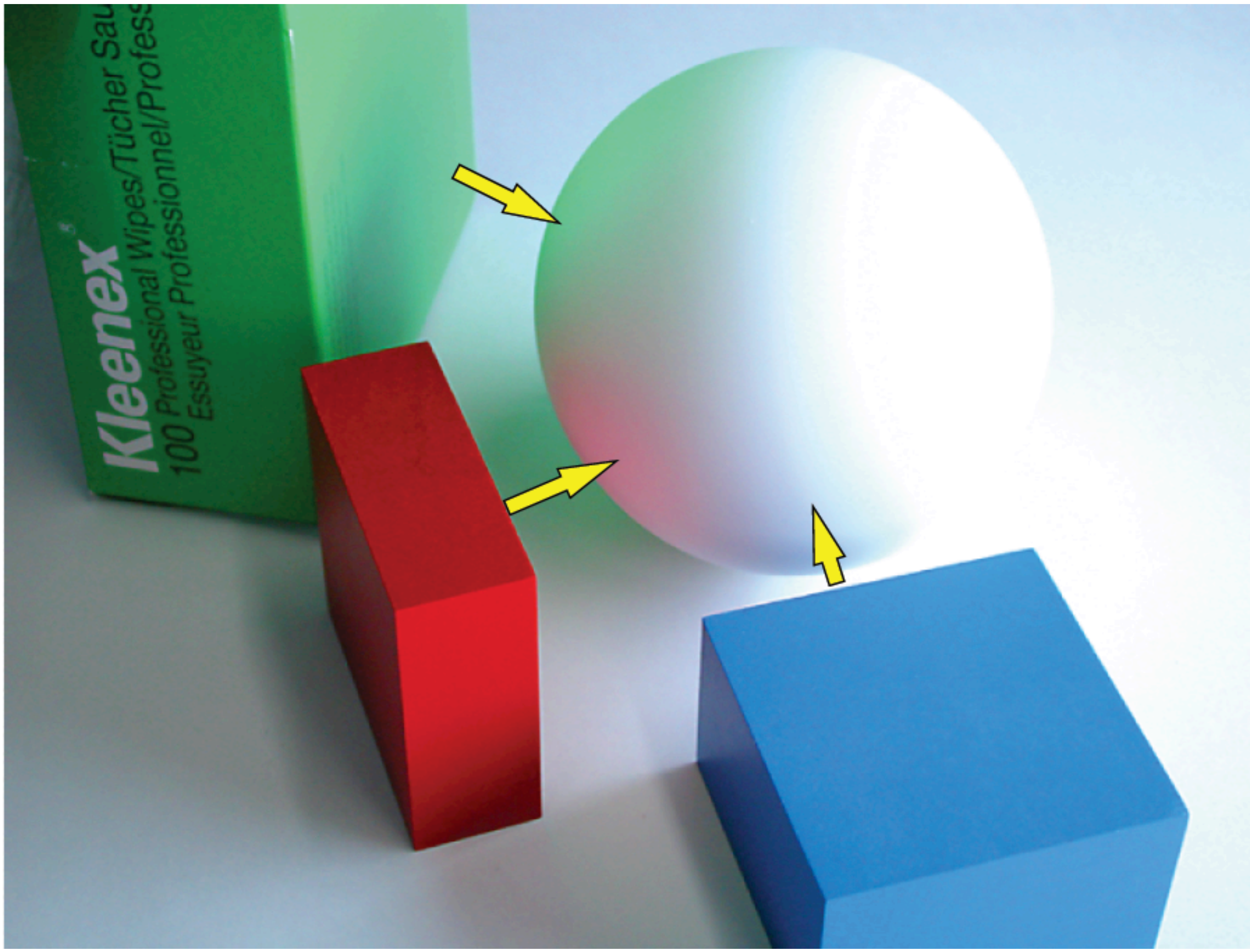
Hæc eadem macula ante secundam quadraturam nigrioribus quibusdam terminis circumvallata conspicitur, qui tanquam altissima montium juga ex parte Soli aversa obscuriores apparent, quà vero Solem respiciunt, lucidiores exstant, cujus oppositum in cavitatibus accidit, quarum pars Soli aversa splendens apparet, obscura verò ac umbrosa, quæ ex parte Solis sita est. Imminuta deinde luminosa superficie, cum primum tota ferme dicta macula tenebris est obducta, clariora montium dorsa eminenter tenebras scandunt. Hanc duplicem apparentiam sequentes figuræ commonstrant.

From Koenderink slides on image texture and the flow of light

Interreflections

- Issue:
  - local shading model is a poor description of physical processes that give rise to images
    - because surfaces reflect light onto one another
  - This is a major nuisance; the distribution of light (in principle) depends on the configuration of every radiator; big distant ones are as important as small nearby ones (solid angle)
  - The effects are easy to model
  - It appears to be hard to extract information from these models

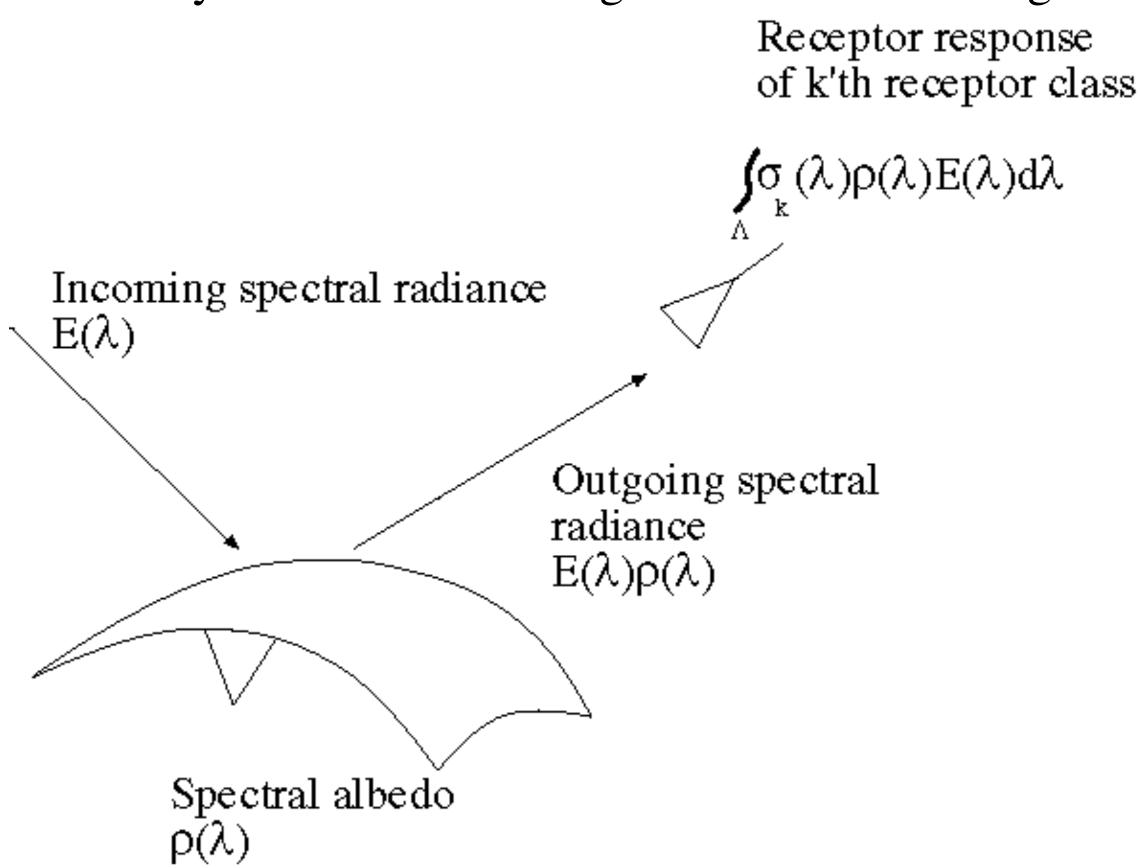
Interreflections



From Koenderink slides on image texture and the flow of light

The color of objects

- Colored light arriving at the camera involves two effects
  - The color of the light source
  - The color of the surface
  - Changes caused by different colored light sources can be large



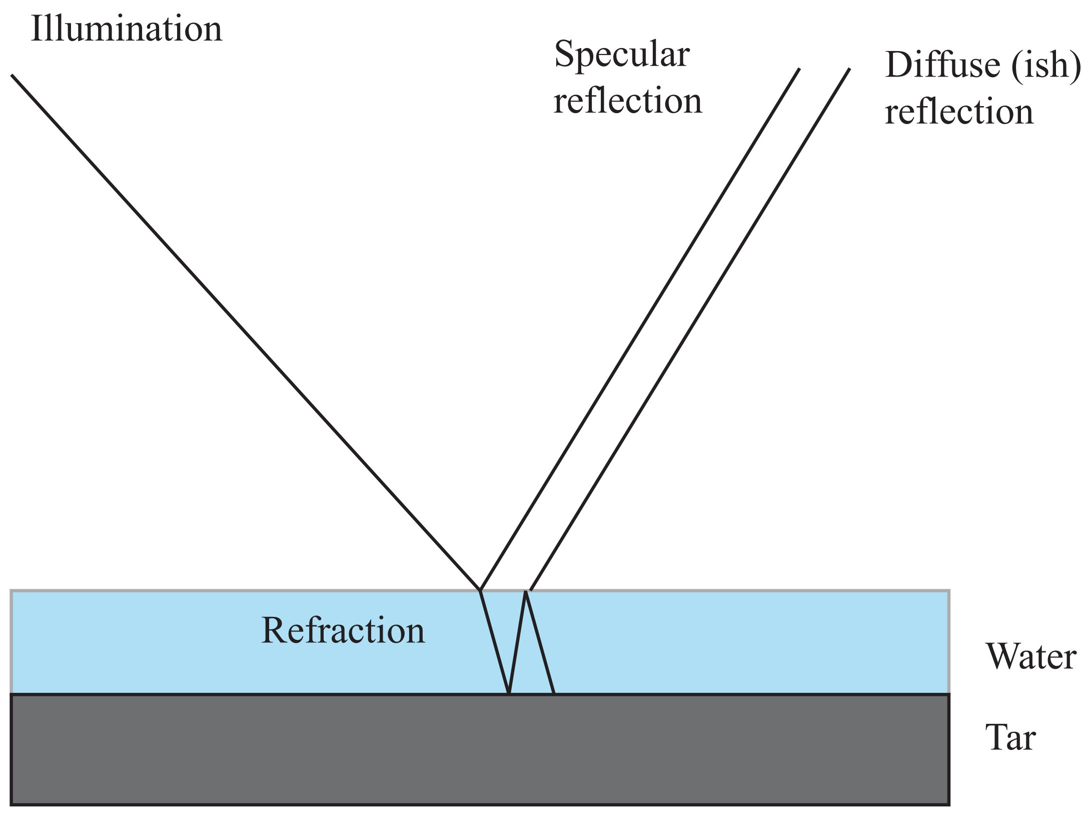
Constancy

- You perceive objects in terms of their properties
  - rather than what they look like in an image
- Examples:
  - size constancy
    - distant objects are small in pictures, nearby objects bigger
      - but you don't think of them as changing size
  - lightness constancy
    - dark things in bright rooms can be brighter than light objects in dark rooms
      - but you perceive their lightness (=albedo)
  - color constancy
    - image color changes when lighting color changes
      - but you perceive the surface color
  - object constancy

Which fish is bigger?

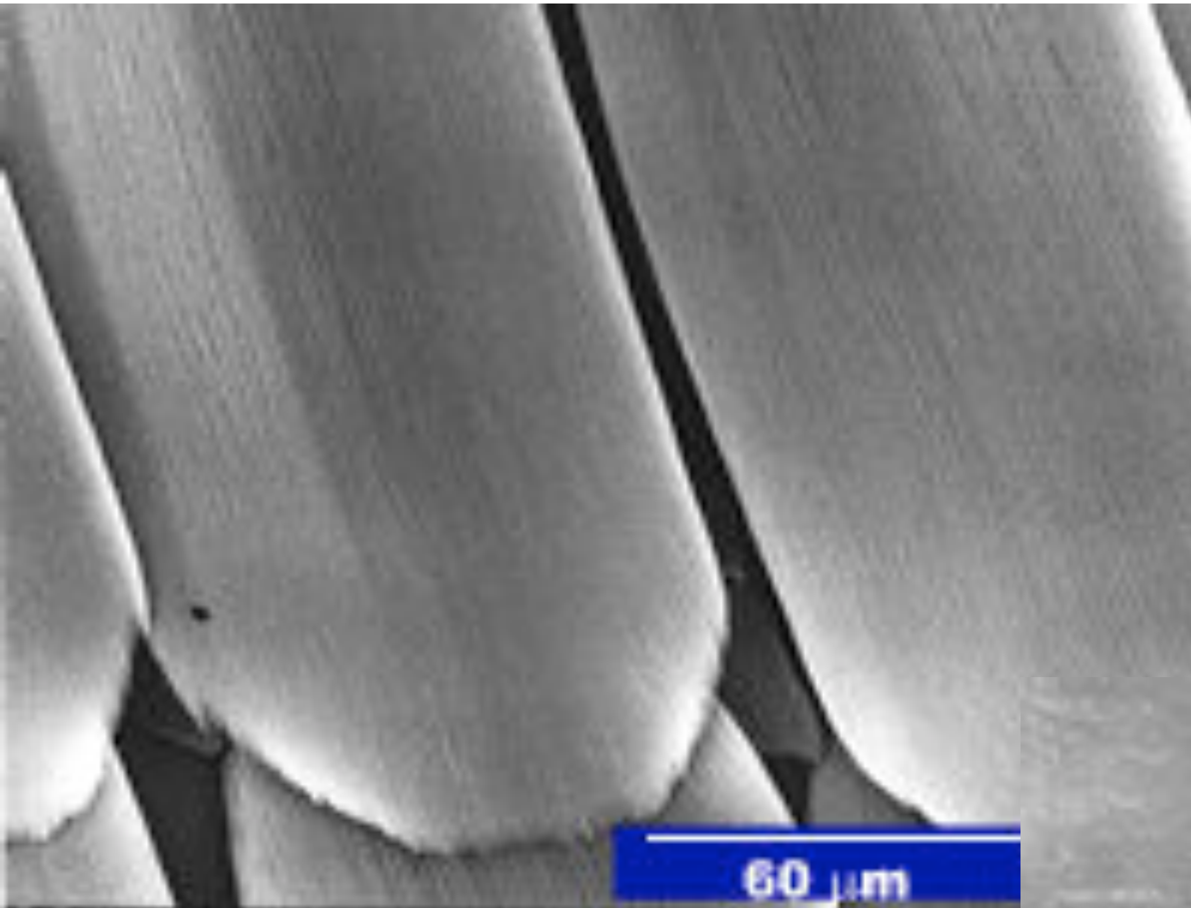
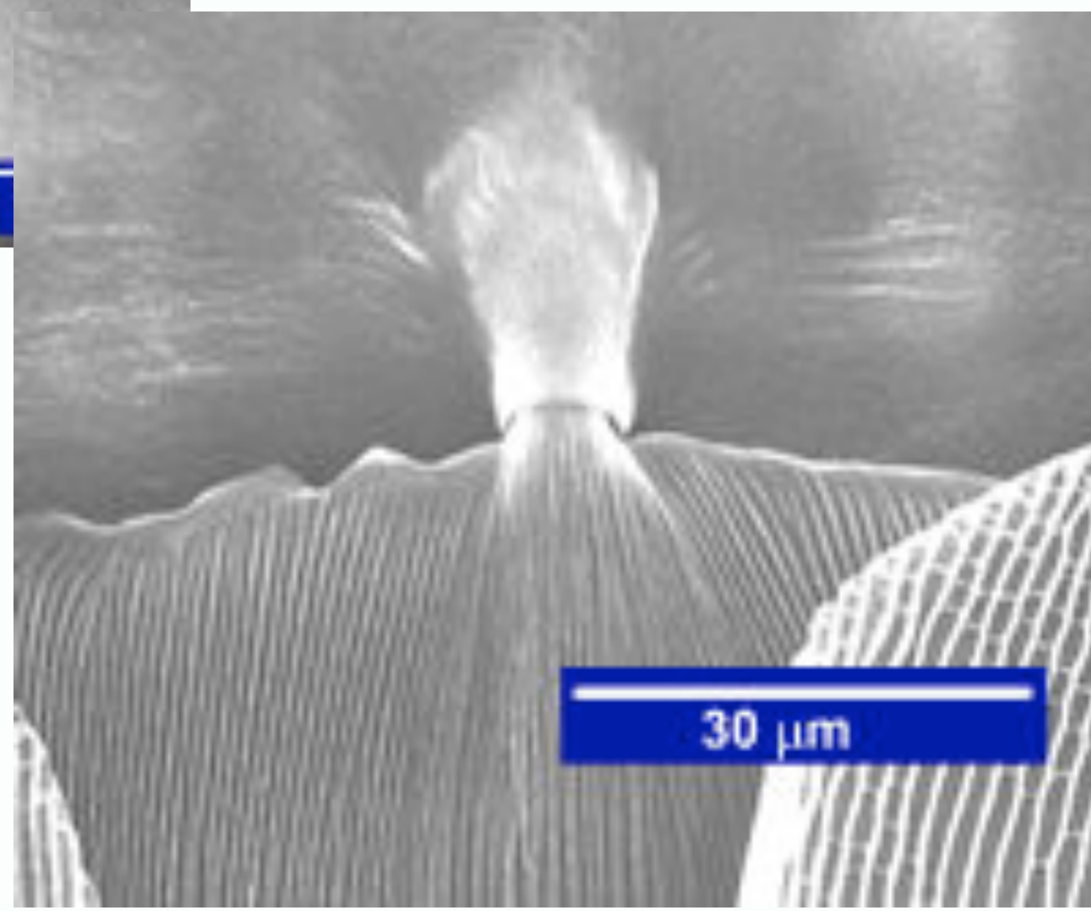
Films on surfaces

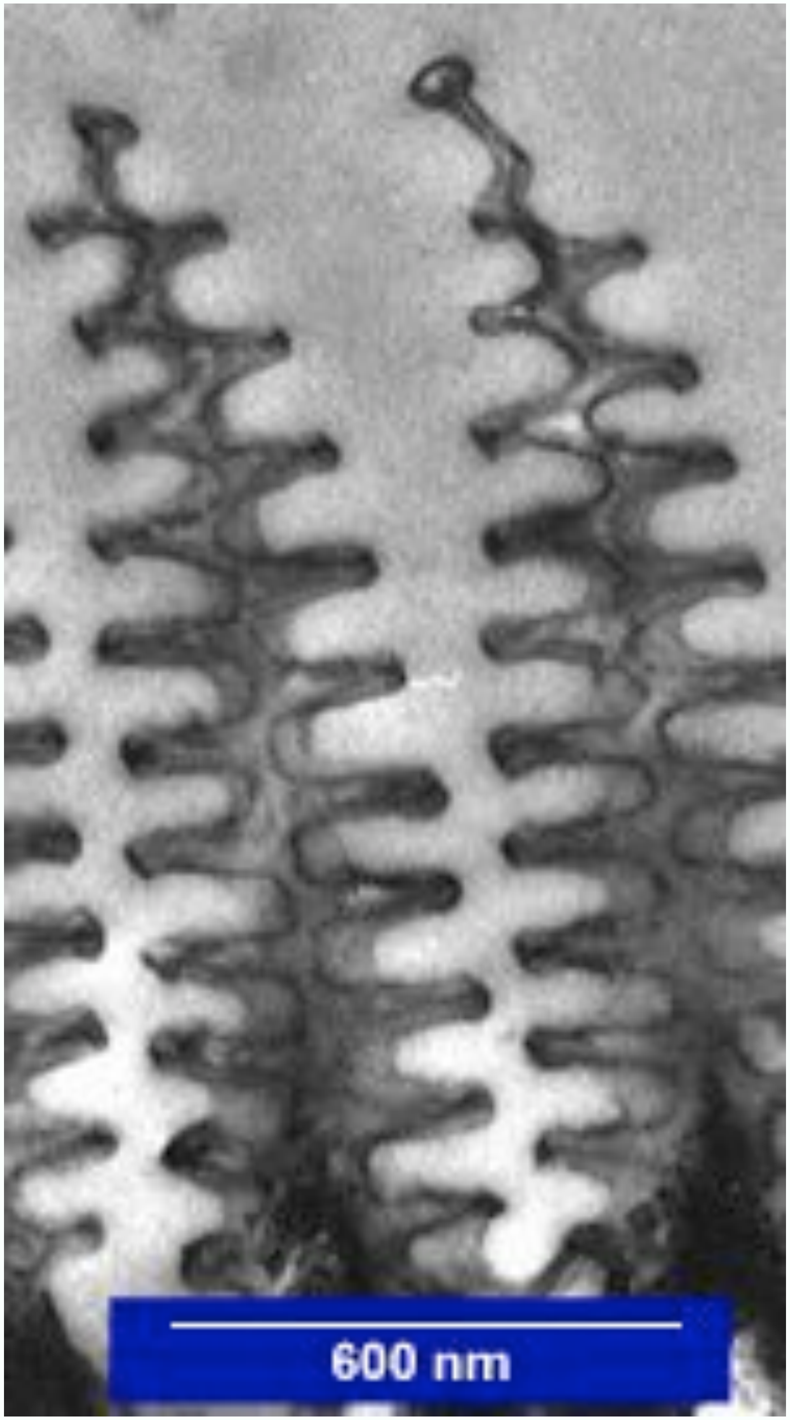
- eg water
- Assume:
  - film is thin
  - not much internal reflection
- You see:
  - diffuse + specular reflection
  - som



Interference effects

- Sometimes seen on films
  - if the film is the right number of wavelengths thick
    - waves will interfere destructively (resp constructively)
    - can give rise to intense colors
      - oil films on water often do this

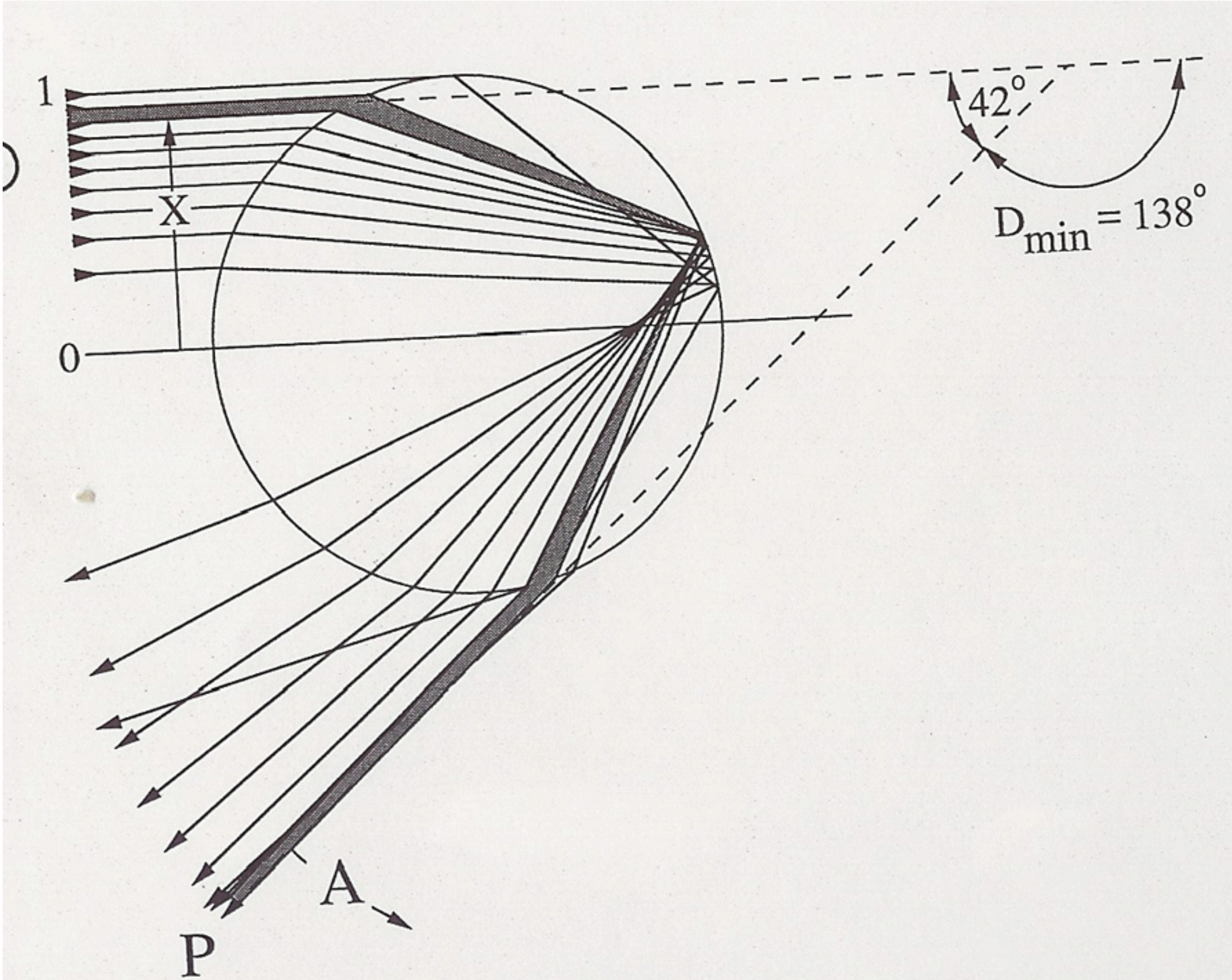

60 μm

30 μm


600 nm

Refraction

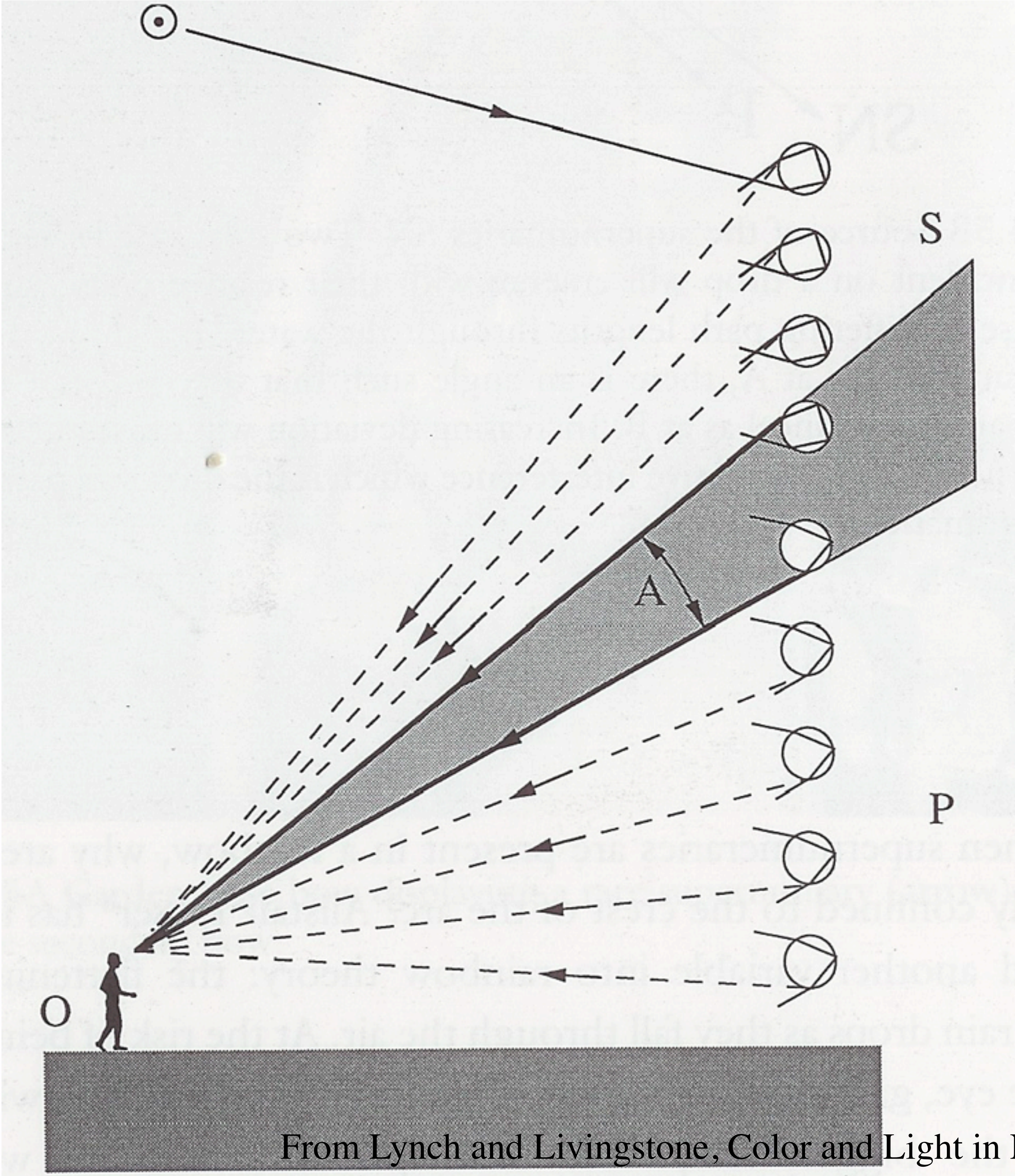
- Light striking an interface changes direction
  - between translucent surfaces with different speed-of-light
  - (refraction)
- At critical angle, total internal reflection

From Lynch and Livingstone, Color and Light in Nature



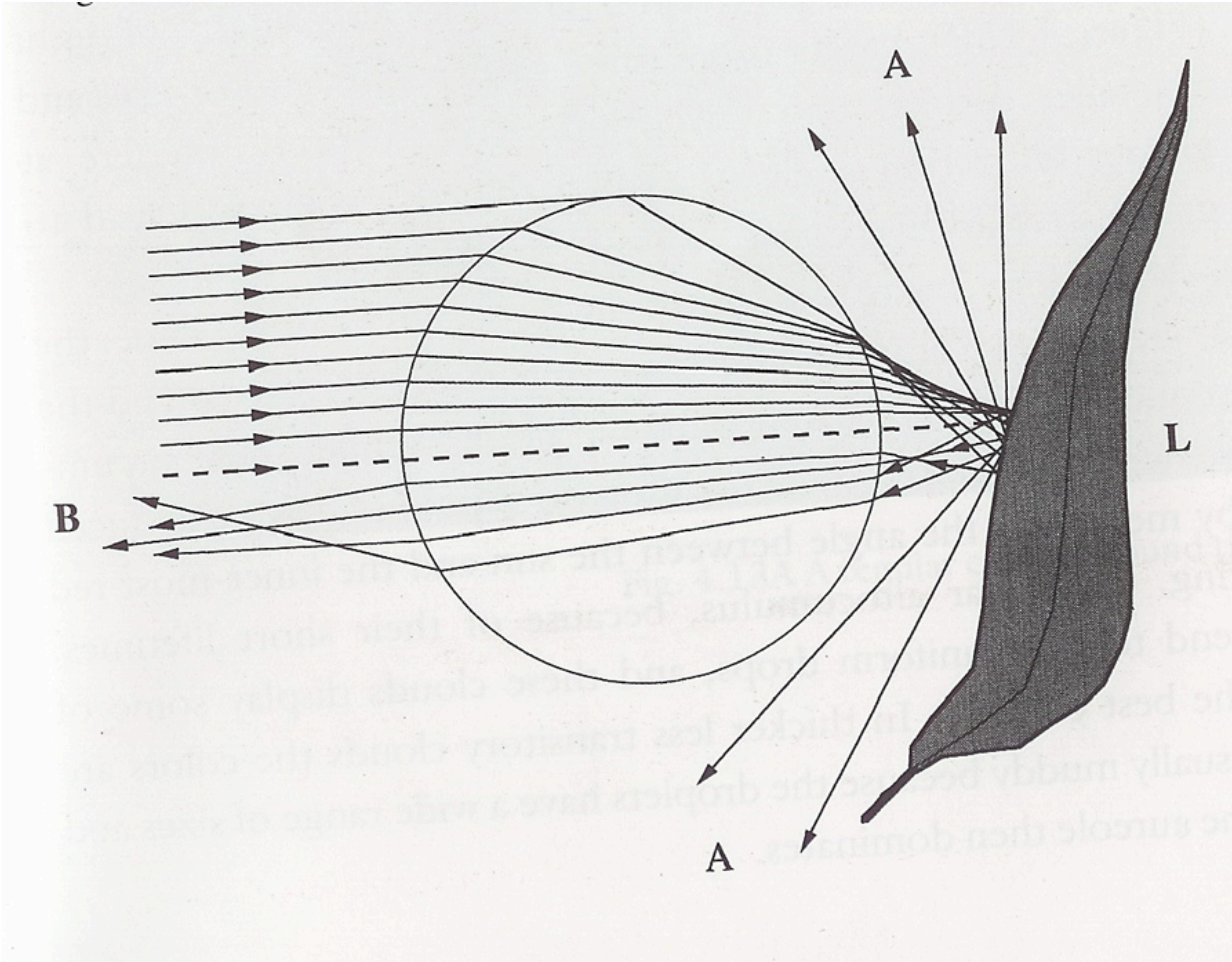
From Lynch and Livingstone, Color and Light in Nature

From Lynch and Livingstone, Color and Light in Nature

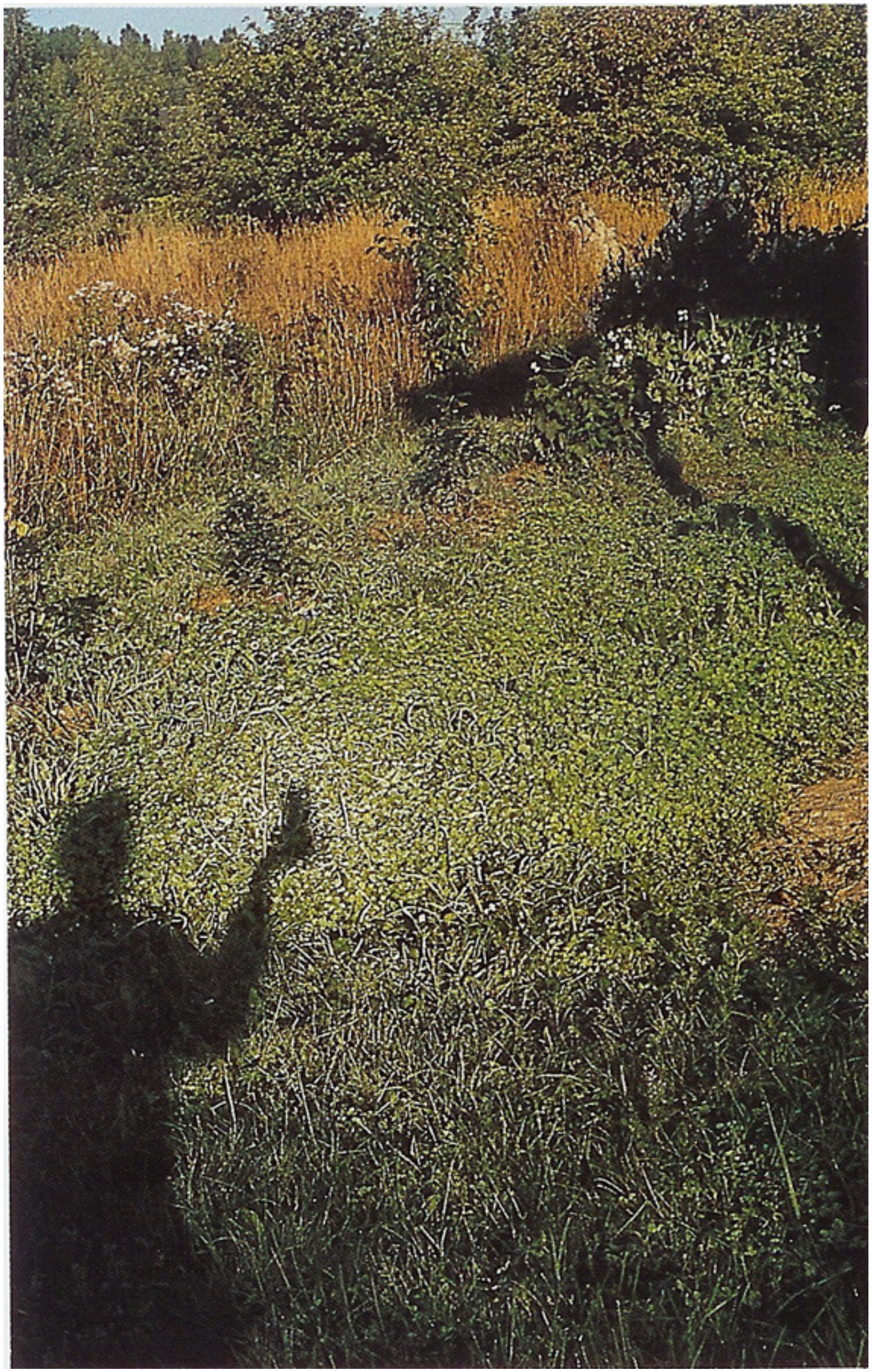


From Lynch and Livingstone, Color and Light in Nature

From Lynch and Livingstone, Color and Light in Nature



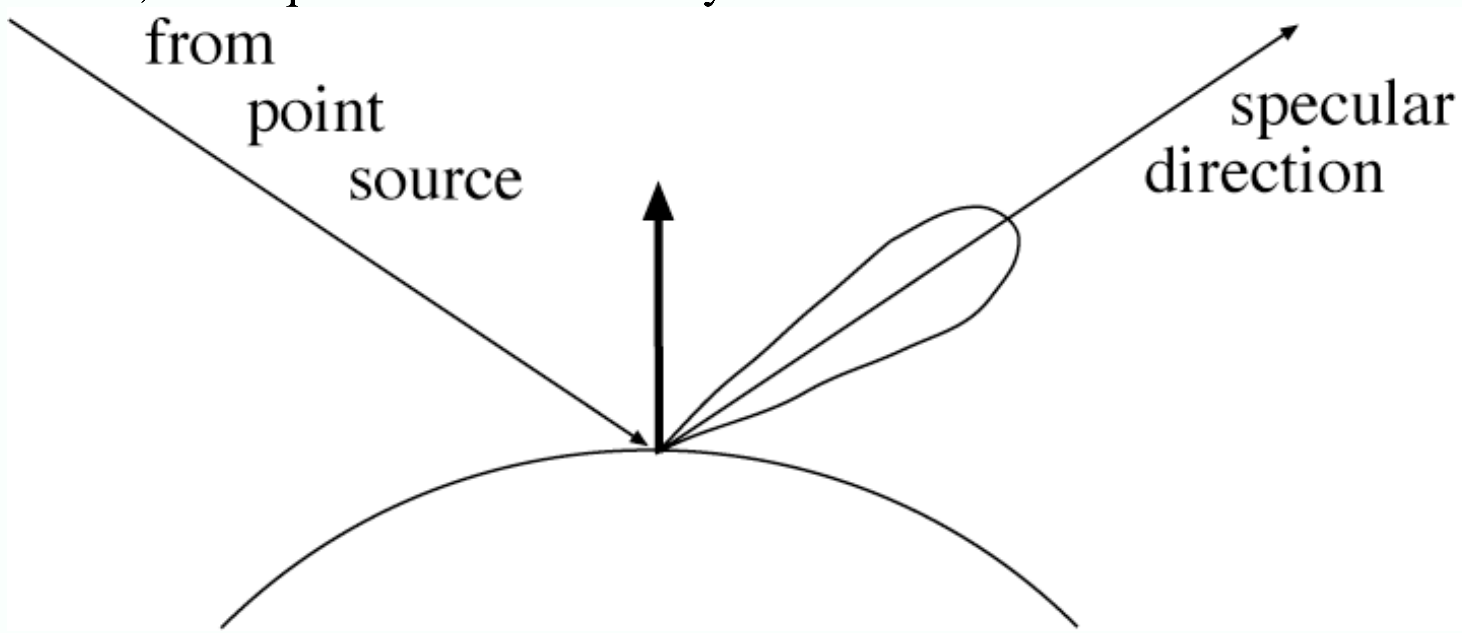
From Lynch and Livingstone, Color and Light in Nature



Minnaert, Light and Color in the outdoors
Heiligenschein

Specular surfaces

- Another important class of surfaces is specular, or mirror-like.
    - radiation arriving along a direction leaves along the specular direction
    - reflect about normal
    - some fraction is absorbed, some reflected
    - on real surfaces, energy usually goes into a lobe of directions
    - can write a BRDF, but requires the use of funny functions



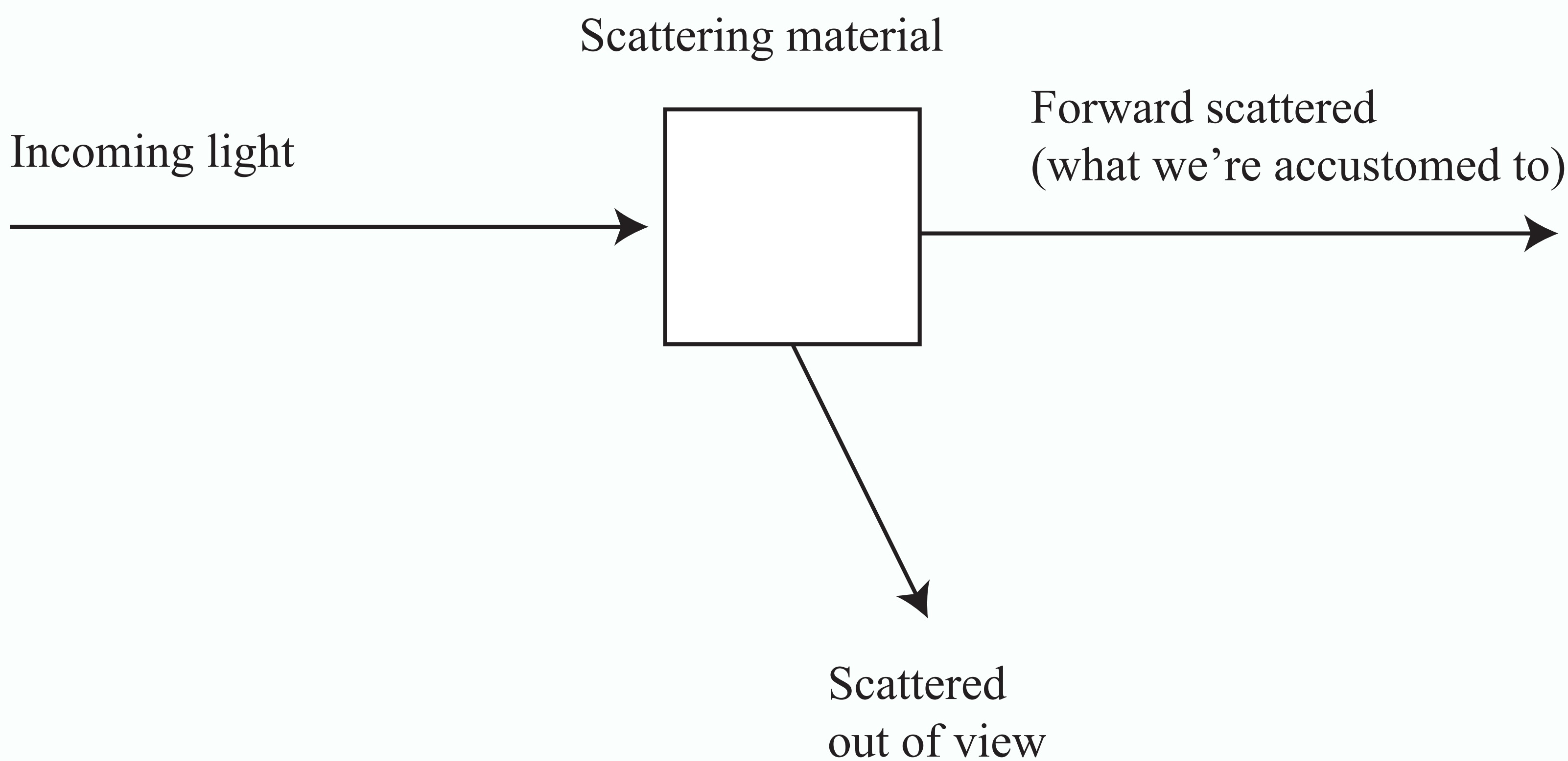
Scattering

- Fundamental mechanism of light/matter interactions
- Visually important for
  - slightly translucent materials (skin, milk, marble, etc.)
  - participating media

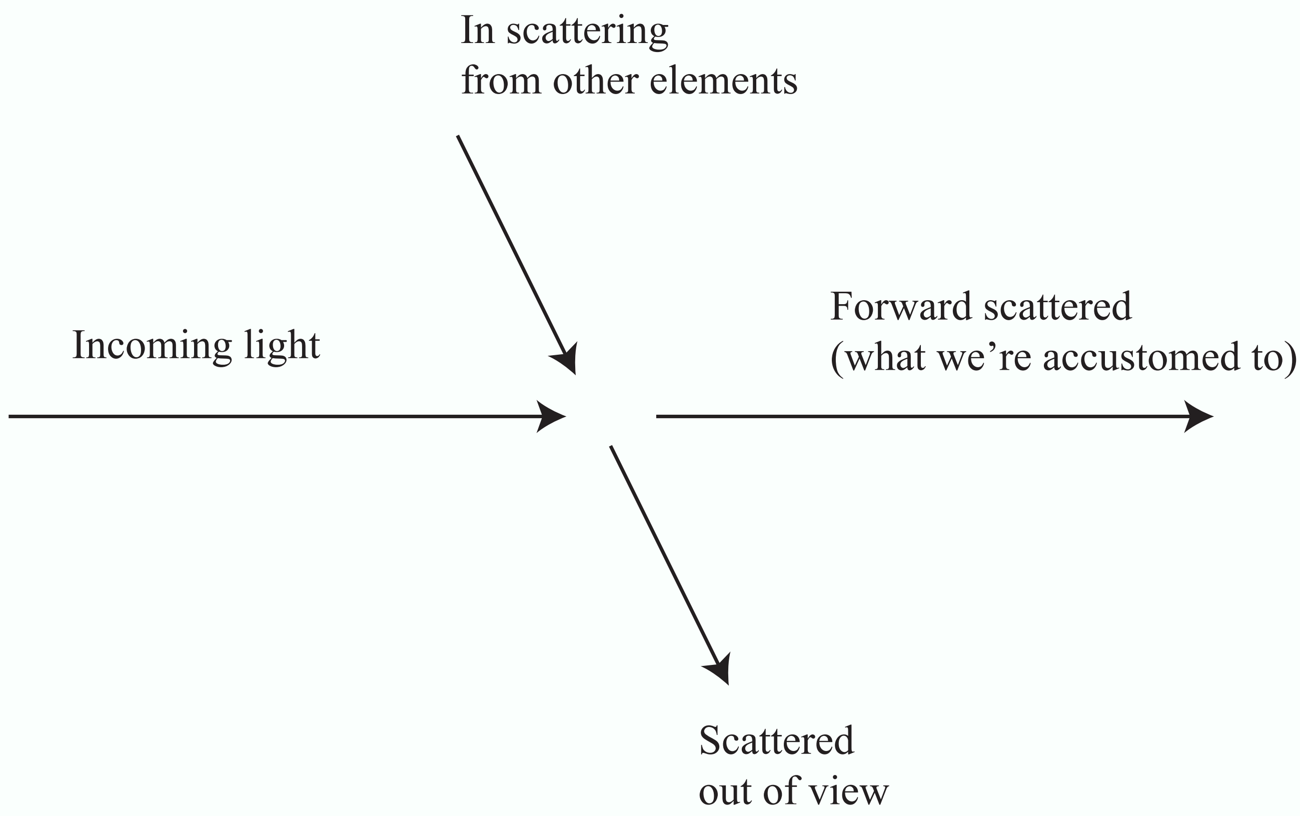
Participating media

- for example,
  - smoke,
  - wet air (mist, fog)
  - dusty air
  - air at long scales
- Light leaves/enters a ray travelling through space
  - leaves because it is scattered out
  - enters because it is scattered in
- New visual effects

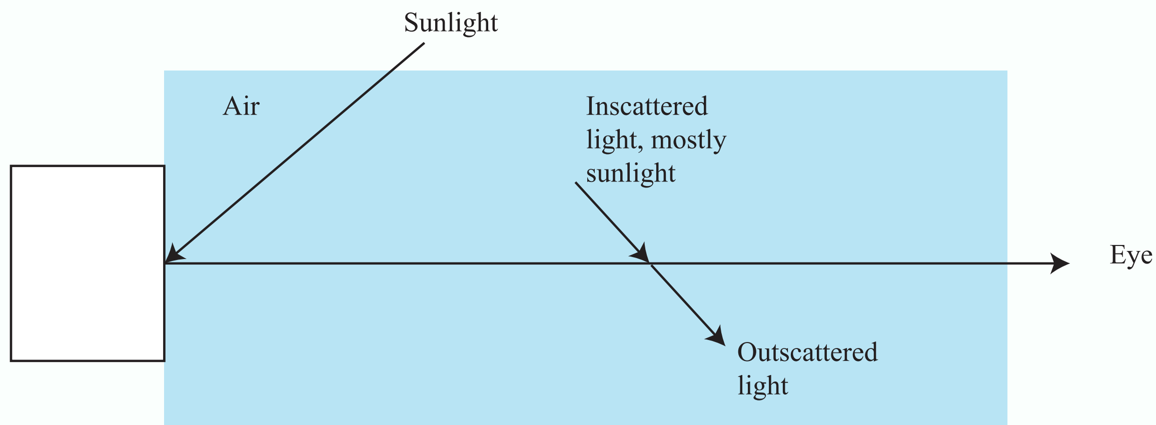
Light hits a small box of material



A ray passing through scattering material

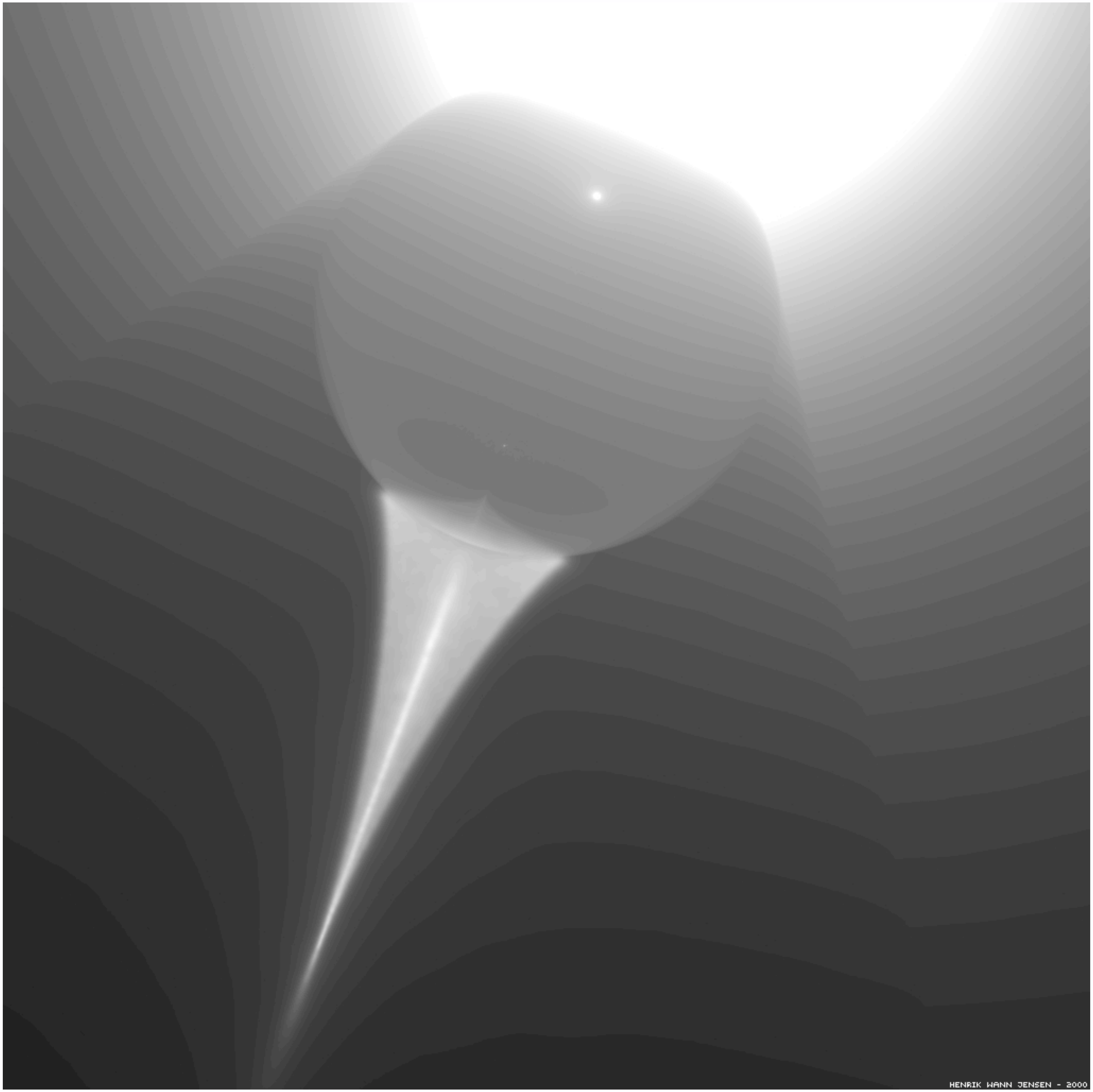


Airlight as a scattering effect




original unique filename: 20180329-141700_baie_des_fourmis.jpg
hosted by www.carto.net
photo ©André M. Winter

From Lynch and Livingstone, Color and Light in Nature

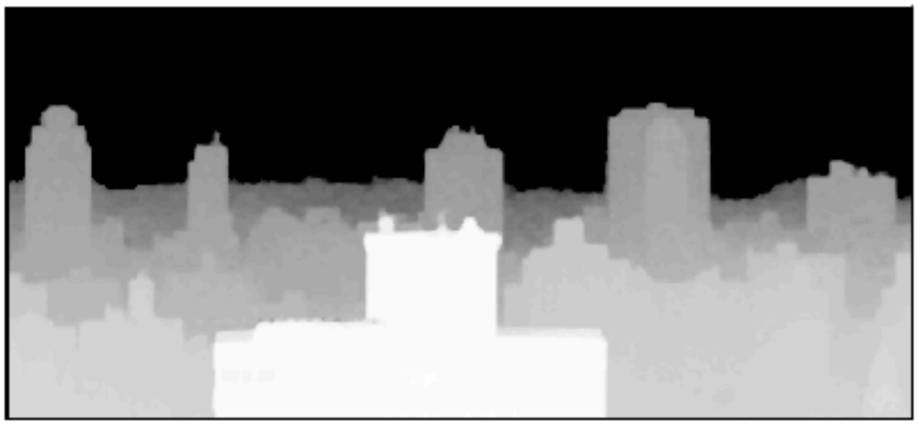

HENRIK WANN JENSEN - 2000

From Lynch and Livingstone, Color and Light in Nature

Airlight yields a depth cue

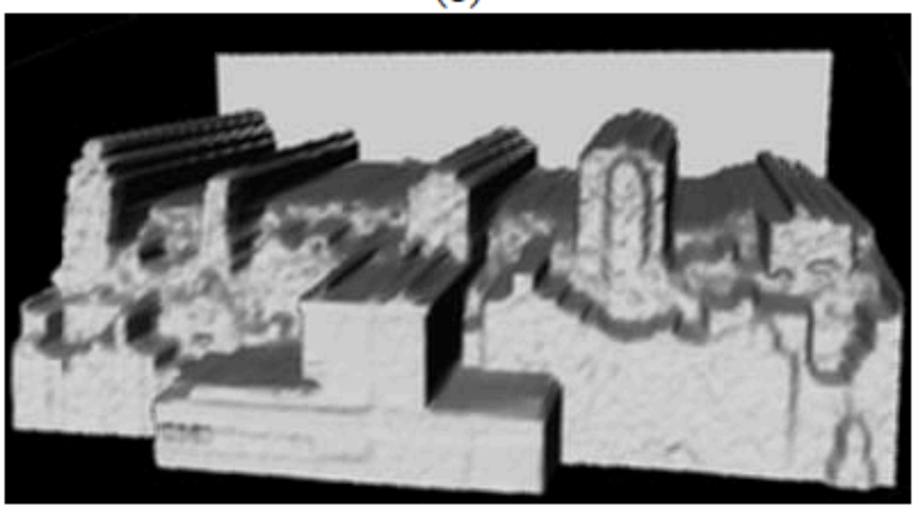
- Assume that airlight is dominant
  - (i.e. most of light arriving at camera is airlight)
  - then you can recover depth from a single image
- Disadvantages
  - requires significant fog (but not too much) or large scales

(a)

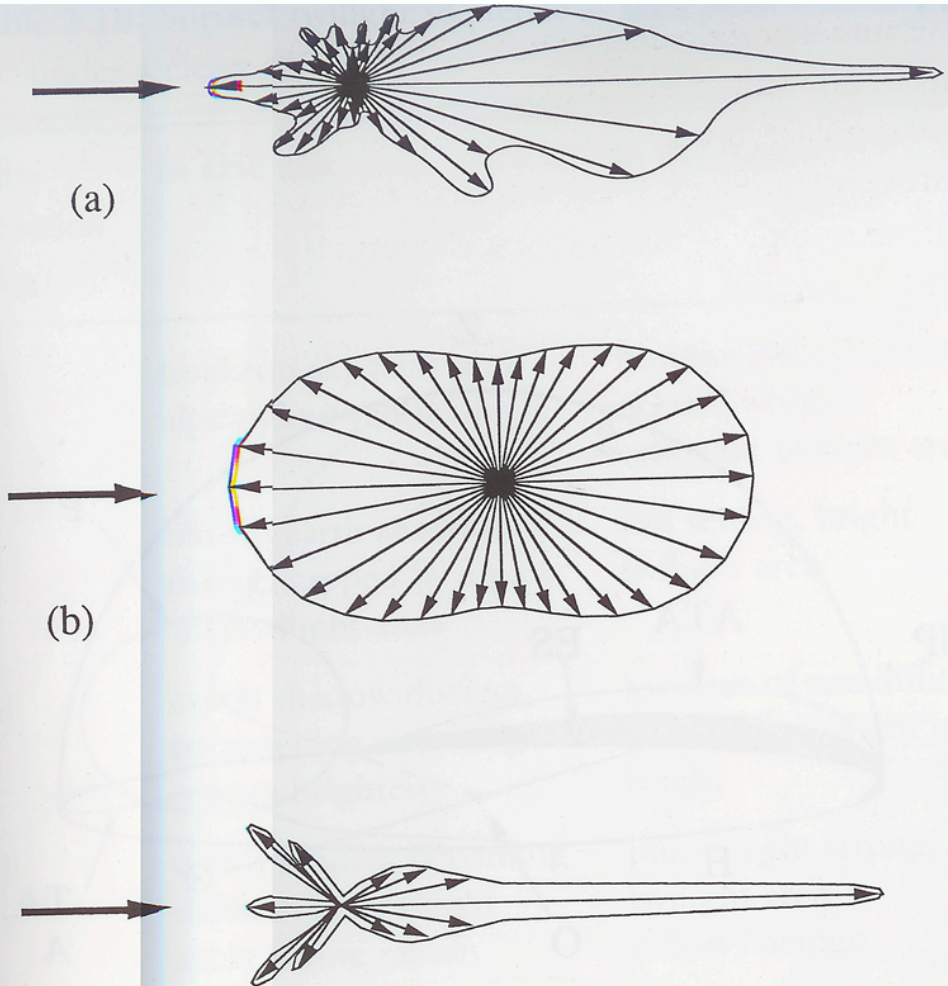


(b)

Nayar and Narasimhan, 1999



(c)



Big (dust, smoke)

Air molecules

Water drops

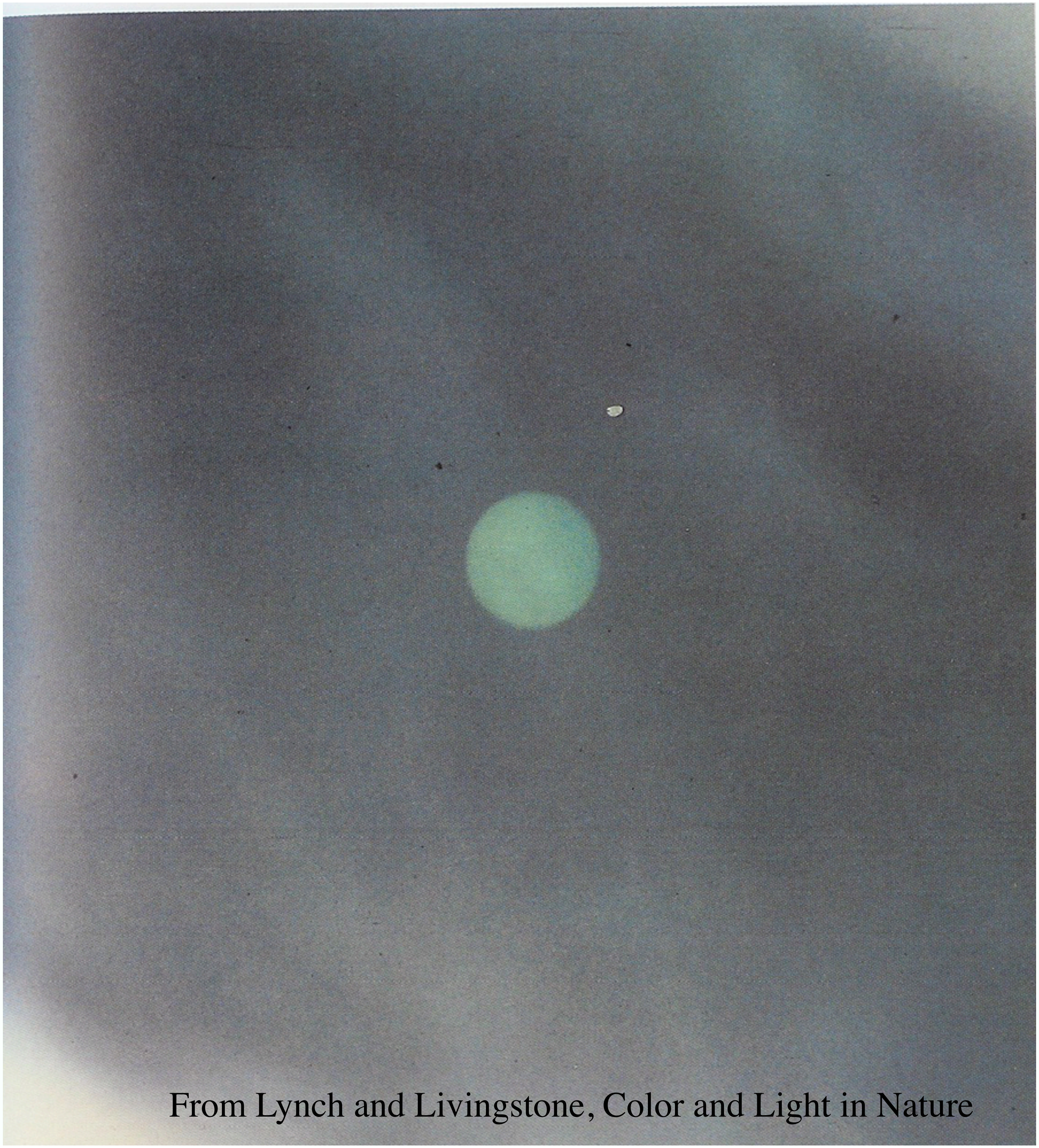
Fig. 2.7C Scattering patterns for different particles. (a) Large irregular particles, like those comprising dust and smoke, are irregular in the sense that they are not symmetric. They do, however, have a strong forward scattering peak and a smaller though still pronounced backscattering peak. (b) Air molecules have a scattering function that is symmetric fore and aft: they scatter the same amount of light in both the forward and backward directions but lack both the forward and backscattering peak. (c) Large water drops have a strong forward and backscattering peak and also show strong enhancements at the primary and secondary rainbow angles.

From Lynch and Livingstone, Color and Light in Nature

Fig. 2.7A (LEFT) Aureole around the sun. The sun is hidden by a street lamp. To the eye, the sky appeared clear.

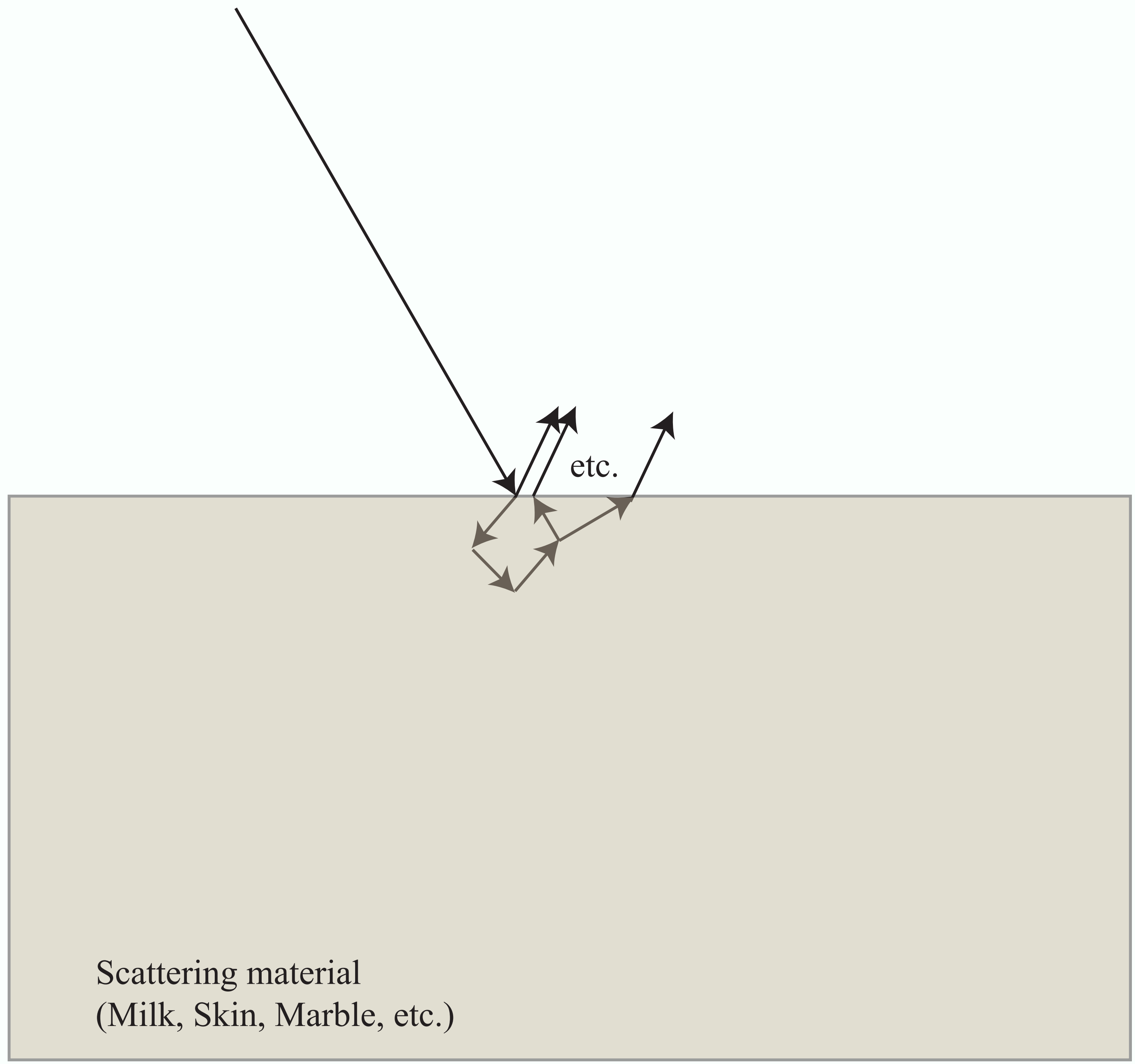
Fig. 2.7B (RIGHT) The next day the sky was exceptionally clear and there was no aureole.

From Lynch and Livingstone, Color and Light in Nature


From Lynch and Livingstone, Color and Light in Nature

Minnaert, Light and Color in the outdoors

Notice flattened sun,
sparkles


etc.
Scattering material
(Milk, Skin, Marble, etc.)

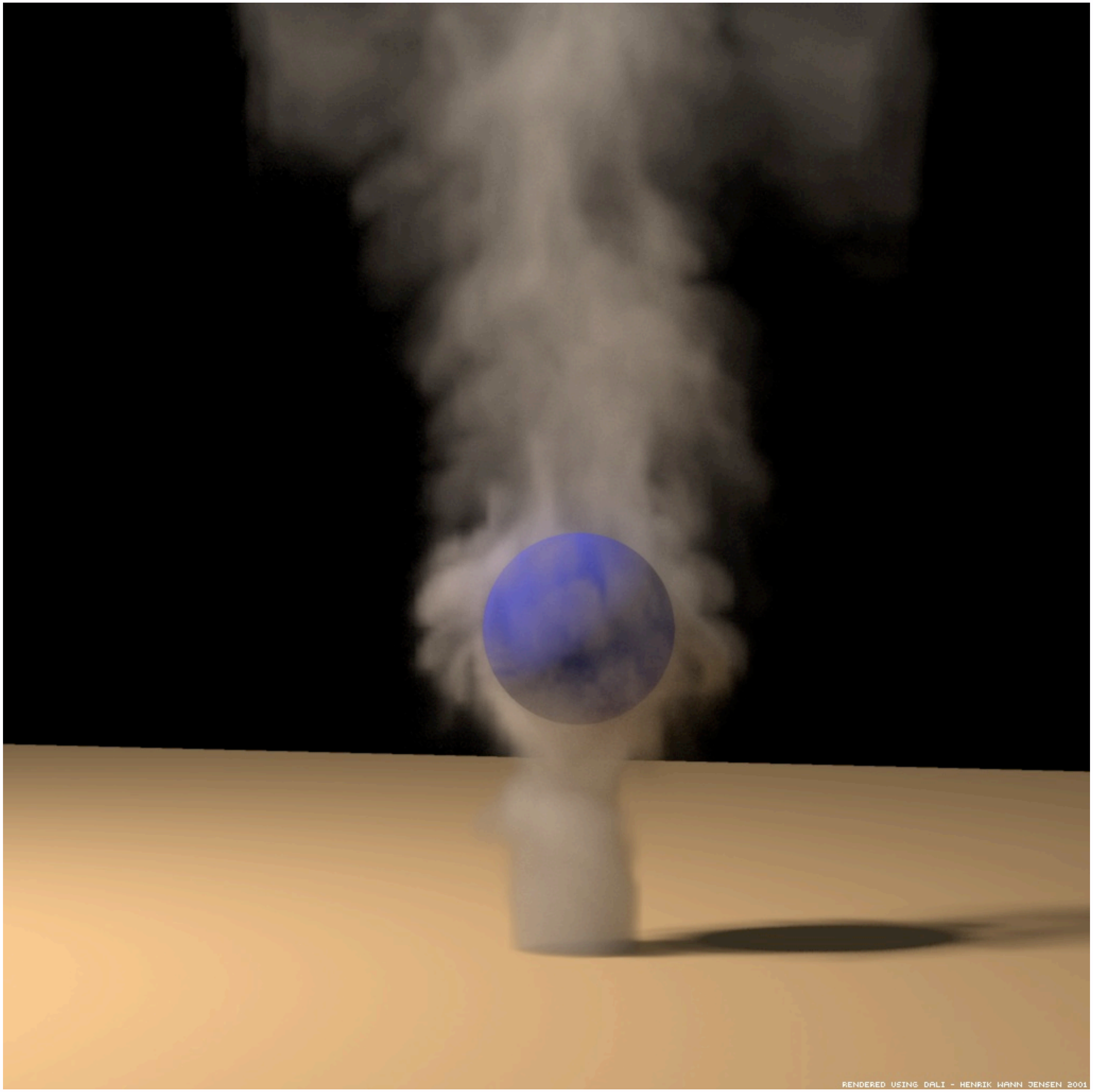

RENDERED USING DALI - HENRIK WANN JENSEN 2001


HENRIK WANN JENSEN 2000

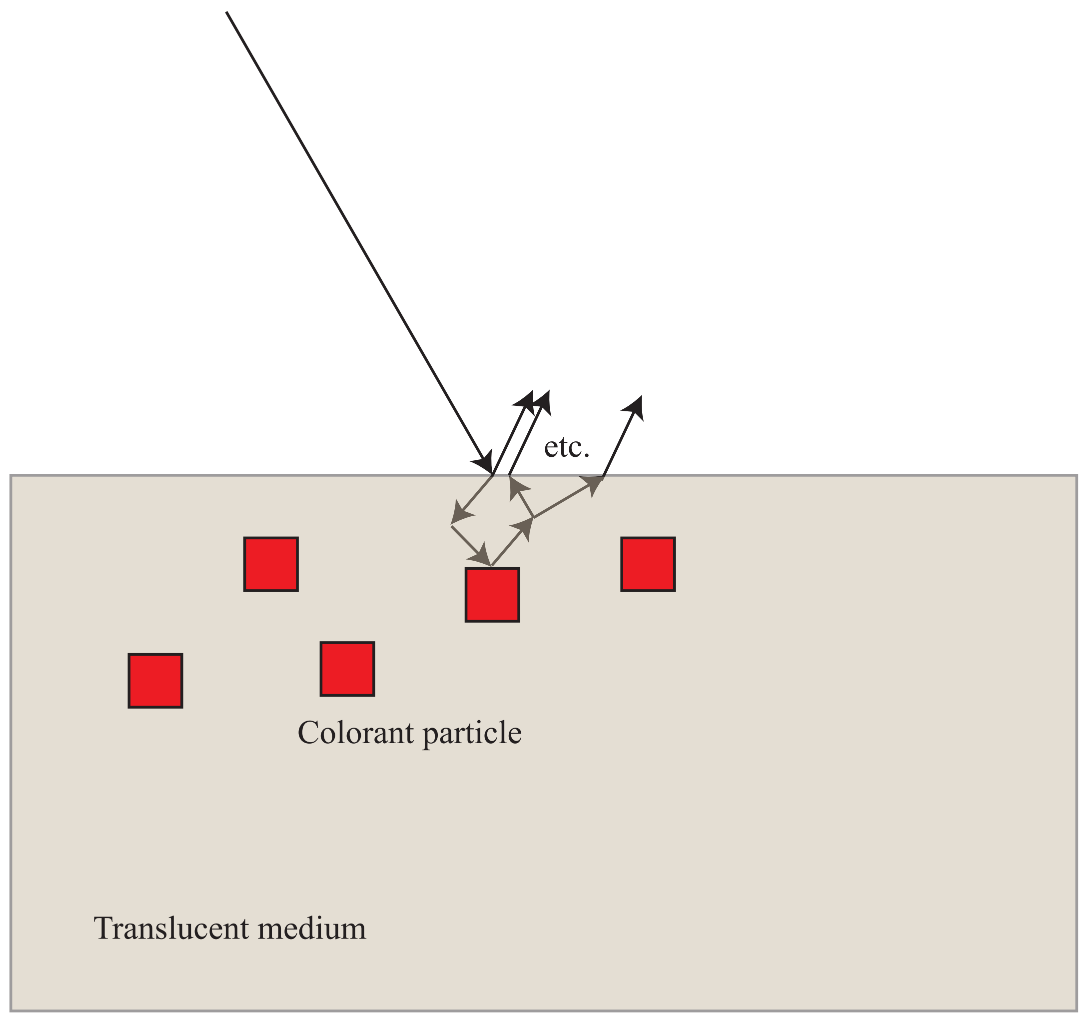

HENRIK WANN JENSEN 2001


HENRIK WANN JENSEN 1999

subsurface scattering in skin (not rendered!)


RENDERED USING DALI - HENRIK WANN JENSEN 2001

Paints are films with colored scatterers

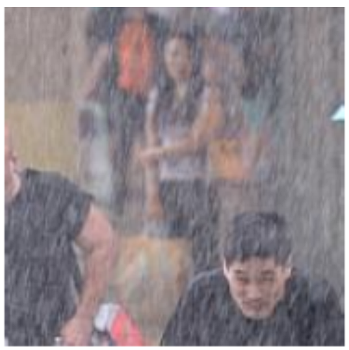


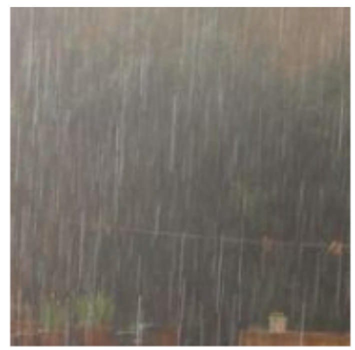
Glowing paint from specular refl’ns

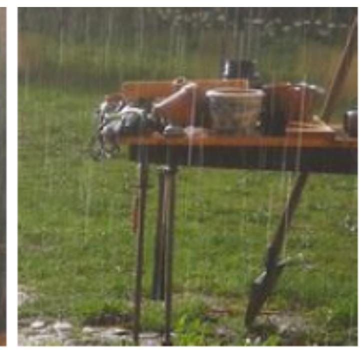
Rain has multiple interesting effects

Blur from wet air

Puddles







Color shifts

Streaks

These are often quite strongly coupled to scene geometry

Rain - multiple extrinsic phenomena,
including smoothing, raindrops, loss of saturation,
glossy/wet surfaces, etc. etc.

Rain - phenomena

Refraction causes each drop to contain a tiny image

(a) An image of a drop hanging from a pipette (b) Perspective views created from (a)

Figure 7. Looking at the world through a raindrop. (a) An image of a drop hanging from a pipette and a magnified version. (b) Near-perspective views computed using the geometric mapping due to refraction. Note that, in the perspective views, straight lines in the scene are mapped to straight lines in the image.

Garg and Nayar 07

Backscatter

- Refraction in drops causes backscatter of headlight light
  - makes driving in rain at night harder
- Neat trick
  - (Tamburo et al 14)
  - Do not illuminate raindrops by
    - having headlights that are highly steerable (multiple micro mirrors)
    - very fast exposure with usual illumination identifies raindrops
      - too fast for driver to resolve
    - now direct light between drops

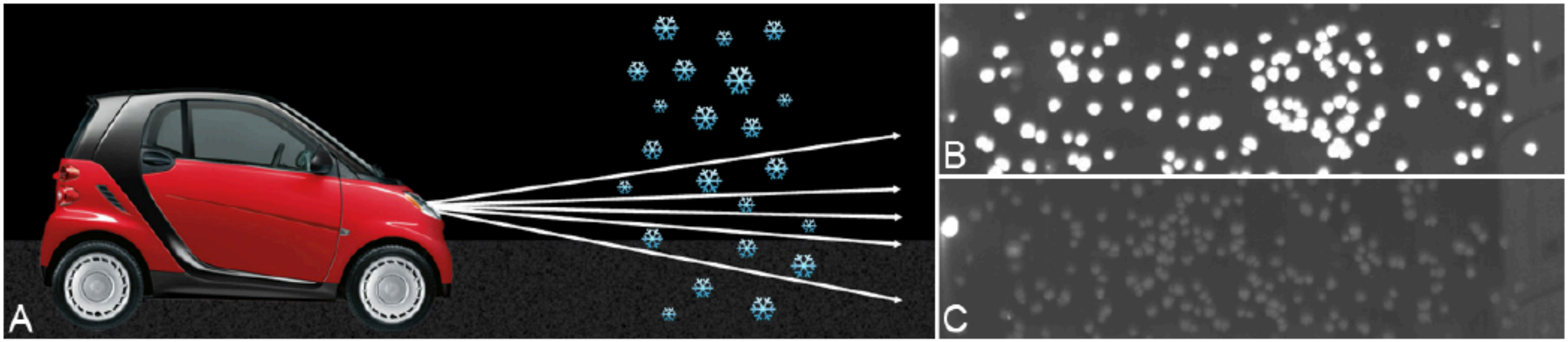
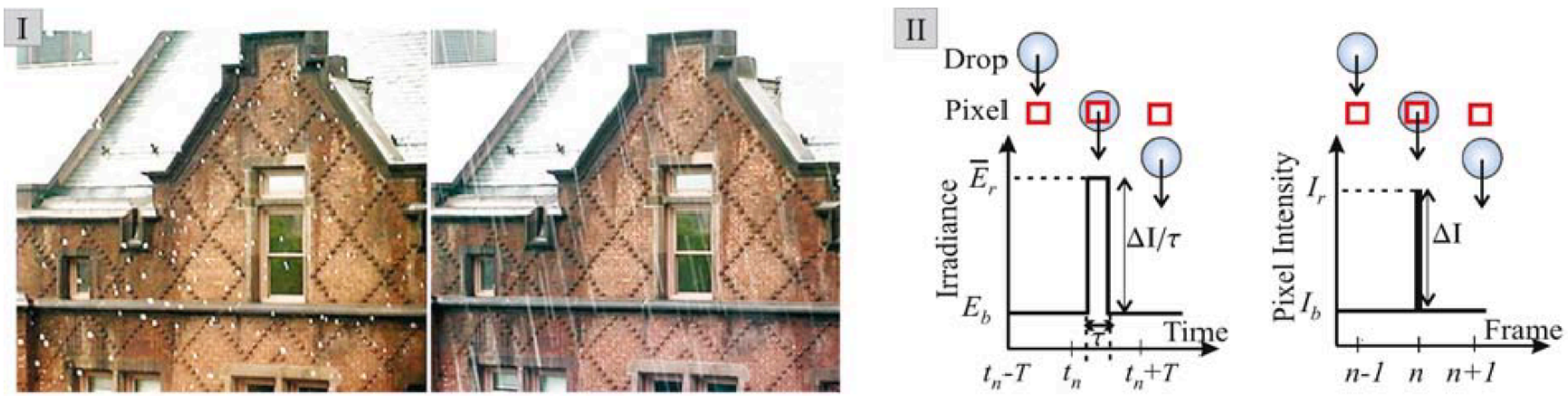


Fig. 7. A: Our headlight has unprecedented resolution over space and time so that beams of light may be sent in between the falling snow. Illustration adapted from [11]. B: Artificial snowflakes brightly illuminated by standard headlight. C: Our system avoids illuminating snowflakes making them much less visible.

Tamburo et al 14

Rain - phenomena

Drops move fast, and so create motion blur (streaks)



(a) Short exposure time (1 ms) (b) Normal exposure time (30 ms) (a) Average irradiance at a pixel (b) Intensity at a pixel

Figure 9. (I) Raindrops and motion-blur. An image of a scene taken in rain with (a) a short exposure time of 1 ms and (b) with typical exposure time of a camera (30 ms). (II) The intensities produced by motion-blurred raindrops. II (a) The average irradiance at the pixel due to the raindrop is $\bar{E}_r$ and that due to the background scene is E_b. Note that $\bar{E}_r > E_b$. The drop projects onto a pixel for time $\tau < 1.18$ ms, which is far less than the typical exposure time T of a camera. (b) Intensities of a pixel in three frames. A drop stays over the pixel in only a single frame and produces a positive intensity fluctuation of unit frame width.

Garg and Nayar 07

Rain - phenomena

Shallow free space - individual rain streaks
Deep free space - more bulk, fog-like effects

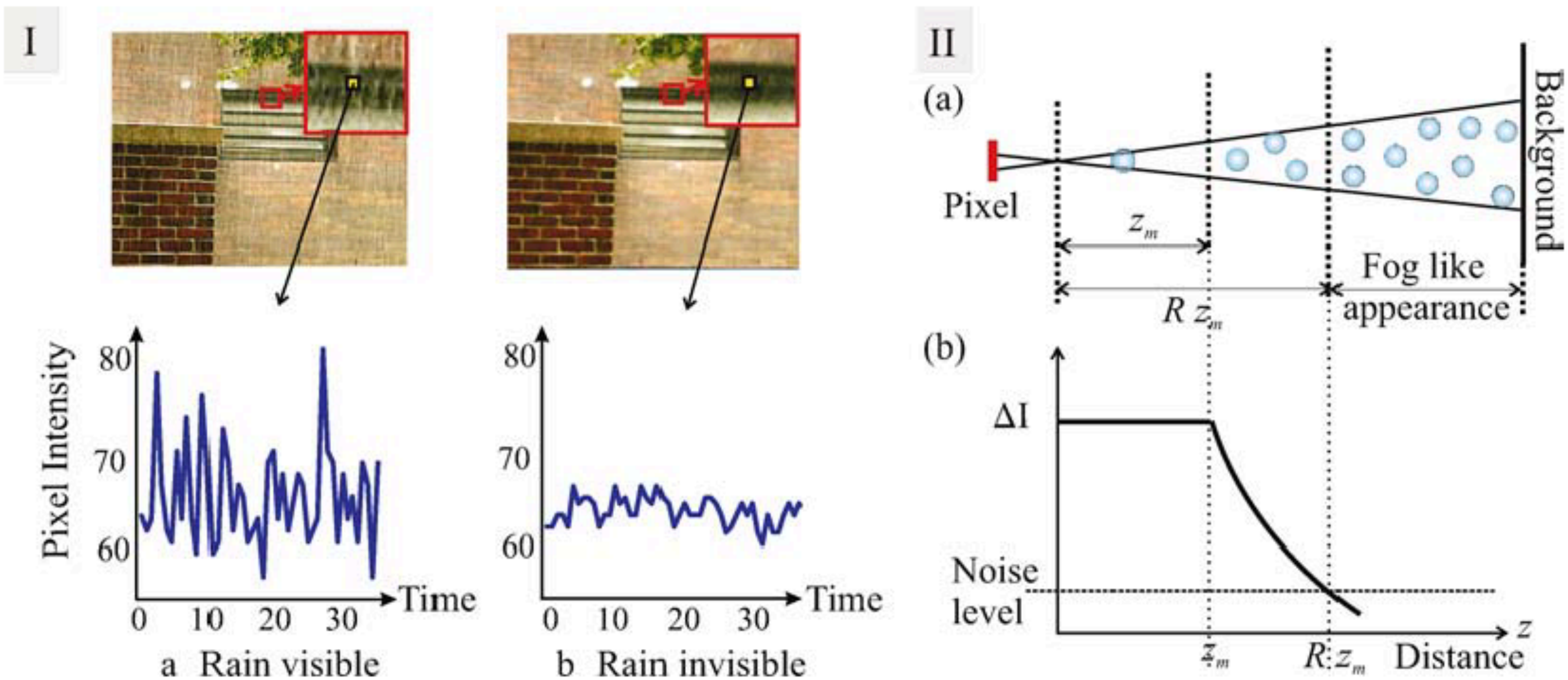
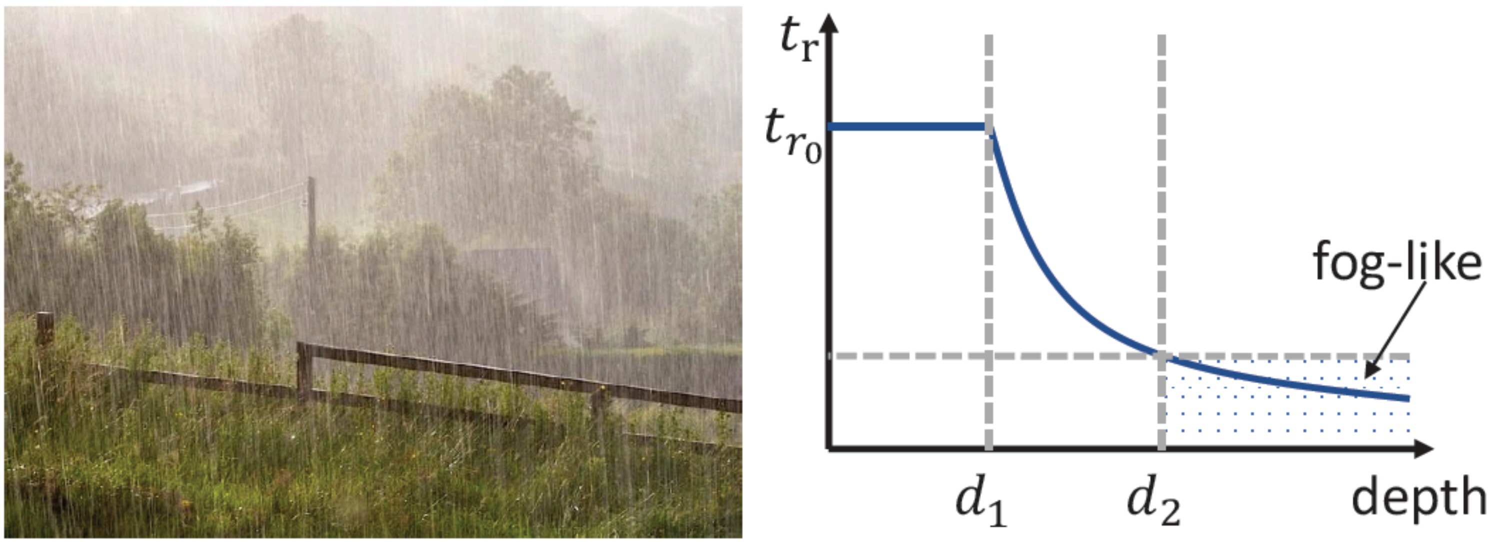


Figure 13. Dynamic weather and visibility: (I)(a) Frame from a video of a scene where rain is visible. The intensity variation due to rain is high. (b) Frame from a video of the same scene taken with camera parameters to reduce the visibility due to rain. The intensity at the same pixel shows low variance over time. (II) The change in intensity produced by a falling raindrop as a function of the drop's distance z from the camera. The change in intensity ΔI does not depend on z for drops that are close to the camera ($z < z_m$). While for raindrops far from the camera ($z > z_m$), ΔI decreases as $1/z$ and for distances greater than $R\,z_m$, ΔI is too small to be detected by the camera. Therefore, the visual effects of rain are only due to raindrops that lie close to the camera ($z < Rz_m$) which we refer to as the *rain visible region*.

Garg and Nayar 07

Rain - phenomena

Shallow free space - individual rain streaks
Deep free space - more bulk, fog-like effects



(a) input real photo (b) rain visibility & depth

Figure 1: (a) An example real photo that demonstrates the scene visibility variation with depth, and the presence of rain streaks and fog; and (b) a plot of rain streak intensity (t_r) against scene depth (d) based on the model in [13].

Hu et al 19

Deraining - strategies

- Essentially
  - obtain images with/without rain (with rain by synthetic)
  - train network to reproduce without rain image from with rain
  - starts with Eigen et al 13

Figure 1. A photograph taken through a glass pane covered in rain, along with the output of our neural network model, trained to remove this type of corruption. The irregular size and appearance of the rain makes it difficult to remove with existing methods. This figure is best viewed in electronic form.

From Eigen et al. 13

Rainy windows

From Eigen et al. 13

Rain streaks

Figure 7: Visual comparison of different rain streak removal methods on real example images.

Li et al 16

Streaks

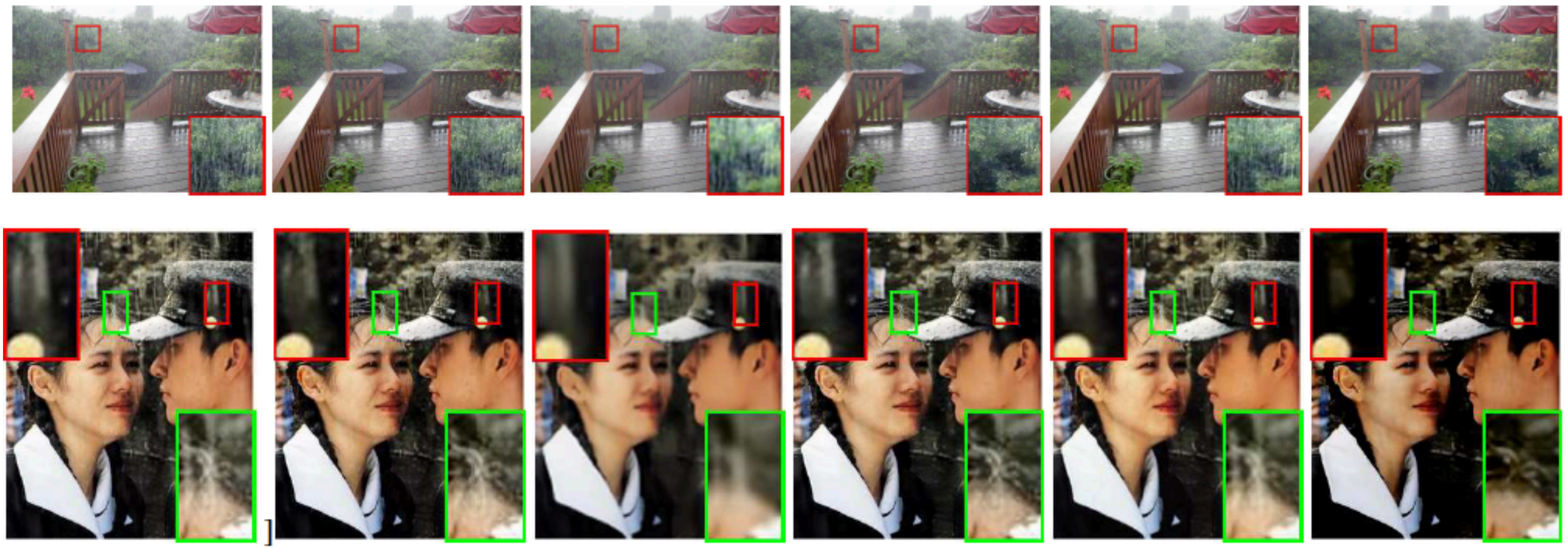


Figure 6: Real rain streaks removal experiments under different scenarios. From left to right are input image, results of DSC[26], LP [24], CNN [10], DID-MDN[31] and ours. Demarcated areas in each image are amplified at a 3 time larger scale.

Wei et al 19

Single image dehazing

- Essentially
  - obtain images with/without haze (with haze by synthetic)
  - train network to reproduce without haze image from with haze

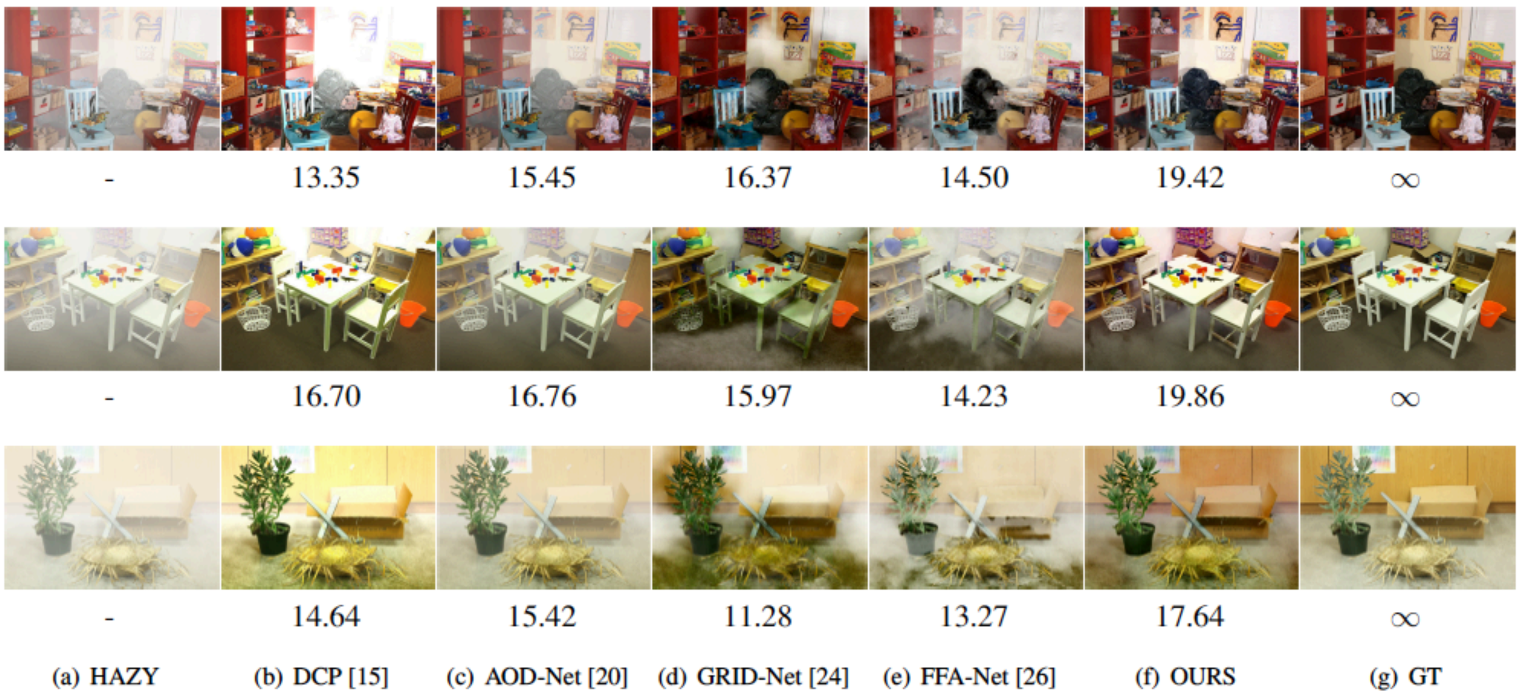


Figure 6. Qualitative comparisons with different state-of-the-art dehazing methods for indoor synthesis hazy images. The top two rows are from SOTS, the third row is from TestA dataset and the bottom three rows are from MiddleBury dehazing dataset. The numbers below image are PSNR (dB) value of each image.

Shen et al 19

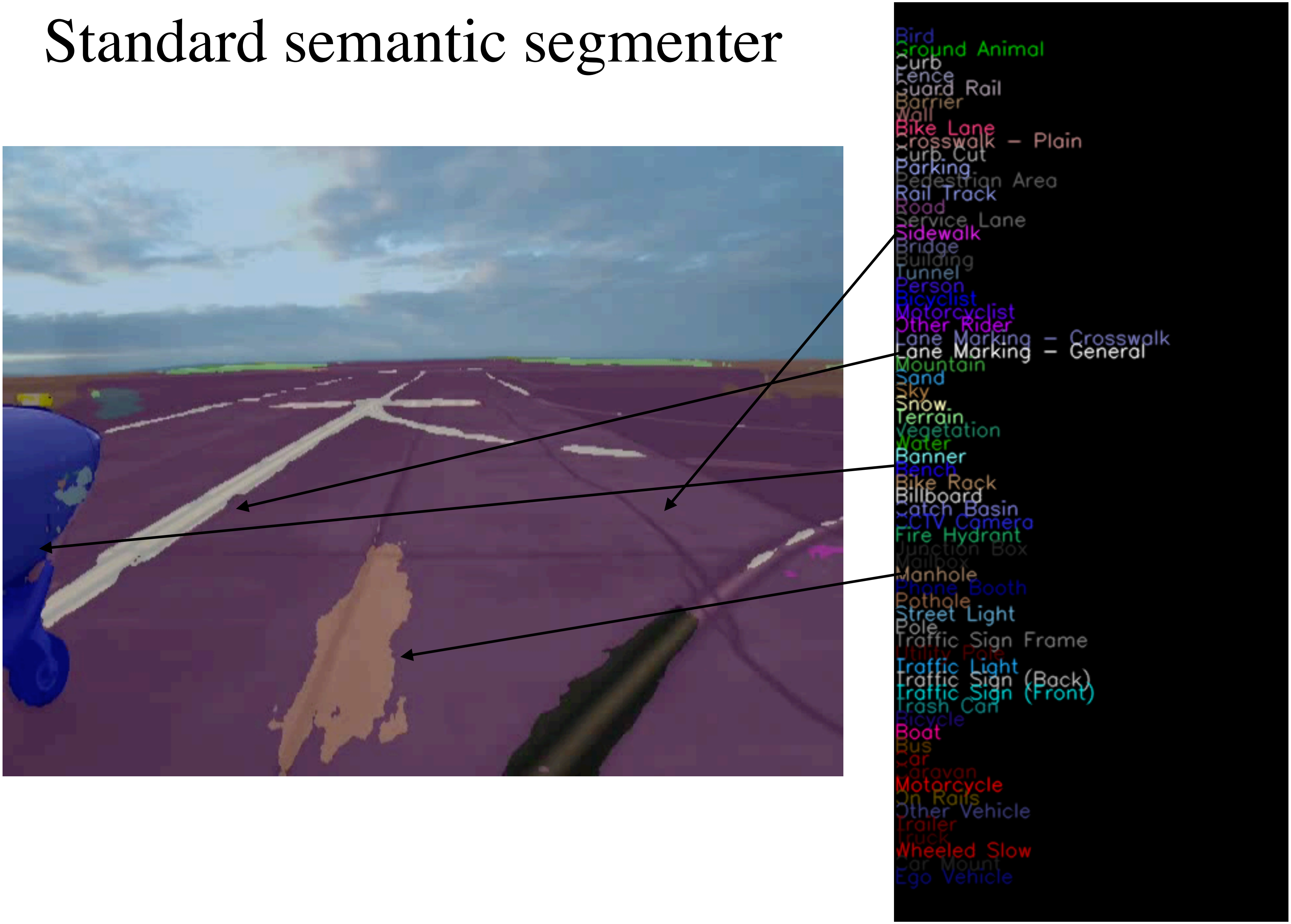
Both rain streaks and haze

Figure 7. Examples of JORDER-R-DEVEIL on heavy rain (left two images) and mist images (right two images).

Yang et al 17

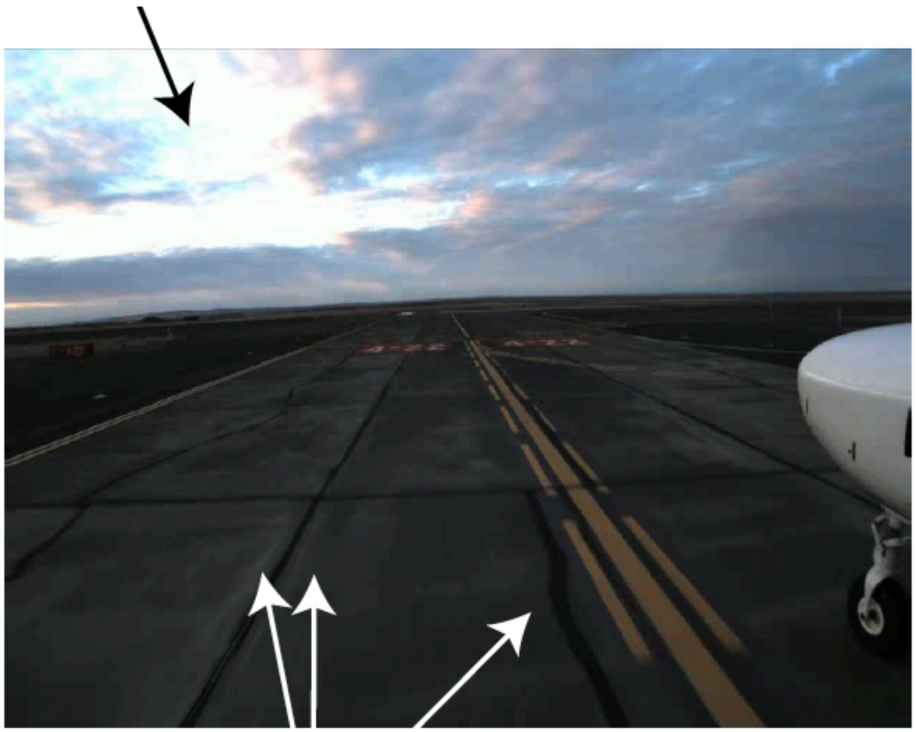
~~Boeing~~ Autonomy data

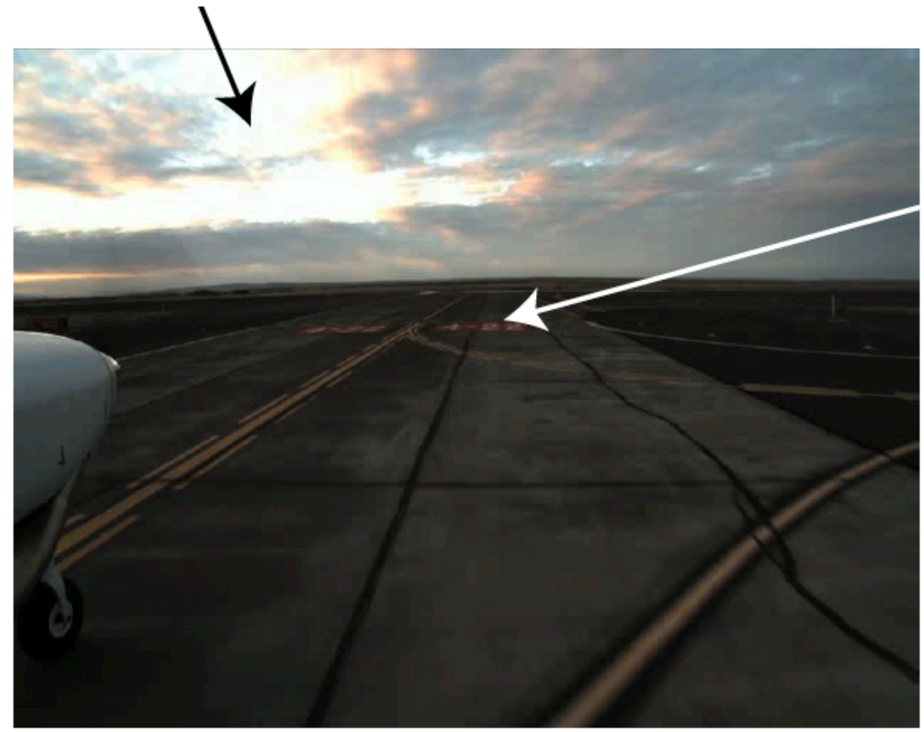
Standard semantic segmenter



Special features: rich appearance variation

Special features: rich appearance variation





Intrinsic images

- (Originally) Maps of an image that explain pixel values
  - Intrinsic properties:
    - independent of viewing; “object” or “world” properties
  - Extrinsic properties:
    - depend on viewing circumstances

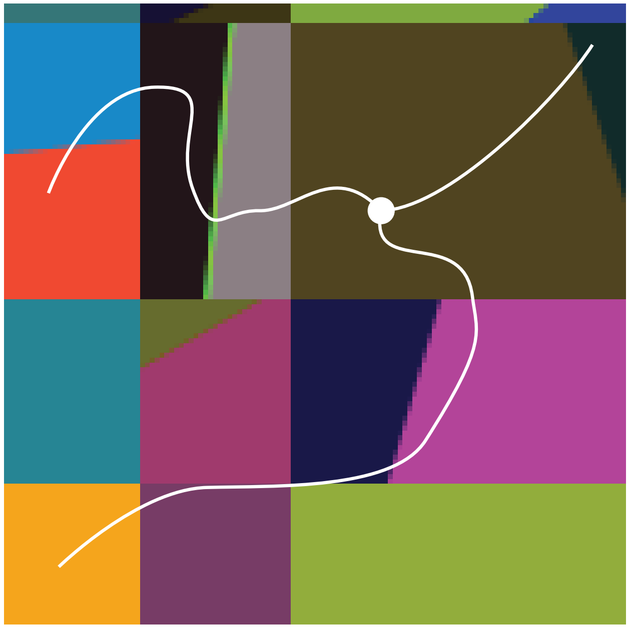
- (Later) Albedo/Shading maps
  - I=A x S
  - Albedo (A) is a natural intrinsic
  - Shading (S) is a natural extrinsic

No ground truth decompositions

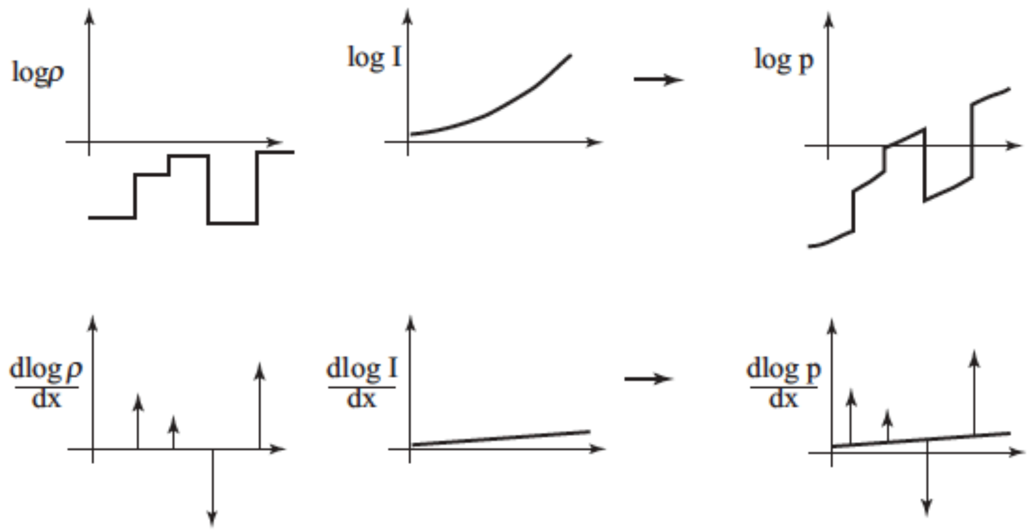
- And there never will be
  - rendering is do-able (but hard)
  - modelling is hopeless
- Q: how do you train an image decomposition method when you don’t know the right answer?
- Retinex provides clues - spatial statistics are the key

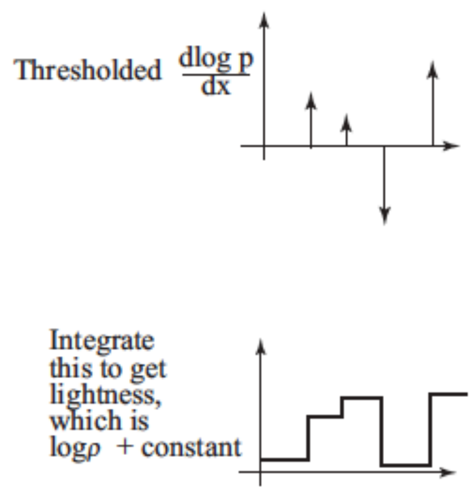
Albedo/shading and Retinex

- Spatial reasoning, Land (59, 59, 77); Land +McCann 71:
  - Surface color changes either quickly or not at all
  - Light color changes slowly
  - Retinex
    - large family of algorithms
    - quite hard to know what Retinex does (Brainard+Wandell, 86)



Computer vision versions of Retinex



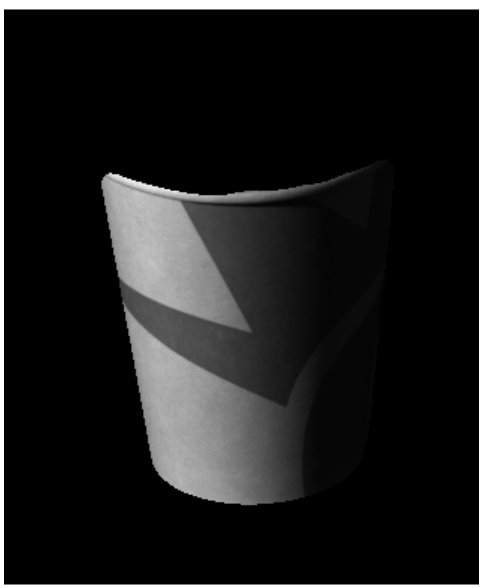


Horn, 73; 74
Brelstaff+Blake, 87;
multiple variants

Real data is hard to collect

- spraypaint, multiple images, etc…

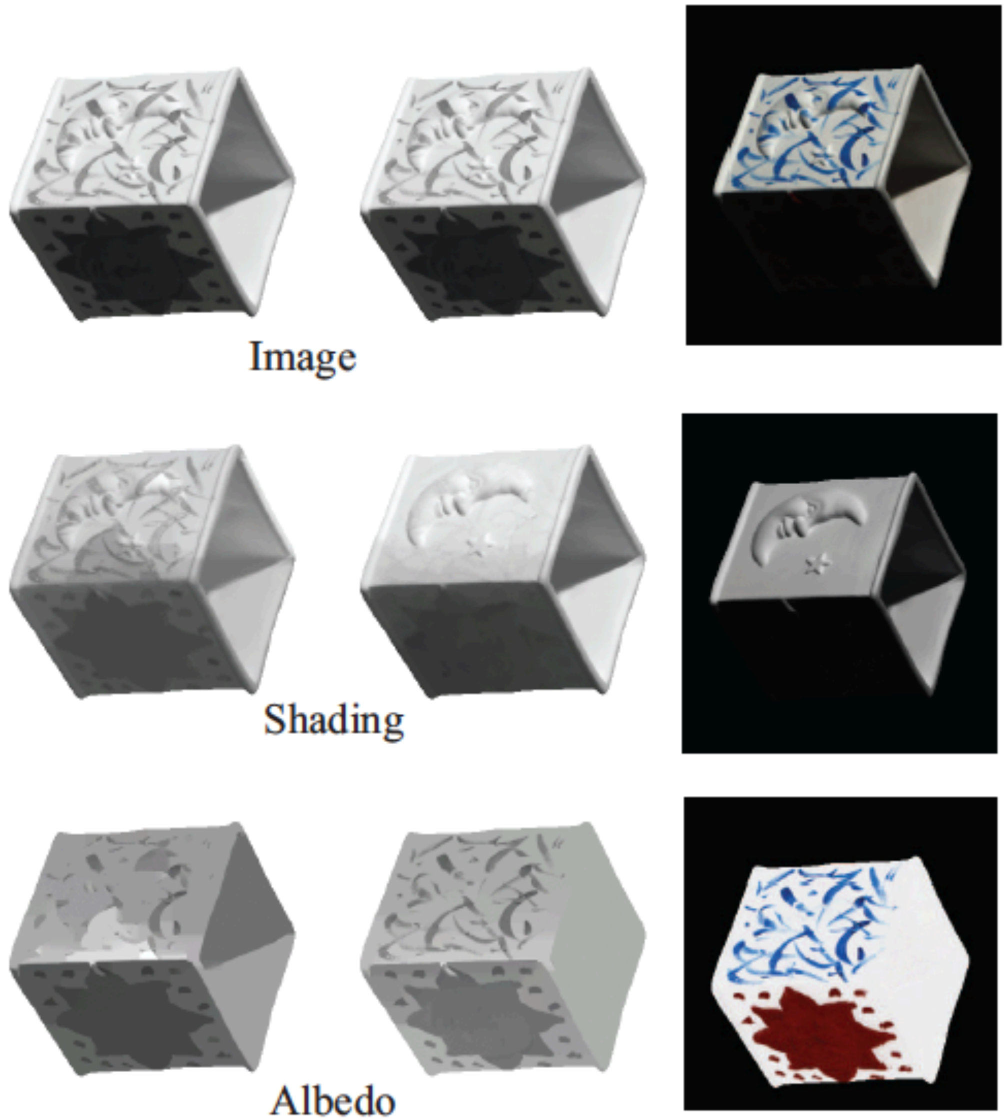
Images from dataset of Gosse et al. 09



Retinex is really quite good

Implementation of Retinex
due to Kevin Karsch

Ground truth
images from dataset of Gosse et al. 09



Human judgements are easier

Code (Github repository) | Pre-computed decompositions (release 0, 4.5M)

Intrinsic Images in the Wild | Publications | Browse | Search | Log i

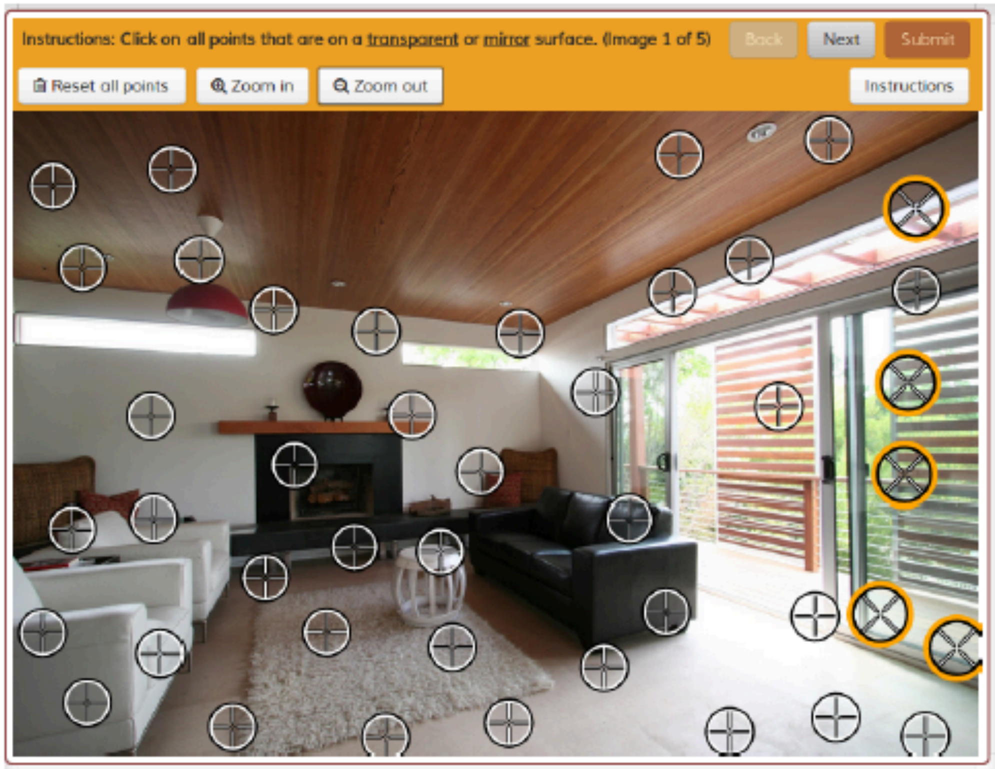
MTurk Tasks

Bell, Bala, Snavely, 2014

We include previews of our instructions, tutorials, and tasks that were shown to online workers.

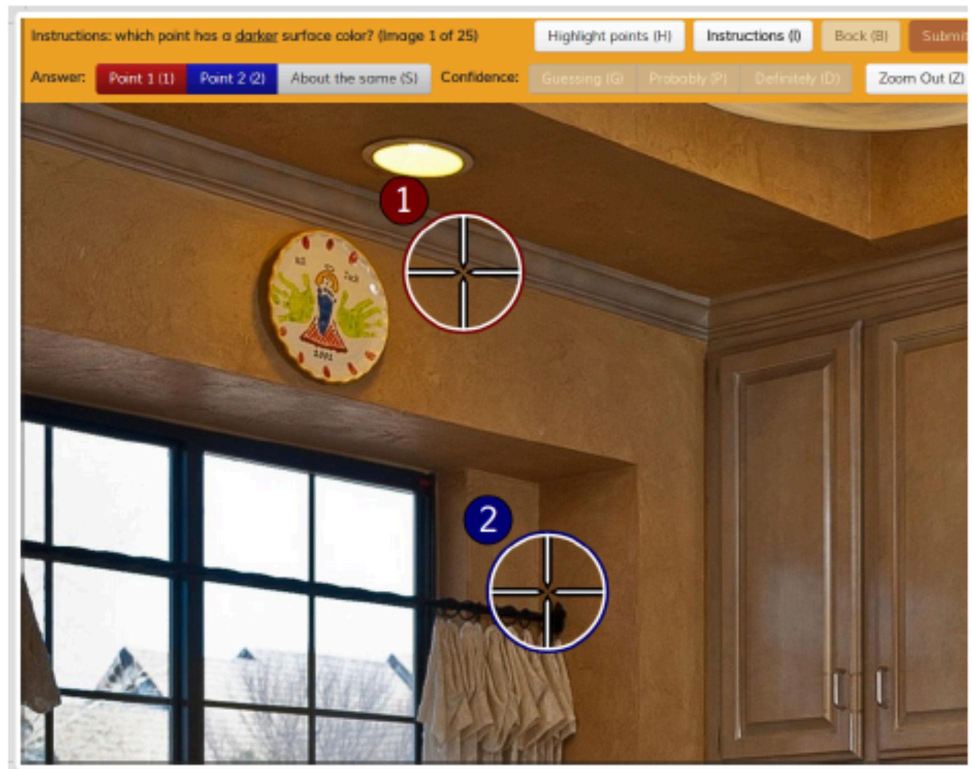
Flag transparent/mirror points

Preview: Intructions | Tutorial | Task



Compare surface reflectance

Preview: Intructions | Tutorial | Task



This gives an evaluation task

- WHDR=Weighted Human Disagreement Ratio
  - compute lightness from intrinsic image representation at points
  - predict
    - A lighter than B
    - B lighter than A
    - Lightness match
  - compute weighted estimate of accuracy
    - weights low where human judgements are uncertain, high otherwise
- There are issues, but allows evaluation
  - and competition

Modern strategies - Optimization

- Apply the priors that
  - albedo is piecewise constant
  - there are “few” albedo values
  - albedo and shading explain image
- Solve
  - eg Bell 14, Nestmeyer 17, Bi 15

Modern strategies - Regression

- Regression of ground truth against image
  - use training set from WHDR data (Narihira et al 2015)
    - and perhaps rendered data
  - surprisingly, rendered data is very helpful
    - Li et al 18; Bi et al 18; Fan et al 18; etc
- Surprising because
  - Albedo in renderings isn't like albedo in the world
  - Illumination in renderings *really* isn't like illumination in the world

Recent history

Method	Source	Training uses IIW labels	Training uses CG	Flattening	Test WHDR
Shi *et al.* '17 [26]	[27]	N	Y	N	54.44
Zhou *et al* '15 [28]	[27]	Y	N	Y	19.95
Narihira *et al* [29]	ibid	N	N	N	18.1
Bi *et al* '18 [27]	ibid	N	Y	Y	17.18
Zhou *et al* '15 [30]	ibid	Y	N	Y	15.7
Li and Snavely '18 [31]	ibid	Y	Y	Y	14.8
Fan *et al* '18 [32]	ibid	Y	N	Y	14.45
*Zhao *et al.* '12 [14]	[29]	N	N	N	26.4
Shen and Yeo '11 [23]	[29]	N	N	N	26.1
Yu and Smith '19 [33]	ibid	N	N	N	21.4 (a)
Retinex (rescaled; color/gray)	[29]	N	N	N	19.5*/18.69*
Bell *et al* '14 [34]	[29]	N	N	Y	18.6
Liu *et al* '20 [35]	ibid	N	Y+	N	18.69
Bi *et al* '15 [36]	ibid	N	N	Y	18.1
Bi *et al* '15 [36]	[27]	N	N	Y	17.69
[redacted]					

TABLE 1

*Summary comparison to recent high performing supervised (above) and unsupervised (below) methods, all evaluated on the standard IIW test set; sources indicated. We distinguish between training with IIW and threshold selection using IIW. WHDR values computed for Retinex use the most favorable scaling, using the rescaling experiments of [29]. For our method, we report the held-out threshold value of WHDR. We report two figures for [36], because we found two distinct figures in the literature. Key: * - method uses IIW training data to set scale or threshold ONLY. + - [35] build models of albedo and shading from CGI, but does not use them for direct supervision. a - [33] use patches of registered images from MegaDepth.*

WHDR is tricky - I

Narihira et al 15

From Fan 18

Methods	WHDR (mean)
Baseline (const shading)	51.37
Baseline (const reflectance)	36.54
Shen *et al.* 2011 [17]	36.90
Retinex (color) [11]	26.89
Retinex (gray) [11]	26.84
Garces *et al.* 2012 [9]	25.46
Zhao *et al.* 2012 [20]	23.20
L_1 flattening [3]	20.94
Bell *et al.* 2014 [2]	20.64
Zhou *et al.* 2015 [21]	19.95
Nestmeyer *et al.* 2017 (CNN) [16]	19.49
Zoran *et al.* 2015* [22]	17.85
Nestmeyer *et al.* 2017 [16]	17.69
Bi *et al.* 2015 [3]	17.67
Ours w/o D-Filter	15.40
Ours w/o joint training	14.52
Ours	**14.45**

Table 1. Quantitative results on the IIW benchmark. All the results are evaluated on the test split of [15], except for the one marked with * which is evaluated on their own test split and is not directly comparable with other methods.

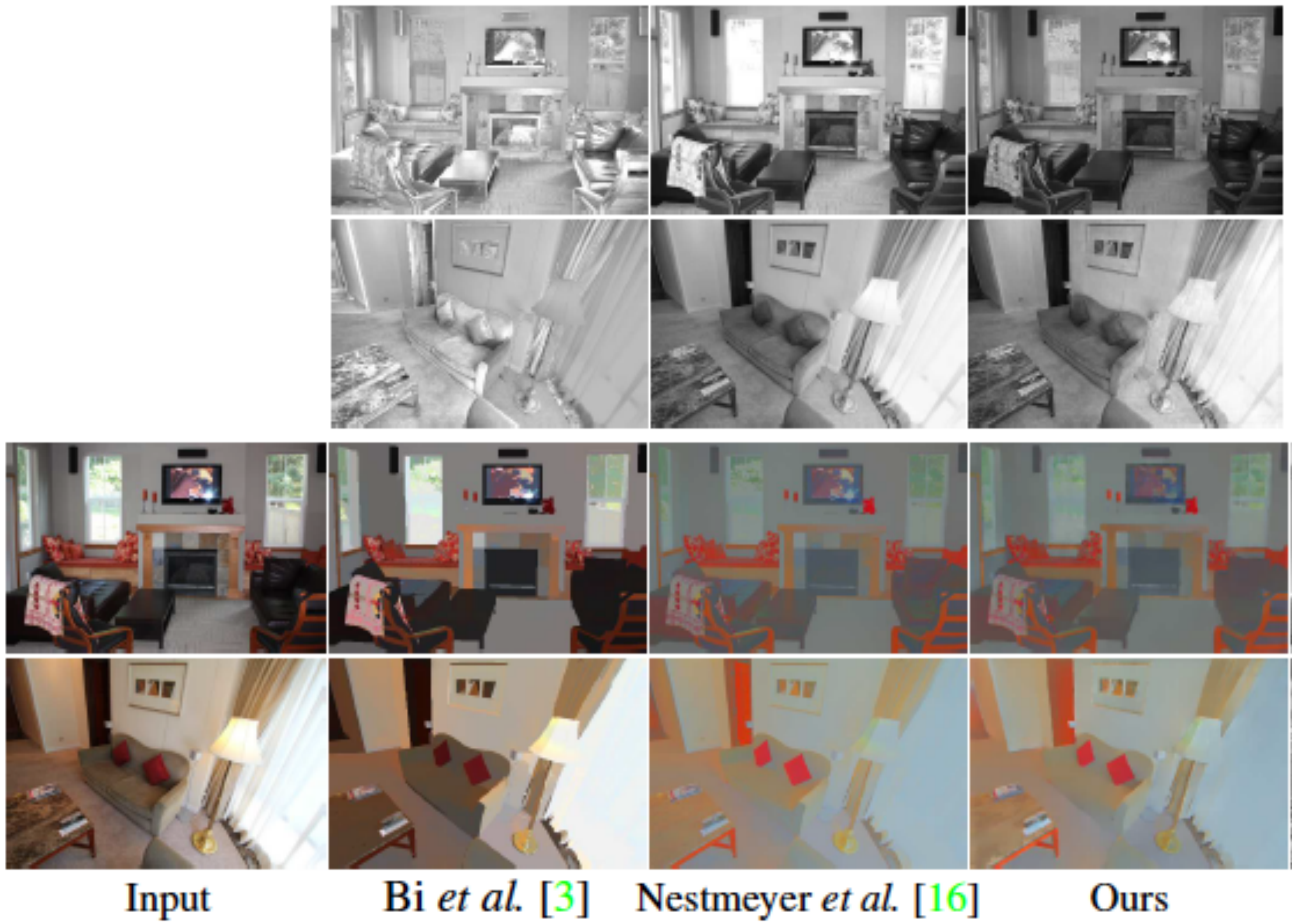
	WHDR (%)	Error Rate (%)
Ours (HSC)	20.9	24.5
Ours (CNN)	18.3	22.3
Ours (CNN-ImageNet)	**18.1**	**22.0**
CRF [4] (rescaled)	18.6	22.3
Retinex-Color [10] (rescaled)	19.5	23.3
Retinex-Gray [10] (rescaled)	19.8	23.8
Shen and Yeo [22] (rescaled)	23.2	26.1
Zhao *et al.* [26] (rescaled)	22.8	26.4
CRF [4]	20.6	25.6
Retinex-Color [10]	26.9	32.4
Retinex-Gray [10]	26.8	32.3
Shen and Yeo [22]	32.5	35.1
Zhao *et al.* [26]	23.8	28.2

Table 1. **Intrinsic Images in the Wild benchmark results.** For each algorithm, we display the weighted human disagreement rate (WHDR, lower is better), as well as the error rate on classifying the sign of lightness change between pairs of points labeled in the ground-truth. We include our own re-evaluation of competing methods, which closely matches the performance reported in [4]. In addition, we report performance of a rescaled version of competing methods, which specifically optimizes their output for the pairwise classification task. Our algorithm is on par with the CRF approach developed by [4] for state-of-the-art performance. We refer the reader to [4] for comparison to an expanded set of prior work.

WHDR is tricky - II

- Predict by
  - $f(m1, m2) > t$ -> 1 is lighter
  - $-t < f(m1, m2) < t$ -> same
  - $f(m1, m2) < -t$ -> 2 is lighter
- Issues:
  - choice of f
    - m1 - m2
    - log(m1/m2)-1
  - choice of m
    - lightness potential
    - predicted albedo
  - choice of threshold
    - interacts with scale

WHDR is tricky - III



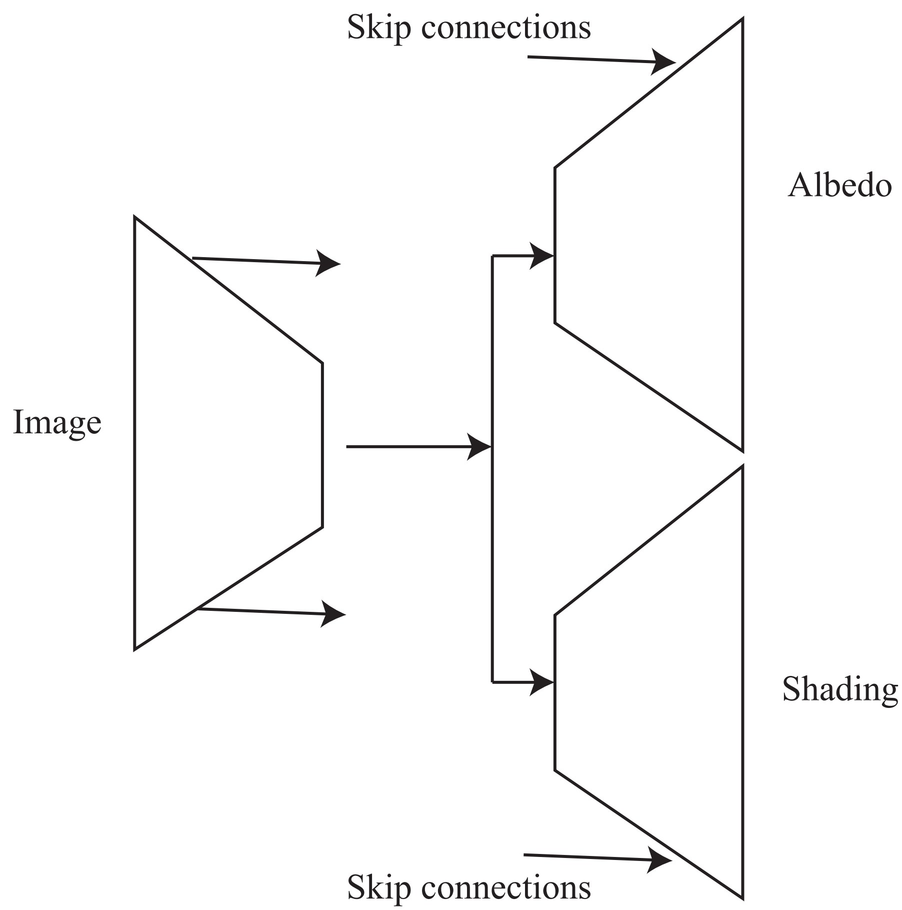
Fan 18 - current SOTA WHDR of 14.45%

WHDR is tricky - IV

Bi et al, 2018 - this image WHDR 6.61%

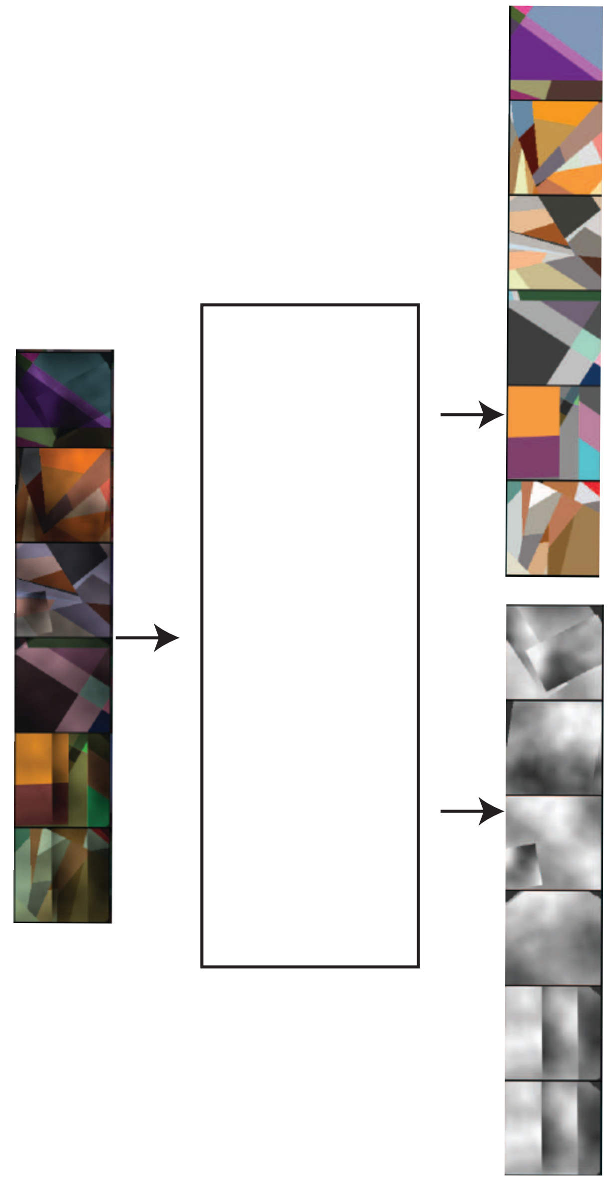
- Note:
  - odd colors
  - “colored paper” effect
  - “indecision”

One approach (local!)

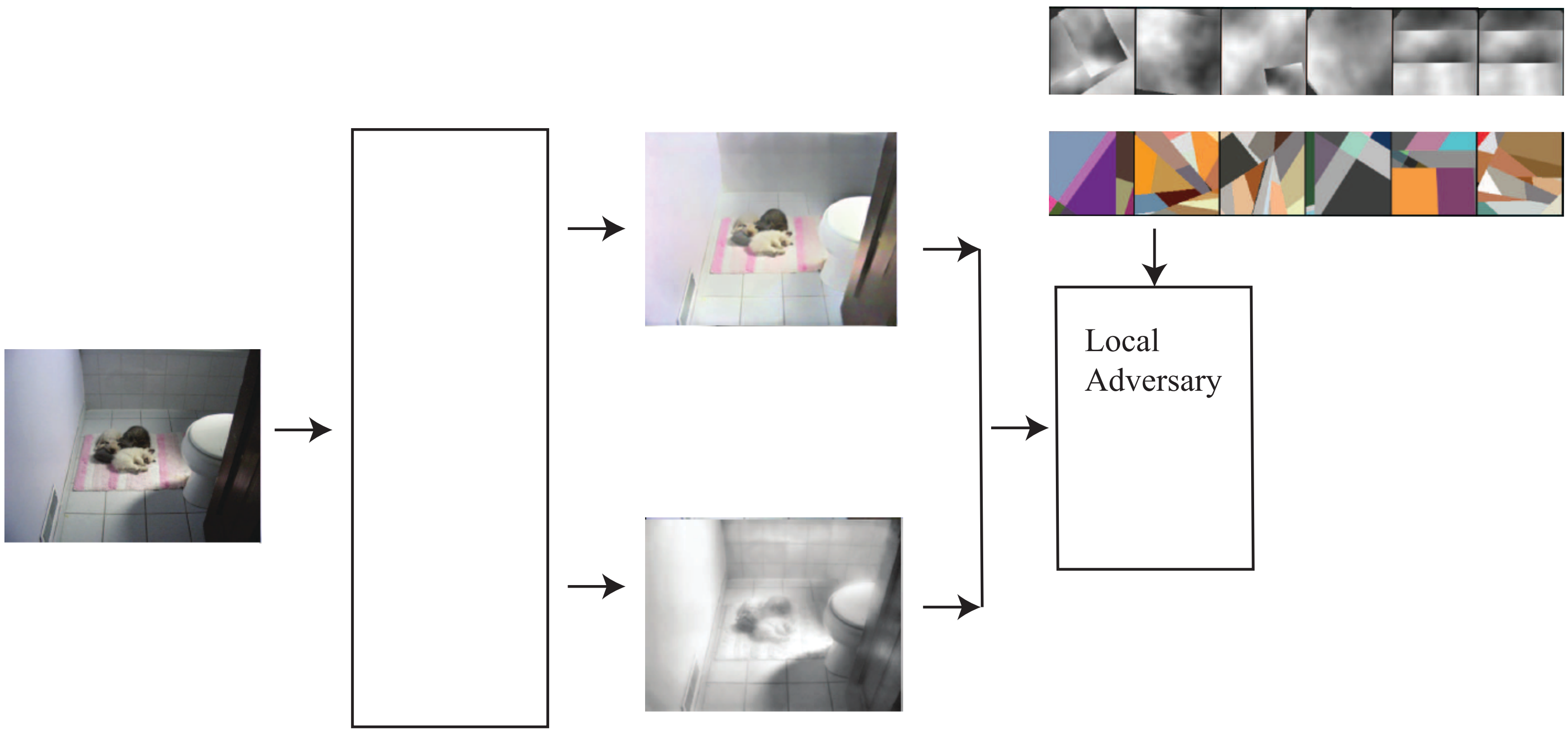


Training - I

Our albedo paradigm uses a surface color model and a spatial model. The qualitative properties it is intended to capture are: albedoes are piecewise constant; the color distribution should reflect likely surface colors; there should be a profusion of edges with no strong orientation bias; there should be at least some vertices with degree greater than three. Surface color is modelled by drawing color samples uniformly and at random from the IIW training set. These must be adjusted for presumed illumination. We do so by assuming the range of illumination intensity is approximately the same as the range of lightnesses, and so dividing by the square root of intensity.



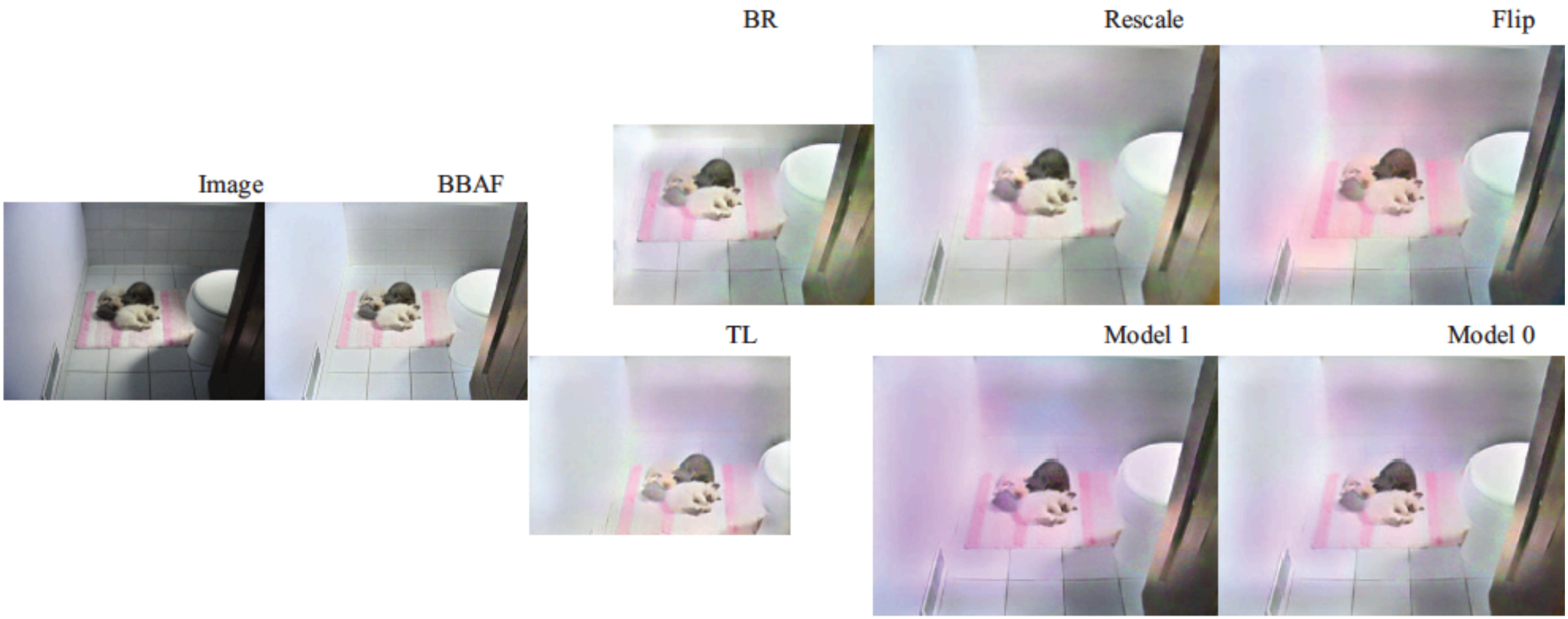
Training - II



Inference

- Network is trained on 128 x 128 tiles of image
- We want equivariance properties from albedo, shading
  - eg translate, rotate, scale image
    - albedo for translated (etc) image should be translated albedo
    - shading for translated (etc) image should be translated shading
- This doesn't come naturally

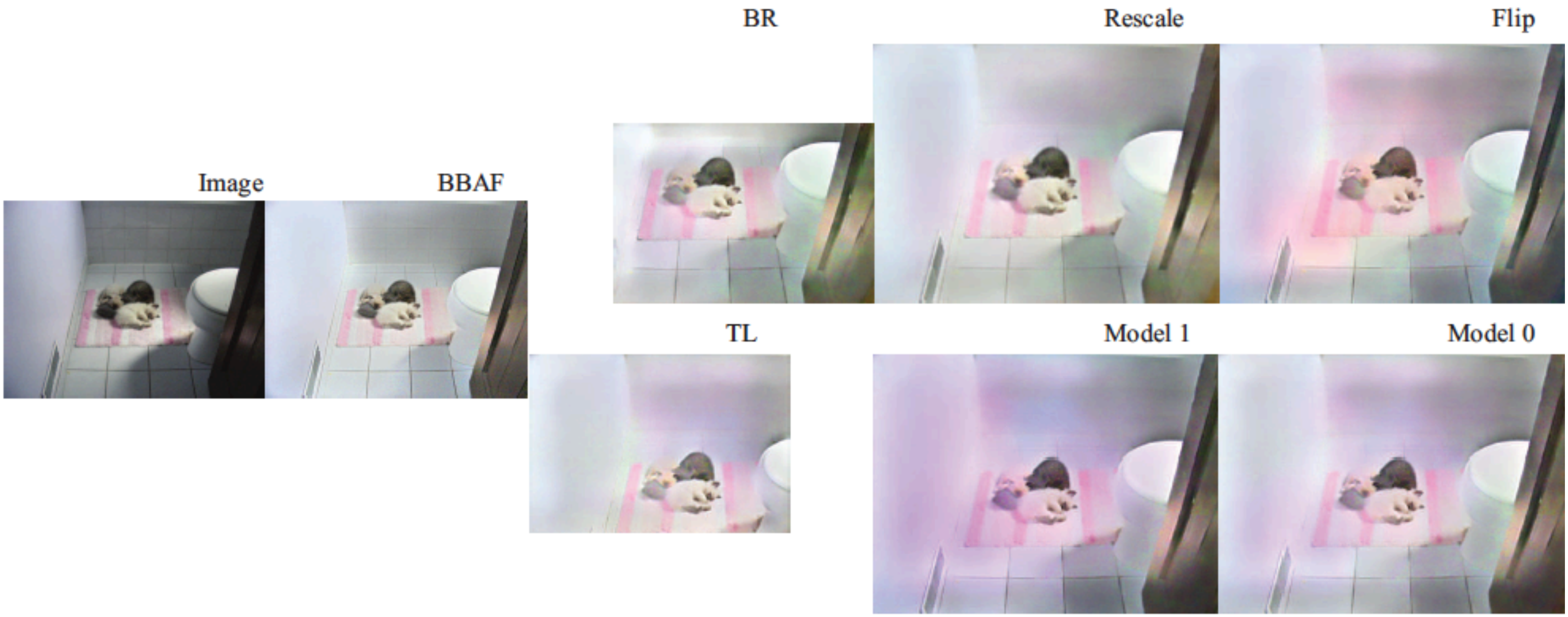
Equivariance must be imposed



Imposing equivariance

- Translation:
  - cover image with many, shifted, overlapping tiles
  - for each, recover albedo, shading
    - albedo at pixel is weighted average of all overlapping tiles
- Scale:
  - rescale image up, down
    - for each, recover albedo/shading using translation averaging
    - then rescale back
  - average results
- Rotation
  - average estimates from above over 8 flips

Averaging very strongly suppresses error



Results

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Bi *et al* '15 [36]	[27]	N	N	Y	17.69
Our **BBA**		N	N	N	17.04*
Our **BBAF**		N	N	N	17.11*

TABLE 1

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Fig. 2. *Qualitative examples, from our best model (*BBAF*), showing (L to R): suppression of indoor shadows; suppression of backscatter from shiny bathroom fittings; suppression of fast shading effects from clothing folds; correctly handled dark shadow (couch back).*

Fig. 6. *Qualitative comparison to [27], [26], [48], [45] and [62], using parts of Figure 1 of [27]. As [27] remark, the methods of [26] and [48] are trained on rendered data alone, and face difficulties due to the difference between rendered data and real images. As [27] remark, the methods of [48] and [45] face difficulties due to the deep shadows in the scene. The albedo produced by our method does not show the "colored paper" effect seen in other methods and does not produce odd colors; this is an advantage (text). Our method reports albedo and shading up to image boundaries, that of [27] appears not to (the crop of the figures is as in the original paper; for our method, we show the whole image).*

Smoothing is important

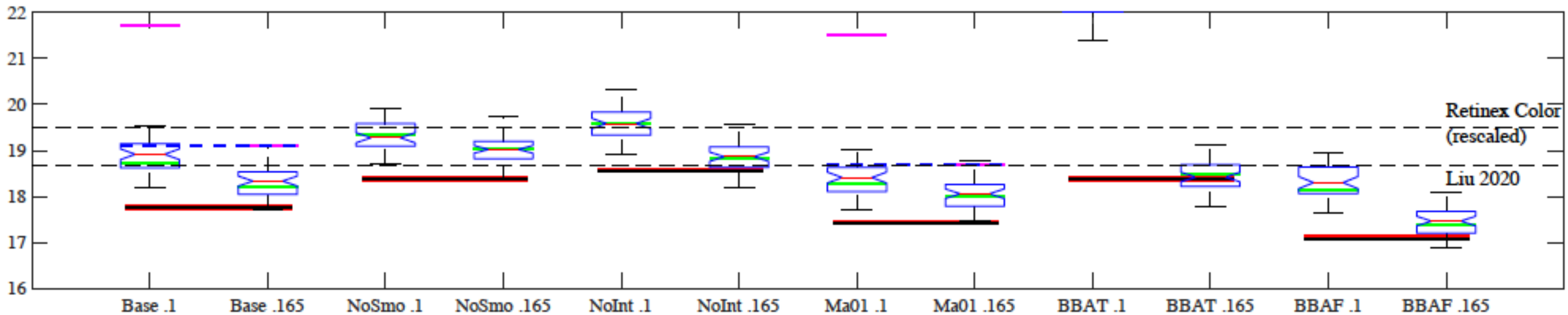


Fig. 8. *Smoothing, averaging and postprocessing are important. Without adversarial smoothing (***NoSmo***), performance is comparable to Retinex. Adversarial smoothing* alone *(***NoInt***) is surprisingly well behaved. Averaging makes a very significant difference (compare blue/black bars and purple/green bars) and averaging over a larger number of tiles is better (cf.* **BBA** *and* **Base***). Discrete image averaging results in improvements (cf.* **BBA** *and* **BBAF***), and is clearly better than discrete tile averaging (cf.* **BBAF** *and* **BBAT***).* **Key:** Fixed thresholds: *shown in boxplots of WHDR values for 50 simulated test sets for the two fixed thresholds, and green bars are the value for the standard test set.* Oracle thresholds: *heavy black bar.* Held out threshold: *heavy red bar.* Oracle threshold without smoothing: *heavy blue dashed bar.* Fixed threshold without smoothing: *heavy purple bar.* Boxplots: *horizontal bar = median; notch = fraction of interquartile range outside which a difference in medians is significant; bottom and top of the box = 25 and 75 percentiles resp.; whiskers extend to the most extreme data points that are not outliers; outliers – greater than 1.5 times the interquartile range outside top and bottom – are '+'.* Best viewed in color.

Paradigms beat graphics

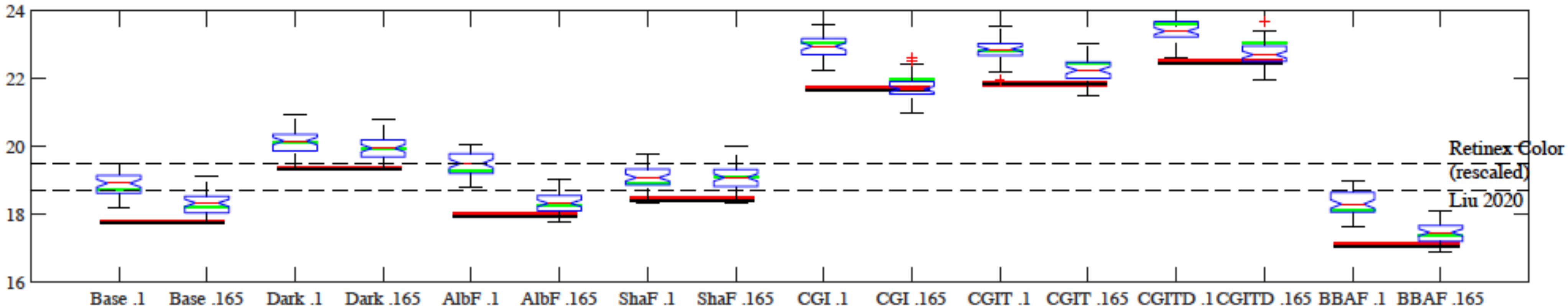


Fig. 9. *Varying the details of the paradigm has some effect; a* Dark *shading paradigm creates notable difficulties, but varying the size of shading (*ShaF*) and albedo (*ShaF*) fragments seems to have only minor effects. Using tiles excerpted from CGIntrinsics [47] leads to significant fall off in performance (*CGI *– tiles extracted from CGIntrinsics at original scale;* CGIT *– extracted from images shrunk so that tiles contain more detaile;* CGITD *– dependency between shading and albedo preserved). Graphical conventions as in Figure 5.* Best viewed in color.

Scale matters

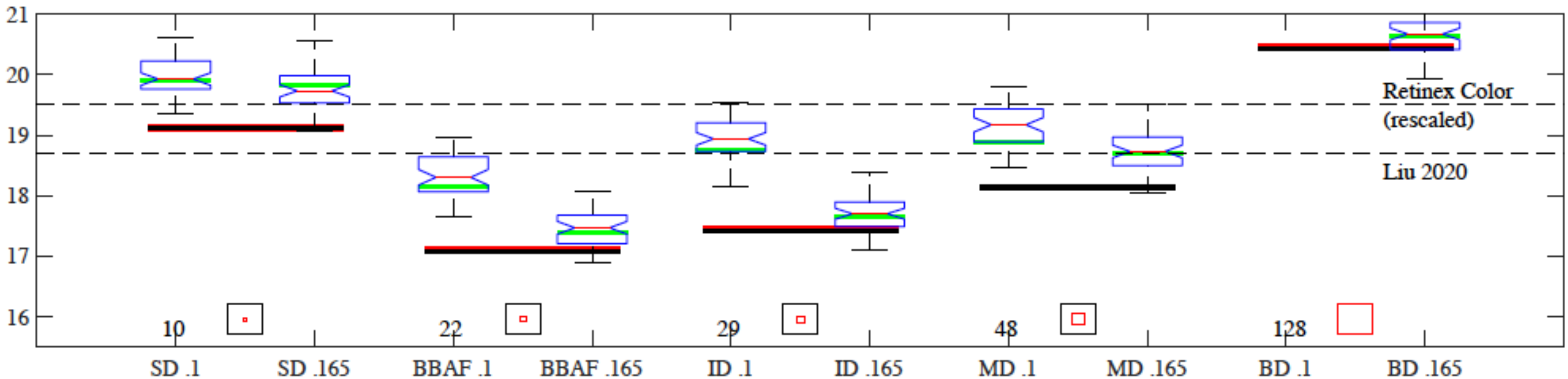


Fig. 10. *Varying the scale of the discriminator has an important effect on performance.* **SD** *the discriminator sees* 10×10 *patches;* **BBAF** *as in other figures our best model,* 22×22*;* **ID** 29×29*;* **MD** 48×48*; and* **BD** 128×128*. The scale of* **ID** *was chosen by interpolating oracle WHDR for the others, then choosing the scale that produced the best predicted WHDR. The red boxes show the scale of the discriminator patches with respect to the tile (black boxes) for each model. Graphical conventions as in Figure 5.* Best viewed in color.

Indecisiveness remains (aargh!)

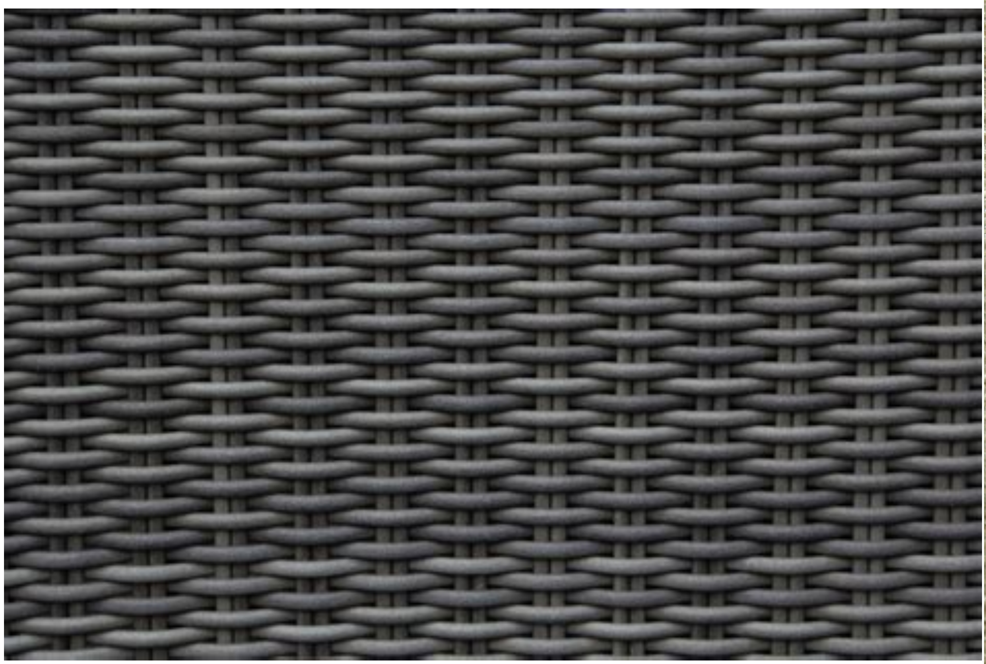
Fig. 13. *Our method suffers indecisiveness, as do others; this is a persistent problem in intrinsic image methods. Figures show a decomposition of an outdoor image, using our method. Note the pronounced shadow leaves effects in both albedo and shading fields; versions of this effect for other methods can be seen in Figure 6.* Best viewed in color.

Other Possible Intrinsics

- Surface relief and material properties
  - and perhaps many of them
- Surface mechanical properties
- Surface glossiness
- Texture flow

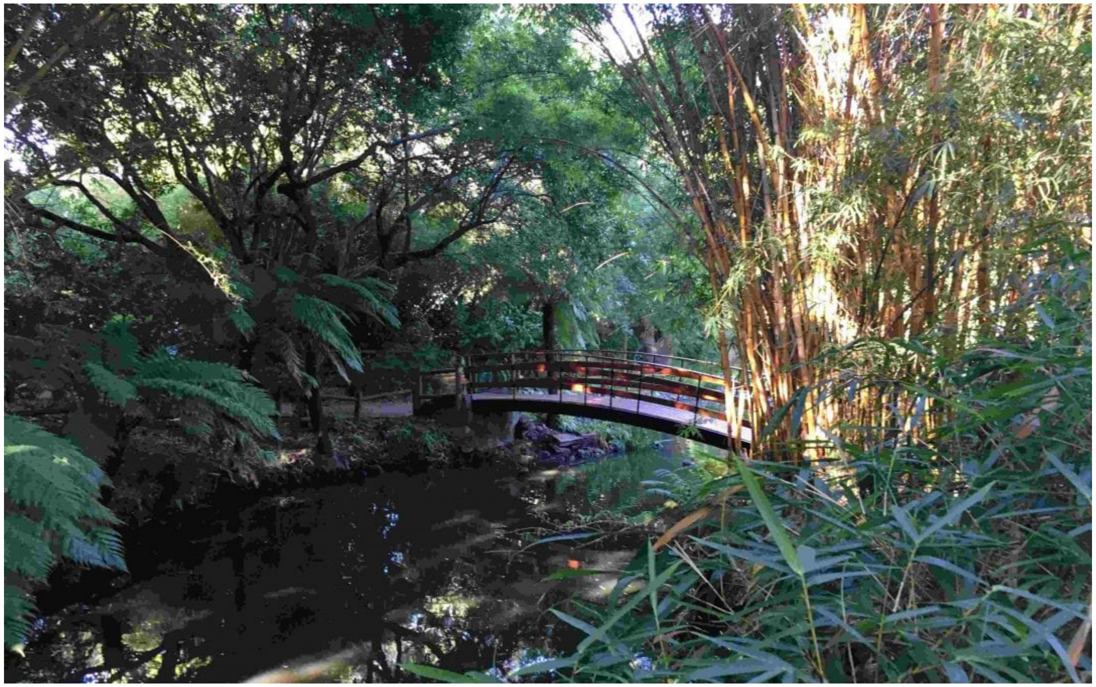
Relief - intrinsic, because
small local shadows do not
move with illumination
(at least Koenderink+Van Doorn, 77)

Relief - intrinsic, because
small local shadows do not
move with illumination
(at least Koenderink+Van Doorn, 77)



Fur - intrinsic, because
small local shadows do not
move with illumination
(at least Koenderink+Van Doorn, 77)

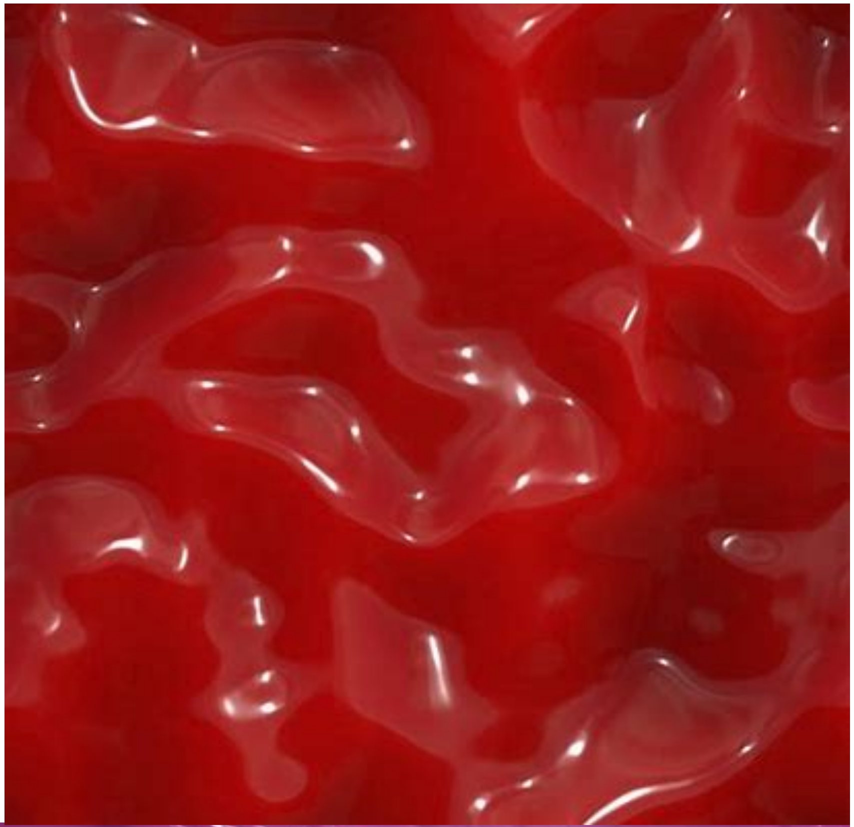
Relief - intrinsic (at least at this scale), because small local shadows do not move with illumination (at least Koenderink+Van Doorn, 77)

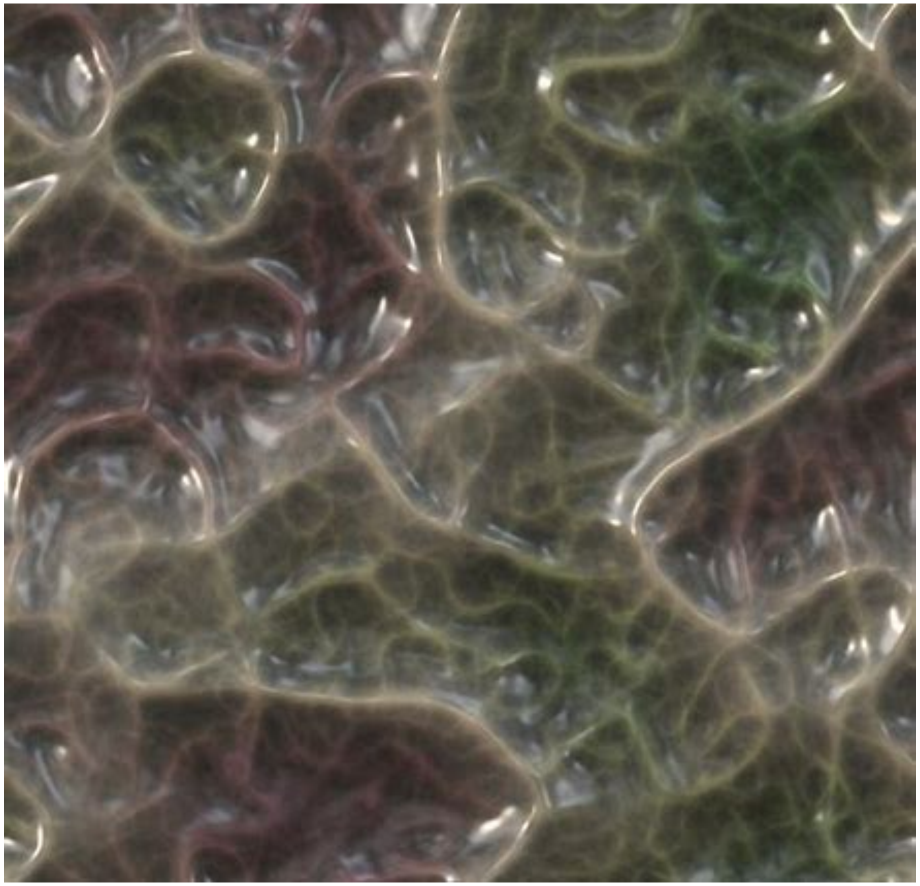


??? - intrinsic, because
mostly not a property of viewing
circumstances (?)

Iridescence
creating intrinsic gloss effects
intrinsic because the color effects will be
there for almost all illumination

??? - intrinsic, the specularities
move but are always there





??? - intrinsic, the specularities
move but are always there

Other Possible Extrinsics

- Glossy reflected component
- Luminaires
- Lens flare
- Rain effects
- etc.

Gloss/specular - clearly extrinsic, when the light moves, this moves

Lens flares - clearly intrinsic, product of viewing circumstances

Luminaires -
extrinsic or intrinsic?
worth knowing about, anyhow

Rain - multiple extrinsic phenomena,
including smoothing, raindrops, loss of saturation,
glossy/wet surfaces, etc. etc.

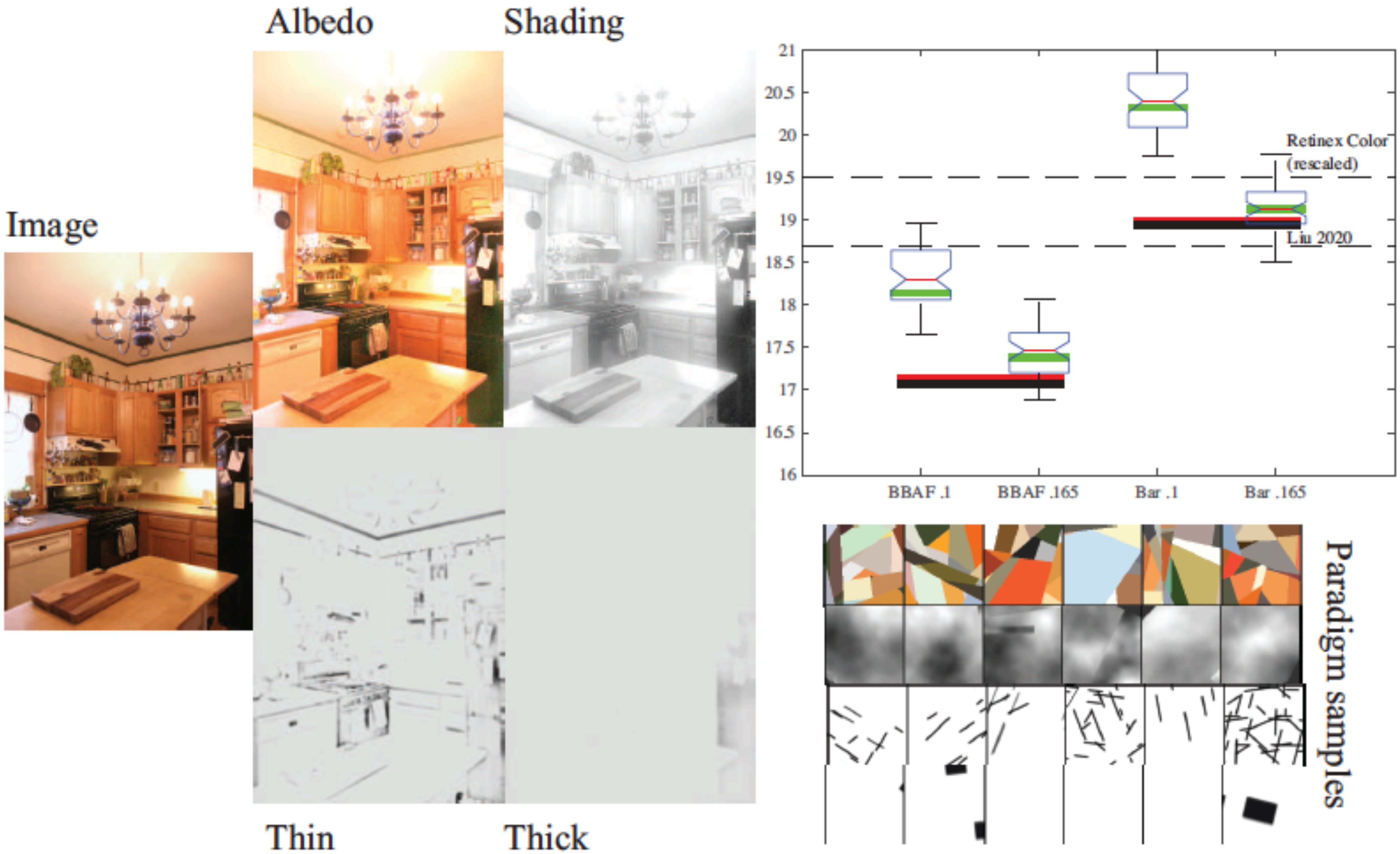


Fig. 12. *The method can be extended to capture thin and thick bars of darkness by extending the decomposer to have four heads (albedo, shading, thin bars, thick bars), and extending the paradigms (*bottom left *shows examples). The advantage of doing so is that a decomposition will then capture the thin bars of darkness associated with grooves separately from albedo (example decomposition shown here). Qualitatively, these thin bars do appear to be associated with grooves (but note the thin dark paint bars on the ceiling, which also appear in this map). The cost in WHDR (*top right *compares to* BBAF*) is noticeable, but may be tolerable in some applications.* Best viewed in color.

No ground truth decompositions

- And there never will be
  - rendering is do-able (but hard)
  - modelling is hopeless
- Q: how do you train an image decomposition method when you don't know the right answer?
- Retinex provides clues - spatial statistics are the key