

Lecture 06 Tone Reproduction

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Today's Agenda

- Reminders:
 - A02 questions?
- Goals for today:
 - Wrap up filtering
 - Introduction point processing and tone reproduction

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Warm-up Questions

3

Why does a lower resolution image still make sense to us? What do we lose?



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Why/How does the technique of hybrid images work?

Hybrid images

Aude Oliva
Antonio Torralba
Philippe G. Schyns



<http://cvcl.mit.edu/hybridimage.htm>

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Why/How does the technique of hybrid images work?

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5-2

Types of Filters: Smoothing

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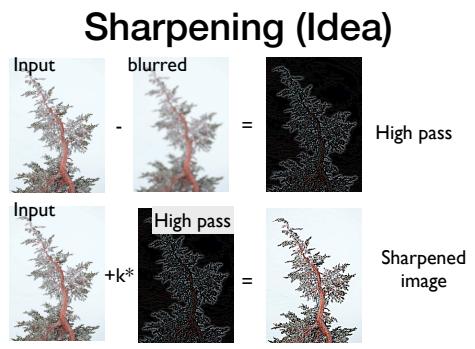
Smoothing Comparison



Figure 6.10. Smoothing examples.

Types of Filters: Sharpening

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Sharpening is a Convolution

$$\begin{aligned} I_{\text{sharp}} &= (1 + \alpha)I - \alpha(I \star f_{g,\sigma}) \\ &= I \star ((1 + \alpha)d - \alpha f_{g,\sigma}) \\ &= I \star f_{\text{sharp}}(\sigma, \alpha), \end{aligned}$$

Note: could also define d as $\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

$$d = \frac{1}{9} \times \begin{bmatrix} 0 & 0 & 0 \\ 0 & 9 & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

$$f_{g,\sigma} = \frac{1}{9} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix},$$

$$((1 + \alpha)d - \alpha f_{g,\sigma}) = \frac{1}{9} \times \begin{bmatrix} -\alpha & -\alpha & -\alpha \\ -\alpha & (9 + 8\alpha) & -\alpha \\ -\alpha & -\alpha & -\alpha \end{bmatrix}$$

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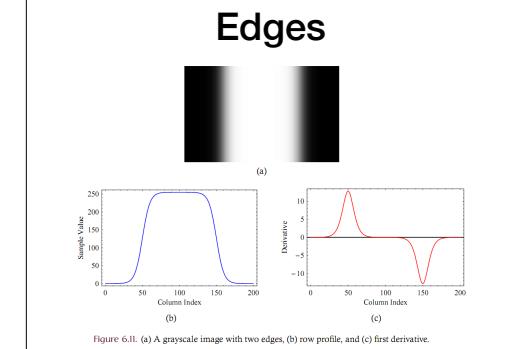


Figure 6.11. (a) A grayscale image with two edges, (b) row profile, and (c) first derivative.

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(Review?) Derivatives via Finite Differences

- We can approximate the derivative with a kernel w:

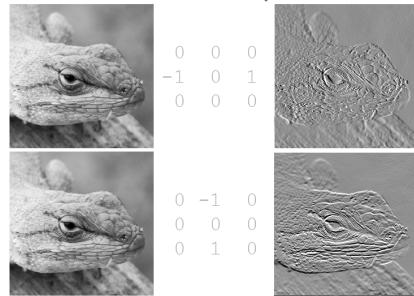
$$\frac{\partial f}{\partial x} \approx \frac{1}{2h} (f(x+1, y) - f(x-1, y))$$

$$\frac{\partial f}{\partial x} \approx w_{dx} \circ f \quad w_{dx} = \begin{bmatrix} -\frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix}$$

$$\frac{\partial f}{\partial y} \approx w_{dy} \circ f \quad w_{dy} = \begin{bmatrix} -\frac{1}{2} \\ 0 \\ \frac{1}{2} \end{bmatrix}$$

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Taking Derivatives with Convolution



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Gradients with Finite Differences

- These partial derivatives approximate the image gradient, ∇I .
- Gradients are the unique direction where the image is changing the most rapidly, like a slope in high dimensions
- We can separate them into components kernels G_x, G_y . $\nabla I = (G_x, G_y)$

$$\nabla I(x, y) = \begin{pmatrix} \delta I(x, y)/\delta x \\ \delta I(x, y)/\delta y \end{pmatrix}.$$

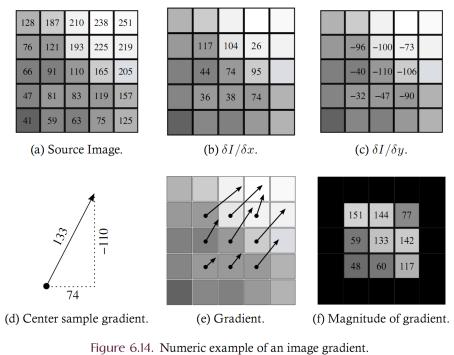
$$G_x = [1, 0, -1] \quad G_y = \begin{bmatrix} 1 \\ -1 \end{bmatrix};$$

$$\nabla I = \begin{pmatrix} \delta I/\delta x \\ \delta I/\delta y \end{pmatrix} \simeq \begin{pmatrix} I \otimes G_x \\ I \otimes G_y \end{pmatrix}.$$



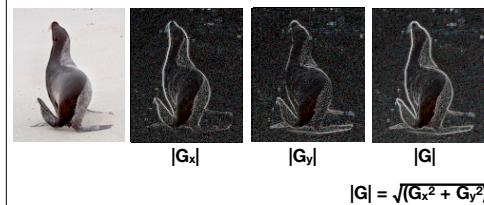
Figure 6.15. Image gradient (partial).

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Gradients G_x, G_y



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Second Derivatives (Sharpening, almost)

- Partial derivatives in x and y lead to two kernels:

$$\frac{\partial^2 f}{\partial x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y)$$

and, similarly, in the y-direction we have

$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y)$$

0	1	0	1	1	1
1	-4	1	1	-8	1
0	1	0	1	1	1

1	1	1
-a	(9+8a)	-a
-a	-a	-a

Compare with Sharpening filter:
unbalanced counts!

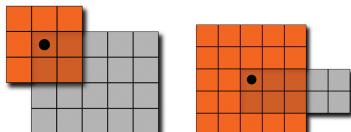
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Boundaries

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Handling Image Boundaries

- What should be done if the kernel falls off of the boundary of the source image as shown in the illustrations below?



(a) Kernel at $I(0,0)$.
(b) Kernel larger than the source.

Figure 6.4. Illustration of the edge handling problem.

Handling Image Boundaries

- When pixels are near the edge of the image, neighborhoods become tricky to define
- Choices:
 1. Shrink the output image (ignore pixels near the boundary)
 2. Expanding the input image (padding to create values near the boundary which are "meaningful")
 3. Shrink the kernel (skip values that are outside the boundary, and reweight accordingly)

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Boundary Padding

- When one pads, they pretend the image is large and either produce a constant (e.g. zero), or use circular / reflected indexing to tile the image:

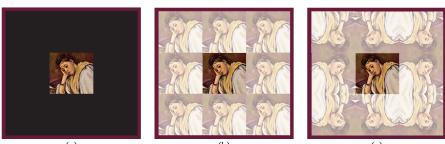


Figure 6.5. (a) Zero padding, (b) circular indexing, and (c) reflected indexing.

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Point Processing

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Recall: Operations on Images

- Point Operations:



- Affect only the range of the image (e.g. brightness)
- Each pixel is processed separately, only depending on the color

23-1

Recall: Operations on Images

- Point Operations:



- Affect only the range of the image (e.g. brightness)
- Each pixel is processed separately, only depending on the color

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Point Processing (Algorithm)

```
//given input: greyscale image
//produces processing image: output

for (let row = 0, row < H; row++) {
    for (let col = 0; col < W; col++) {
        let i = row*W + col;
        output[i] = some_func(input[i]);
    }
}
```

- This basic, but simple algorithm can be extended in lots of ways, depending on the function that we apply to each pixel and each color channel

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First Example: Linear Rescaling

- Rescaling** is a point processing technique that alters the contrast and/or brightness of an image.
- In photography, **exposure** is a measure of how much light is projected onto the imaging sensor.
 - Overexposure**: more light than what the sensor can measure.
 - Underexposure**: sensor is unable to detect the light.
- Images which are underexposed or overexposed can frequently be improved by brightening or darkening them.
- The contrast of an image can be altered to bring out the internal structure of the image.

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Rescaling Math

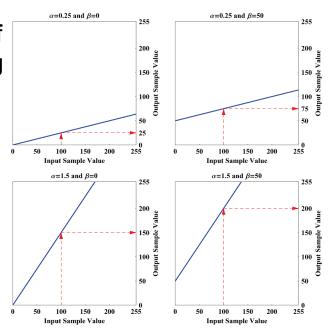
- Given a sample C_{in} of the source image, rescaling computes the output sample, C_{out} , using the scaling function

$$C_{out} = \alpha C_{in} + \beta$$

- α is a real-valued scaling factor known as **gain**
- β is a real-valued scaling factor known as **bias**

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Effects of Rescaling



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Why Use Both α , β ?

- Consider two rescaled source samples of S rescaled to S' .

$$\begin{aligned} S'_1 &= \alpha S_1 + \beta \\ S'_2 &= \alpha S_2 + \beta \end{aligned}$$

- Calculate the **contrast** (the absolute difference) between the source and destination, called ΔS and $\Delta S'$.

$$\begin{aligned} \Delta S' &= |S'_1 - S'_2| \\ \Delta S &= |S_1 - S_2| \end{aligned}$$

- Now consider the relative change in contrast between the source and destination.

$$\frac{\Delta S'}{\Delta S} = \frac{|S'_1 - S'_2|}{|S_1 - S_2|}$$

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Why Use Both α , β ?

- The relative change in contrast can be simplified as

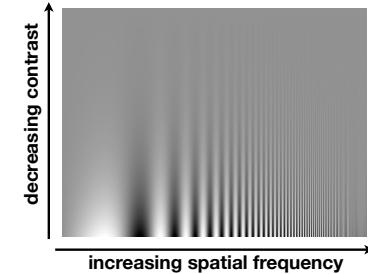
$$\begin{aligned}\frac{\Delta S'}{\Delta S} &= \frac{|(\alpha S_1 + \beta) - (\alpha S_2 + \beta)|}{|S_1 - S_2|} \\ &= \frac{|\alpha| \cdot |S_1 - S_2|}{|S_1 - S_2|} \\ &= |\alpha|.\end{aligned}$$

- Thus, gain (α) controls the change in contrast.
- Whereas bias (β) does *not* affect the contrast
- Bias, however, controls the final **brightness** of the rescaled image. Negative bias darkens and positive bias brightens the image

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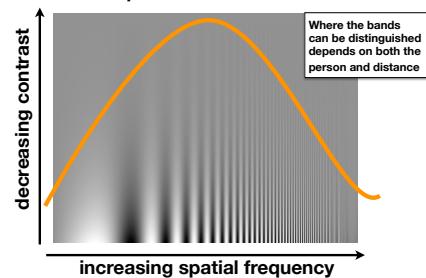
Sidebar: Relating Contrast Sensitivities to Signal Processing

Contrast Sensitivity Function Campbell-Robson Chart



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Contrast Sensitivity Function Campbell-Robson Chart



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Contrast Sensitivities Vary by Channel

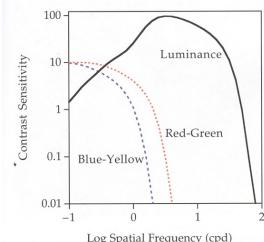


Figure I-18. Spatial contrast sensitivity functions for luminance and chromatic contrast.

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Photoshop demo

- Image > Mode > Lab color
- Go to channel panel, select Lightness
- Filter > Blur > Gaussian Blur , e.g. 4 pixel radius
 - very noticeable
- Undo, then select a & b channels
- Filter > Blur > Gaussian Blur , same radius
 - hardly visible effect



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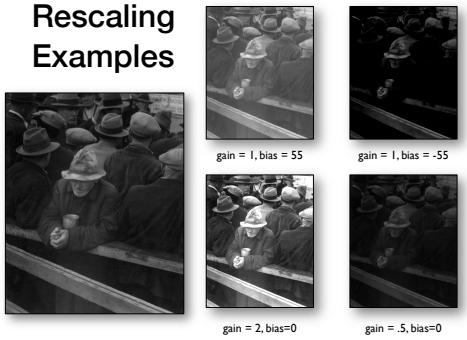
Important: Clamping

- Rescaling may produce samples that lie outside of the output images (e.g. below 0 or above 255 in 8-bit images)
- Clamping** the output values ensures that the output samples are truncated to the 8-bit dynamic range limit
- Note that clamping does 'lose' information, since it truncates.

$$\text{clamp}(x, \min, \max) = \begin{cases} \min & \text{if } [x] \leq \min \\ \max & \text{if } [x] \geq \max \\ [x] & \text{otherwise.} \end{cases}$$

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Rescaling Examples

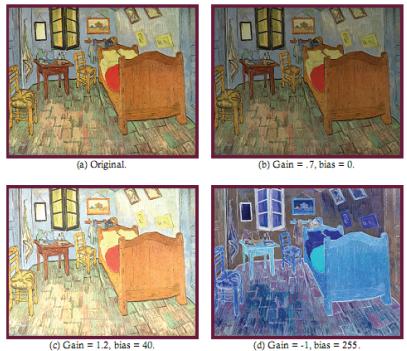


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Rescaling Color Images

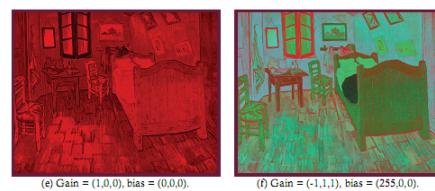
- Often, it is desirable to apply different gain and bias values to each channel of a color image separately
- Example: A color image that utilizes the HSB color model. Since all color information is contained in the H and S channels, it may be useful to adjust ONLY the brightness, encoded in channel B, without altering the color of the image in any way.
- Rescaling the channels of a color image in a non-uniform manner is also possible rescaling each color channel separately.

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Rescaling Channels Separately



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Gamma Correction

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Gamma Correction

- **Gamma correction** is an image enhancement operation that seeks to maintain perceptually uniform sample values
- Gamma correction seeks to eliminate the nonlinear distortions introduced by the first (acquisition) and the final (display) phases of the image processing pipeline.

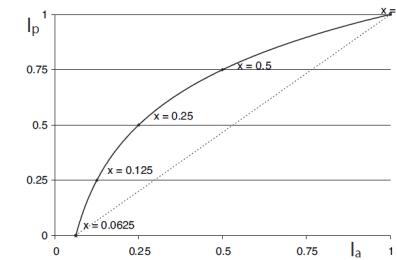
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Human Perception

- Eye distinguishes color intensities as a function of the ratio between intensities.
- Consider $I_1 < I_2 < I_3$, for the step between I_1 and I_2 to look like the step from I_2 to I_3 , it must be that:
$$I_2 / I_1 = I_3 / I_2$$
- As opposed to the differences in contrast! $I_2 - I_1 \neq I_3 - I_2$

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Perceived (I_p) vs. Actual (I_a) Intensity



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Perceived (I_p) vs. Actual (I_a) Intensity

- Perceived light actually behaves like $I_p = (I_a)^\gamma$

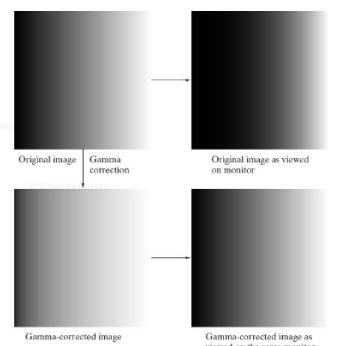


<http://www.anywhere.com/gward/hdrenc/>

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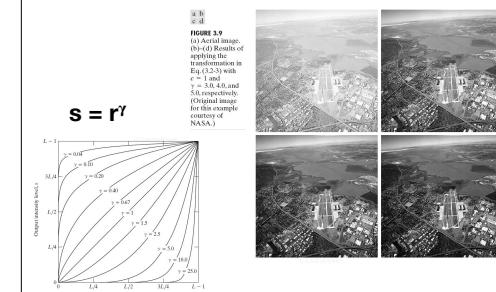
a b
c d

FIGURE 3.7
(a) Intensity ramp image. (b) Image as viewed on a simulated monitor with $\gamma = 2.5$. (c) Gamma-corrected image. (d) Corrected image as viewed on the same monitor. Compare (d) and (a).



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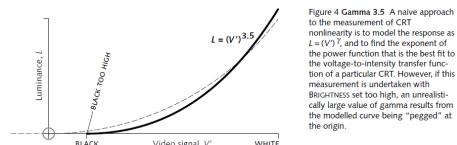
Example: Gamma Correction



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Gamma Correction vs. Scaling with Gain/Bias Adjustments

- Gamma changes curve instead of sliding it (bias) or changing just slope (gain)



http://www.poynton.com/PDFs/Rehabilitation_of_gamma.pdf

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Putting it all together: Gain, Bias, and Gamma

- $C_{out} = (\alpha C_{in} + \beta)^\gamma$
- α is known as gain (exposure)
- β is known as bias (offset)
- γ maps to a non-linear curve (gamma correction)



Image of Photoshop from Christian Bloch - The HDR! Handbook 2.0

Dynamic Range

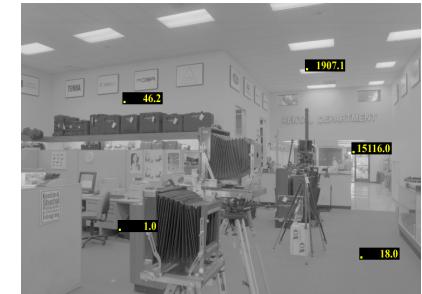
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The World is a High Dynamic Range (HDR)



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The World is a High Dynamic Range (HDR)



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Examples

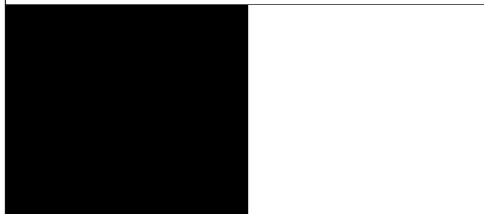
Inside is too dark
Outside is too bright



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Dynamic Range in Displays?

- Range of pure black vs. pure white?



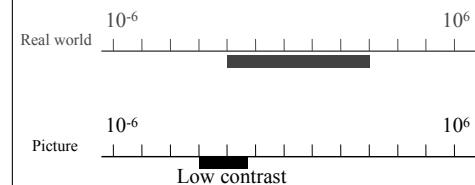
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Dynamic Range in Displays?

- Typically 1:20 or 1:50

– Black is ~50x darker than white

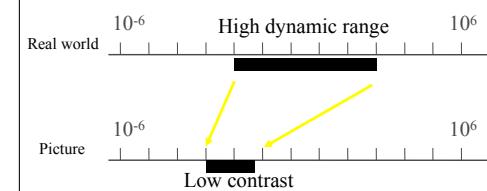
- Max 1:500



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Problem: Displaying the Information

- Problem: How should we map scene radiances (up to 1:100,000) to display radiances (only around 1:100) to produce a satisfactory image?
- Goal: match limited contrast of the display medium while preserving details
- Solution: Tone Mapping



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Without HDR + Tone Mapping



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With HDR + Tone Mapping



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Before



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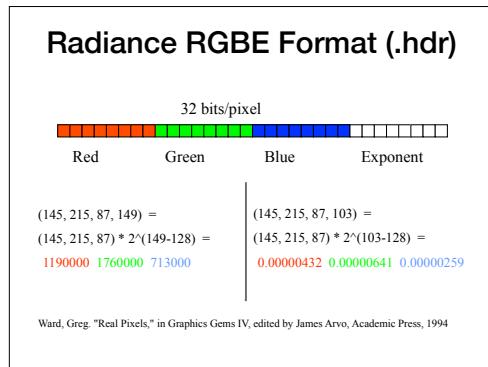
59



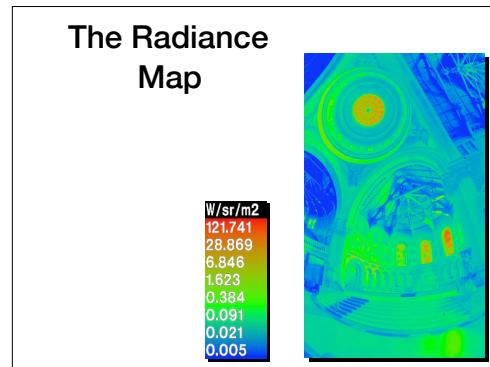
60

Tone Mapping

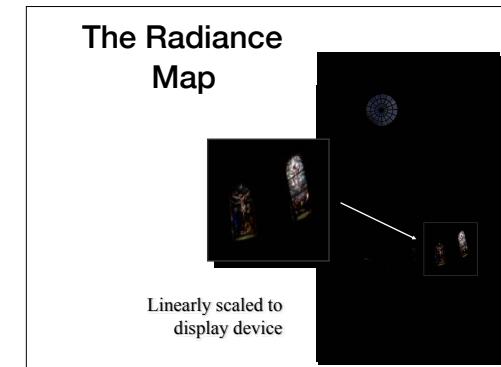
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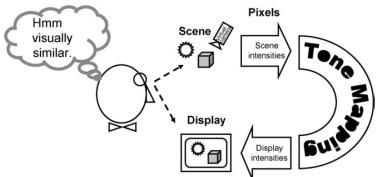


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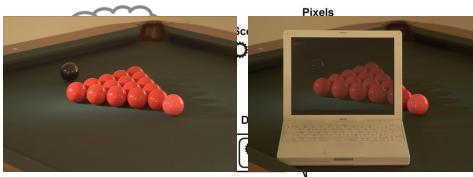
Approach: Visual Matching



- We do not need to reproduce the true radiance as long as it gives us a visual match.

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Approach: Visual Matching



- We do not need to reproduce the true radiance as long as it gives us a visual match.

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Eyes and Dynamic Range

- We're sensitive to change (multiplicative)
 - A ratio of 1:2 is perceived as the same contrast as a ratio of 100 to 200
 - Use the log domain as much as possible
- But, eyes are **not** photometers
 - Dynamic adaptation (very local in retina)
 - Different sensitivity to spatial frequencies



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Eyes and Dynamic Range

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Eyes and Dynamic Range

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 - Use the log domain as much as possible
- But, eyes are **not** photometers
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Can we just scale? Maybe!

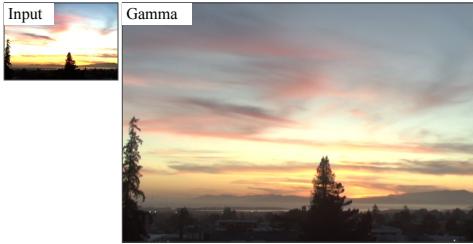
- For a color image, try to convert the input (world) luminance L_w to a target display luminance L_d
- This type of scaling works (sometimes). In particular, it works best in the log and/or exponential domains

$$\begin{bmatrix} R_d \\ G_d \\ B_d \end{bmatrix} = \begin{bmatrix} L_d \frac{R_w}{L_w} \\ L_d \frac{G_w}{L_w} \\ L_d \frac{B_w}{L_w} \end{bmatrix}$$

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What scale value to use? How about Gamma compression

- $C_{out} = C_{in}\gamma$, where $0 < \gamma < 1$ applied to each R,G,B channel
- Colors are washed out, why?



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Gamma compression on Intensity

- Colors ok, but details in intensity are blurry



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Bilateral Filtering

(slides from Frédo Durand)

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Oppenheim 1968, Chiu et al. 1993

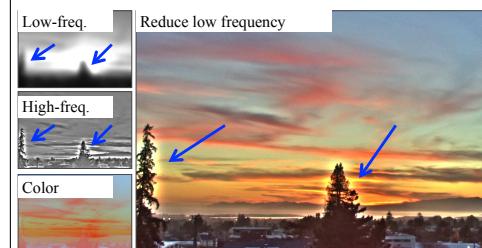
- Reduce contrast of low-frequencies
- Keep mid and high frequencies



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The halo nightmare

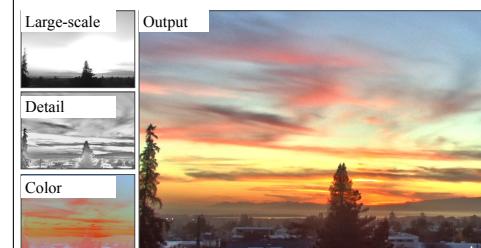
- For strong edges
- Because they contain high frequency



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Our approach

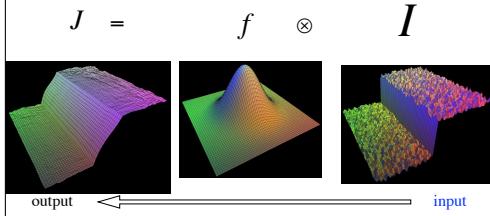
- Do not blur across edges
- Non-linear filtering



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Start with Gaussian filtering

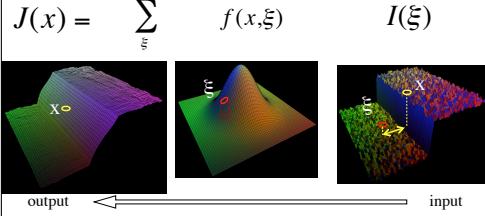
- Here, input is a step function + noise



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Gaussian filter as weighted average

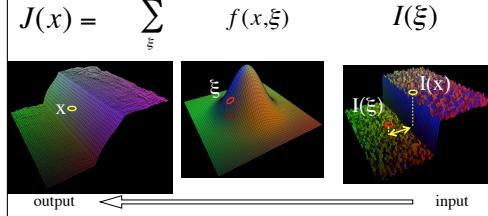
- Weight of ξ depends on distance to x



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The problem of edges

- Here, $I(\xi)$ “pollutes” our estimate $J(x)$
- It is too different

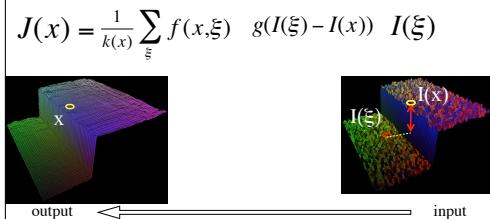


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Principle of Bilateral filtering

[Tomasi and Manduchi 1998]

- Penalty g on the intensity difference

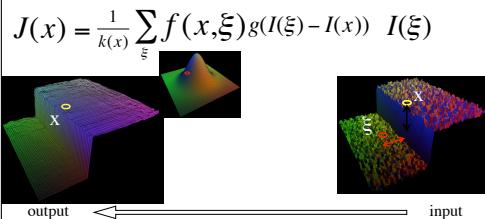


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Bilateral filtering

[Tomasi and Manduchi 1998]

- Spatial Gaussian f

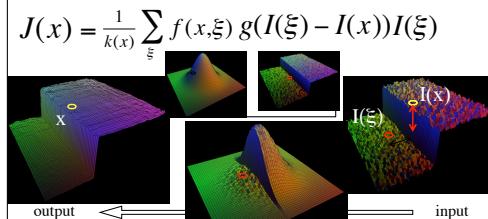


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Bilateral filtering

[Tomasi and Manduchi 1998]

- Spatial Gaussian f
- Gaussian g on the intensity difference



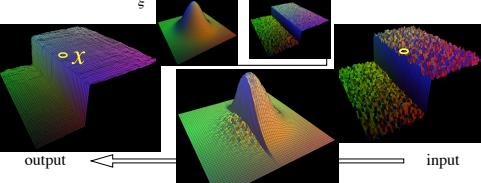
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Normalization factor

[Tomasi and Manduchi 1998]

$$\bullet k(x) = \sum_{\xi} f(x, \xi) g(I(\xi) - I(x))$$

$$J(x) = \frac{1}{k(x)} \sum_{\xi} f(x, \xi) g(I(\xi) - I(x)) I(\xi)$$



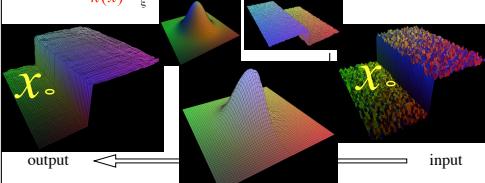
80

Bilateral filtering is non-linear

[Tomasi and Manduchi 1998]

- The weights are different for each output pixel

$$J(x) = \frac{1}{k(x)} \sum_{\xi} f(x, \xi) g(I(\xi) - I(x)) I(\xi)$$



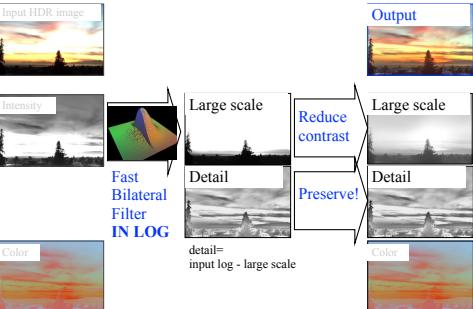
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Log domain

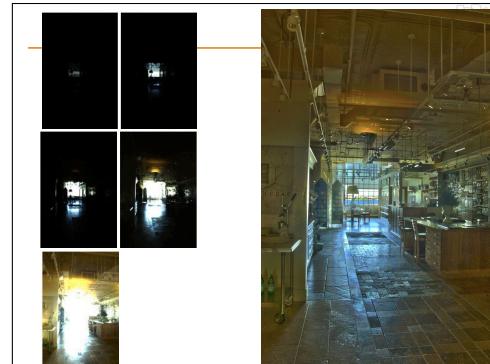
- Very important to work in the log domain
- Recall: humans are sensitive to multiplicative contrast
- With log domain, our notion of “strong edge” always corresponds to the same contrast

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Recap



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Lec07 Required Reading

- FOOG, Ch. 3.4, 20.1-20.2
- Compositing Digital Images. Thomas Porter and Tom Duff, SIGGRAPH Comput. Graph. 18(3): 253-259, 1984.
- See also optional readings!

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