Lecture 13:

Tone Mapping

Contents

Contrast Handling

- Input: HDR intensities in real-world scenes (*e.g.* from rendering)
- Output: Typically LDR devices

Acquisition of HDR input

- HDR cameras
    - Still rather exotic (*e.g.* Litro)
- LDR cameras
    - Requires multiple exposures to fully cover the high dynamic range

Display

- HDR displays
    - Modern displays are now getting more and more HDR capable
- Display on LDR monitors
    - Tone mapping to perceptively compress HDR to LDR

Limited dynamic range of cameras is a problem

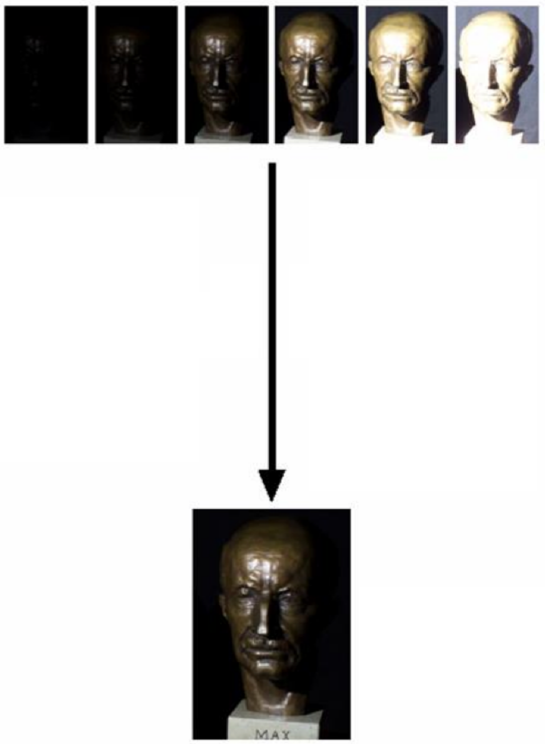
- Shadows are underexposed
- Bright areas are overexposed
- Sensor's temporal sampling density is not sufficient → saturation

Good sign

- Some modern CMOS imagers have a higher (and often sufficient) dynamic range than most traditional CCD sensors

Basic idea of multi-exposure techniques

- Combine multiple images with different exposure settings
- Makes use of available sequential dynamic range



Other techniques available

- *E.g.* HDR video

Acquiring HDR from LDR input devices

- Take multiple photographs with different times of exposure

Issues

- How many exposure levels?
- How much difference between exposures?
- How to combine them?

Application

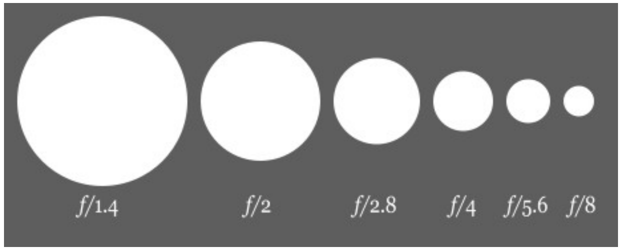
Capture HDR environment maps from series of input images:

1 / 2'000 sec   1 / 500 sec   1 / 125 sec   1 / 30 sec   1 / 8 sec

Used to illuminate virtual scenes
with real-world environment

In photography

- <f-*number* (N)> = <focal length (f)> / <aperture diameter (D)>
- 1 f-stop increment: $\sqrt{2}N$ → <aperture area> / 2



Doubling the f-number decreases the aperture area by a factor of four (*i.e.* need to quadruple exposure time to preserve same brightness)

Natural scenes

- 37 stops (~ 10 orders of magnitude)
- 18 stops (2^{18} = ~262 000) at given time of day

Humans

- After adaptation: 30 stops (~ 9 orders of magnitude)
- Simultaneously: 17 stops (~ 5 orders of magnitude)

Photo cameras

- 10-16 stops (~3 orders of magnitude)
- Fish-eye picture of sky with different exposures show saturation (*e.g.* sun)

f/4, 1s | f/4, $\frac{1}{4}$s | f/4, $\frac{1}{32}$s | f/16, $\frac{1}{16}$s | f/16, $\frac{1}{125}$s | f/16, $\frac{1}{1000}$s | f/16, $\frac{1}{8000}$s

E.g. photo camera with standard CCD sensor

• Dynamic range of sensor	1:1’000
• Varying exposure time: 1/60s – 1/6’000s	1:100
• Varying aperture: f/2.0 – f/22.0	1:100 (approximately)
• Electronic: varying “sensitivity”: ISO	1:10
• Total (sequential) dynamic range	1:100’000’000

But simultaneous dynamic range still only 1:1’000

- ⇒ Aperture: varying depth of field
- ⇒ Exposure time: only works for static scenes

Similar situation for analog cameras

- Chemical development of film instead of electronic processing
- → Get varying sensitivity

Analog film

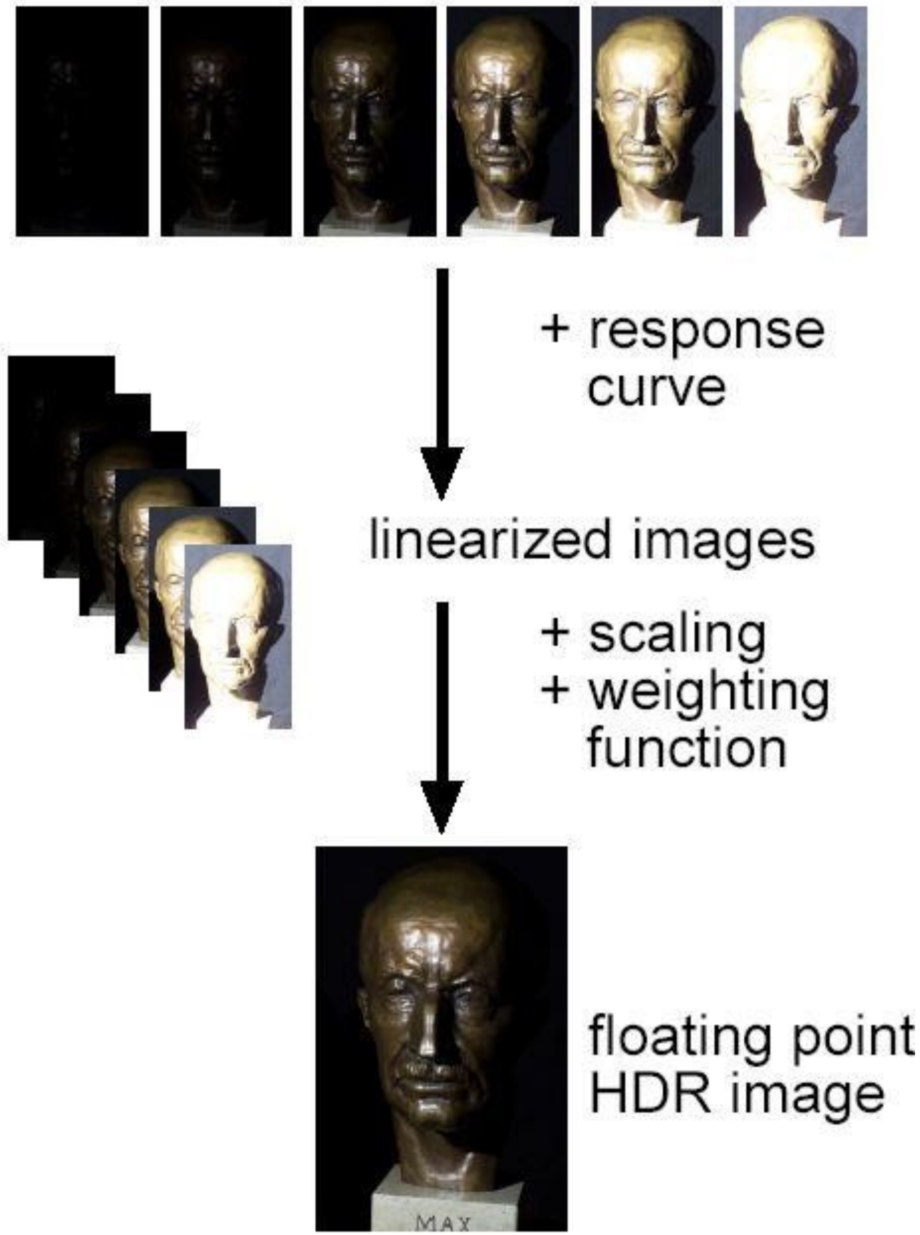
- Several emulsions of different sensitivity levels [Wyckoff 1960s]
  - Dynamic range of about 10^8

Digital domain

- Similar approaches for digital photography
- Commonly used method [Debevec *et al.* 97]
  - Select a small number of pixels from all images
  - Perform optimization of response curve with smoothness constraint
- Newer method by [Robertson *et al.* 99]
  - Optimization over all pixels in all images

General idea of HDR imaging

- Combine multiple images with different exposure times
  - Pick for each pixel a well-exposed image
  - Camera's response function needs to be known to calibrate values between images
  - Change only exposure time, not aperture due to different depth-of-field !!


+ response
curve
linearized images
+ scaling
+ weighting
function
floating point
HDR image
MAX

Input

- N pictures of a static scene with known exposure times $t_i,\ i = 1, \ldots, N$
- y_{ij} is the j^{th} pixel of the i^{th} exposed image

Task

- Determine the underlying light values (irradiances) x_j
  - Since only the exposure time is being varied, the amount of light contributing to y_{ij} will be $t_i x_j$.
  - The quantity $t_i x_j$ is mapped by the camera's response function $f(\cdot)$ to give the output values:

$$y_{ij} = f\left(t_i x_j\right)$$

- If the camera's response function is known: $f^{-1}\left(y_{ij}\right) = t_i x_j$

$$x_j = {f^{-1}\left(y_{ij}\right)}\Big/{t_i}$$

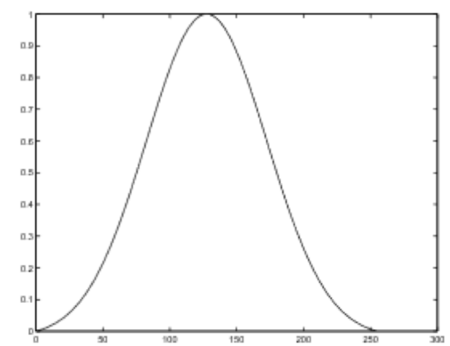
Principle of the approach

- Calculate an HDR image using the given camera's response function
- Optimize camera's response function to better match resulting HDR image
- Iterate till convergence: approximate non-linear process with linear steps

Calculate estimates of HDR input values x_j from images via maximum likelihood approach

$$x_j = \frac{\sum_{i=0}^{N} w(y_{ij}) t_i^2 x_{ij}}{\sum_{i=0}^{N} w(y_{ij}) t_i^2}$$

Use a bell-shaped weighting function $w(y_{ij})$



- Do not trust as much pixel values at extremes
  - Under-exposed: high relative error prone to noise
  - Over-exposed: saturated value

Use an initial camera response curve

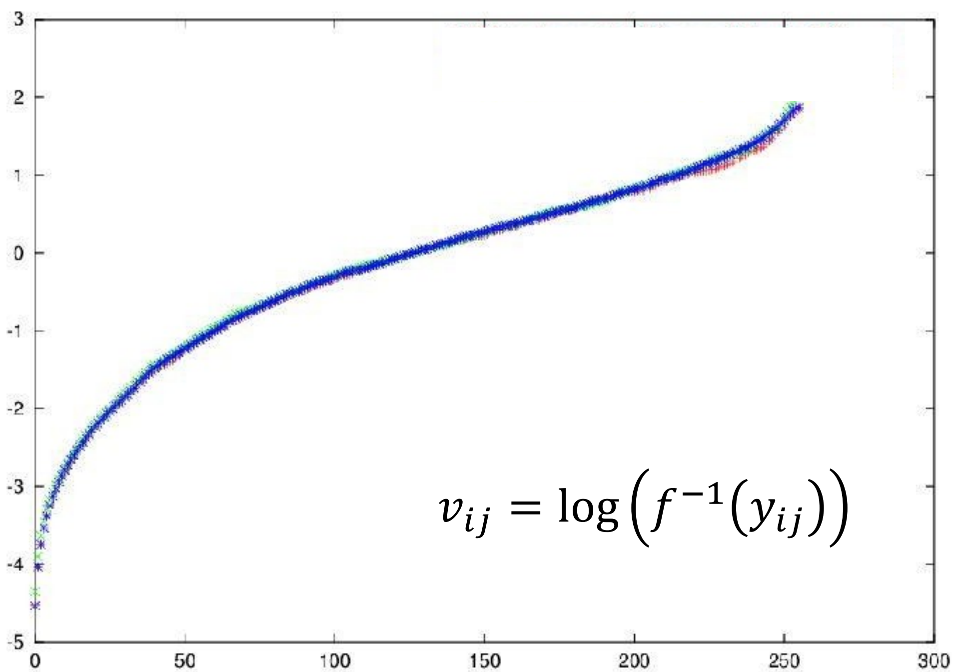
- Simple assumption: linear response

Both steps …

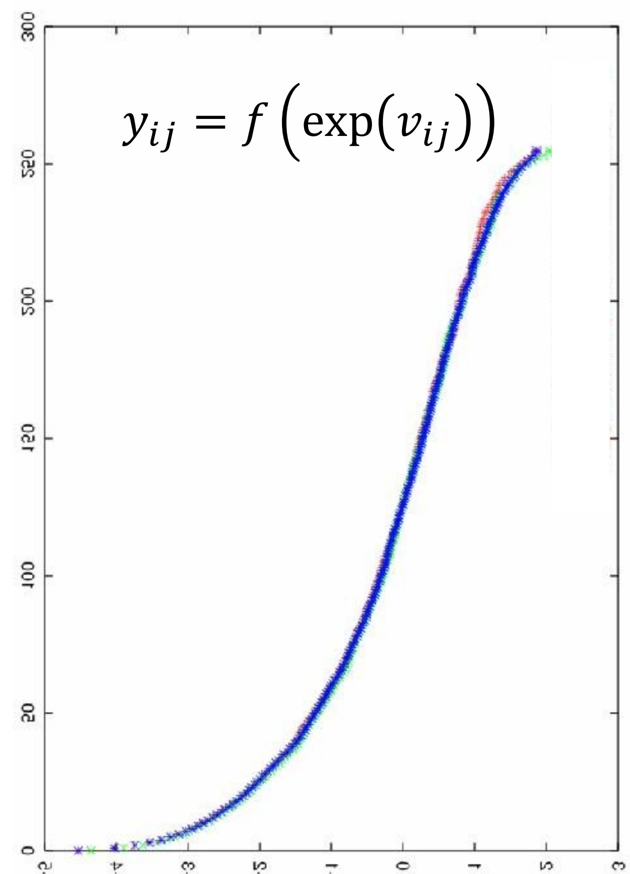
- Calculation of an HDR image pixels v_{ij} using irradiances x_j: $v_{ij} = \log(t_i x_j)$
- Optimization of irradiances x_j using the HDR image v_{ij}: $t_i x_j = \exp(v_{ij})$

… are now iterated until convergence

- Criterion: decrease of error to be below some threshold
    - Usually about 5 iterations are enough



Logarithmic plot of the camera response function $f(\cdot)$

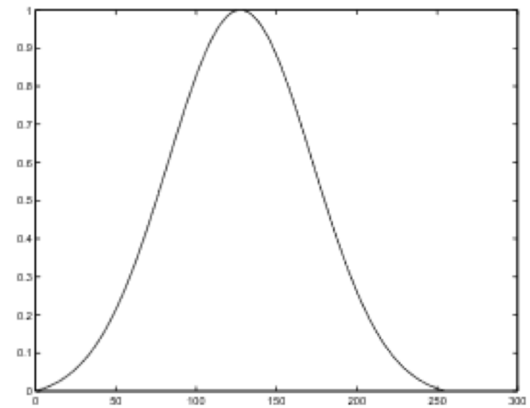


Typical S shape of inverse function $f^{-1}(\cdot)$

Choice of Weighting Function

$w(y_{ij})$ for response [Robertson *et al.* 99]

$$w(y_{ij}) = \exp\left(-4\frac{(y_{ij} - 127.5)^2}{127.5^2}\right)$$



- Gaussian-like bell-shaped function
- For 8-bit images, centered around $(2^8 - 1) / 2 = 127.5$
- Possible width correction at both ends: over- and under-exposure
- Motivated by general noise model: downweight high relative error

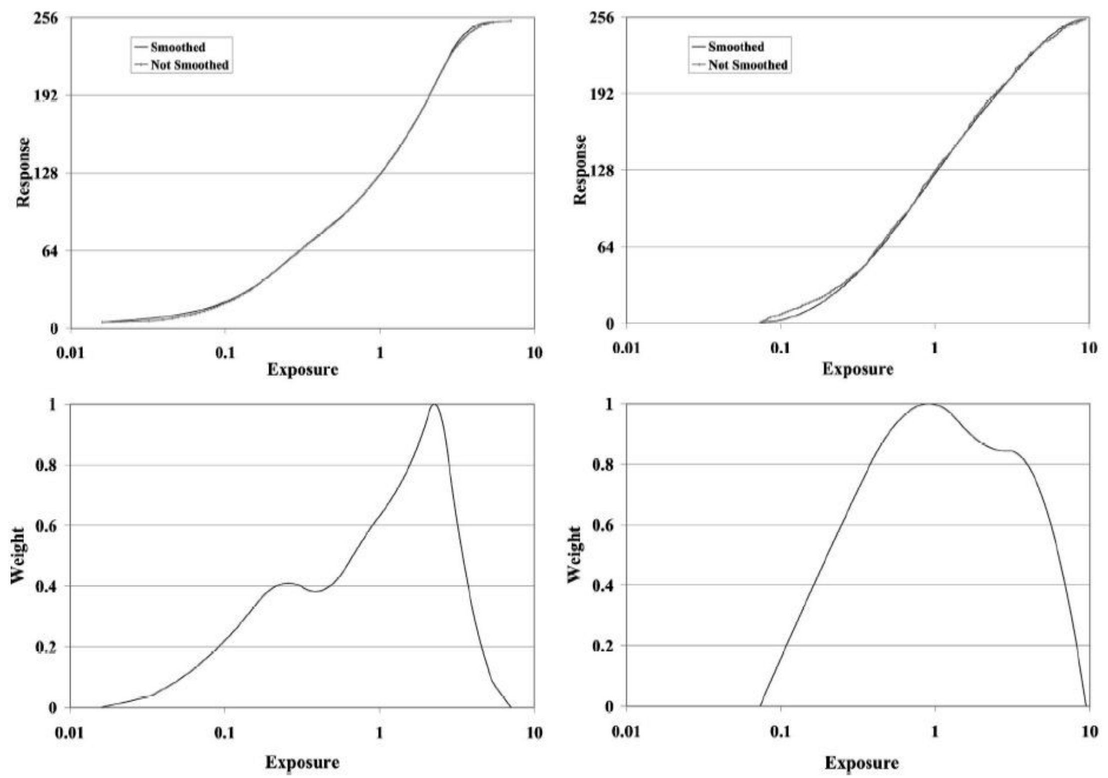
$w(y_{ij})$ for HDR reconstruction [Robertson *et al.* 03]

- Introduce *certainty function* $c(\cdot)$ as derivative of response curve with logarithmic exposure axis: *S*-shape response → bell-shaped curve
- Approximate response curve with cubic spline to compute derivative

$$w(y_{ij}) = c(t_i x_j)$$

Consider response curve gradient

- Higher weight where response curve maps to large extent



[Robertson *et al.* 2003]

Difference between exposures levels

- Ideally such that respective trusted regions (central part of weighting function) are roughly adjacent

What difference to pick between exposures levels?

- Most often a difference of 2 stops (factor of 4) between exposures is sufficient
- See [Grossberg & Nayar 2003] for more details

How many input images are necessary to get good results?

- Depends on dynamic range of scene illumination and on quality requirements

Discussion

- Method is very easy
- Doesn’t make assumptions about response curve shape
- Converges quickly
- Takes all available input data into account
    - As opposed to [Debevec *et al.* 97]
- Can be extended to > 8-bit color depth
    - 16 bits should be followed by smoothing
    - Quantization to 8 bits eliminates large amount of noise
    - Higher precision with 16 bits more likely to still contain notable noise

Terms and Definitions

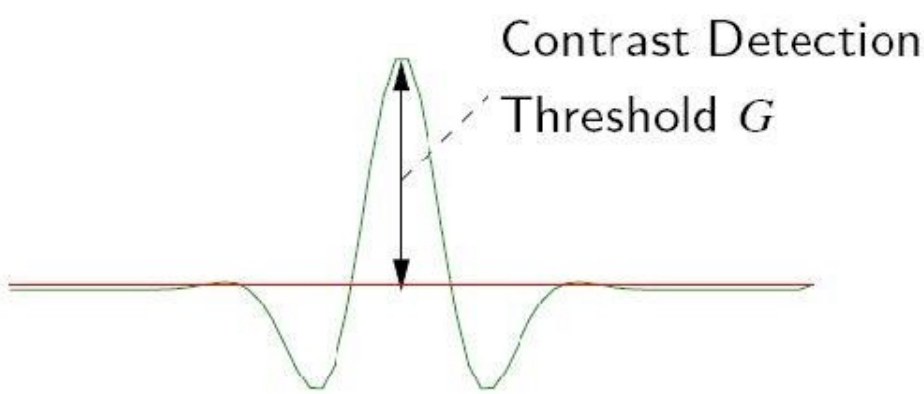
- **Dynamic range**
  - Factor between the highest and the smallest representable value
  - 2 strategies to increase dynamic range:
    - Make white brighter, or make black darker (more practical)
    - Reason for trend towards reflective rather than diffuse displays
- **Contrast**
  - Simple contrast: $C_S = \frac{L_{max}}{L_{min}}$
  - Weber fraction: $C_W = \frac{\Delta L}{L_{min}}$ with $\Delta L = L_{max} - L_{min}$
  - Michelson contrast: $C_M = \frac{|L_{max} - L_{min}|}{L_{max} + L_{min}}$
  - Logarithmic ratio: $C_L = \log_{10}\left(\frac{L_{max}}{L_{min}}\right)$
  - Signal to noise ratio (SNR): $C_{SNR} = 20 \cdot \log_{10}\left(\frac{L_{max}}{L_{min}}\right)$

Contrast detection threshold

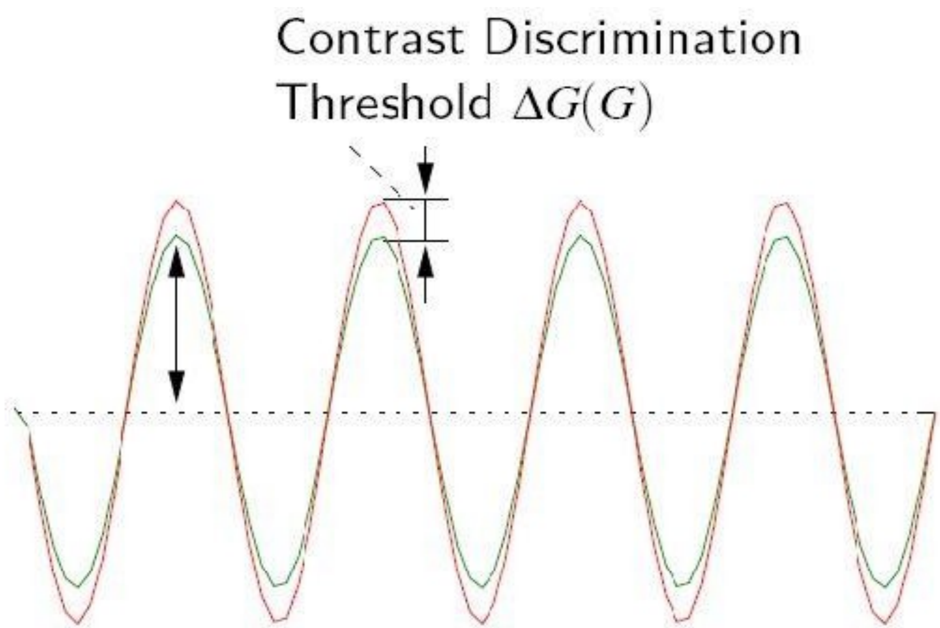
- Smallest detectable intensity difference in a uniform field of view
- *E.g.* Weber-Fechner perceptual experiments

Contrast discrimination threshold

- Smallest visible difference between two similar signals
- Works in supra-detection-threshold domain (*i.e.* signals above it)
- Often sinusoidal or square-wave pattern



Contrast Detection



Contrast Discrimination

Mapping HDR radiance values to LDR pixel values?

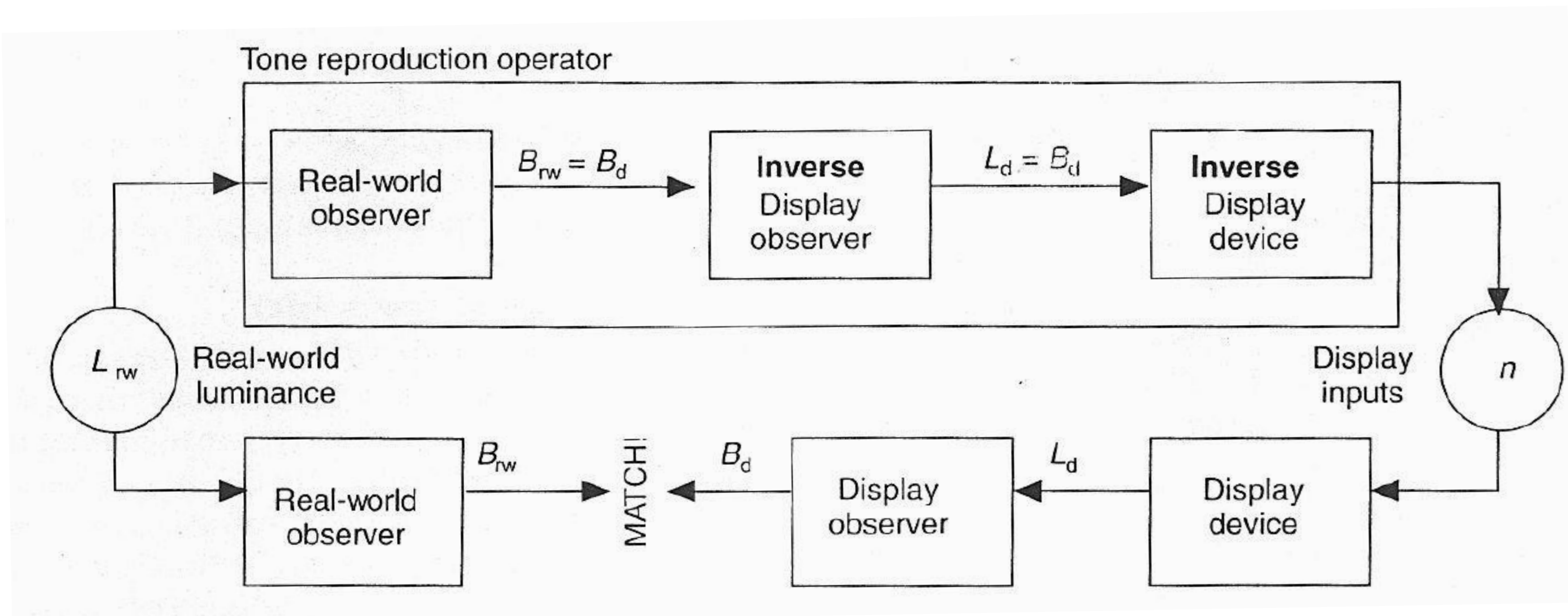
- Luminance range for human visual perception
  - Min 10^{-5} cd/m^2 : shadows under starlight
  - Max 10^5 cd/m^2 : snow in direct sunlight
- Luminance of typical desktop displays
  - Up to a few 100 cd/m^2 : about 2-3 orders of magnitude

Goal

- Compress the dynamic range of an input image to fit output range
- Reproduce HVS to closely match perception of the real scene
  - Brightness and contrast
  - Adaptation of the eye to environment
  - Bright / dark input: glare, color perception, loss of visual acuity, …

Original approach [Tumblin / Rushmeier]

- Create model of the observer
- Requirement: observer looking at displayed virtual image should perceive the same brightness as when staring at the real scene
- Compute tone-mapping as concatenation / inversion of operators
- Model usually operates only on luminance (not on color)



Other models aim for visually pleasing images

Linearly scale brightest value to 1 (in gray value)

- **Problem**: light sources are often several orders of magnitude brighter than the rest → the rest will be black

Linearly scale brightest non-light-source value

- Capping light source values to 1
- Scale the rest to a value slightly below 1
- Problem: bright reflections of light sources

General problem of simple linear scaling

- Absolute brightness gets lost
- Scaling of light source intensity gets factored out → has no effect

Much better: linear scaling in the logarithmic domain

- Linear scaling of perceived brightness instead of input luminance
- Much closer to human perception
- Typically using $\log_{10}$

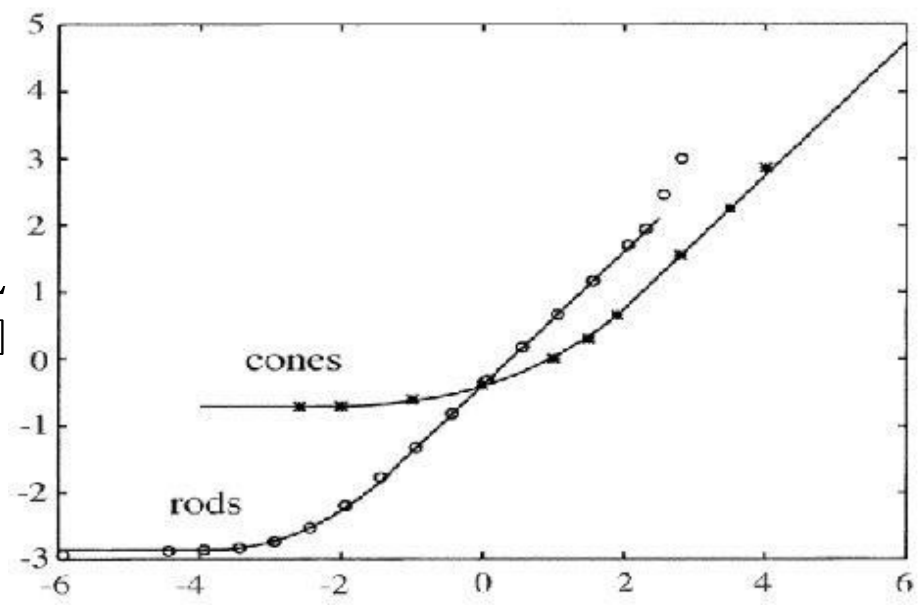
Contrast-based linear scaling factor [Ward 94]

- Make just visible differences in real world just visible on display
  - Preserve the visibility in the scene based on Weber's contrast
- Just noticeable contrast differences according to Blackwell [CIE 81] (subjective measurements)

$$\Delta L(L_a) = 0.0594(1.219 + L_a^{0.4})^{2.5}$$

  - Minimum discernible difference in luminance for given visual adaptation level L_a
- Goal: proportionality constant m
  - Relates world luminance values L_w to display luminance values L_d
  - $L_d = m\, L_w$

Threshold ΔL [log cd/m2]



Adaptation luminance L_a [log cd/m[2]]

Approach using "just noticeable difference" (JND)

- Find m such that JND $\Delta L(L_{wa})$ at world adaptation luminance L_{wa} and JND $\Delta L(L_{da})$ at display adaptation luminance L_{da} verify

$$\Delta L(L_{da}) = m(L_{wa})\Delta L(L_{wa})$$

- Substitution results in

$$m(L_{wa}) = \left(\frac{1.219 + L_{da}^{0.4}}{1.219 + L_{wa}^{0.4}}\right)^{2.5}$$

- Compute L_{da} from maximum display luminance: $L_{da} = {}^{L_{dmax}}/_{2}$
- Normalize scaling factor sf in [0, 1]

$$sf = \frac{1}{L_{dmax}}\left(\frac{1.219 + \left({}^{L_{dmax}}/_{2}\right)^{0.4}}{1.219 + L_{wa}^{0.4}}\right)^{2.5}$$

Deriving the real-world adaptation L_{wa}

- Depends on light distribution in field of view of observer
- Simple approximation using a single value
  - Eyes try to adjust to average incoming brightness
  - Brightness B based on input luminances:
    - $B = kL_{in}^{a}$: Power-law [Stevens 61]
  - Comfortable brightness based on average of input luminances:
    - $\log_{10} L_{wa} = E\{\log_{10} L_{in}\} + 0.84 \Rightarrow L_{wa} = 10^{\sum_n \frac{\log_{10} L_{in}}{n}}$

Problems of this approach

- Single factor for entire image
  - Does not handle different adaptation for different locations in image
  - We do not perceive absolute differences in luminance: neighborhood
- Brightness adaptation mainly acts on 1° field of view of fovea rather than periphery → would require eye tracking
- Adaptation to average results in clamping for too bright regions

Optimal mapping of the dynamic range [Ward 97]

- Compute an adjustment image
  - Assume known view point with respect to the scene
  - Blur input image with distance-dependent kernel
    - Filter (average) non-overlapping regions covering 1° field of view, *i.e.* foveal solid angle of adaptation
    - Reference uses simple box filter
  - Reduce resolution
- Compute the histogram of the image
  - Bin the luminance values
- Adjust the histogram based on restrictions of HVS
  - Limit contrast enhancement

$\Longrightarrow$ Distributes contrast in the image in a visually meaningful way, but does not try to model human vision per se as outlined by [Tumblin/Rushmeier]

Definitions

- $B_w = \log L_w$: compute world brightness from world luminance
- b_i : create N bins i corresponding to ranges of B_w
- $f(b_i)$: number of B_w samples in bin b_i: $\propto$ PDF
- $P(b) = {}^{\sum f(b_i)}/_{T}$: normalized sum of $f(b_i)$ for $b_i < b$: CDF ($\int$ of PDF)
- T : sum over all $f(b_i)$, *i.e.* total number of samples

$$T = \sum f(b_i)$$

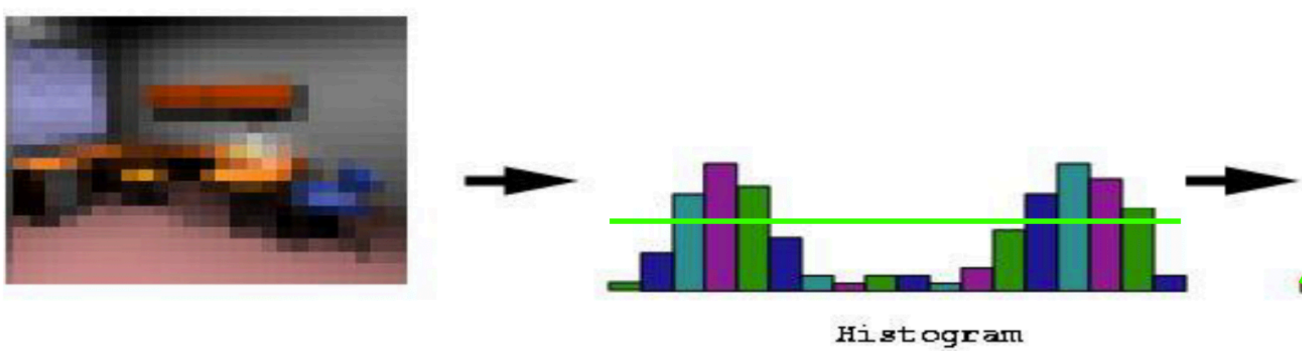
$$\Delta b = \frac{log(L_{w}max) - log(L_{w}min)}{N}$$

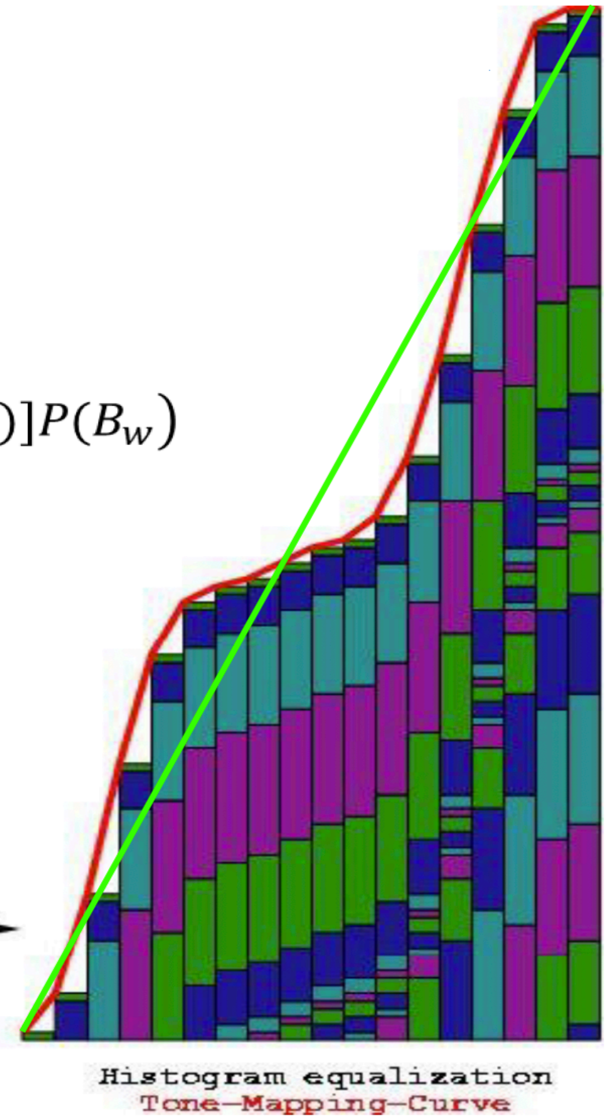
- Bin step size Δb (in log(cd/m^2)) defined by min/max world luminance for the scene and number of histogram bins N
- Therefore the PDF is

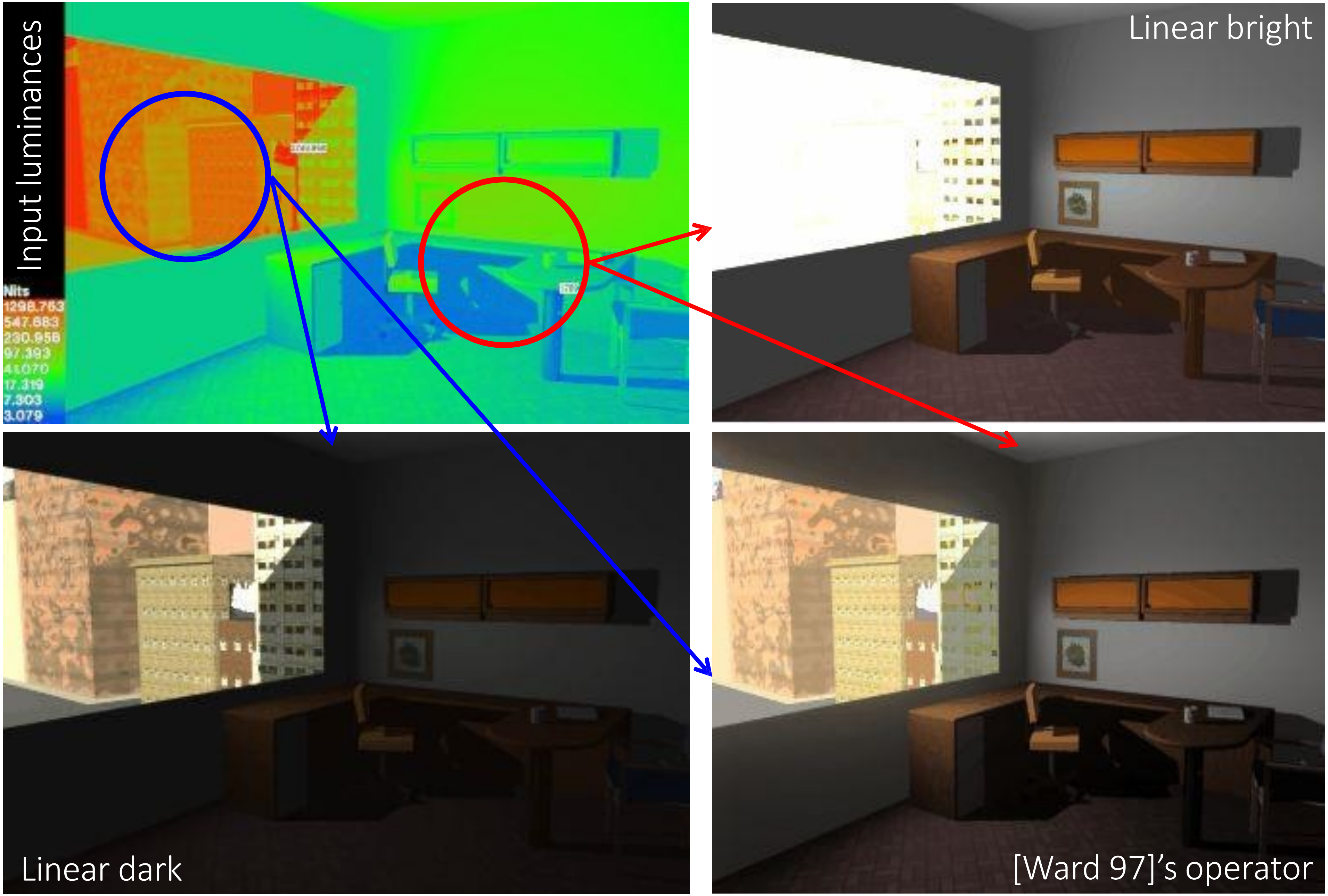
$$\frac{dP(b)}{db} = \frac{f(b_i)}{T\Delta b}$$

Compute display brightness $B_d = \log(L_d)$ using min and max display luminance L_{dmin} and L_{dmax}

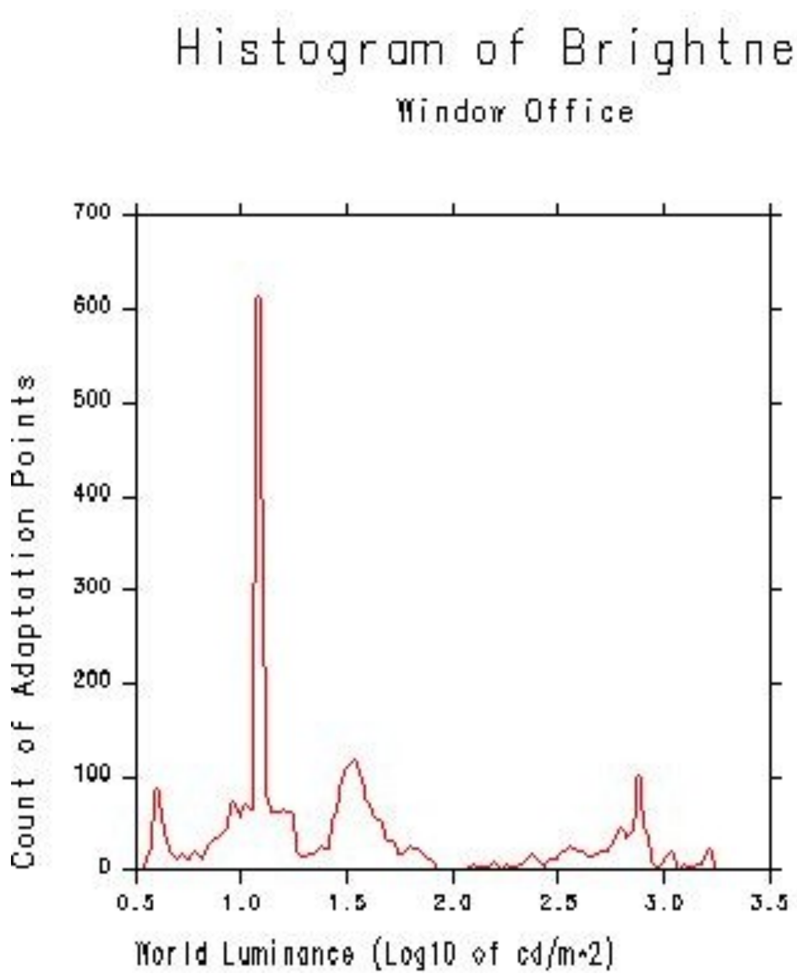
$$B_d = \log(L_{dmin}) + [\log(L_{dmax}) - \log(L_{dmin})]P(B_w)$$

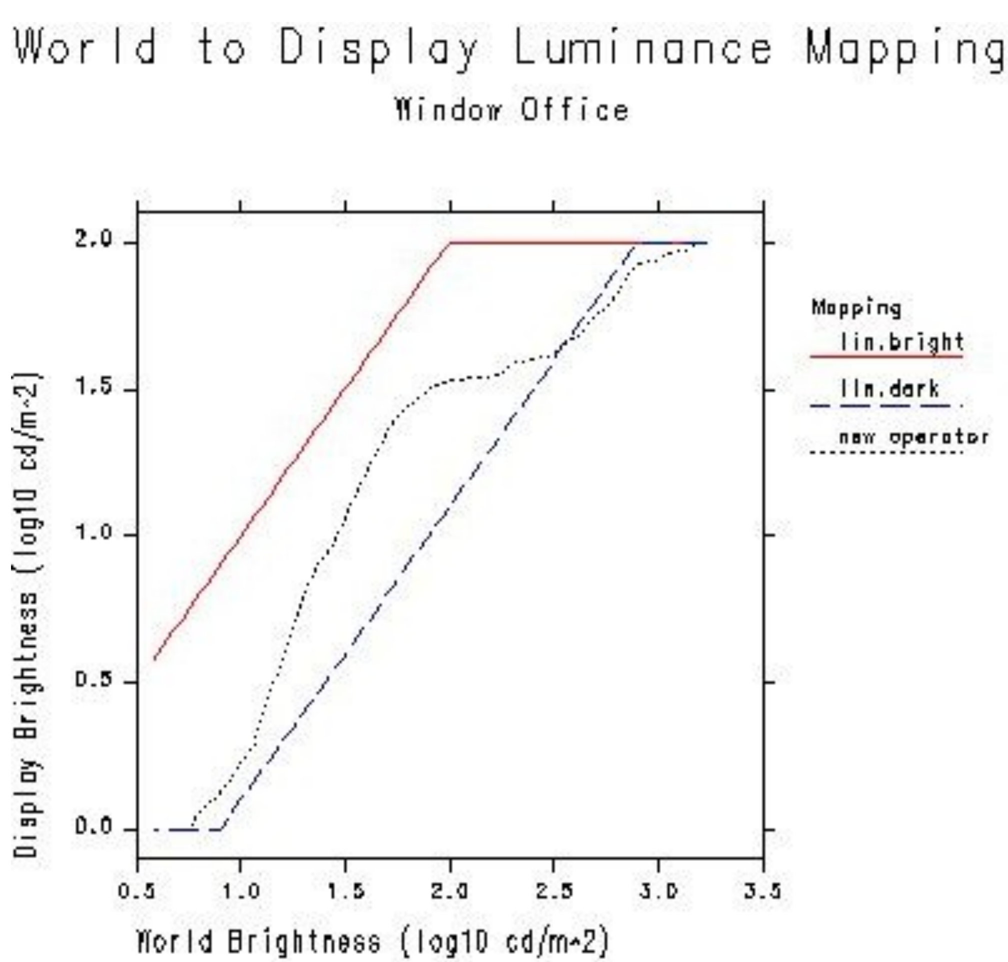





Input luminances
Nits
1298.763
547.683
230.958
97.393
41.070
17.319
7.303
3.079
Linear bright
Linear dark
[Ward 97]'s operator

Linear mapping (scaling) vs. histogram adjustment





Problem

- Too exaggerated contrast in large highly-populated regions of the dynamic range: enhances features more than the HVS would

Idea

- Contrast-limited histogram equalization using a linear ceiling (linear scaling works well for low contrast images)

$$\frac{dL_d}{L_d} \leq \frac{dL_w}{L_w} \Longrightarrow \frac{dL_d}{dL_w} \leq \frac{L_d}{L_w}$$

- Differentiate $L_d = e^{B_d}$ with respect to L_w using the chain rule

$$\frac{dL_d}{dL_w} = e^{B_d} \frac{f(B_w)}{T\Delta b} \frac{\log L_{dmax} - \log L_{dmin}}{L_w} \leq \frac{L_d}{L_w}$$

Result

- Limiting the sample count per bin in the histogram
- $\Longleftrightarrow$ limit the magnitude of the PDF, *i.e.* the slope of the CDF

$$f(B_w) \leq \frac{T\Delta b}{\log L_{dmax} - \log L_{dmin}}$$

Implementing the contrast limitation

- Truncate too large bins with redistribution to neighbors (repeatedly)
- Ditto without redistribution (gives better results)
- Use modified $f(B_w)$ in histogram equalization vs. naïve approach

Histogram Adjustment with Linear Ceiling

Linear mapping (simple scaling)

Naïve histogram equalization

Histogram adjustment with linear ceiling on contrast

Adjustment for JND

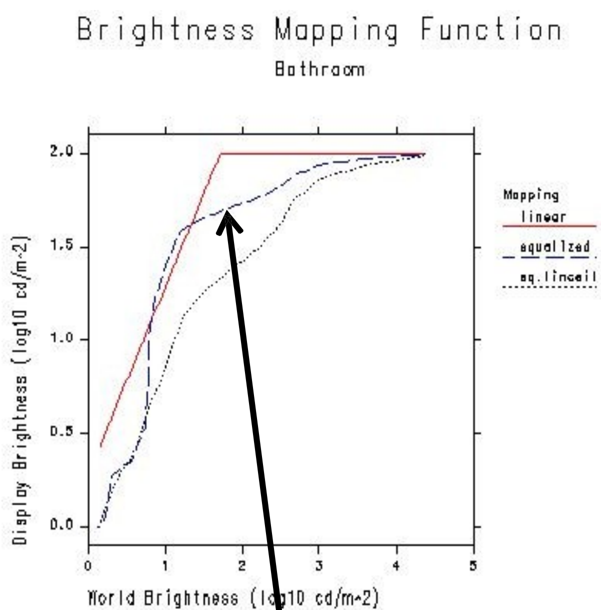
- Limiting the contrast to the ratio of JNDs (global scale factor)

$$\frac{dL_d}{dL_w} \leq \frac{\Delta L_t(L_d)}{\Delta L_t(L_w)}$$

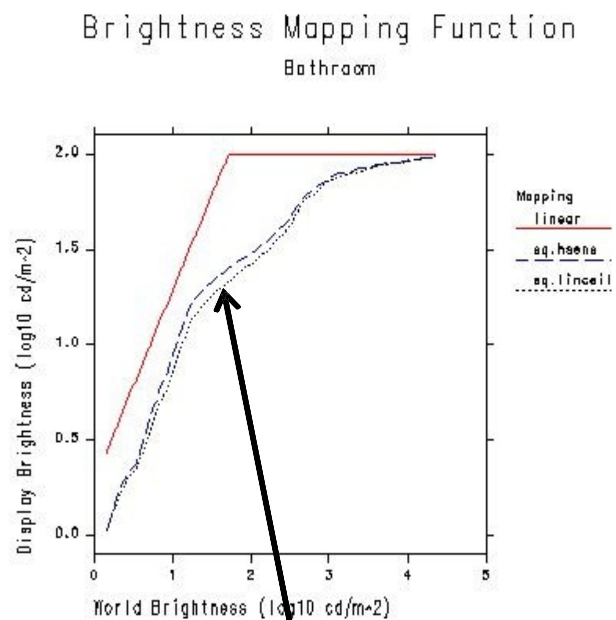
- That results in

$$f(B_w) \leq \frac{\Delta L_t(L_d)}{\Delta L_t(L_w)} \frac{L_w}{L_d} \frac{T \Delta b}{\log L_{dmax} - \log L_{dmin}}$$

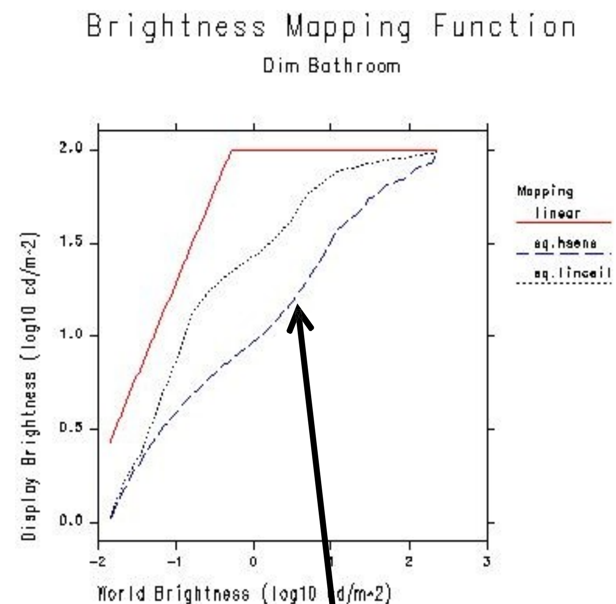
- Implementation is similar as for previous histogram equalization



Naïve histogram equalization



Histogram Adjustment with human sensitivity in bright bathroom



Histogram Adjustment with human sensitivity in dim bathroom

Reduction of contrast sensitivity in dark scenes

Histogram adjustment with linear ceiling on contrast

Dim bathroom (1 / 100) with reduced contrast

[Tumblin / Rushmeier]

- Sound methodology from a theoretical standpoint
- Maybe not optimal models of HVS used in practical experiments

Maximum linear scaling tone mapping

[Tumblin/Rushmeier] tone mapping

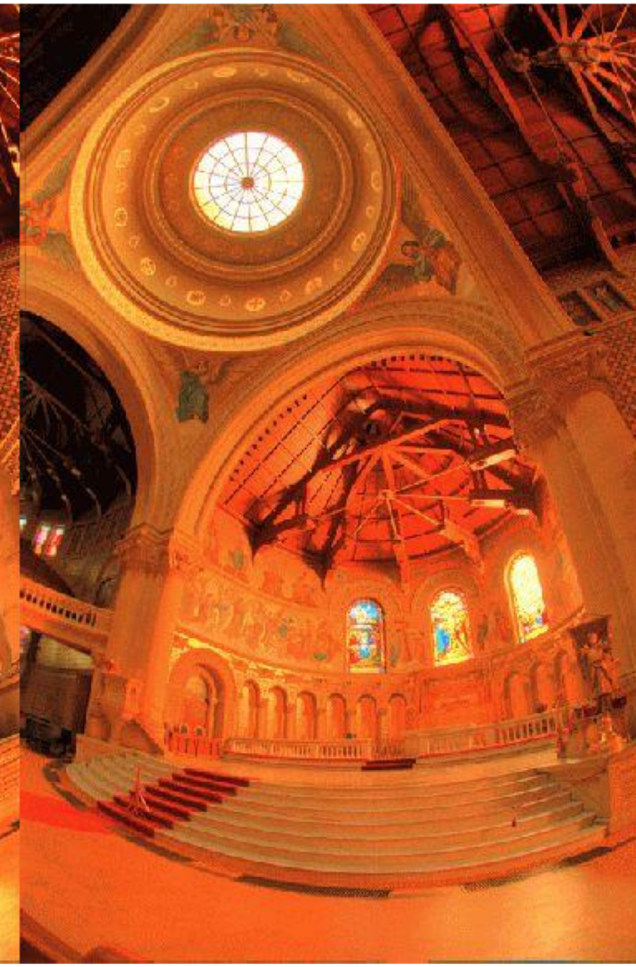
Contrast-based linear scaling [Ward 94] tone mapping

Histogram adjustment [Ward 97] tone mapping

Comparison

[Tumblin/Rushmeier] tone mapping

Contrast-based linear scaling [Ward 94] tone mapping



Histogram adjustment [Ward 97] tone mapping

Usual contrast enhancement techniques

- Global tone-mapping operator: apply same operation on entire image
- Either enhance everything or require manual intervention
- Change image appearance

Tone map. often gives numerically optimal solution

- No dynamic range left for enhancement

Local operators

- HVS adapts locally ⇒ apply ≠ tone-mapping operators in ≠ areas

Restore missing contrast

by doing local processing

HDR image (reference)

[Krawczyk 06]

Tone-mapping result

Idea: Enhance Local Contrast

Reference HDR image

Tone-mapped image

Measure lost contrast at several feature scales (preserve small-scale details but adjust overall large-scale contrast)

Enhance lost small-scale contrast in tone-mapped image (best allocation of LDR contrast rather than simulate HVS)

Enhanced tone-mapped image

Communicate lost image contents

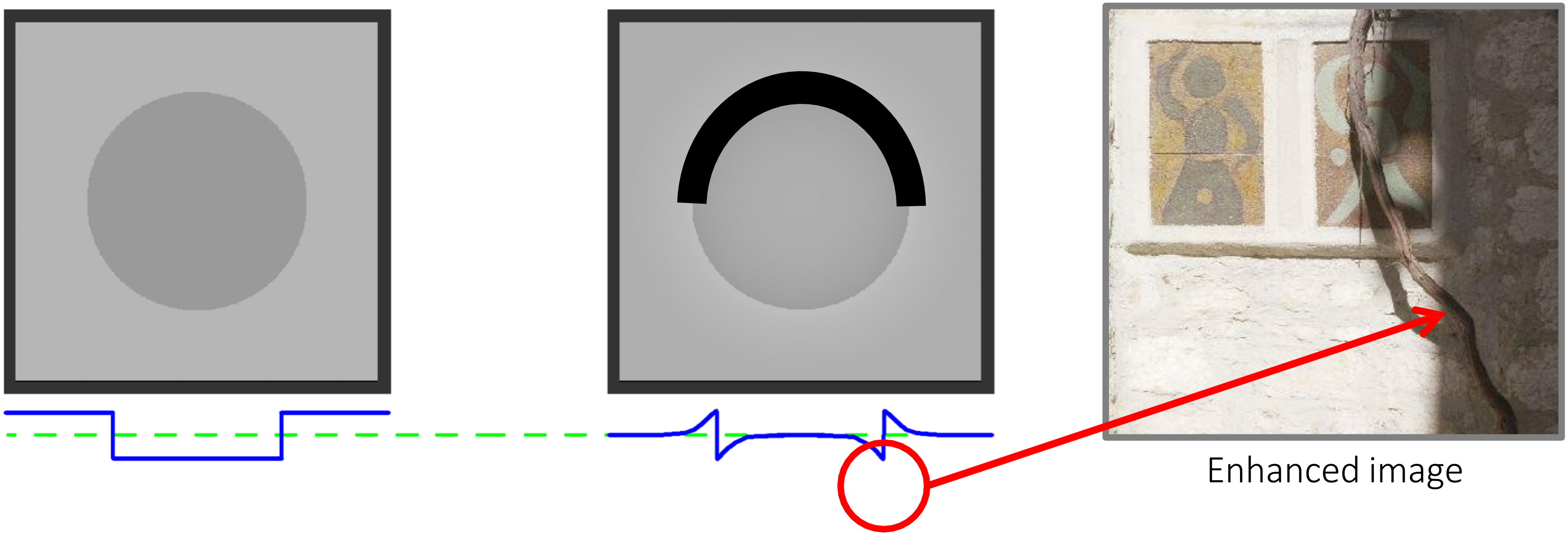
Maintain image appearance

Create apparent contrast based on Cornsweet illusion

- Introduce sharp visible edges between similar-brightness regions

Countershading

- Gradual darkening / brightening towards a contrasting edge
- Restore contrast of small features with economic use of dyn. range

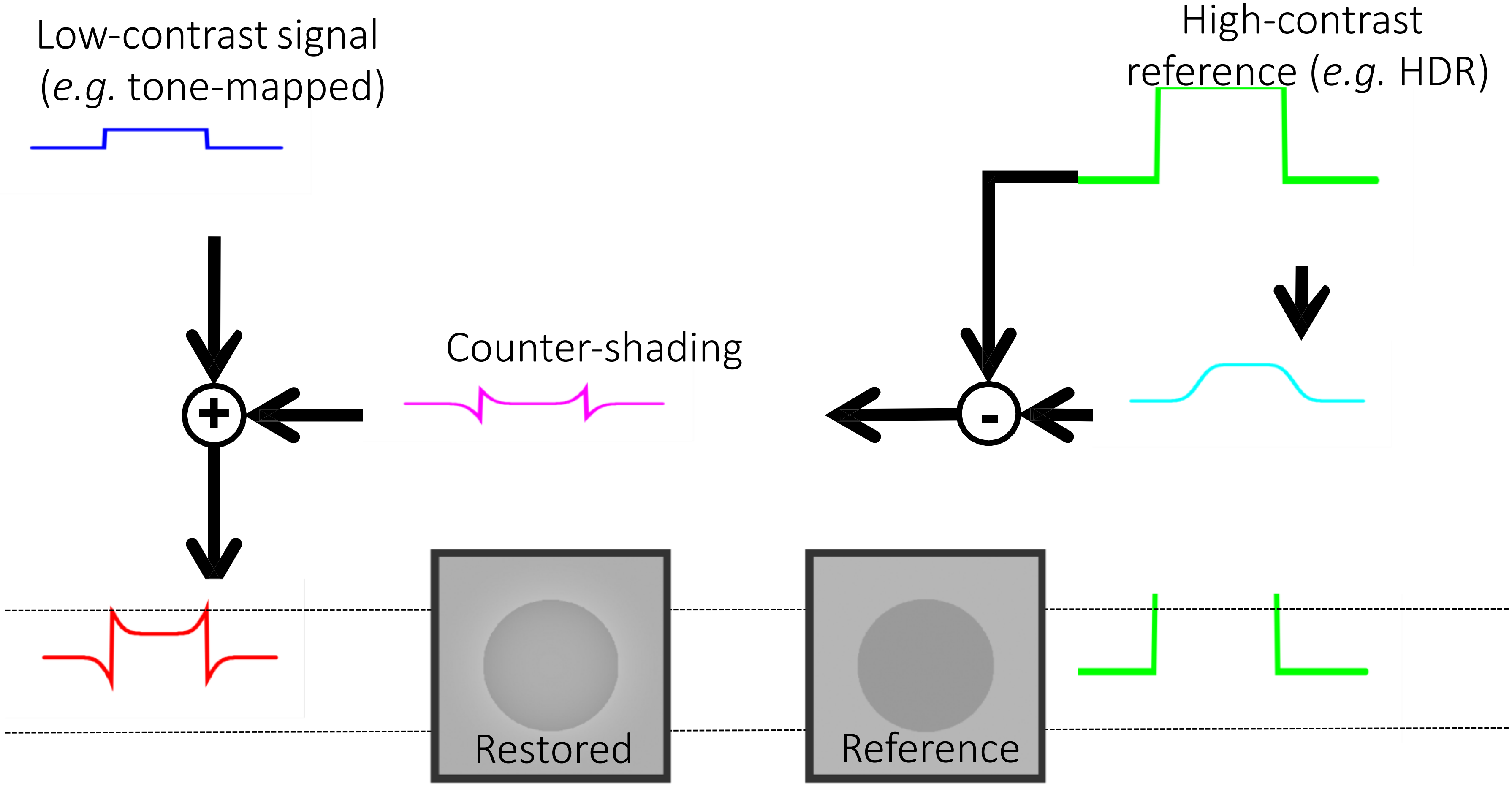


Enhanced image

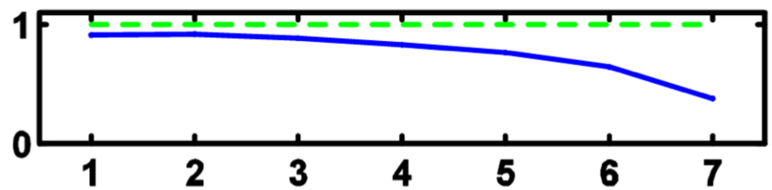
Profile from low-pass filtered reference

Size and amplitude adjusted manually

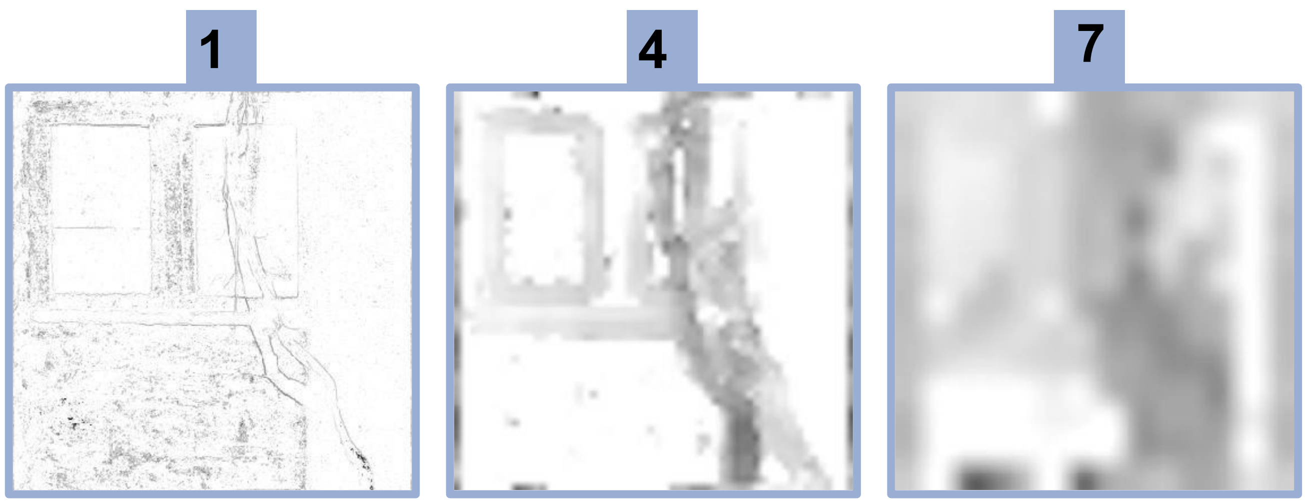
This is unsharp masking



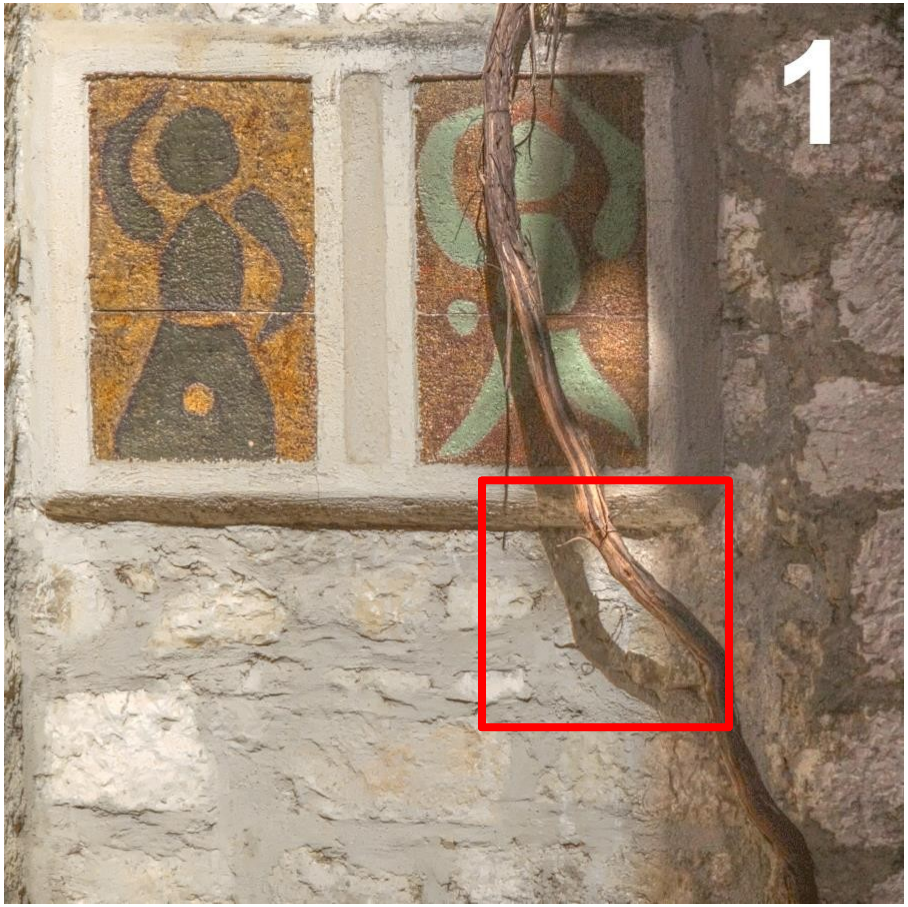
Measure lost contrast at several feature scales



Change in contrast at several scales



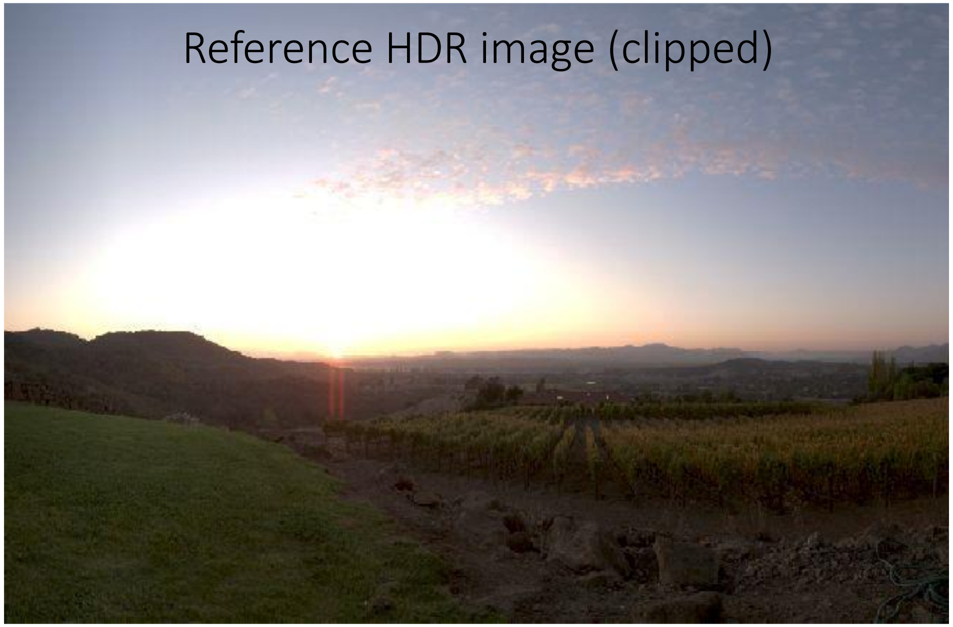
Objectionable visibility of counter-shading profiles

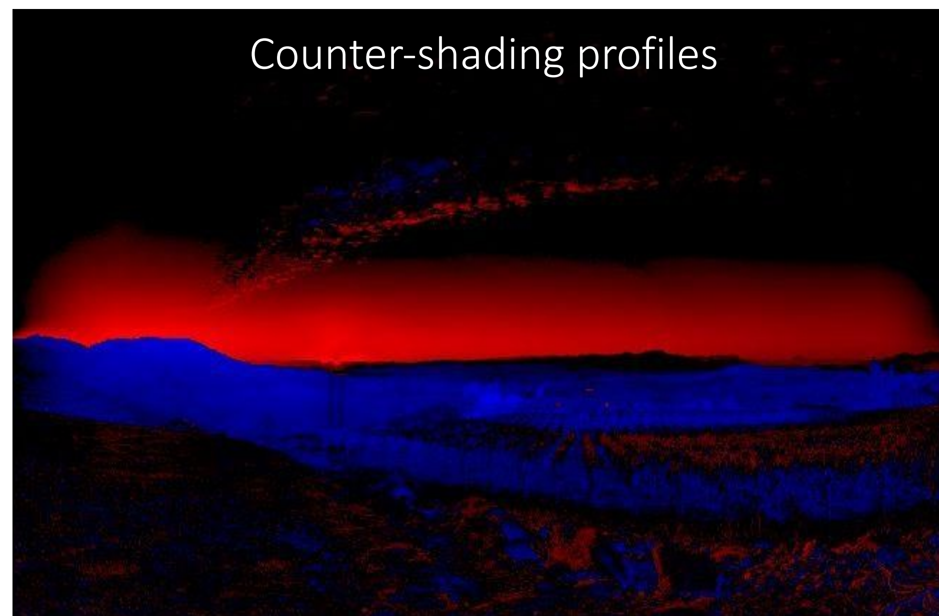


Progress of restoration

Final contrast restoration

Subtle Correction of Details





Improved Separation