Recovering High Dynamic Range Radiance Maps from Photographs

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and

Fast Bilateral Filtering for the Display of High-Dynamic-Range Images

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What is a High Dynamic Range Radiance Map?

- HDR: >> 2 orders of magnitude variation.
  - different formats, incl Greg Ward's RADIANCE
    - 32-bit: R,G,B,exponent

- Radiance: Linear relation to recorded photons
  - “brightness” value of digital photo, used for display
Recovering Radiance

- Non-linear mapping
  - Actually a composition of mappings from every step.

- But it is consistent!
  - We can determine it with known input OR image sets
Recovering Radiance

- Reciprocity
  - exposure \( X = \text{irradiance } E \times \text{exposure time } \Delta t \)
  - Holds under all but extreme conditions
    - For film, \( 10^{-4}\text{sec} < \Delta t < 10\text{sec} \)
    - For digital, so long as CCD is actually counting photons
  - We ignore spectral response, etc.
Recovering Radiance

• Analyzing input

  – image j, pixel i value $Z_{ij} = f(E_i \Delta t_j)$

  – Scene (E) is constant – no position or lighting changes!

  – assume $f$ is monotonic, and therefore invertible.

  • $f^{-1}(Z_{ij}) = E_i \Delta t_j$

  • $g = \ln f^{-1} \implies g(Z_{ij}) = \ln E_i + \ln \Delta t_j$
Recovering Radiance

- domain of $Z$ is finite, number of pixels $N$ is finite
  - phrase search as least-squares error minimization:

\[
O = \sum_{i=1}^{N} \sum_{j=1}^{P} \left[ g(Z_{ij}) - \ln E_i - \ln \Delta t_j \right]^2 + \lambda \sum_{z=Z_{min}+1}^{Z_{max}-1} g''(z)^2
\]

- Add a smoothing term.

- Linear Least-Squares, heavily overdetermined
Recovering Radiance

• Refinement: anticipate response function shape
  - enforce linearity more in middle of curve

\[
w(z) = \begin{cases} 
  z - Z_{\text{min}} & \text{for } z \leq \frac{1}{2}(Z_{\text{min}} + Z_{\text{max}}) \\
  Z_{\text{max}} - z & \text{for } z > \frac{1}{2}(Z_{\text{min}} + Z_{\text{max}}) 
\end{cases}
\]

\[
O = \sum_{i=1}^{N} \sum_{j=1}^{P} \left\{ w(Z_{ij}) \left[ g(Z_{ij}) - \ln E_i - \ln \Delta t_j \right] \right\}^2 + \\
\lambda \sum_{z=Z_{\text{min}}+1}^{Z_{\text{max}}-1} \left[ w(z) g''(z) \right]^2
\]
Recovering Radiance

- Now we have response curve $g$, and want the map
  - Re-use weighting function to improve accuracy
    - counteract saturation & bloom
  - Can do this now for any image set!

$$\ln E_i = \frac{\sum_{j=1}^{P} w(Z_{ij})(g(Z_{ij}) - \ln \Delta t_j)}{\sum_{j=1}^{P} w(Z_{ij})}$$
Recovering Radiance

● How many do we need?

plot of $g(Z_iz)$ from three pixels observed in five images, assuming unit radiance at each pixel

normalized plot of $g(Z_iz)$ after determining pixel exposures
Recovering Radiance

- **Response curve:**
  - Minimum 2 samples per 'segment' => 2 photos
  - More photos => better noise resistance.

- **Radiance map:**
  - Photos must cover full dynamic range.
  - Min # = [Range of interest] / [Range of 'film']
Recovering Radiance

- This method recovers to within a scale factor
  - Value can be determined with calibrated input.

- Multiple color channels need to be aligned
  - Most digicams color-compensate for some color C
    - \((Z_{\text{mid}}, Z_{\text{mid}}, Z_{\text{mid}})\) should map to radiance w/ ratios \(\sim C\)
Recovering Radiance: Results

- Example response curve: Kodak DCS460
Recovering Radiance: Results

- [Image sets, HDRView]

- Applications:
  - Accurate motion blur
  - Perceptually-accurate scenes
    - w/ histogram compression & human visual model
  - Virtual photographs
  - Scene lighting models
No single exposure looks good.

We want to preserve detail in all areas
  - But we have to reduce contrast range for any medium

Human vision is sensitive to local context
  - So, separate image into large-scale contrast base and remaining detail layer.
Existing tone-mapping methods

- **Global**: same for all pixels => indirect approach
  - S-curve preserves some detail in shadow and highlight
  - Histogram adjustment discarding empty portions
    - Fails when histogram lacks significant gaps
- **Local**: neighborhood-dependent mapping
  - Most use varying scale filters
    - Compress low frequencies and preserve detail in higher
    - Haloing is a big problem (not constrained to 2 orders mag.)
  - Intrinsic property layers: reflectance and illumination
    - Very good, but requires 3d model information
  - Anisotropic diffusion + edge-preservation
    - Effective but slow and requires per-image tuning
  - Bilateral Filtering has properties of previous two.
Anisotropic Diffusion

- Treat intensities as heat, propagate to neighbors
  - iterative process, no set stopping point, and blurs edges
- Add “edge-stopping” function: alter conductance
  - strong gradients stop diffusion entirely
  - terminates at *piecewise* uniform image
- Powerful but very slow
Bilateral Filtering

- Tomasi & Manduchi 1998, alternative to AD
- Smooths & preserves edges via weighted avg.
- Weights on distance in space and range (value)

\[
J_s = \frac{1}{k(s)} \sum_{p \in \Omega} f(p - s) \ g(I_p - I_s) \ I_p,
\]

where \(k(s)\) is a normalization term:

\[
k(s) = \sum_{p \in \Omega} f(p - s) \ g(I_p - I_s).
\]
Bilateral Filtering

- Original uses Gaussian on both space and range
  - effect: gaussian kernel minus all distant-value pixels
[Switch to Durand&Dorsey slides]