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

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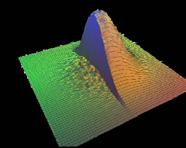
Contributions

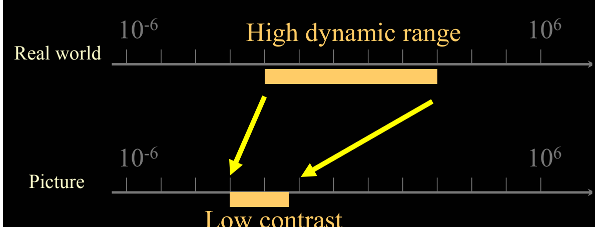
- Contrast reduction for HDR images
- Edge-preserving filter



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

Contrast reduction

- Match limited contrast of the medium
- Preserve details



A typical photo

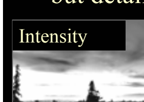
- Sun is overexposed
- Foreground is underexposed

Gamma compression

- $X \rightarrow X^{\gamma}$
- Colors are washed-out

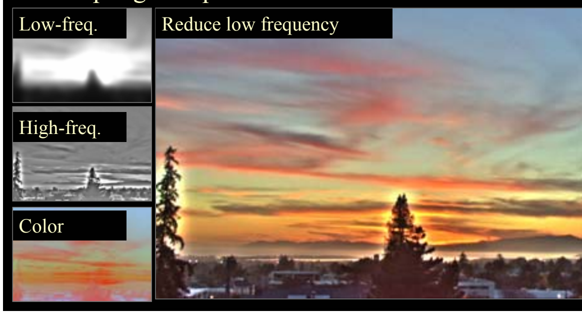
Gamma compression on intensity

- Colors are OK,
  but details (intensity high-frequency) are blurred



Chiu et al. 1993

- Reduce contrast of low-frequencies
- Keep high frequencies

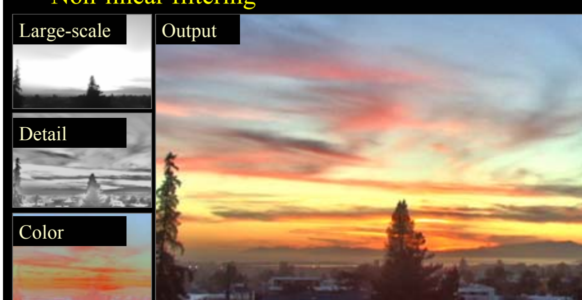


The halo nightmare

- For strong edges
- Because they contain high frequency

Our approach

- Do not blur across edges
- Non-linear filtering



Multiscale decomposition

- Multiscale retinex [Jobson et al. 1997]

Compressed Compressed Compressed

- Perceptual filters [Pattanaik et al. 1998]

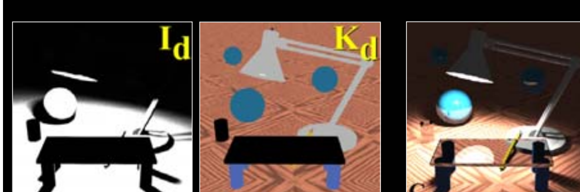
Edge-preserving filtering & LCIS

- [Tumblin & Turk 1999]
- Multiscale decomposition using LCIS (anisotropic diffusion)

Simplified (at multiple scales) Compressed — Details — Output

Layer decomposition

- [Tumblin et al. 1999]
- For 3D scenes
- Reduce only illumination layer



Illumination layer Compressed — Reflectance layer — Output

Comparison with our approach

- We use only 2 scales
- Can be seen as illumination and reflectance
- Different edge-preserving filter from LCIS

Compressed

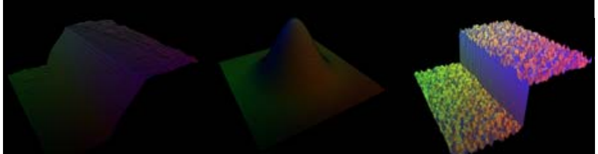
Plan

- Review of bilateral filtering [Tomasi and Manduchi 1998]
- Theoretical framework
- Acceleration
- Handling uncertainty
- Use for contrast reduction

Start with Gaussian filtering

- Here, input is a step function + noise

$$J = f \otimes I$$

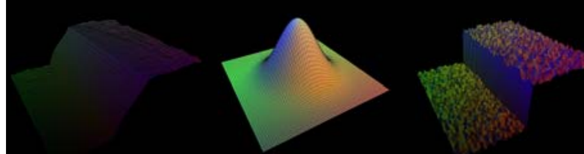


output ⟵ input

Start with Gaussian filtering

- Spatial Gaussian f

$$J = f \otimes I$$

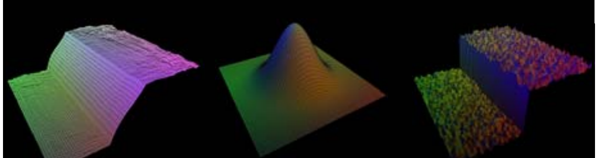


output ⟵ input

Start with Gaussian filtering

- Output is blurred

$$J = f \otimes I$$

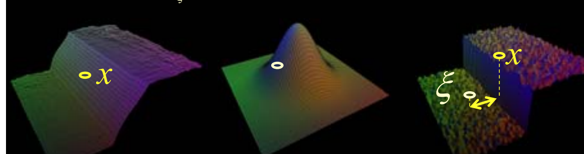


output ⟵ input

Gaussian filter as weighted average

- Weight of ξ depends on distance to x

$$J(x) = \sum_{\xi} f(x,\xi) \; I(\xi)$$

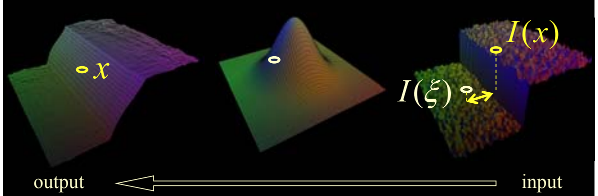


output ⟵ input

The problem of edges

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

$$J(x) = \sum_{\xi} f(x,\xi) \quad I(\xi)$$



Principle of Bilateral filtering

[Tomasi and Manduchi 1998]

- Penalty g on the intensity difference

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

Bilateral filtering

[Tomasi and Manduchi 1998]

- Spatial Gaussian f

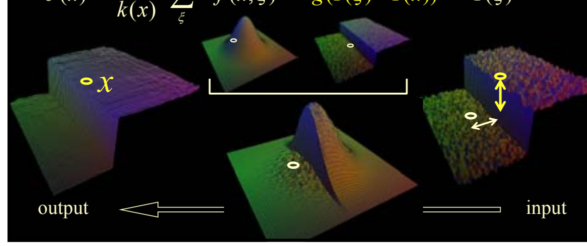
$$J(x) = \frac{1}{k(x)} \sum_{\xi} f(x,\xi) \quad g(I(\xi)-I(x)) \quad I(\xi)$$

Bilateral filtering

[Tomasi and Manduchi 1998]

- Spatial Gaussian f
- Gaussian g on the intensity difference

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

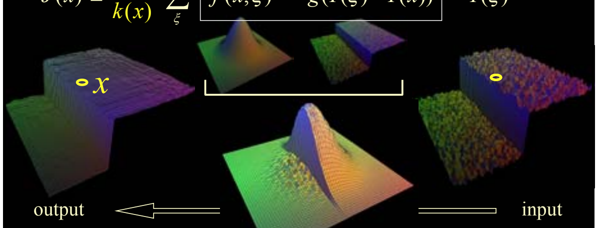


Normalization factor

[Tomasi and Manduchi 1998]

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

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

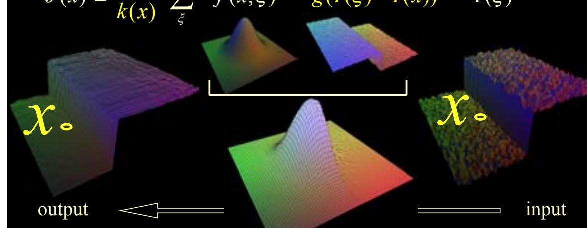


Bilateral filtering is non-linear

[Tomasi and Manduchi 1998]

- The weights are different for each output pixel

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



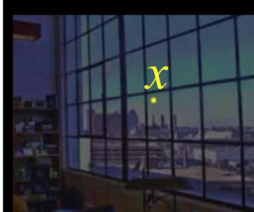
Plan

- Review of bilateral filtering [Tomasi and Manduchi 1998]
- Theoretical framework
- Acceleration
- Handling uncertainty
- Use for contrast reduction

Theoretical framework

- Framework of robust statistics
  - Output = estimator at each pixel
  - Less influence to outliers (because of g)
- Unification with anisotropic diffusion
  - Mostly equivalent
  - Some differences
- Details and other insights in paper

Spatial support



Spatial support

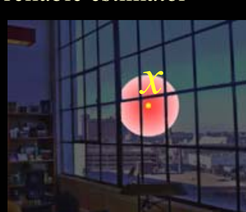
- Anisotropic diffusion cannot diffuse across edges

Support of anisotropic diffusion

Spatial support

- Anisotropic diffusion cannot diffuse across edges
- Bilateral filtering can
- Larger support => more reliable estimator

Support of anisotropic diffusion

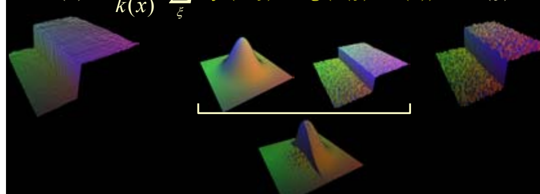


Support of bilateral

Acceleration

- Non-linear because of g

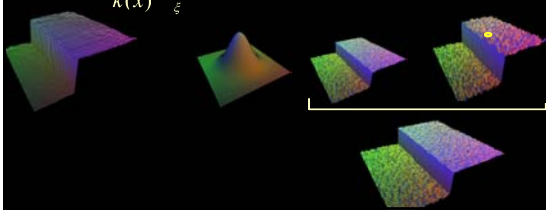
$$J(x) = \frac{1}{k(x)} \sum_{\xi} \; f(x,\xi) \quad g(I(\xi)-I(x)) \quad I(\xi)$$



Acceleration

- Linear for a given value of I(x)
- Convolution of g I by Gaussian f

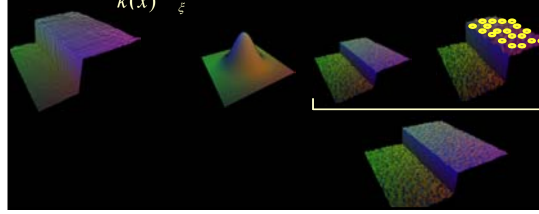
$$J(x) = \frac{1}{k(x)} \sum_{\xi} f(x,\xi) \quad g(I(\xi)-I(x)) \quad I(\xi)$$



Acceleration

- Linear for a given value of I(x)
- Convolution of g I by Gaussian f
- Valid for all x with same value I(x)

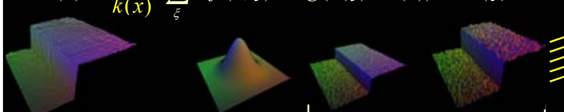
$$J(x) = \frac{1}{k(x)} \sum_{\xi} f(x,\xi) \quad g(I(\xi)-I(x)) \quad I(\xi)$$



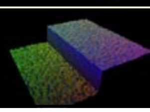
Acceleration

- Discretize the set of possible I(x)
- Perform linear Gaussian blur (FFT)
- Linear interpolation in between

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



- k(x) treated similarly

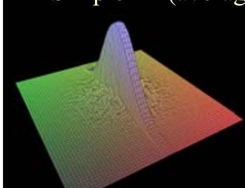


Acceleration

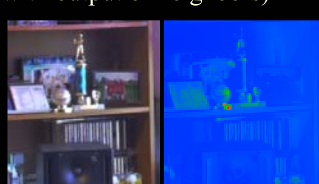
- Piecewise-linearization
  - x10 for a 80pixel kernel on 576*768 image
- Subsampling
  - x30 for a 4x subsampling
  - Superlinear because of cache
- 2 seconds for 2MPixel image (for he complete tone mapping)

Handling uncertainty

- Sometimes, not enough “similar” pixels
- Happens for specular highlights
- Can be detected using normalization k(x)
- Simple fix (average with output of neighbors)



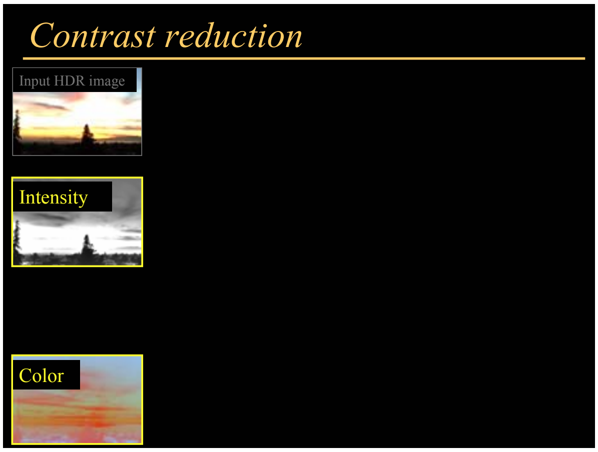
Weights with high uncertainty

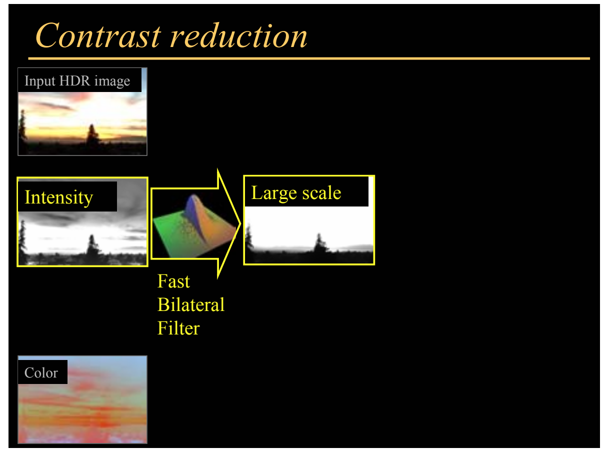


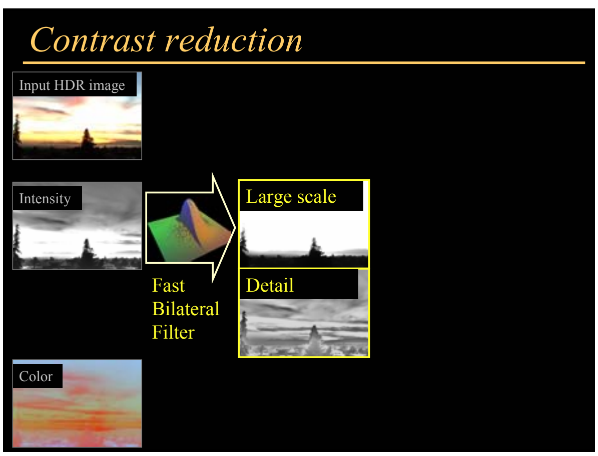
Uncertainty

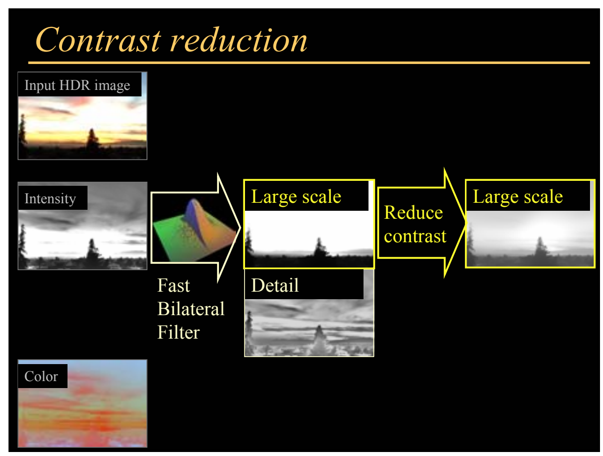
Contrast reduction

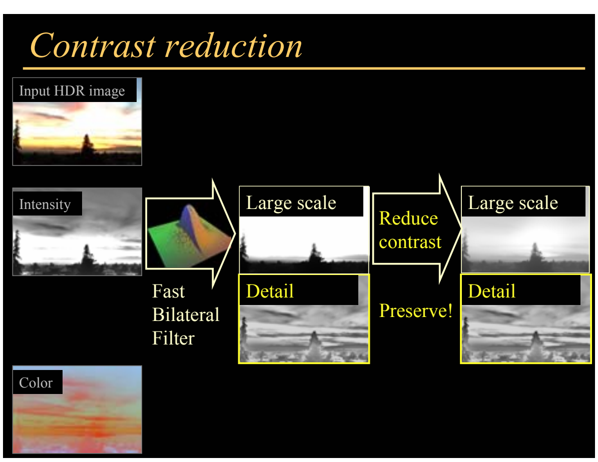
Contrast too high!

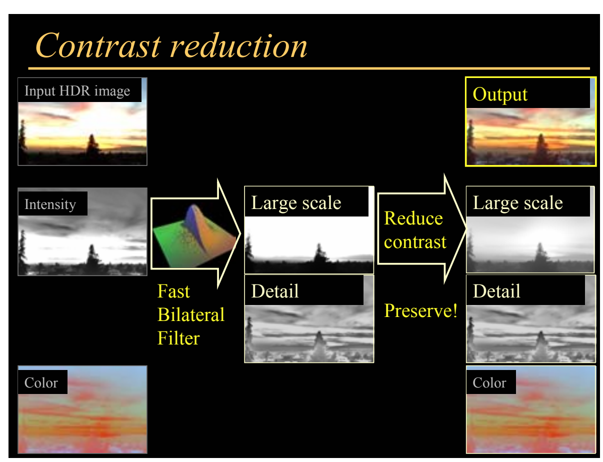

Contrast reduction
Input HDR image
Intensity
Color


Contrast reduction
Input HDR image
Intensity
Large scale
Fast Bilateral Filter
Color


Contrast reduction
Input HDR image
Intensity
Large scale
Detail
Fast Bilateral Filter
Color


Contrast reduction
Input HDR image
Intensity
Large scale
Reduce contrast
Large scale
Detail
Fast Bilateral Filter
Color


Contrast reduction
Input HDR image
Intensity
Large scale
Reduce contrast
Large scale
Detail
Preserve!
Detail
Fast Bilateral Filter
Color


Contrast reduction
Input HDR image
Output
Intensity
Large scale
Reduce contrast
Large scale
Detail
Preserve!
Detail
Fast Bilateral Filter
Color
Color

Live demo

- Xx GHz Pentium Whatever PC

Conclusions

- Edge-preserving filter
- Framework of robust statistics
- Acceleration (x300)
- Handling uncertainty

- Contrast reduction
- Can handle challenging photography issues
- Richer sensor + post-processing

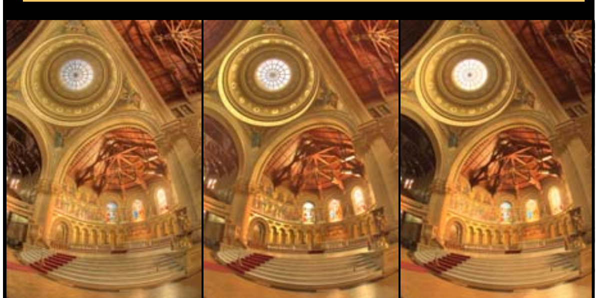
Future work

- Uncertainty fix
- Other applications of bilateral filter (meshes, MCRT)
- Video sequences
- High-dynamic-range sensors
- Other pictorial techniques

Acknowledgments

- Mok Oh
- Ray Jones
- Paul Debevec
- Jack Tumblin
- Reviewers
- NSF
- Pixar

Informal comparison



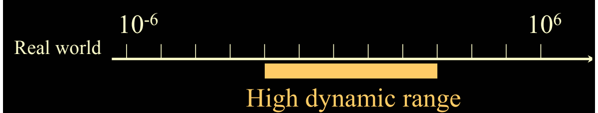
Gradient domain [Fattal et al.] | Bilateral [Durand et al.] | Photographic [Reinhard et al.]

Informal comparison

Gradient domain [Fattal et al.] | Bilateral [Durand et al.] | Photographic [Reinhard et al.]

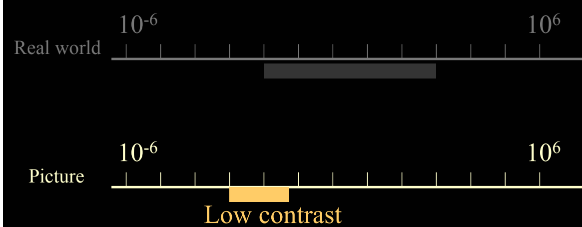
Real world dynamic range

- ~ 10^{-6} to 10^{6} cd/m^2
- Often 1 : 100,000 in a scene



Picture dynamic range

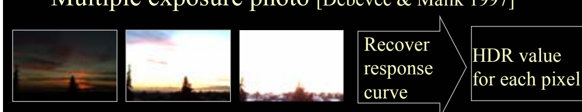
- Typically 1:50
  - Black is ~ 50x darker than white
- Max 1:500



High-dynamic-range (HDR) images

- CG Images

- Multiple exposure photo [Debevec & Malik 1997]



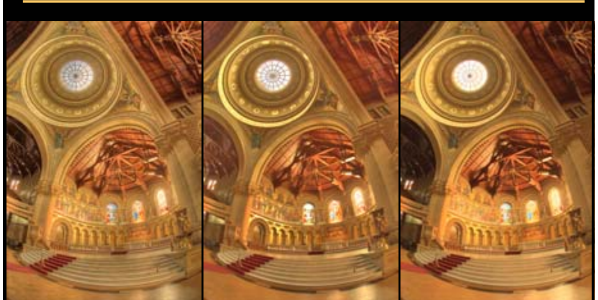
- HDR sensors

Edge-preserving filtering

- Blur, but not across edges

- Anisotropic diffusion [Perona & Malik 90]
  - Blurring as heat flow
  - LCIS [Tumblin & Turk]
- Bilateral filtering [Tomasi & Manduci, 98]

Informal comparison



Gradient-space [Fattal et al.]	Bilateral [Durand et al.]	Photographic [Reinhard et al.]

Informal comparison

Gradient-space [Fattal et al.]	Bilateral [Durand et al.]	Photographic [Reinhard et al.]