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

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Contributions
- Contrast reduction for HDR images
  - Local tone mapping
  - Preserves details
  - No halo
  - Fast
- Edge-preserving filter

High-dynamic-range (HDR) images
- CG Images
- Multiple exposure photo [Debevec & Malik 1997]
- HDR sensors

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]
- Perceptual filters [Pattanaik et al. 1998]

**Edge-preserving filtering**
- Blur, but not across edges
- Anisotropic diffusion [Perona & Malik 90]
  - Blurring as heat flow
  - Low Curvature Image Simplifiers (LCIS) [Tumblin & Turk]
- Bilateral filtering [Tomasi & Manduc, 98]
**Edge-preserving filtering & LCIS**
- [Tumblin & Turk 1999]
- Multiscale decomposition using LCIS (anisotropic diffusion)

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

**Comparison with our approach**
- We use only 2 scales
- Can be seen as illumination and reflectance
- Different edge-preserving filter from LCIS

**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

**Start with Gaussian filtering**
- Spatial Gaussian $f$
Start with Gaussian filtering

- Output is blurred

Gaussian filter as weighted average

- Weight of $\xi$ depends on distance to $x$

The problem of edges

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

Principle of Bilateral filtering

- Penalty $g$ on the intensity difference

Bilateral filtering

- Spatial Gaussian $f$
- Gaussian $g$ on the intensity difference
**Normalization factor**

[Tomasi and Manduchi 1998]

- \( k(x) = \sum_{\Theta} I(x+\Theta) \sum_{\Theta} I(x-\Theta) \)

**Bilateral filtering is non-linear**

[Tomasi and Manduchi 1998]

- The weights are different for each output pixel

**Plan**

- Review of bilateral filtering [Tomasi and Manduchi 1998]
- Theoretical framework
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**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**

- Anisotropic diffusion cannot diffuse across edges
**Spatial support**

- Anisotropic diffusion cannot diffuse across edges
- Bilateral filtering can
- Larger support $\Rightarrow$ more reliable estimator

Support of anisotropic diffusion  Support of bilateral

**Contrast reduction**

Contrast too high!

Input HDR image

Contrast reduction

Input HDR image

Intensity

Large scale

Fast Bilateral Filter

Detail

Color

Contrast reduction

Input HDR image

Intensity

Large scale

Fast Bilateral Filter

Detail

Color

Contrast reduction

Input HDR image

Intensity

Reduce contrast

Large scale

Fast Bilateral Filter

Detail

Color

Contrast reduction

Input HDR image

Intensity

Large scale

Fast Bilateral Filter

Detail

Color
Contrast reduction

Input HDR image

Intensity
Fast Bilateral Filter
Color

Large scale
Reduce contrast
Detail
Preserve

Output
Intensity
Fast Bilateral Filter
Color

Large scale
Reduce contrast
Detail
Preserve

Conclusions

- Edge-preserving filter
- Framework of robust statistics
- Acceleration
- 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

Informal comparison

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

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**Real world dynamic range**
- $\sim 10^{-6}$ to $10^6$ cd/m²
- Often 1 : 100,000 in a scene

**Picture dynamic range**
- Typically 1:50
  - Black is ~ 50x darker than white
- Max 1:500

**Gaussian filter as weighted average**
- Weight = spatial Gaussian $f$

**Further acceleration**
- Most costly operation are low-pass filters
- Subsampling
- But interpolation between discretized values must be done at full resolution
  - To respect sharp edges