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
    - LCIS [Tumblin & Turk]
  - Bilateral filtering [Tomasi & Manduci, 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

\[
J = f \otimes I
\]


**Start with Gaussian filtering**

- Output is blurred

\[ J = f \otimes I \]

**Gaussian filter as weighted average**

- Weight of \( \xi \) depends on distance to \( x \)

\[ J(x) = \sum_{\xi} f(x, \xi) I(\xi) \]

**The problem of edges**

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

\[ J(x) = \sum_{\xi} f(x, \xi) I(\xi) \]

**Principle of Bilateral filtering**

- Penalty \( g \) on the intensity difference

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

**Bilateral filtering**

- Spatial Gaussian \( f \)

\[ J(x) = \frac{1}{k(x)} \sum_{\xi} f(x, \xi) g(I(\xi) - I(x)) I(\xi) \]
Normalization factor

\[ k(x) = \sum_{\xi} f(x, \xi) \cdot g(I(\xi) - I(x)) \]

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

Plan

- Review of bilateral filtering [Tomasi and Manduchi 1998]
- Theoretical framework
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Bilateral filtering is non-linear

- The weights are different for each output pixel

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

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

Support of anisotropic diffusion
**Spatial support**

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

**Acceleration**

- Non-linear because of \( g \)

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

**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
Contrast reduction

Input HDR image

Contrast too high!

Contrast reduction

Input HDR image

Intensity

Fast Bilateral Filter

Large scale

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

Detail

Reduce contrast

Large scale

Preserve!

Fast Bilateral Filter

Color

Contrast reduction

Input HDR image

Intensity

Large scale

Detail

Reduce contrast

Large scale

Preserve!

Fast Bilateral Filter

Color
**Contrast reduction**

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

**Live demo**

- Xx GHz Pentium Whatever PC

**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.]