Computational Photography

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http://www.cs.pdx.edu/~fliu/courses/cs510/

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Last Time

- Filters and its applications
Today

- De-noise
  - Median filter
  - Bilateral filter
  - Non-local mean filter
  - Video de-noising
Filter Re-cap

noisy image

naïve denoising Gaussian blur

better denoising edge-preserving filter

Slide credit: Sylvain Paris and Frédo Durand
Median Filter

- Replace pixel by the median value of its neighbors
- No new pixel values introduced
- Removes spikes: good for impulse, salt & pepper noise

Slide credit: C. Dyer
Median Filter

Salt and pepper noise

Median filtered

Plots of a row of the image

**Matlab:** output \( \text{im} = \text{medfilt2}(\text{im}, [h\ w]) \)

Slide credit: M. Hebert, C. Dyer
Median Filter

- Median filter is edge preserving

Slide credit: C. Dyer
Slide credit: C. Dyer
19x19 median filter

input

output

images by J. Plush

Slide credit: C. Dyer
Bilateral filter

- Tomasi and Manduci 1998
  [http://www.cse.ucsc.edu/~manduchi/Papers/ICCV98.pdf](http://www.cse.ucsc.edu/~manduchi/Papers/ICCV98.pdf)

- Related to
  - SUSAN filter
    [Smith and Brady 95]
    [http://citeseer.ist.psu.edu/smith95susan.html](http://citeseer.ist.psu.edu/smith95susan.html)
  - Digital-TV [Chan, Osher and Chen 2001]
    [http://citeseer.ist.psu.edu/chan01digital.html](http://citeseer.ist.psu.edu/chan01digital.html)
  - sigma filter

Slide credit: F. Durand
Start with Gaussian filtering

- Here, input is a step function + noise

\[
J = f \odot I
\]

Slide credit: F. Durand
Gaussian filter as weighted average

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

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

Slide credit: F. Durand
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

[Tomasi and Manduchi 1998]

- Penalty $g$ on the intensity difference

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

Spatial Gaussian filter

\[ J(x) = \frac{1}{k(x)} \sum_{\xi} f(x, \xi) g(I(\xi) - I(x)) \cdot I(\xi) \]
Bilateral filtering [Tomasi and Manduchi 1998]

- Spatial Gaussian \( f \)
- Gaussian \( g \) on the intensity difference

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

Slide credit: F. Durand
Normalization factor  [Tomasi and Manduchi 1998]

\[ k(x) = \sum f(x, \xi) \cdot g(I(\xi) - I(x)) \]

\[ J(x) = \frac{1}{k(x)} \sum f(x, \xi) \cdot g(I(\xi) - I(x)) \cdot I(\xi) \]
Blur from averaging across edges

Same Gaussian kernel everywhere.

Slide credit: P. Sylvain
Bilateral filter: no averaging across edges

The kernel shape depends on the image content.

Slide credit: P. Sylvain
Parameter for spatial distance Gaussian $f$

- $\sigma_f = 2$
- $\sigma_f = 6$
- $\sigma_f = 18$

Parameter for intensity difference Gaussian $g$

- $\sigma_g = 0.1$
- $\sigma_g = 0.25$
- $\sigma_g = \infty$ (Gaussian blur)

Slide credit: P. Sylvain
Parameter for spatial distance Gaussian $f$

- $\sigma_s = 2$
- $\sigma_s = 6$
- $\sigma_s = 18$

Parameter for intensity difference Gaussian $g$

- $\sigma_t = 0.1$
- $\sigma_t = 0.25$
- $\sigma_t = \infty$ (Gaussian blur)

Slide credit: P. Sylvain
Result

Input

Output

Tomasi and Manduchi 1998
Other view

- The bilateral filter uses the 3D distance
Speed

- Direct bilateral filtering is slow (minutes)

- Accelerations exist:
  - Subsampling in space & range
    - Durand & Dorsey 2002
    - Paris & Durand 2006
  - Limit to box kernel & intelligent maintenance of histogram
    - Weiss 2006
Local filters

- Compute a new value at each pixel using its neighboring pixels
- Box filter
- Gaussian filter
- Median filter
- Bilateral filter
Non-local means filter

- Compute a new value at each pixel from the whole image

\[
NL[v](i) = \sum_{j \in I} w(i, j)v(j)
\]

- final value at pixel \(i\)
- weight of pixel \(j\)
- value at pixel \(j\)

Weight

\[ w(i, j) = \frac{1}{Z(i)} e^{-\frac{\|v(N_i) - v(N_j)\|_2^2}{h^2}} \]

\( v(N_i) \): patch centered at pixel \( i \)

\( v(N_j) \): patch centered at pixel \( j \)

Similar pixel neighborhoods give a large weight

Reprint from Buades et al. 2005
Input                      Gaussian                  Anisotropic
Total variation

Reprint from Buades et al. 2005
Non-local means filter

- High-quality
- Slow
  - Fast non-local means algorithms available
Video de-noise

- We know how to de-noise an image
- How about video?

E. P. Bennett and L. McMillan. Video Enhancement using Per-pixel Virtual Exposures
SIGGRAPH 2005
Gaussian filter in video cube

- Blurring artifacts
  - Not edge-preserving
  - Motion blur
Bilateral filter in video cube

- Cannot remove shot noise

Figure 3: Left: The bilateral filter recovers the signal (blue) from the noisy input (red). Right: The bilateral filter is unable to attenuate the shot noise because no other pixels fall within the intensity dissimilarity Gaussian.

Reprint from [Bennett and McMillan 2005]
ASTA Filter [Bennett and McMillan ‘05]

- Build upon bilateral filter
- Find similar pixels in a video cube for filtering
  - Patch-based similarity measurement
- Adaptive Spatial-temporal Accumulation Filter
  - Prefer temporal neighbors
Patch-based similarity measurement

$$D(p_{x,y,t}, s_{x,y,t}) = \frac{\sum_{x=sx-n}^{sx+n} \sum_{y=sy-n}^{sy+n} g(\|x-p_x, y-p_y\|, \sigma_e) |I_{x,y,pt} - I_{x,y,st}|}{\sum_{x=sx-n}^{sx+n} \sum_{y=sy-n}^{sy+n} g(\|x-p_x, y-p_y\|, \sigma_e)}$$
Similarity measure

Figure 4: Illustration of our spatial neighborhood dissimilarity value used in temporal filtering. The original frame is shown in the upper left. Each \((x,y)\) for a pair of nearby frames are shown in the upper right. Two metronome arms are seen because the dissimilarity value is based on absolute value. The bottom image is the same frame processed using ASTA and our tone mapper.

Reprint from [Bennett and McMillan 2005]
Adaptive Filtering

Figure 5: Illustration of the temporal-only and spatial-only nature of ASTA. The temporally filtered red pixels are preferred to be integrated into the filter, but if not enough are similar to the center of the kernel, the blue spatial pixels begin to be integrated.

Reprint from [Bennett and McMillan 2005]
Results (filtering + tone mapping)

Input                         Naïve method                     ASTA

Reprint from [Bennett and McMillan 2005]
Next Time

☐ Color
☐ Lighting