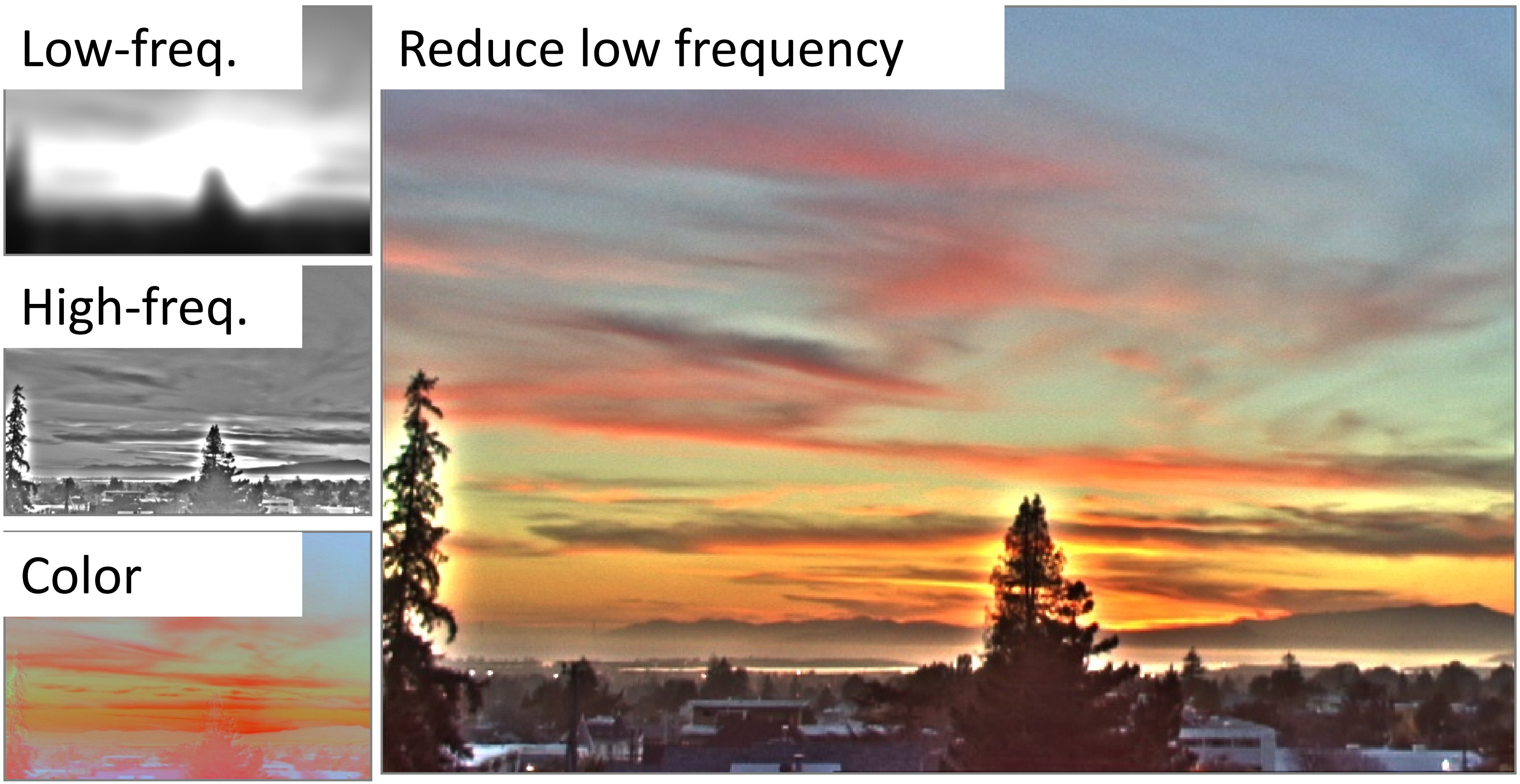
Bilateral Filtering for Tone Mapping

Chiu et al. 1993

- Reduce contrast of low-frequencies
- Keep high frequencies

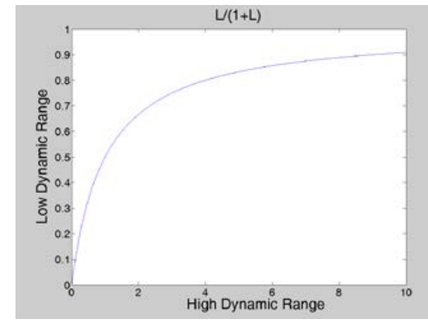


How Does It Work?

- Local tone mapping function

$$L = H \times V$$

$$\varphi(x) = \frac{x}{1+x}$$



compress it by the global mapping function

$$L' = H \times V'$$

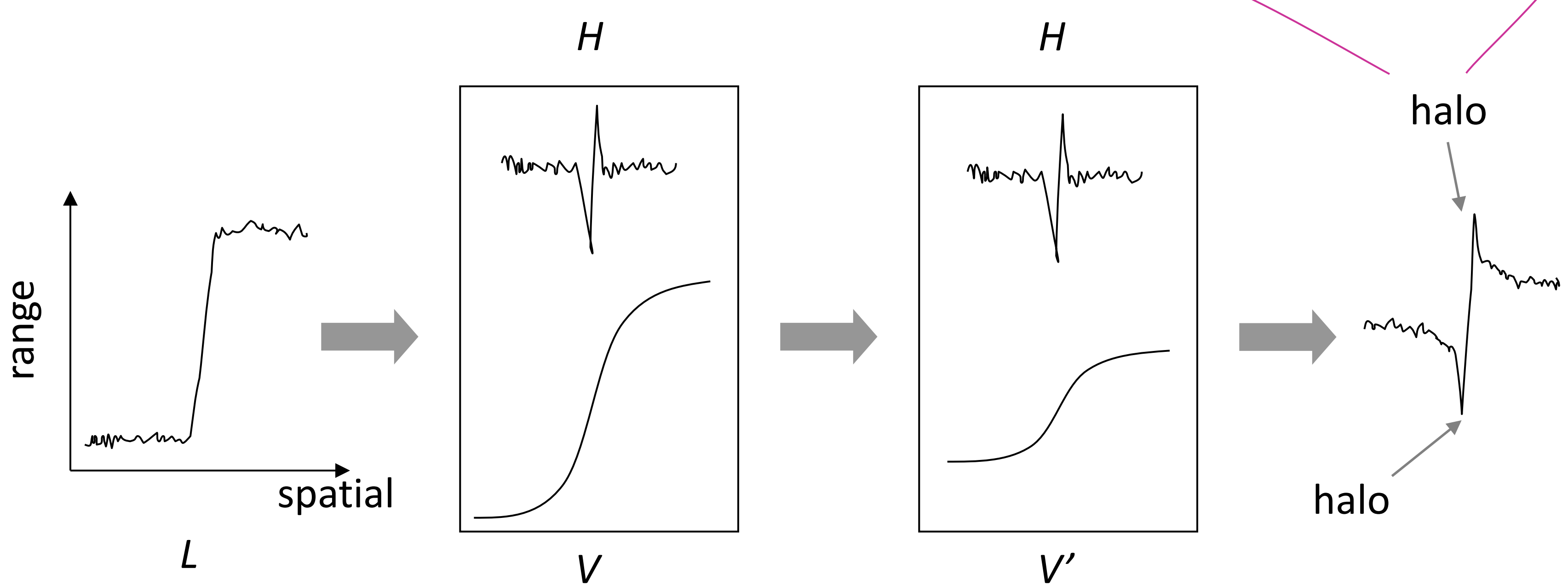
$$= \left(\frac{L}{V}\right) \times \left(\frac{V}{1+V}\right) = \boxed{\frac{L}{1+V}}$$

spatial varying

local mapping function

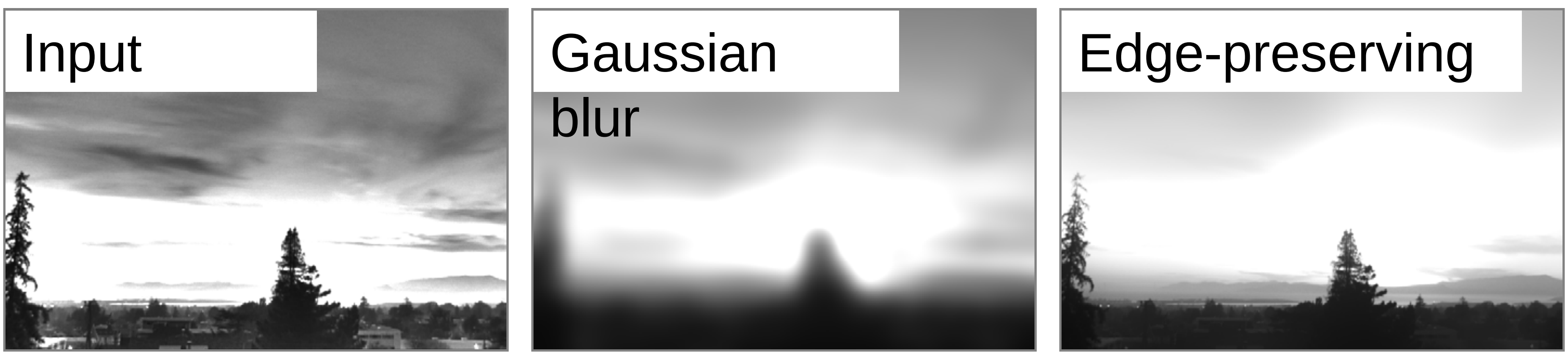
Halos

- Inverse contrasts/gradients



Preventing Halos

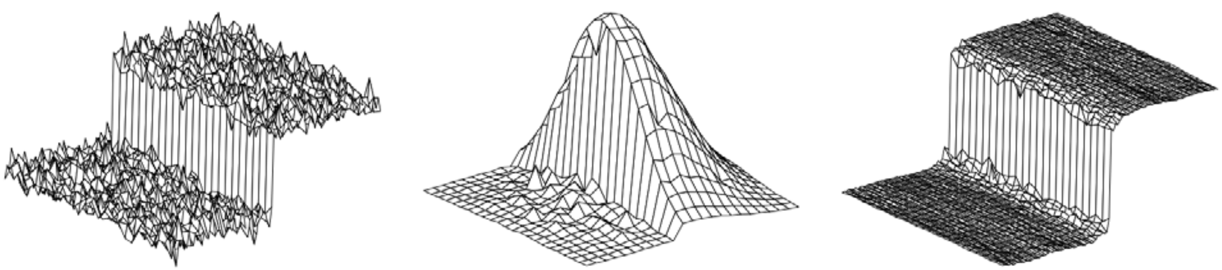
- Need to construct a more appropriate local adaptation luminance V
- Local averaging without blurring edges
  - Multi-scale center-surround



Bilateral Filtering

- Bilateral Filtering for Gray and Color Images, Tomasi and Manduchi
  - ICCV 1998

$$J(s) = \frac{1}{k(s)} \sum_{p \in \Omega} f(p - s)\, g(I_p^t - I_s^t)\, I_p^t$$



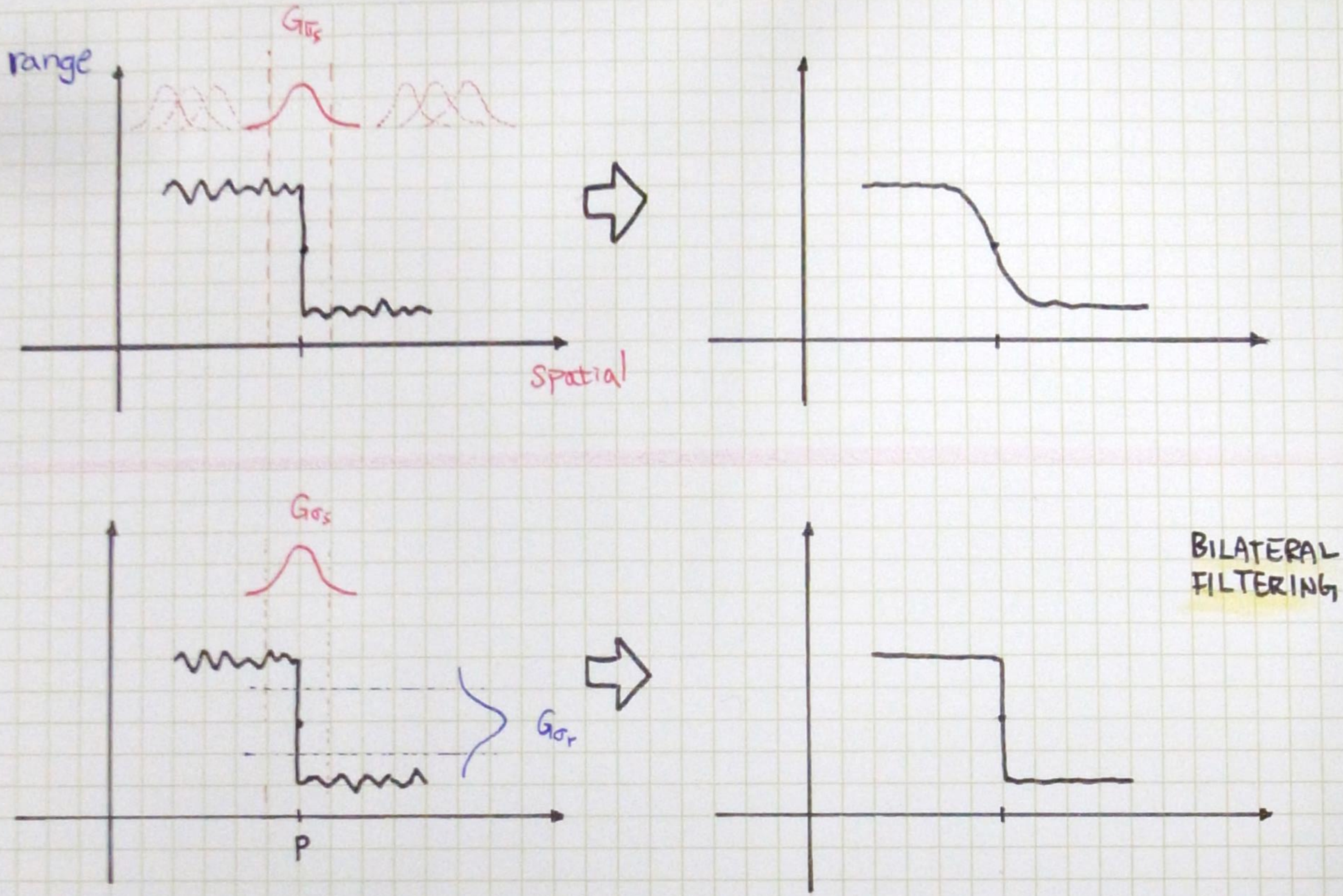
(a) (b) (c)

(a)

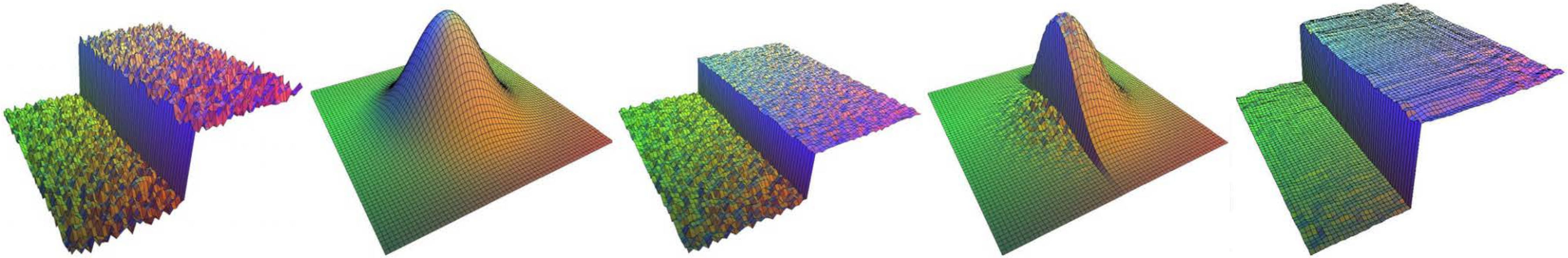
(b)

DATE/NO. TITLE

BILATERAL FILTERING & JOINT BILATERAL FILTERING



$$J(s) = \frac{1}{k(s)} \sum_{p \in \Omega} f(p - s)\, g(I_p^t - I_s^t)\, I_p^t$$



input | spatial kernel f | influence g in the intensity domain for the central pixel | weight $f \times g$ for the central pixel | output

- *Fast Bilateral Filtering for the Display of High-Dynamic-Range Images*
  - F. Durand's ppt slides

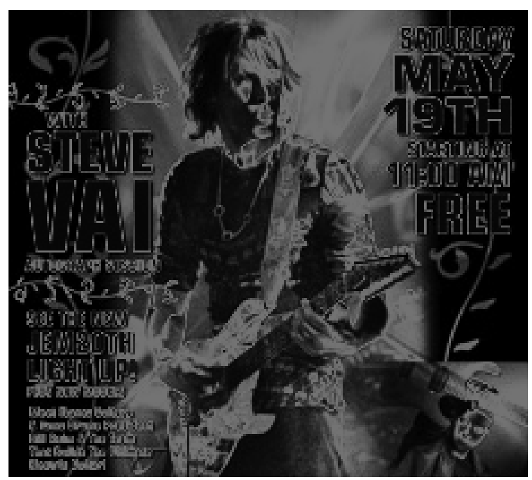
Acceleration

$$\begin{aligned} J_s^j &= \frac{1}{k^j(s)} \sum_{p \in \Omega} f(p-s) \quad g(I_p - i^j) \ I_p \\ &= \frac{1}{k^j(s)} \sum_{p \in \Omega} f(p-s) \quad H_p^j \end{aligned}$$

$$\begin{aligned} k^j(s) &= \sum_{p \in \Omega} f(p-s) \ g(I_p - i^j) \\ &= \sum_{p \in \Omega} f(p-s) \ G^j(p). \end{aligned}$$

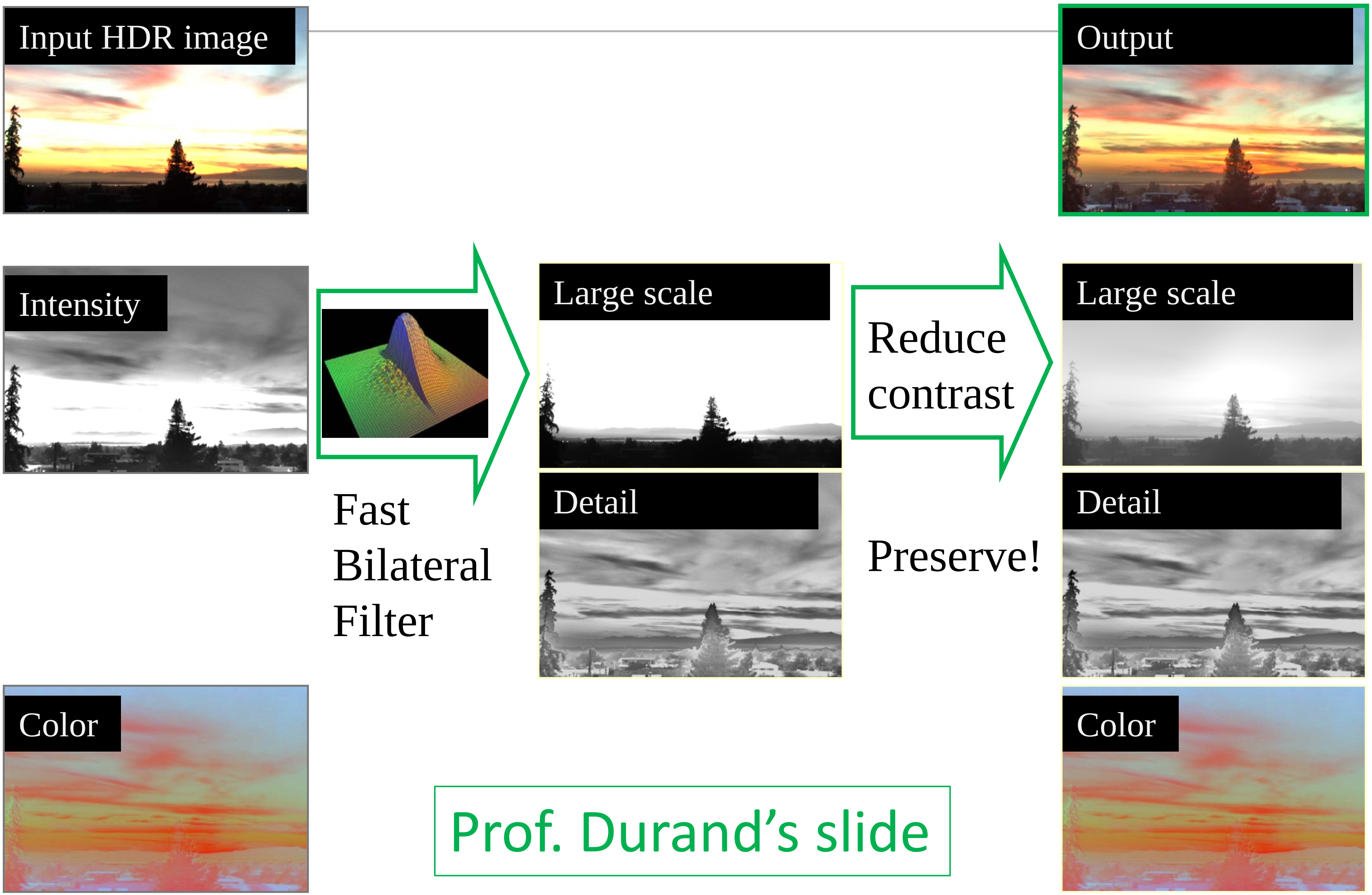

SATURDAY
MAY
19TH
STARTING AT
11:00 AM
FREE
WITH
STEVE
VAI
AUTOGRAPH SESSION
SEE THE NEW
JEM20TH
LIGHT UP!
PLUS NEW MODELS
Meet Ibanez Guitars
& Tama Drums President
Bill Reim & The Team
That Builds The Ultimate
Electric Guitar!


SATURDAY
MAY
19TH
STARTING AT
11:00 AM
FREE
STEVE
VAI


SATURDAY
MAY
19TH
11:00 AM
FREE
STEVE
VAI

```
PiecewiseBilateral
        (Image I, spatial kernel f_σs, intensity influence g_σr)
    J=0                     /* set the output to zero */
    for j=0..NB_SEGMENTS
        i^j = minI+j × (max(I)-min(I))/NB_SEGMENTS
        G^j = g_σr (I - i^j)                    /* evaluate g_σr at each pixel */
        K^j = G^j ⊗ f_σs          /* normalization factor */
        H^j = G^j × I                         /* compute H for each pixel */
        H*^j = H^j ⊗ f_σs
        J^j = H*^j / K^j                      /* normalize */
        J = J + J^j × InterpolationWeight(I, i^j)
```

Contrast reduction



Prof. Durand’s slide

Anisotropic Diffusion

- Heat propagation

$$\frac{\partial I}{\partial t} = \text{div}\left[g(\|\nabla I\|)\nabla I\right] \qquad \text{for edge stoping, } g = ?$$

- Perona & Malik

$$g_1(x) = \frac{1}{1 + \frac{x^2}{\sigma^2}} \qquad g_2(x) = e^{-x^2/\sigma^2}$$

a large ∇I means a small g

- Discrete version $I_s^{t+1} = I_s^t + \frac{\lambda}{4} \sum_{p \in N_4(s)} g(I_p^t - I_s^t)\,(I_p^t - I_s^t)$

Robust Anisotropic Diffusion

- Robust to outliers
  - Black et al.

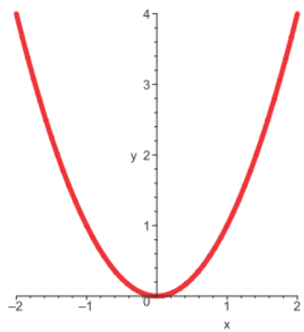
$$\text{minimize} \sum_{s\in\Omega} \sum_{p\in N_4(s)} \rho(I_p^t - I_s^t)$$

minimize error
over the whole image

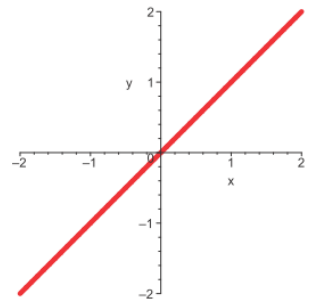
$$I_s^{t+1} = I_s^t + \frac{\lambda}{4} \sum_{p\in N_4(s)} \Psi(I_p^t - I_s^t)$$

$$\text{the influence } \Psi(x) = \rho'(x)$$

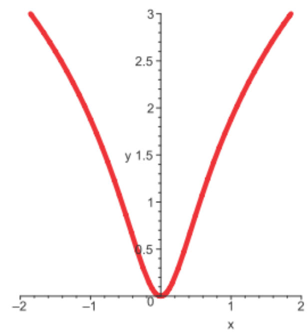
$$\text{Perona \& Malik } \Psi(\nabla I) = g(\nabla I)\nabla I$$



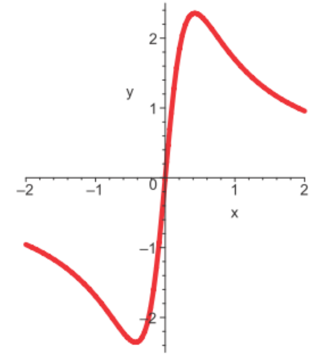
Least square $\rho(x)$



$\psi(x)$

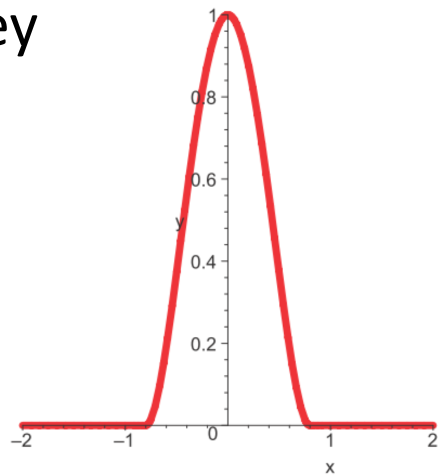


Lorentz $\rho(x)$

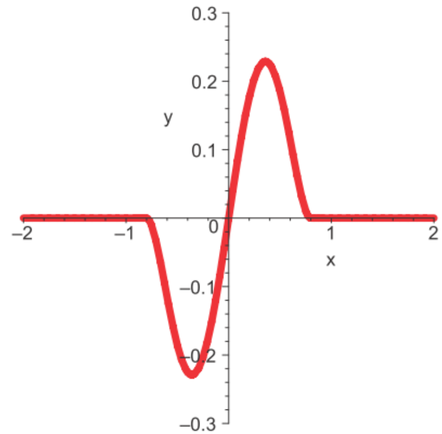


$\psi(x)$

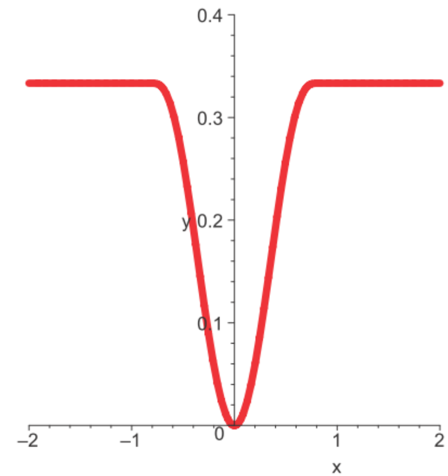
Tuckey



$g(x)$



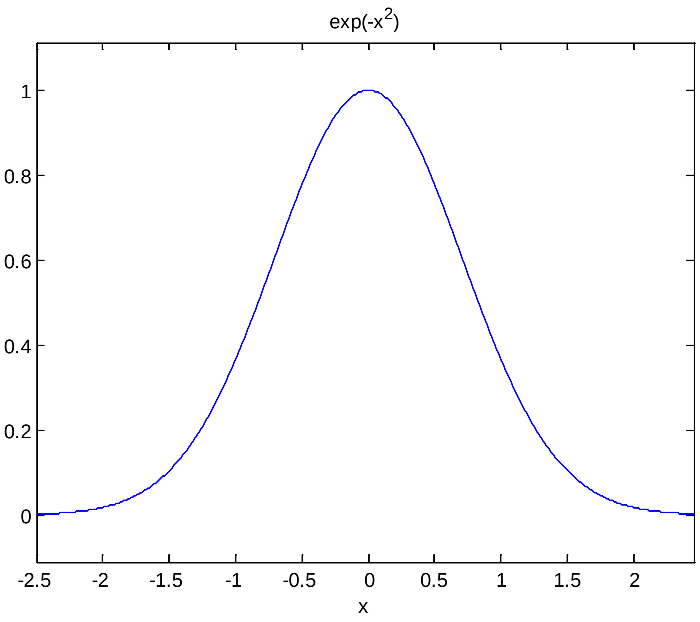
$\psi(x)$



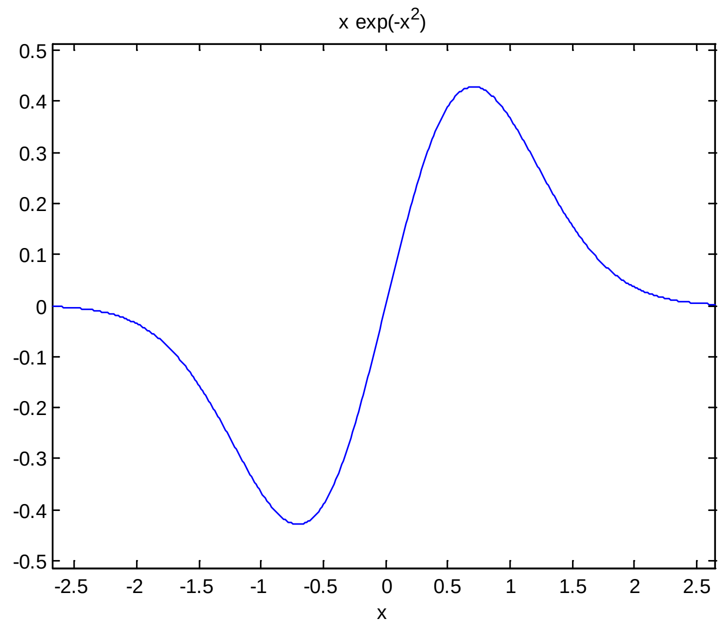
$\rho(x)$

Gaussian

$$g(x)$$



$$\Psi(x)$$



$$\Psi(x) = x\, g(x)$$

Huber	Lorentz
$g_\sigma(x) = \begin{cases} \frac{1}{\sigma} & \lvert x\rvert \le \sigma \\ \frac{1}{\lvert x\rvert}, & \text{otherwise} \end{cases}$	$g_\sigma(x) = \frac{2}{2+\frac{x^2}{\sigma^2}}$
σ	$\sigma/\sqrt{2}$
Tukey	**Gauss**
$g_\sigma(x) = \begin{cases} \frac{1}{2}[1-(x/\sigma)^2]^2 & \lvert x\rvert \le \sigma \\ 0, & \text{otherwise} \end{cases}$	$g_\sigma(x) = e^{-\frac{x^2}{2\sigma^2}}$
$\sigma * \sqrt{5}$	σ

Extend the 0-Oder Anisotropic Diffusion to a Larger Support

$$I_s^{t+1} = I_s^t + \frac{\lambda}{4} \sum_{p \in N_4(s)} g(I_p^t - I_s^t)\,(I_p^t - I_s^t)$$

⇩

$$I_s^{t+1} = I_s^t + \frac{\lambda}{4} \sum_{p \in \Omega} f(p-s)\, g(I_p^t - I_s^t)\,(I_p^t - I_s^t)$$

- Energy preserving
  - Symmetric

Bilateral Filtering

- Non-iterative

$$J(s) = \frac{1}{k(s)} \sum_{p \in \Omega} f(p - s)\, g(I_p^t - I_s^t)\, I_p^t$$

- Not energy preserving

$k(s)$ differs

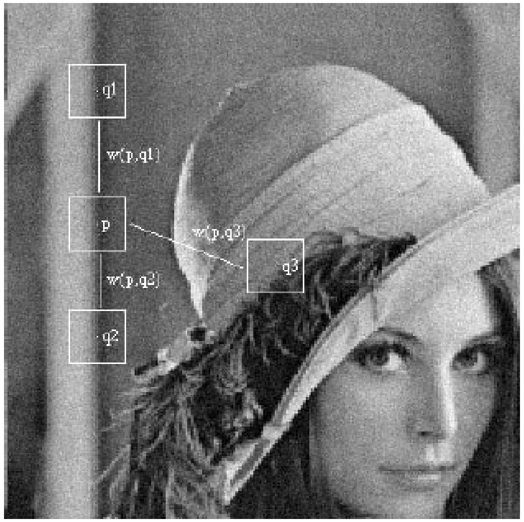
Related Work on Bilateral Filtering

- Bilateral Filtering: Papers, Resources, Applications, Paris and Durand
- Constant time O(1) bilateral filtering Porikli
  - CVPR 2008
- Real-Time O(1) Bilateral Filtering, Yang, Tan and Ahuja
  - CVPR 2009
- SVM for Edge-Preserving Filtering, Yang, Wang and Ahuja
  - CVPR 2010
- Image Smoothing via L0 Gradient Minimization, Xu, Lu, Xu, and Jia
  - SIGGRAPH Asia 2011.

Beyond Bilateral Filtering

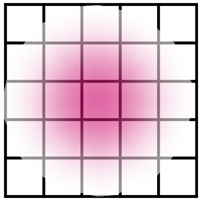
- Non-local averaging
  - For denoising

self-similarity



$$NLu(\mathbf{x}) = \frac{1}{C(\mathbf{x})} \int_{\Omega} e^{-\frac{(G_\rho * |u(\mathbf{x}+.)-u(\mathbf{y}+.)|^2)(0)}{h^2}} u(\mathbf{y}) d\mathbf{y}$$

$$(G_\rho * |u(\mathbf{x}+.) - u(\mathbf{y}+.)|^2)(0) = \int_{\mathbb{R}^2} G_\rho(\mathbf{t}) |u(\mathbf{x}+\mathbf{t}) - u(\mathbf{y}+\mathbf{t})|^2 d\mathbf{t}.$$



  - http://mw.cmla.ens-cachan.fr/megawave/demo/nlmeans/
  - Buades, Coll, and Morel

- Cross/joint bilateral filtering

Trilateral Filter [Choudhury&Tumblin]

$$G_{\theta}(\mathbf{x}) = \frac{1}{k_{\theta}(\mathbf{x})} \int_{\infty}^{\infty} \nabla I_{in}(\mathbf{x}+\zeta) \underline{c(\zeta) s(\|\nabla I_{in}(\mathbf{x}+\zeta) - \nabla I_{in}(\mathbf{x})\|)} d\zeta$$

modified gradient