SIGGRAPH2007

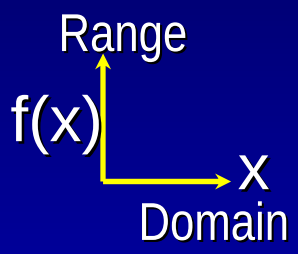
A Gentle Introduction to Bilateral Filtering and its Applications

07/10: Novel Variants of the Bilateral Filter

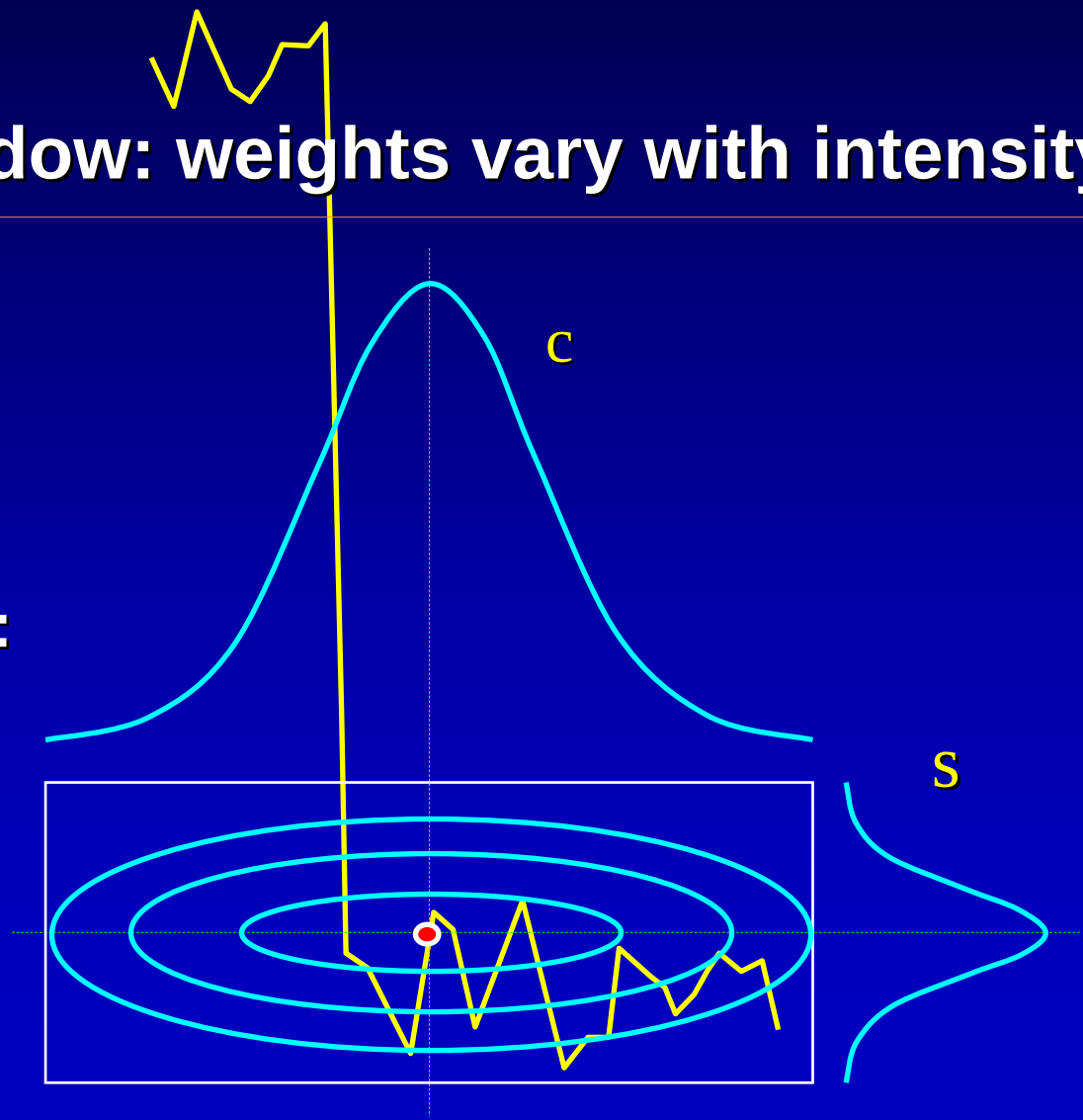
Jack Tumblin – EECS, Northwestern University

Review: Bilateral Filter

A 2-D filter window: weights vary with intensity



2 Gaussian Weights:
product =
ellisoidal footprint

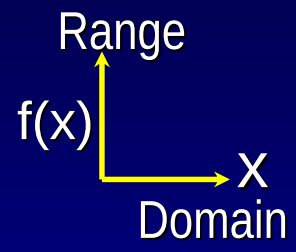


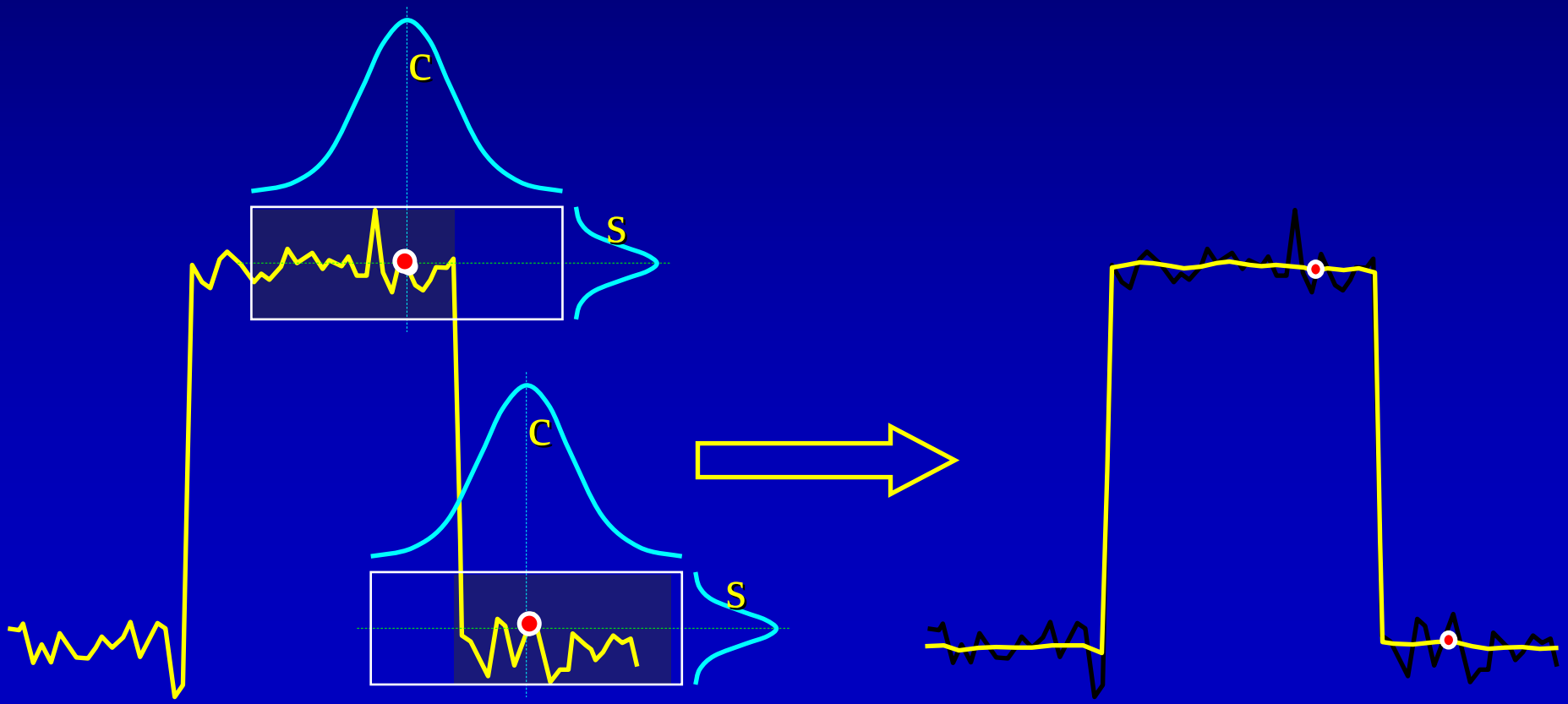
Normalize weights to always sum to 1.0

Review: Bilateral Filter

Why it works: graceful segmentation

- Smoothing for ‘similar’ parts *ONLY*
- Range Gaussian **s** acts as a ‘filtered region’ finder





Bilateral Filter Variants

- before the ‘Bilateral’ name :
  - Yaroslavsky (1985): T.D.R.I.M.
  - Smith & Brady (1997): SUSAN

And now, a growing set of named variants:

- ‘Trilateral’ Filter (Choudhury et al., EGSR 2003)
- Cross-Bilateral (Petschnigg04, Eisemann04)
- NL-Means (Buades 05)

And more coming: application driven…

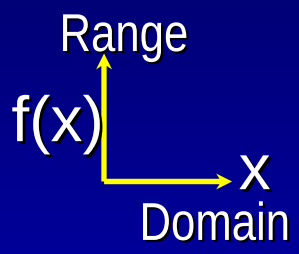
Who was first? Many Pioneers

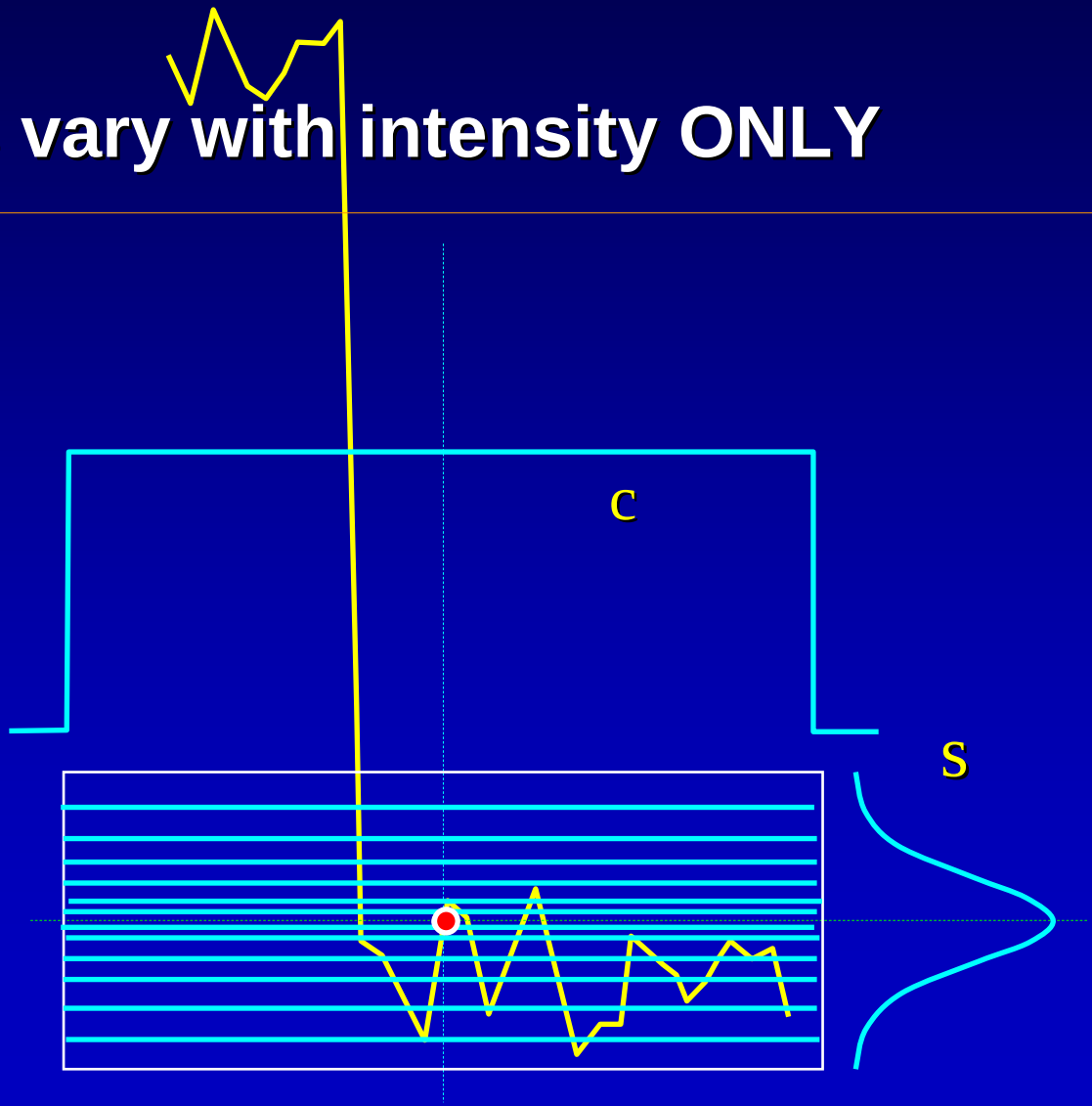
- Elegant, Simple, Broad Idea
  → →
  'Invented' several times

- Different Approaches, Increasing Clarity
  - Tomasi & Manduchi(1998): 'Bilateral Filter'
  - Smith & Brady (1995): 'SUSAN'
    "Smallest Univalue Segment Assimilating Nucleus"
  - Yaroslavsky(1985)
    'Transform Domain Image Restoration Methods'

New Idea!
1985 Yaroslavsky:

A 2-D filter window:
weights vary with intensity ONLY



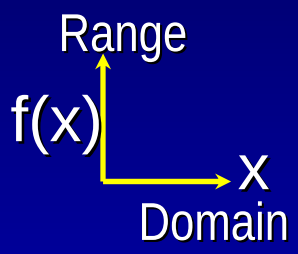


Square neighborhood,
Gaussian Weighted
'similarity'

Normalize weights to always sum to 1.0

New Idea!
1995 Smith: 'SUSAN' Filter

A 2-D filter window: weights vary with intensity



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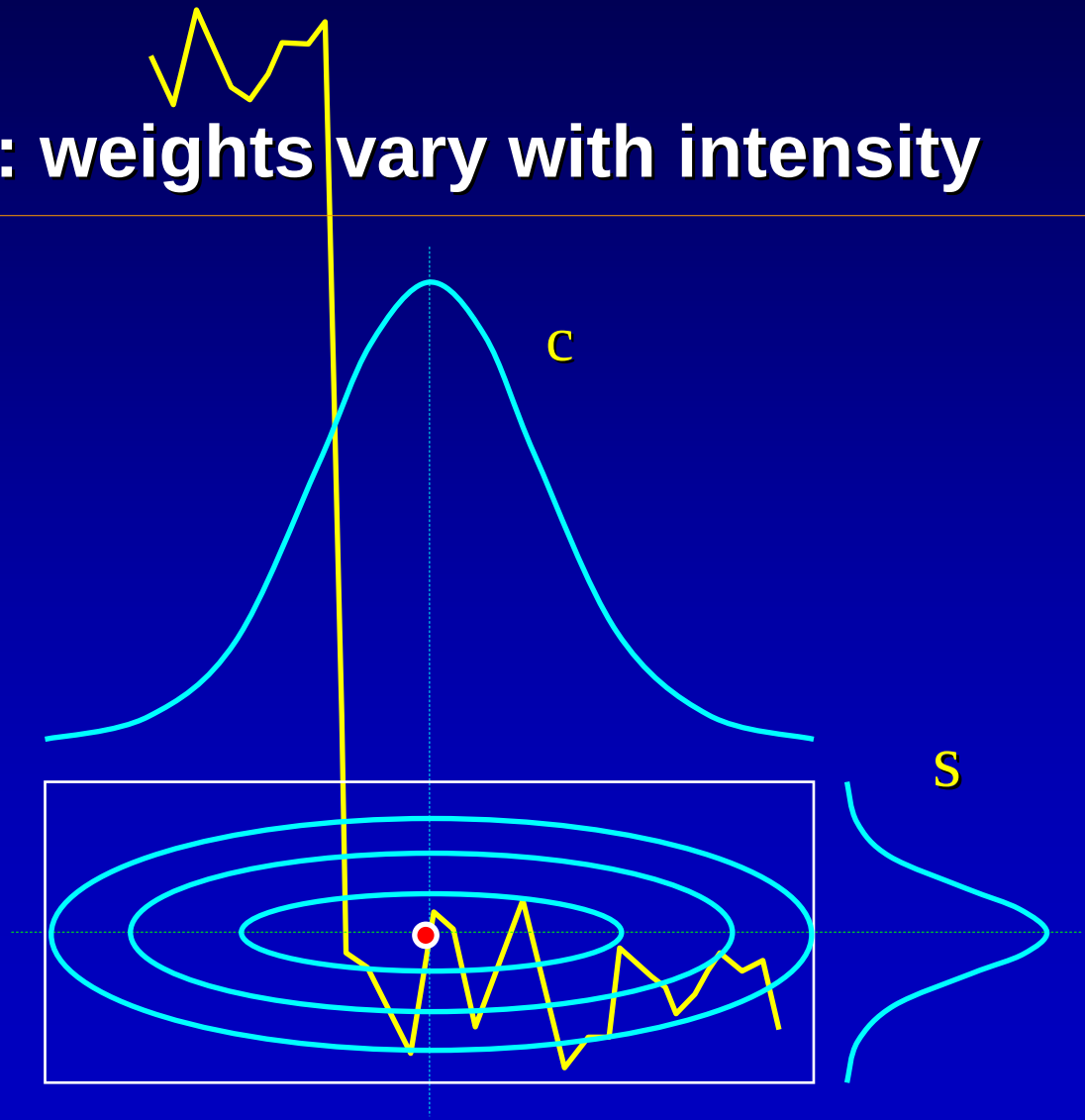


Normalize weights to always sum to 1.0

Background: ‘Unilateral’ Filter

e.g. traditional, linear, FIR filters

Key Idea: Convolution

- Output(x) = local weighted avg. of inputs.
- Weights vary within a ‘window’ of nearby x

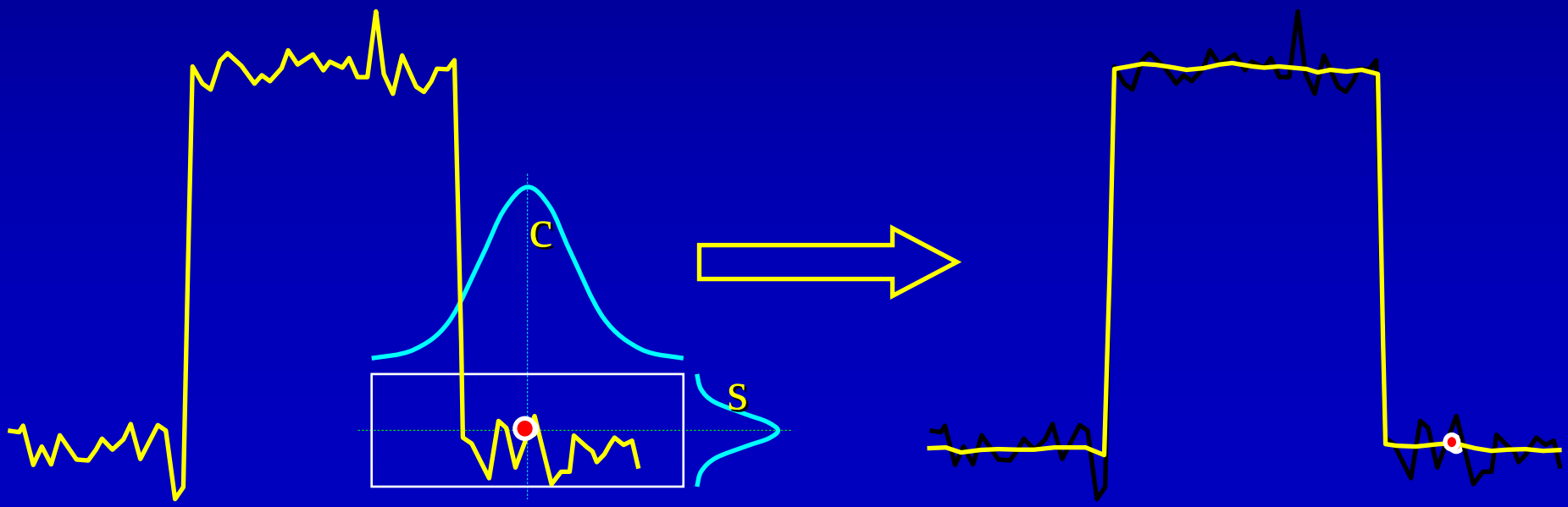
- Smoothes away details, **BUT** blurs result

Bilateral Filter: Strengths

Piecewise smooth result

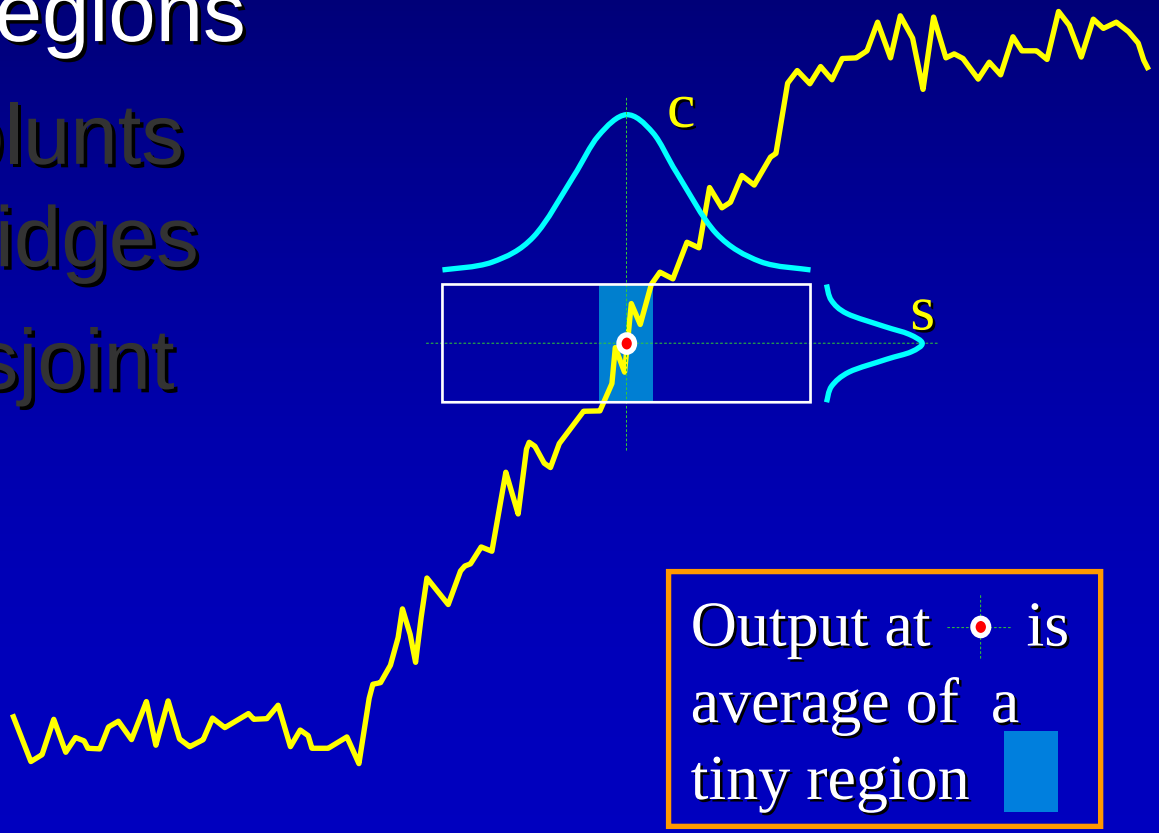
- averages local small details, ignores outliers
- preserves steps, large-scale ramps, and curves,...

- Equivalent to anisotropic diffusion and robust statistics [Black98,Elad02,Durand02]
- Simple & Fast (esp. w/ [Durand02] FFT-based speedup)



Bilateral Filter: 3 Difficulties

- Poor Smoothing in High Gradient Regions
- Smoothes and blunts cliffs, valleys & ridges
- Can combine disjoint signal regions



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- Smoothes and blunts cliffs, valleys & ridges
- Can combine disjoint signal regions

‘Blunted Corners’ → Weak Halos

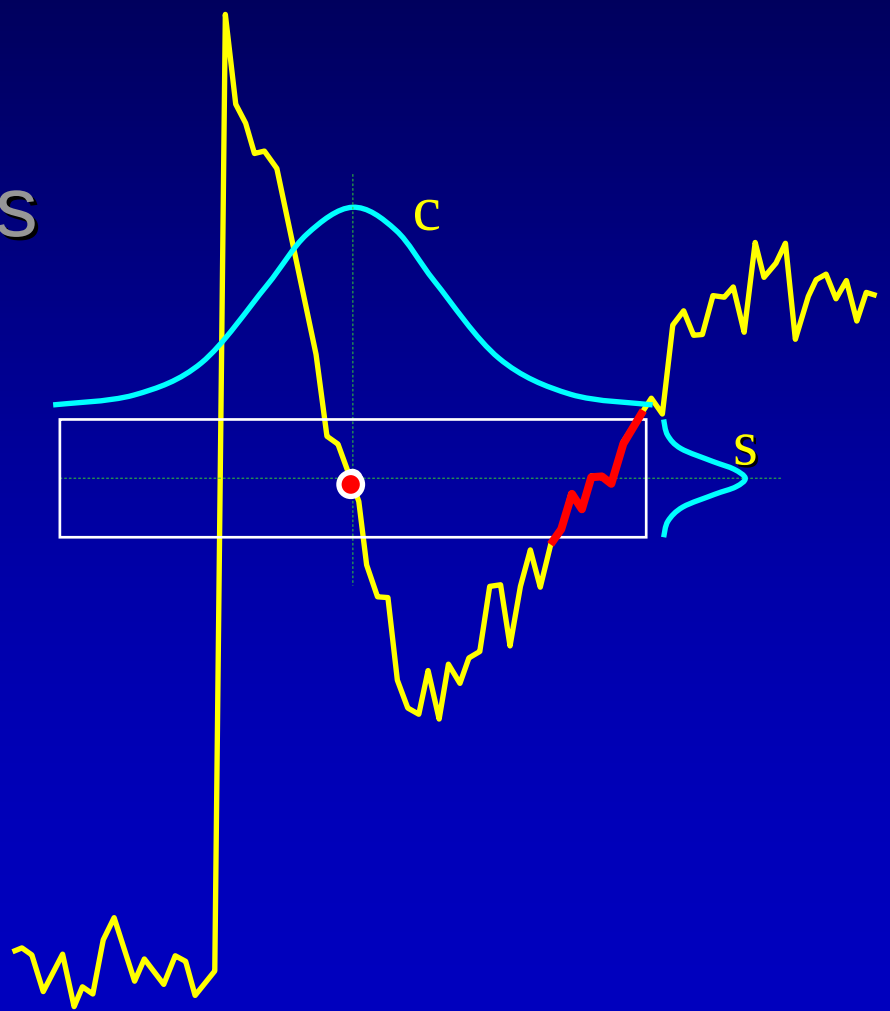
Bilateral :

‘Blunted Corners’ → Weak Halos

‘Trilateral’:

Bilateral Filter: 3 Difficulties

- Poor Smoothing in High Gradient Regions
- Smoothes and blunts cliffs, valleys & ridges
- Disjoint regions can blend together



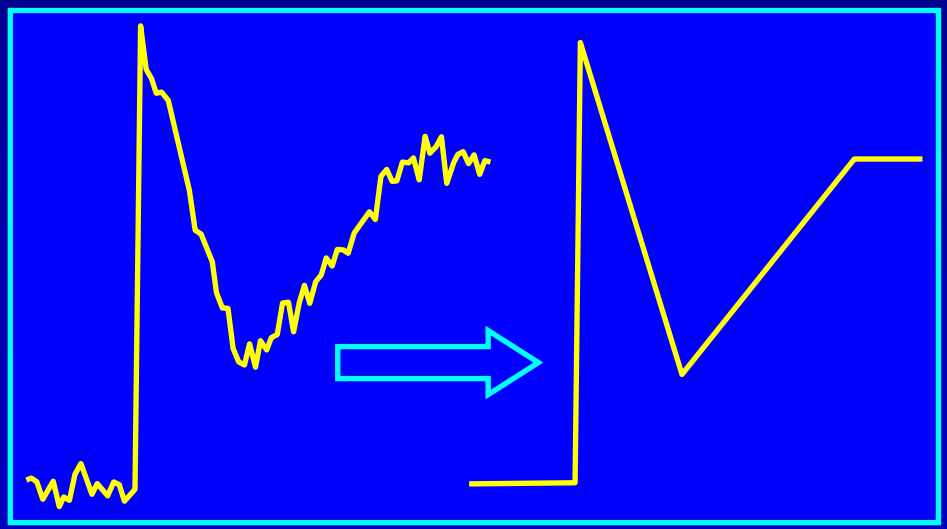
New Idea!
Trilateral Filter (Choudhury 2003)

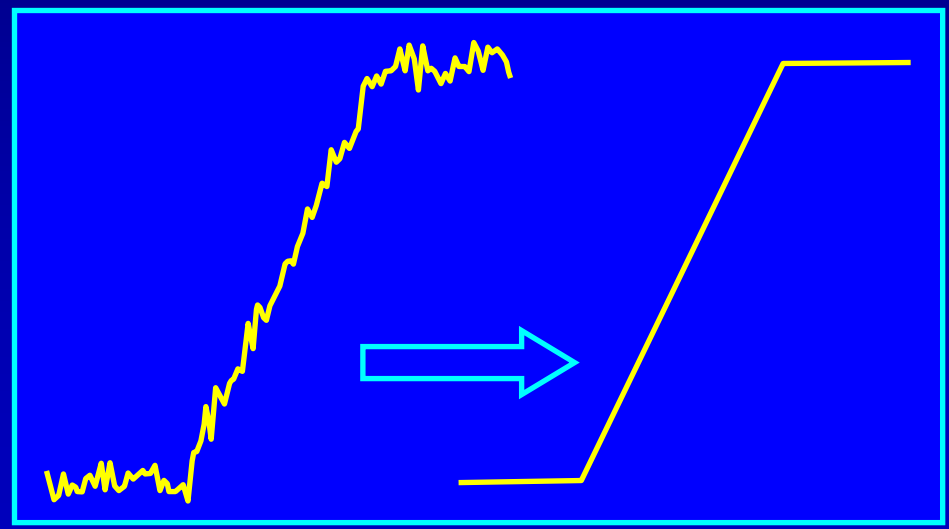
Goal:

Piecewise linear smoothing, not piecewise constant

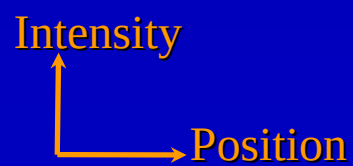
Method:

Extensions to the Bilateral Filter





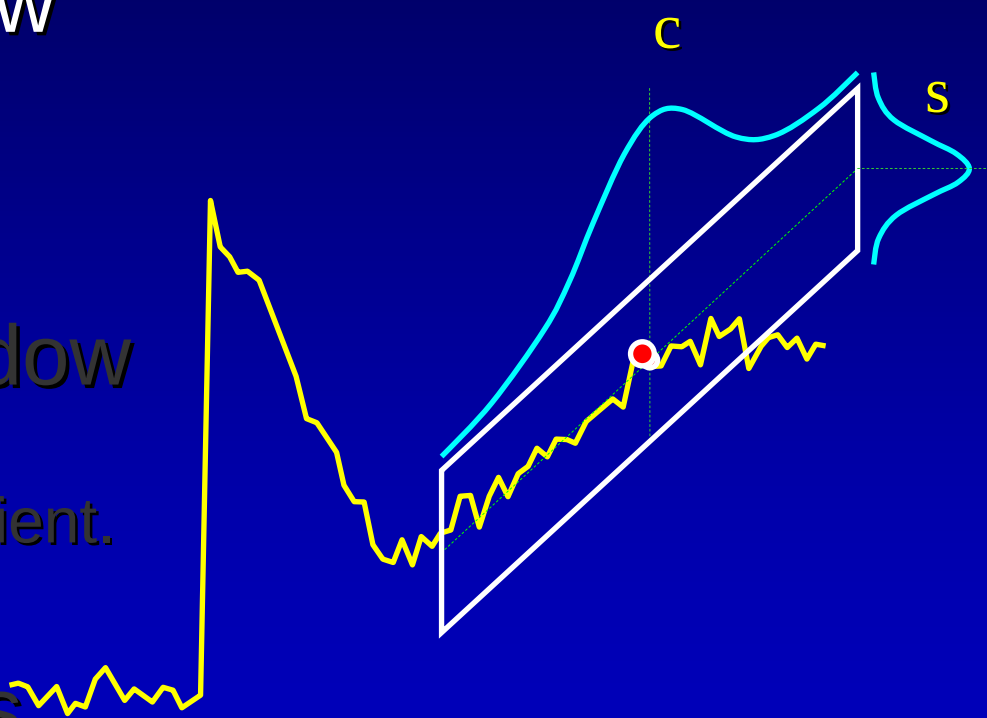
EXAMPLE: remove noise from a piecewise linear scanline



Outline: Bilateral→Trilateral Filter

Three Key Ideas:

- **Tilt** the filter window
  according to bilaterally-smoothed gradients
- **Limit** the filter window
  to connected regions of similar smoothed gradient.
- **Adjust** Parameters
  from measurements of the windowed signal



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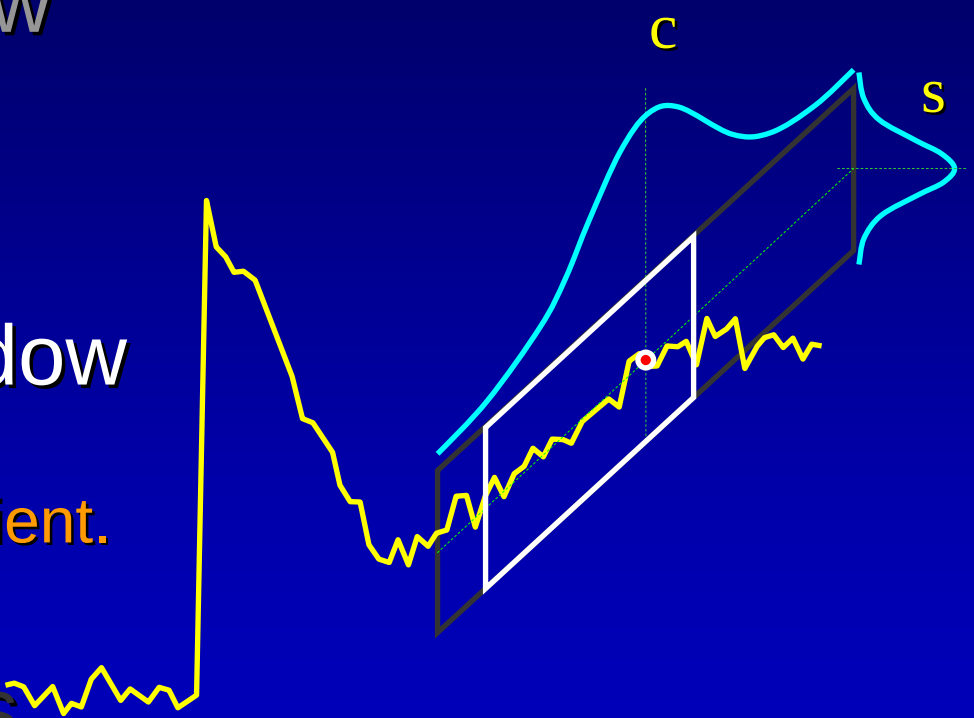

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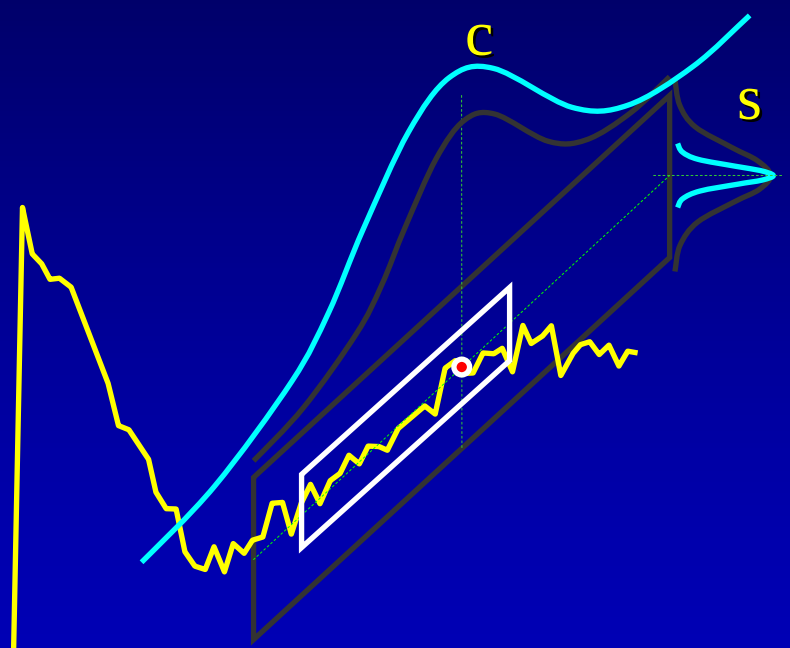
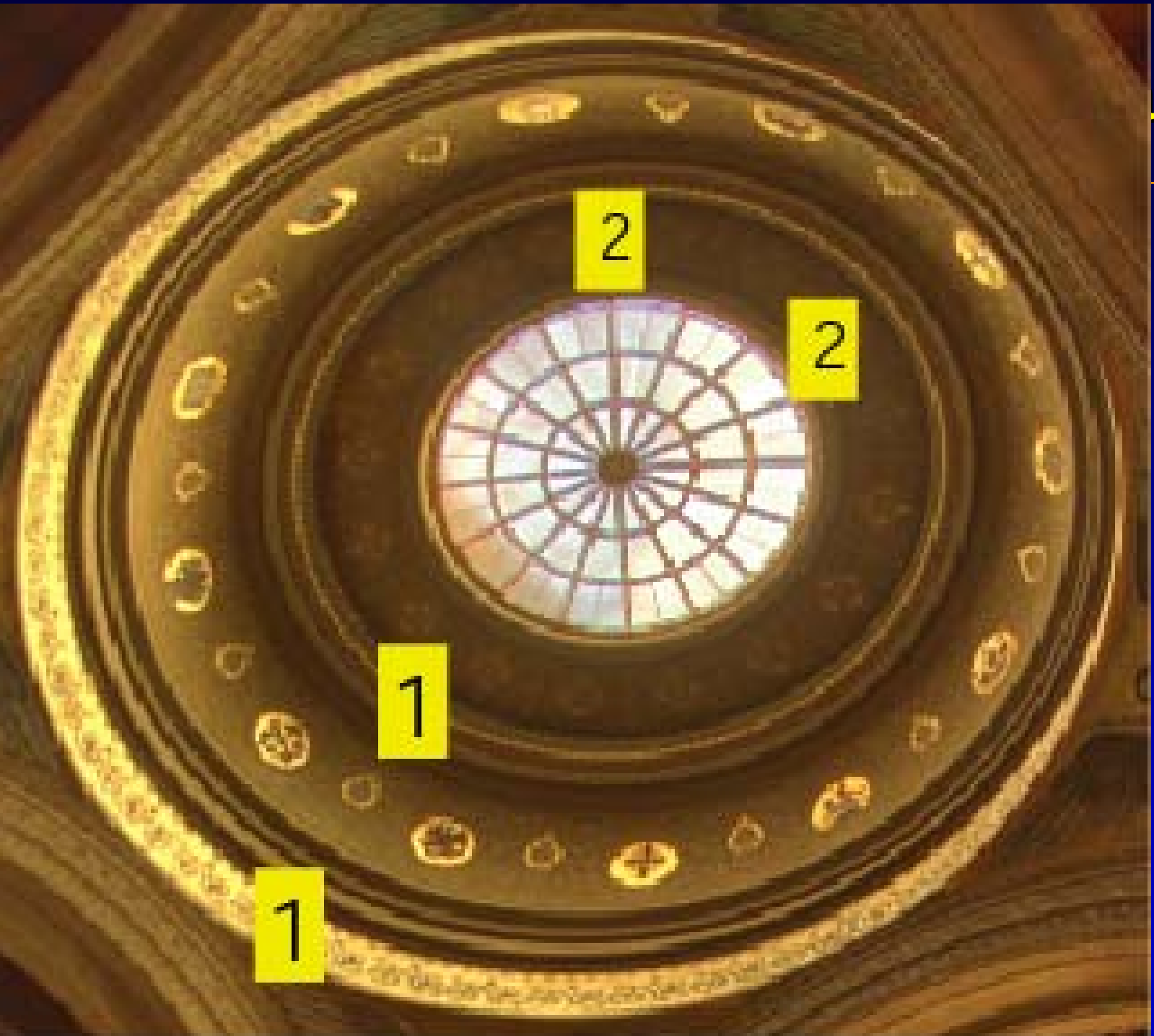
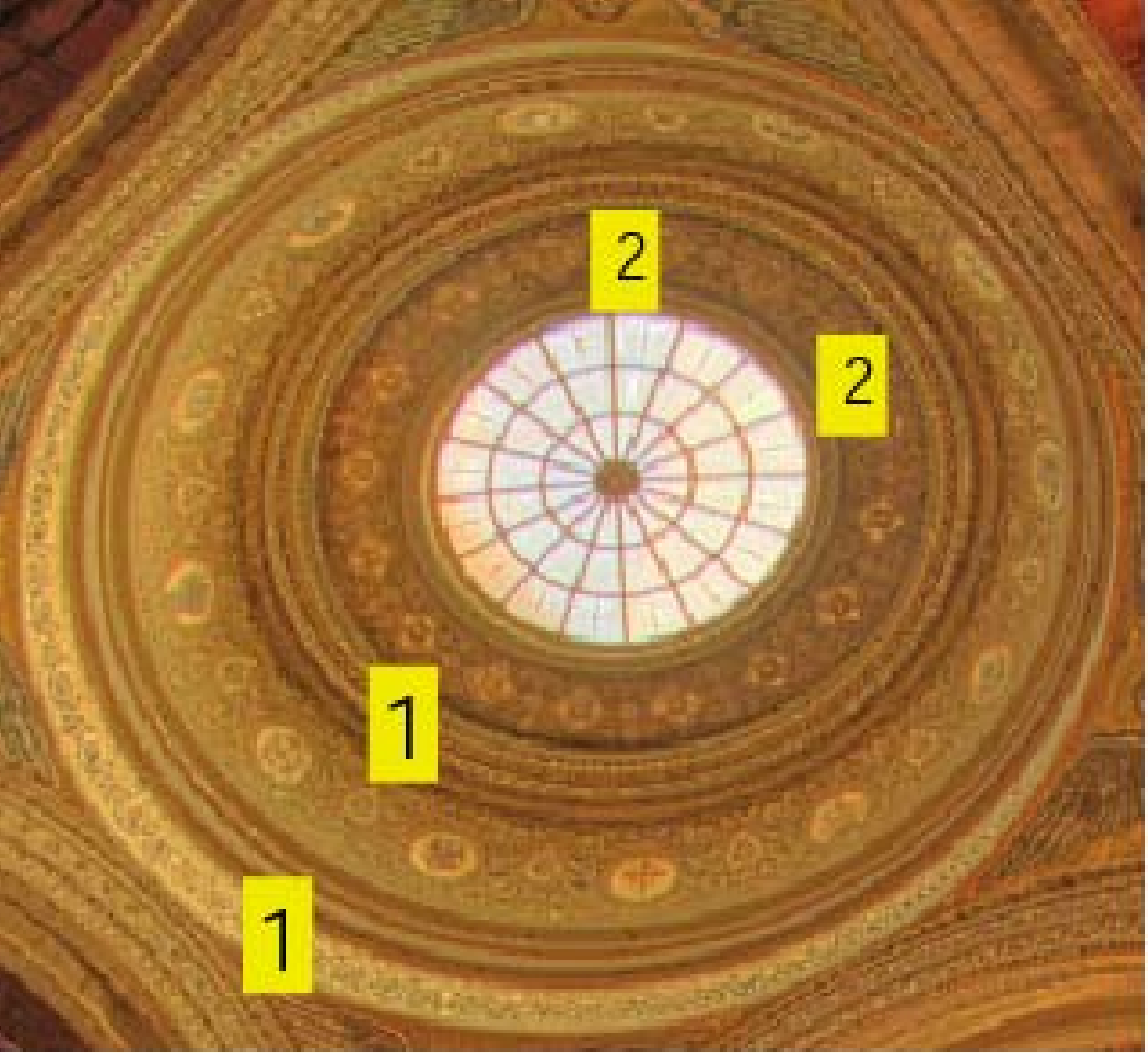


ils

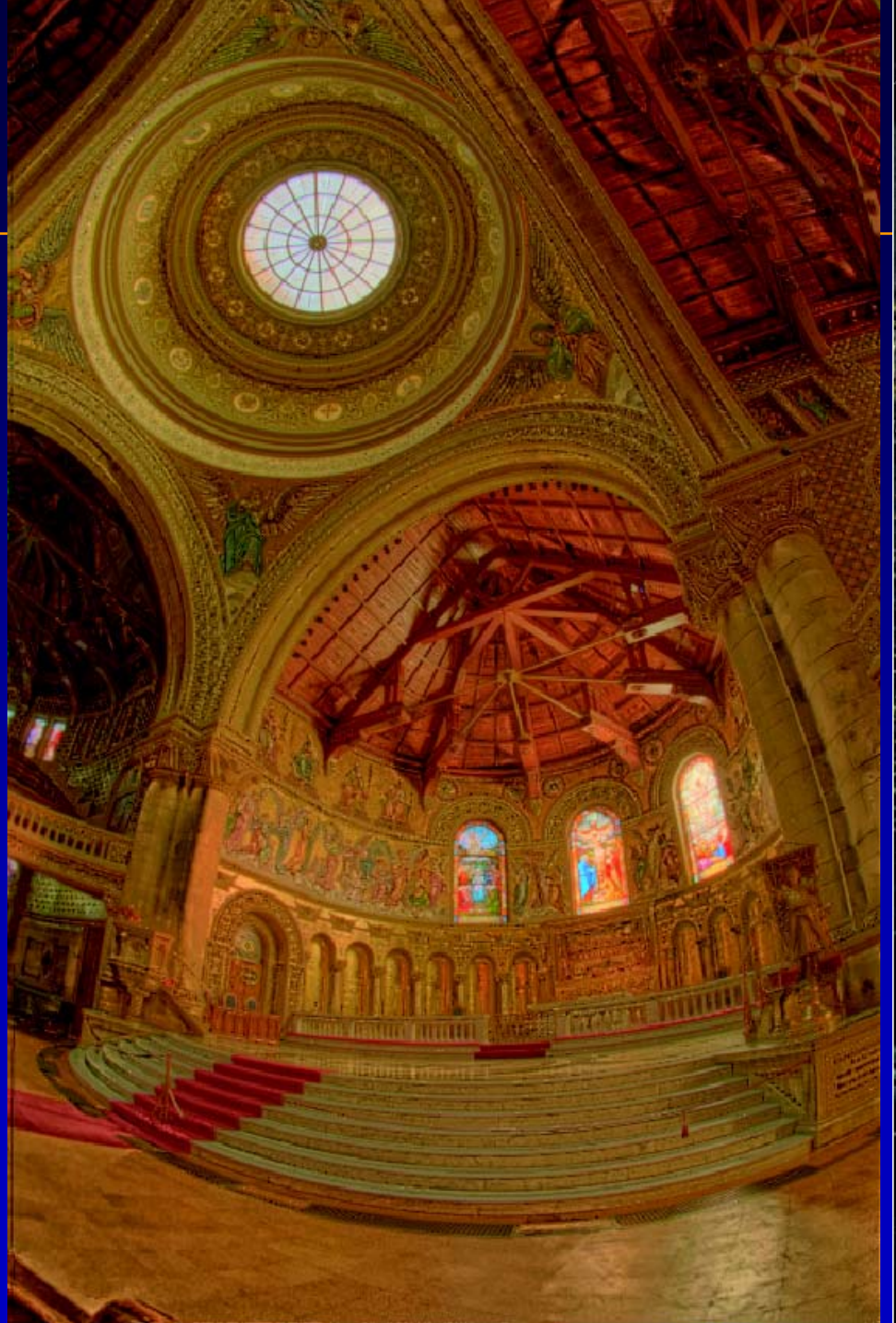


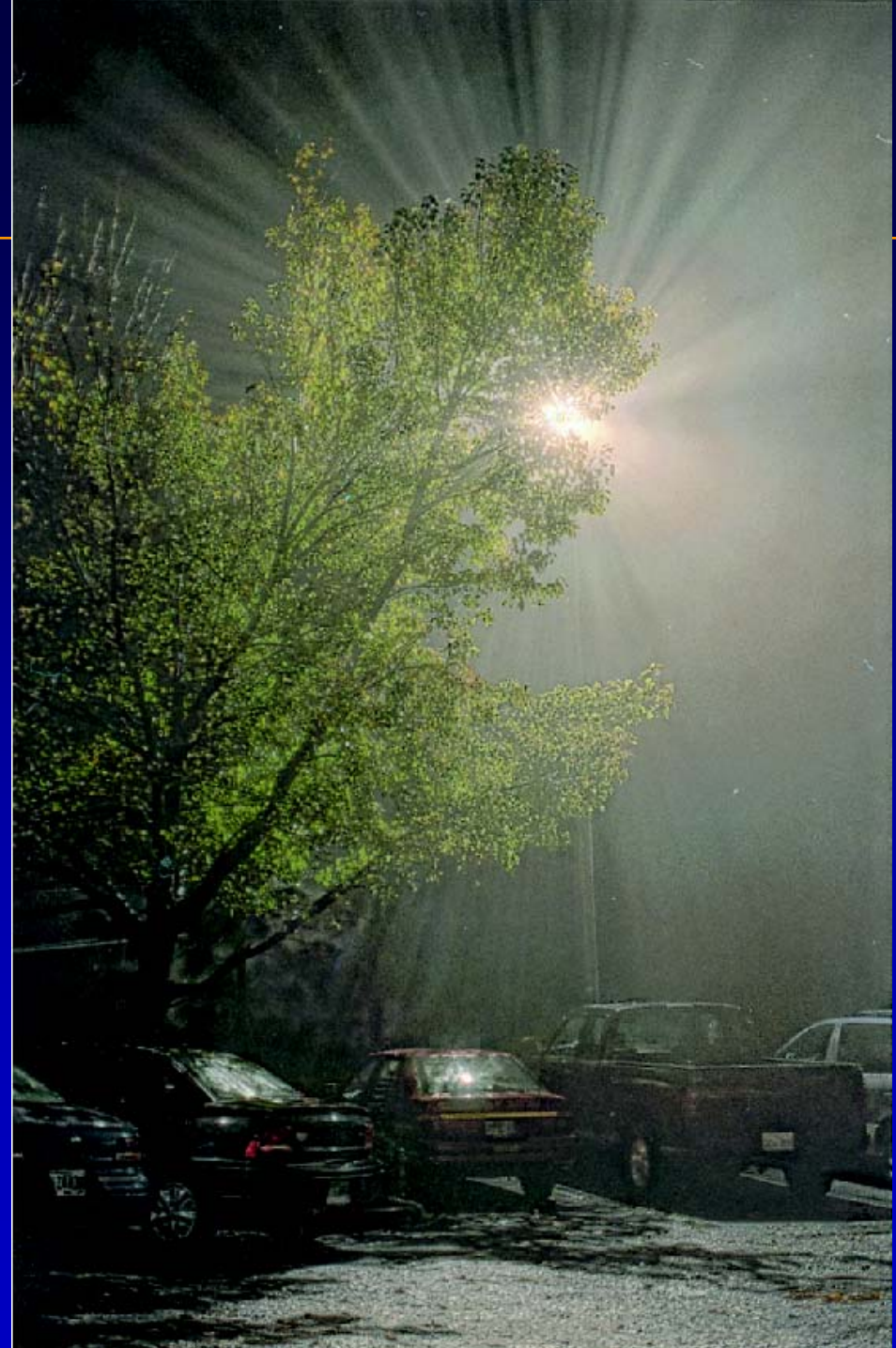
Bilateral

ails



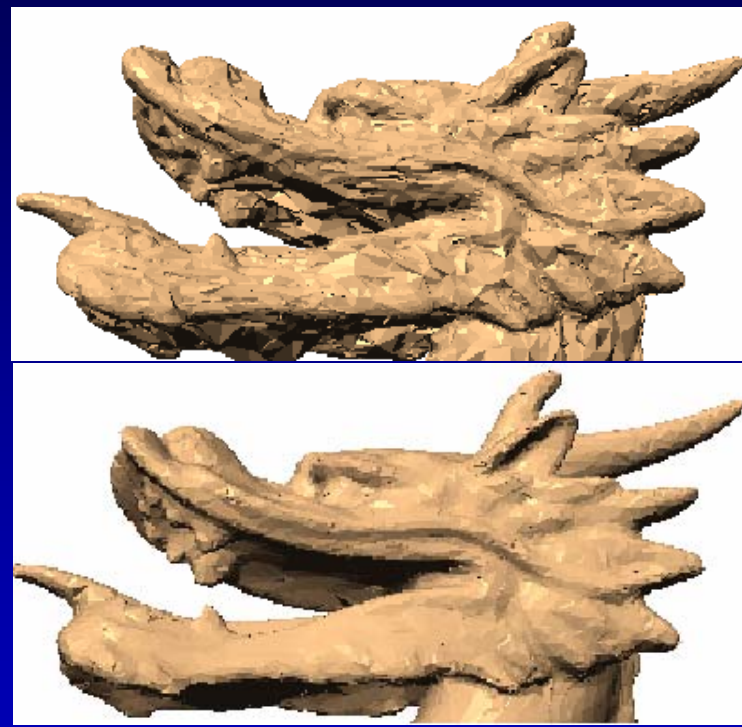
Trilateral





Trilateral Filter (Choudhury 2003)

- Strengths
  - Sharpens corners
  - Smoothes similar gradients
  - Automatic parameter setting
  - 3-D mesh de-noising, too!



- Weaknesses
  - S-L-O-W; very costly connected-region finder
  - Shares Bilateral's 'Single-pixel region' artifacts
  - Noise Tolerance limits; disrupts 'tilt' estimates

NEW IDEA : 'Joint' or 'Cross' Bilateral'
Petschnigg(2004) and Eisemann(2004)

Bilateral → *two kinds* of weights

NEW : get them from *two kinds* of images.

- Smooth image **A** pixels locally, but
- Limit to 'similar regions' of image **B**

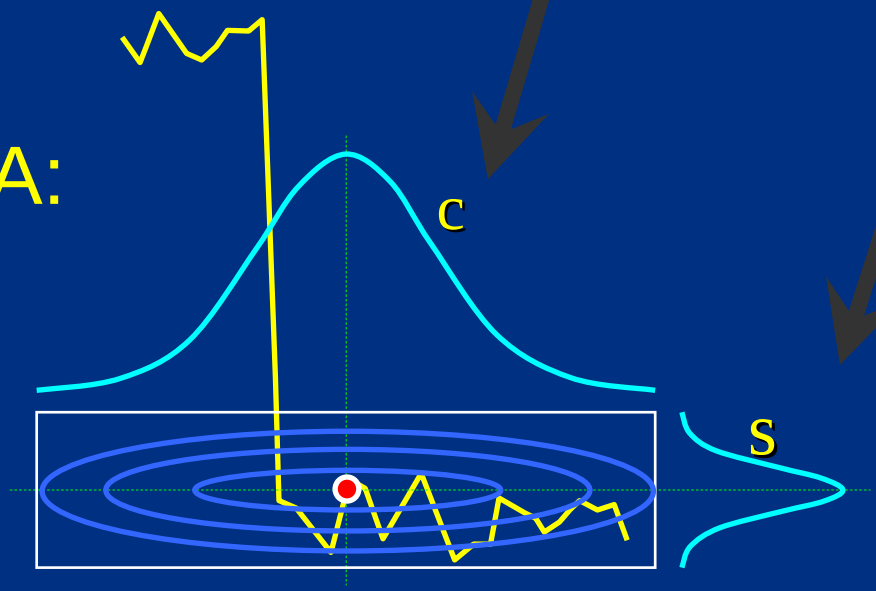
Why do this? To get **'best of both images'**

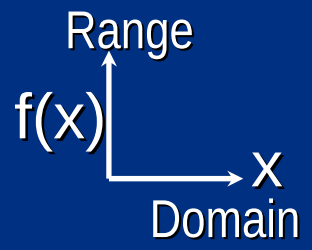
Ordinary Bilateral Filter

Bilateral → *two kinds* of weights, one image A :

$$BF[A]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}\left(\| \mathbf{p} - \mathbf{q} \|\right) G_{\sigma_r}\left(| A_{\mathbf{p}} - A_{\mathbf{q}} |\right) A_{\mathbf{q}}$$

Image A:





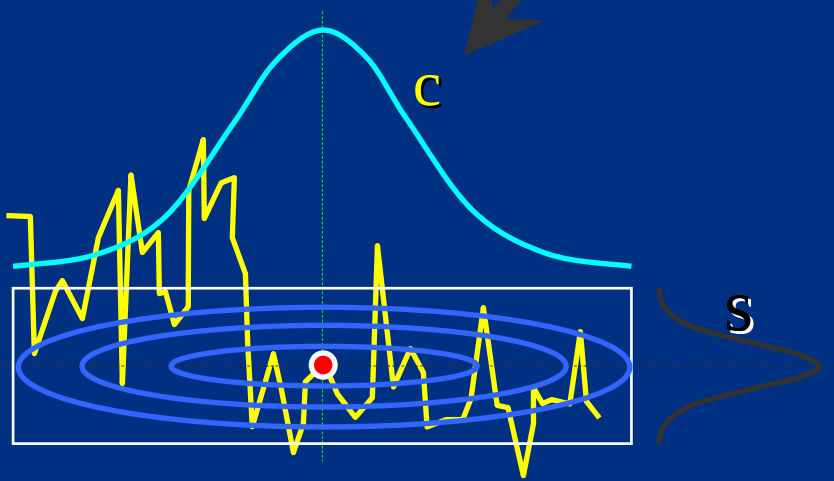
‘Joint’ or ‘Cross’ Bilateral Filter

NEW: *two kinds* of weights, *two* images

$$BF[A]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}\left(\| \mathbf{p} - \mathbf{q} \|\right) G_{\sigma_r}\left(| B_{\mathbf{p}} - B_{\mathbf{q}} |\right) A_{\mathbf{q}}$$

A: Noisy, dim
(ambient image)

B: Clean,strong
(Flash image)



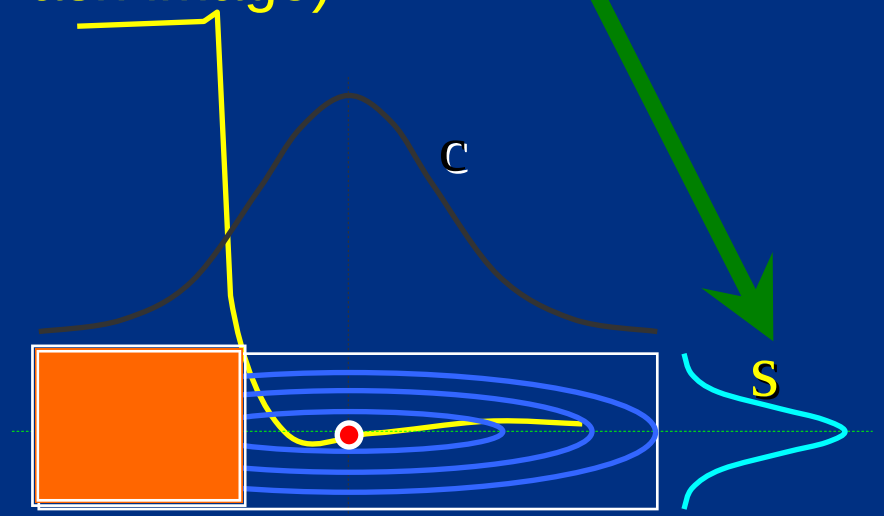


Image A: Warm, shadows, but too Noisy

(too dim for a good quick photo)

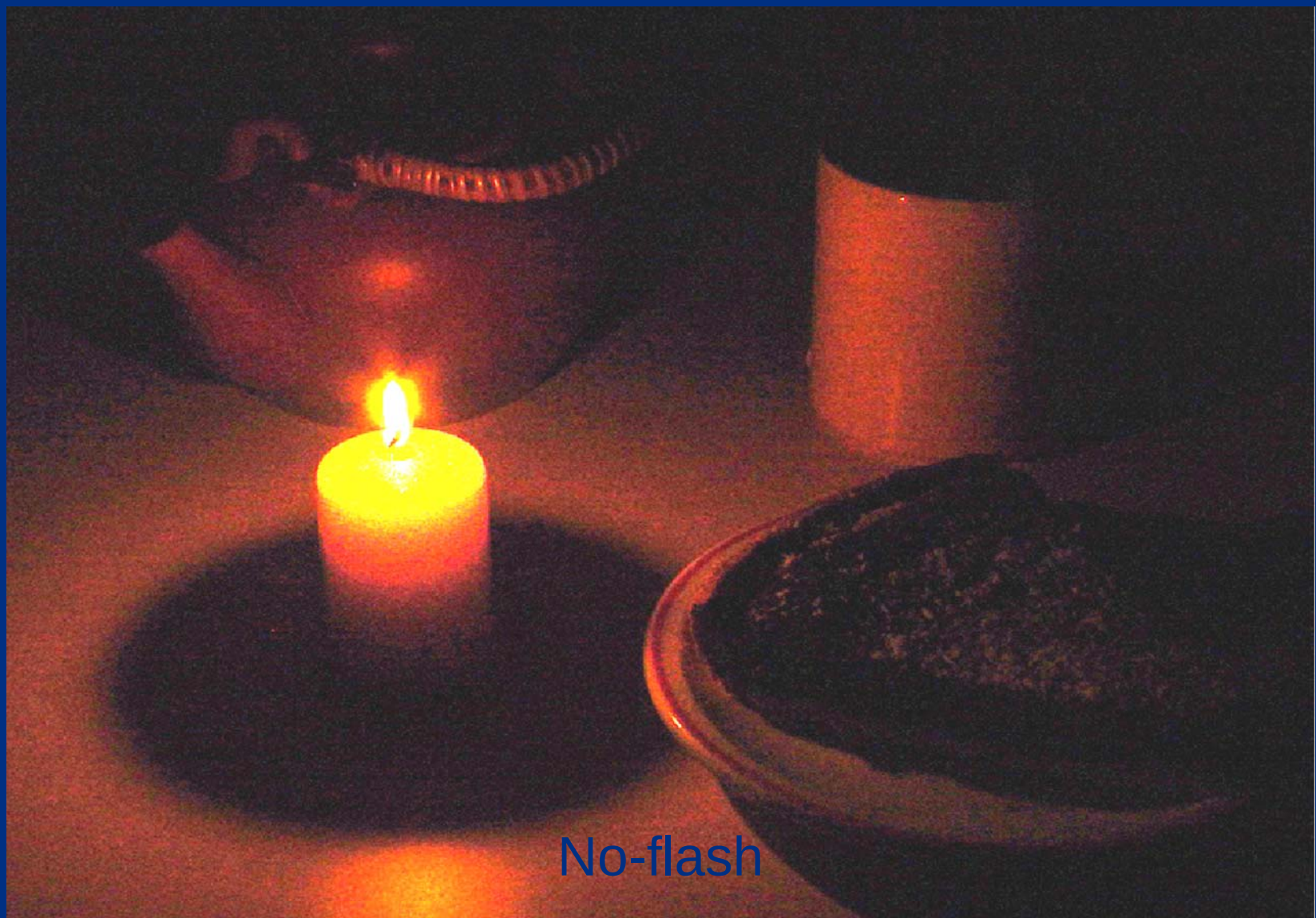


Image B: Cold, Shadow-free, Clean
(flash: simple light, ALMOST no shadows)

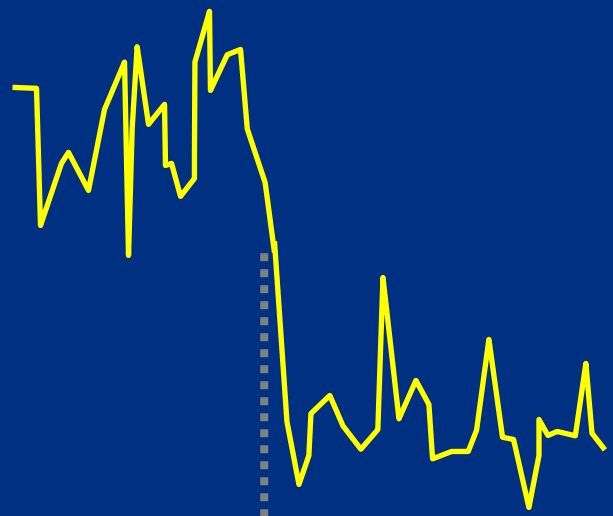
MERGE BEST OF BOTH: apply ‘Cross Bilateral’ or ‘Joint Bilateral’

(it really is *much* better!)

Recovers Weak Signals Hidden by Noise

Noisy but Strong…

+ Noise =

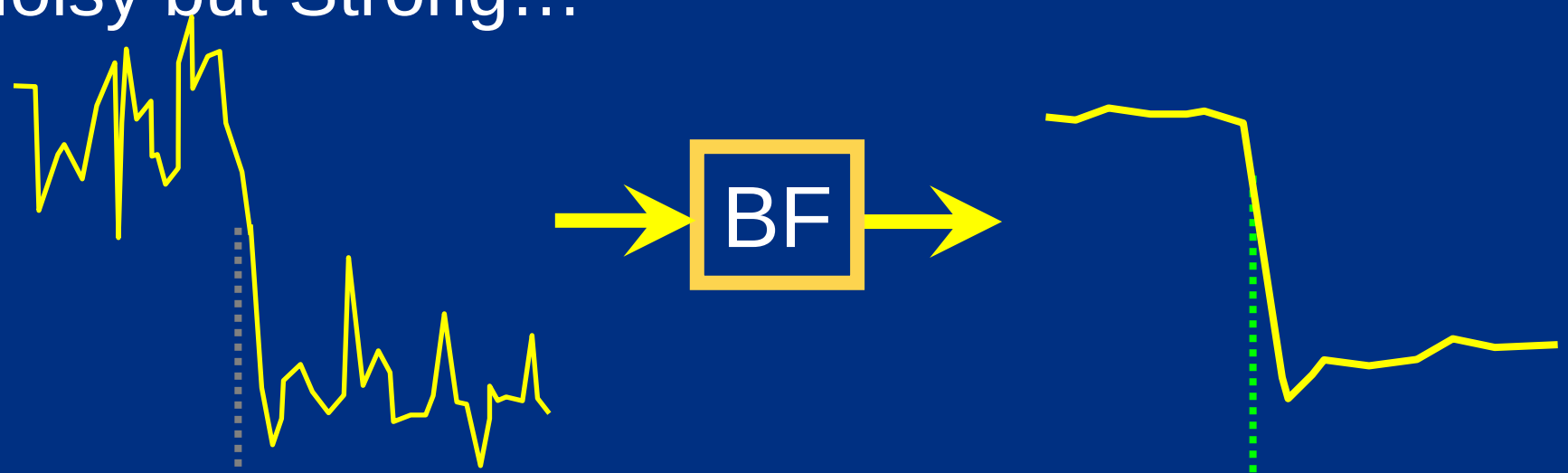


Noisy and Weak…

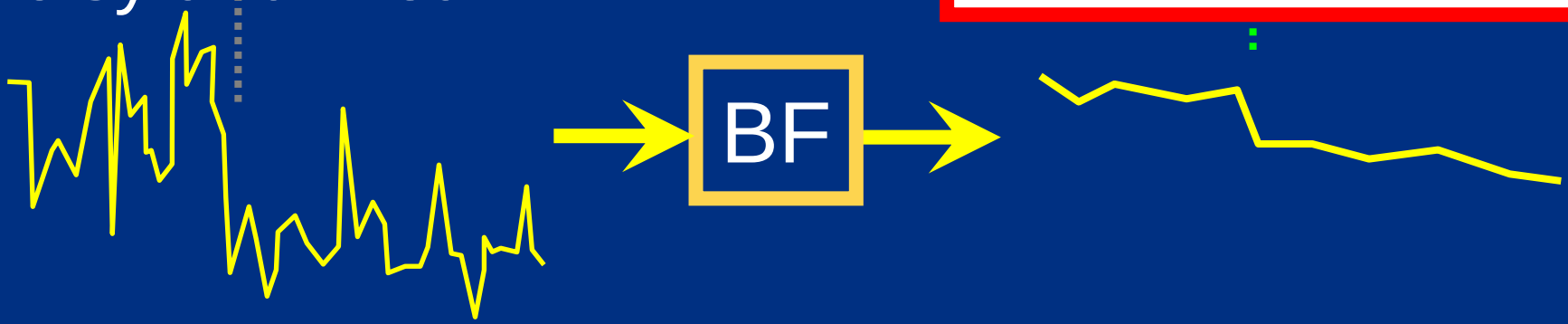
+ Noise =

Ordinary Bilateral Filter?

Noisy but Strong…



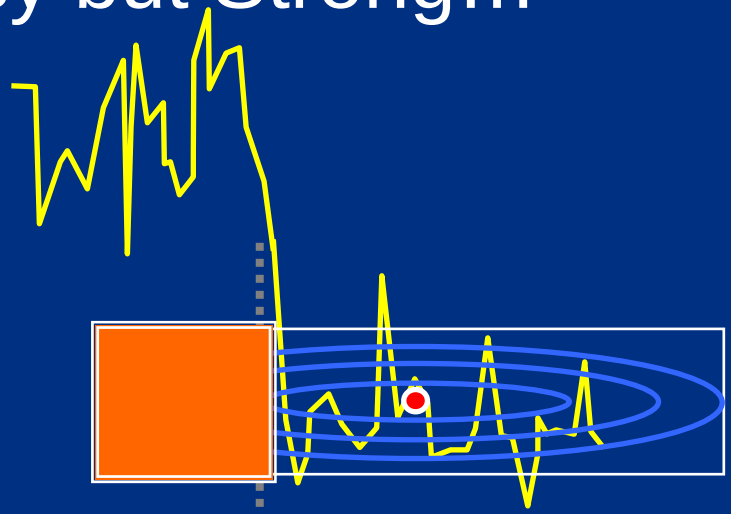
Noisy and Weak…



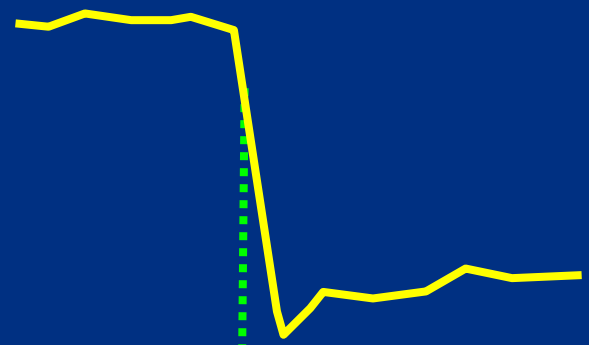
Step feature GONE!!

Ordinary Bilateral

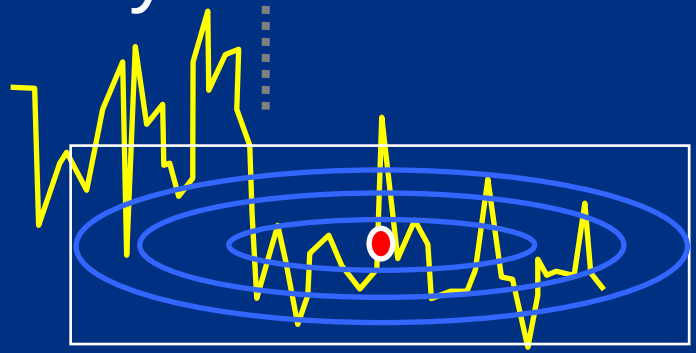
Noisy but Strong…

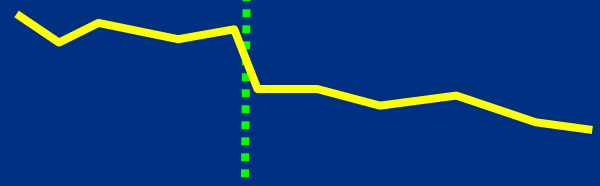


Range filter preserves signal



Noisy and Weak…

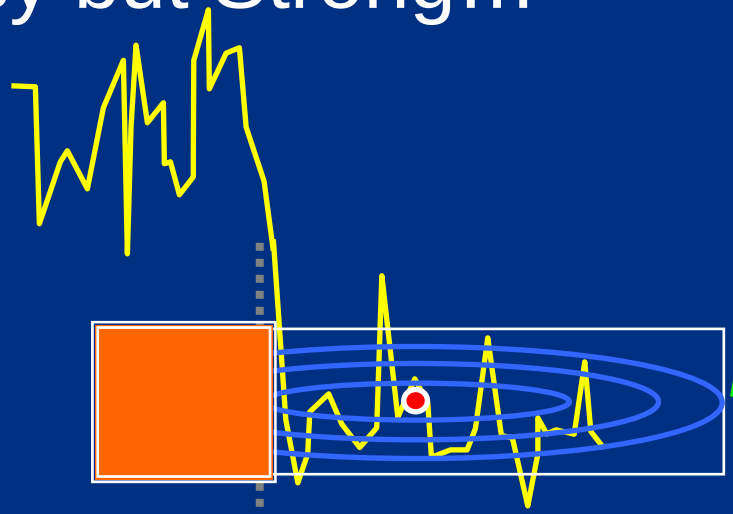




Signal too small to reject

‘Cross’ or ‘Joint’ Bilateral Idea:

Noisy but Strong…



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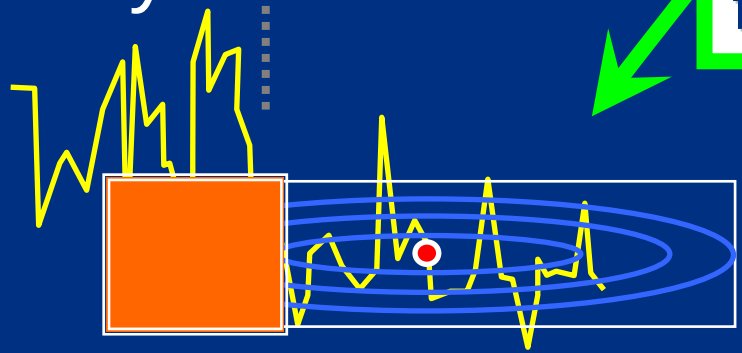
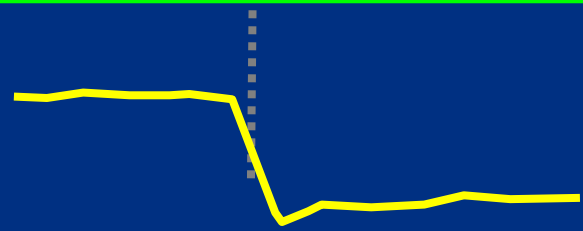


Use stronger signal’s range filter weights…



‘Joint’ or ‘Cross’ Bilateral Filter
Petschnigg(2004) and Eisemann(2004)

- CBF(A,B): smoothes image A only;
  (e.g. no flash)
- Limits smoothing to stay within regions where Image B is ~uniform (e.g. flash)

- **Useful Residues.** To transfer details,
  - CBF(A,B) to remove A’s noisy details
  - CBF(B,A) to remove B’s clean details;
  - add to CBF(A,B) – clean, detailed image!

New Idea:
NL-Means Filter (Buades 2005)

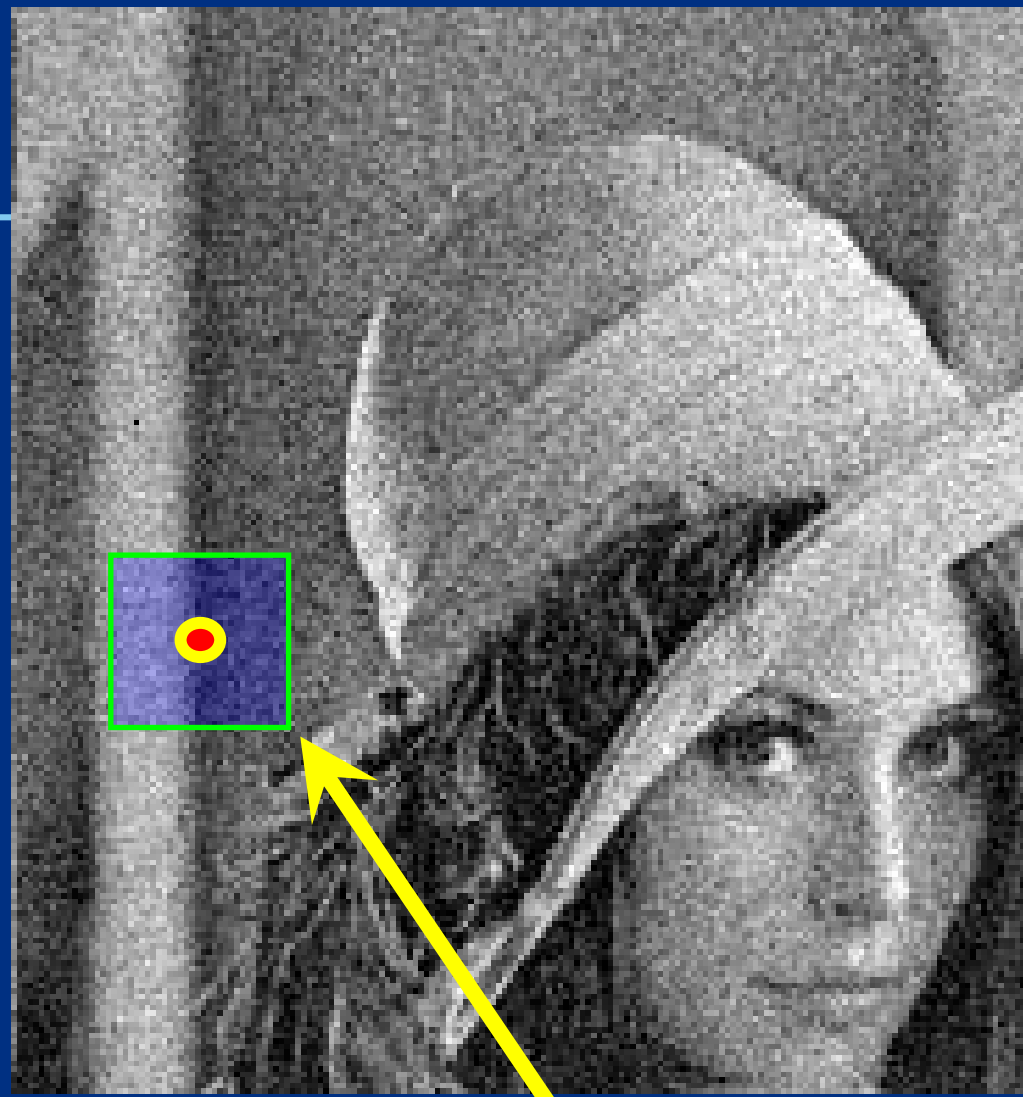
- Same goals: ‘Smooth within Similar Regions’

- **KEY INSIGHT**: Generalize, extend ‘Similarity’
  - **Bilateral:**
    Averages neighbors with **similar intensities**;
  - **NL-Means:**
    Averages neighbors with **similar neighborhoods!**

NL-Means Method: Buades (2005)

- For each and every pixel **p:**

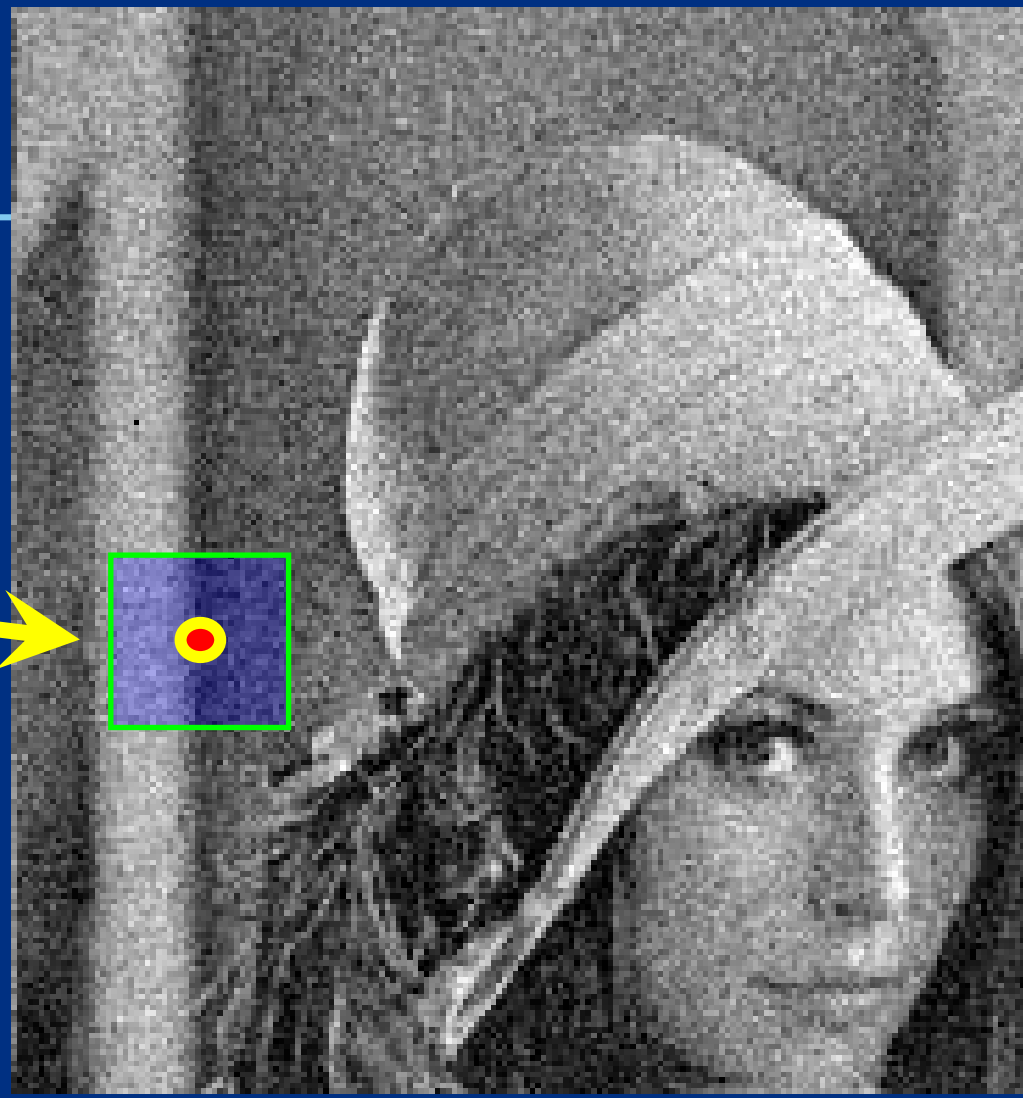
NL-Means Method: Buades (2005)



- For each and every pixel **p:**
  - Define a small, simple fixed size neighborhood;

NL-Means Method: Buades (2005)

$$V_p = \begin{bmatrix} 0.74 \\ 0.32 \\ 0.41 \\ 0.55 \\ \dots \\ \dots \\ \dots \end{bmatrix}$$



- For each and every pixel **p:**
  - Define a small, simple fixed size neighborhood;
  - Define vector V_p: a list of neighboring pixel values.

NL-Means Method: Buades (2005)

‘Similar’ pixels **p, q**

→ **SMALL**
vector distance;

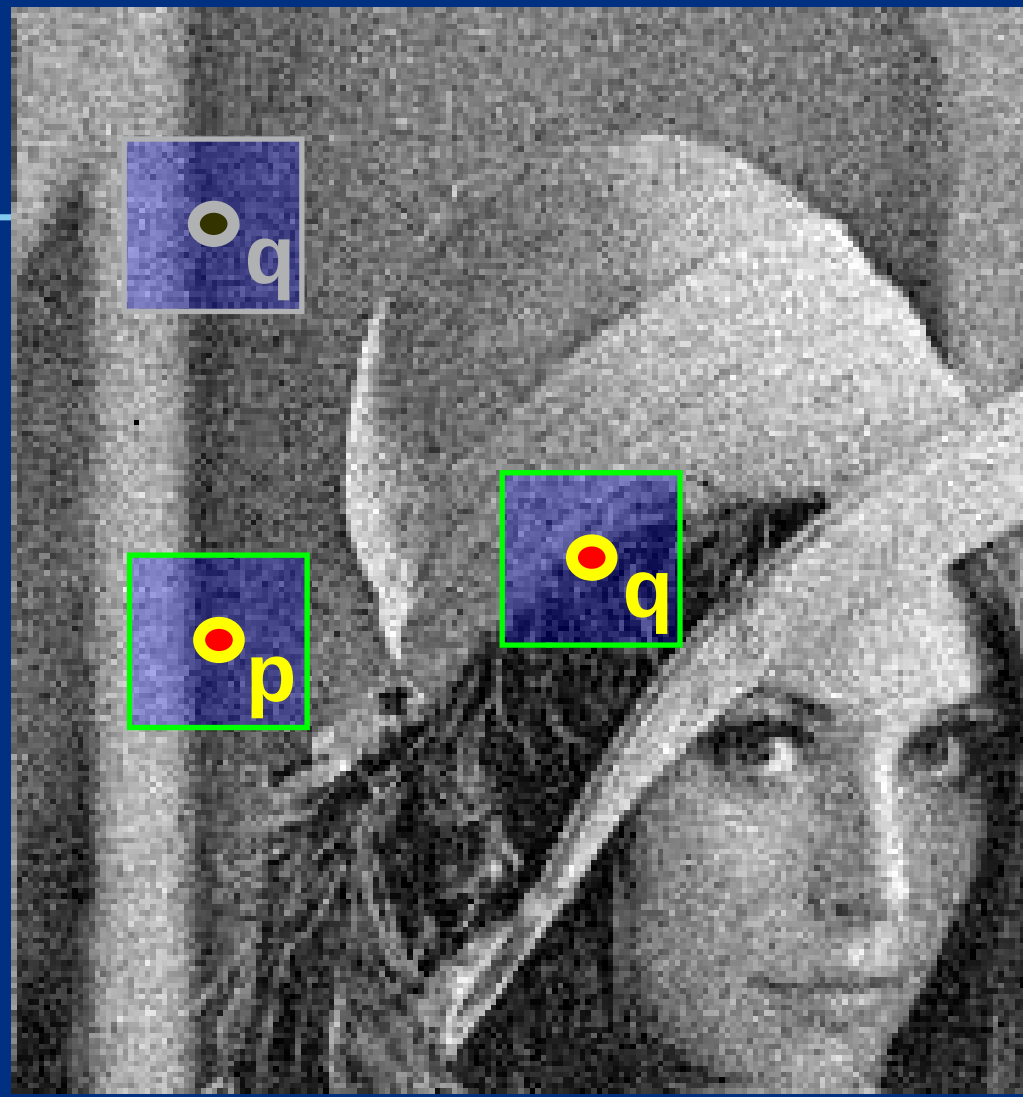
$$\| V_p - V_q \|^2$$

NL-Means Method: Buades (2005)

‘Dissimilar’ pixels **p, q**

→ **LARGE**
vector distance;

$$\| V_p - V_q \|^2$$



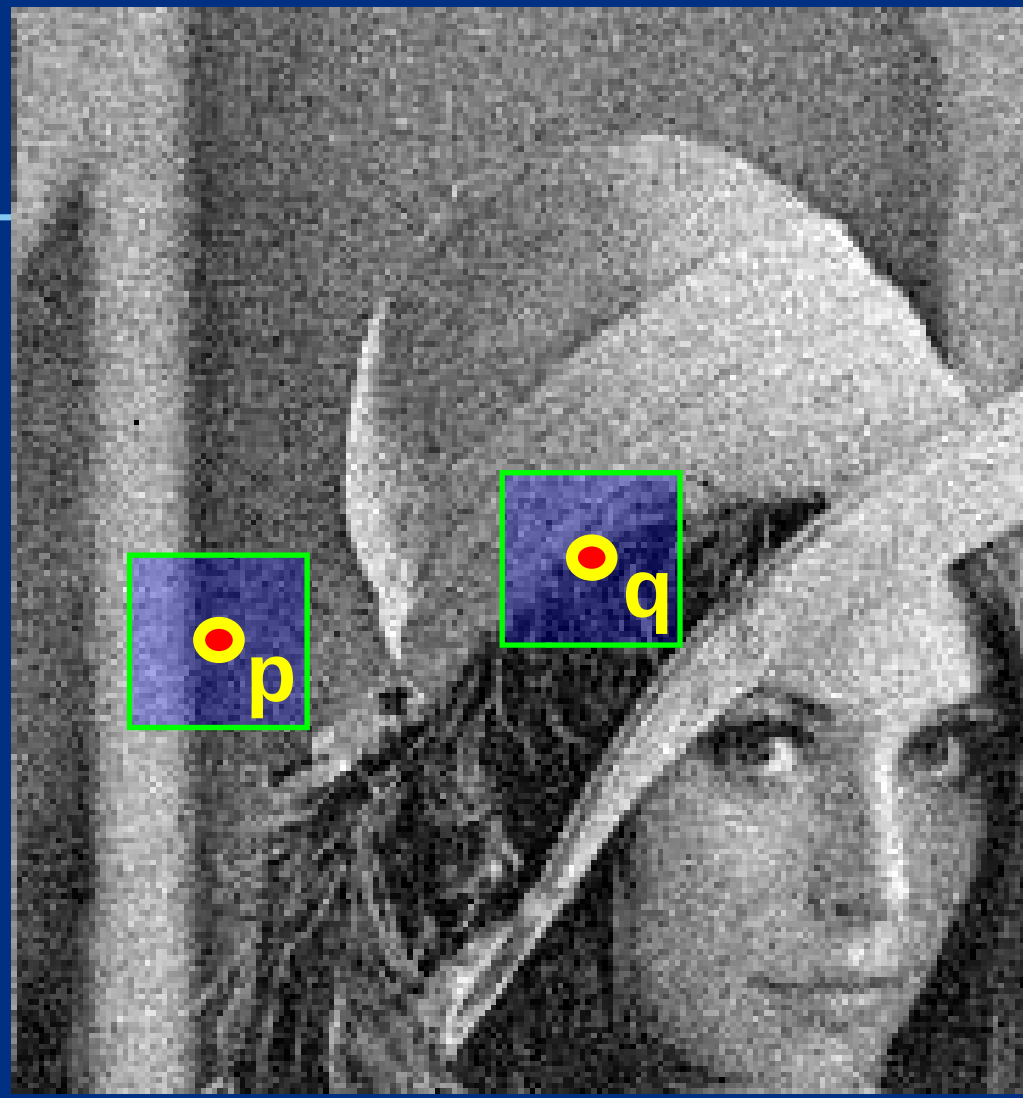
NL-Means Method: Buades (2005)

‘Dissimilar’ pixels **p, q**

→ **LARGE**
vector distance;

$$\| V_p - V_q \|^2$$

Filter with this!



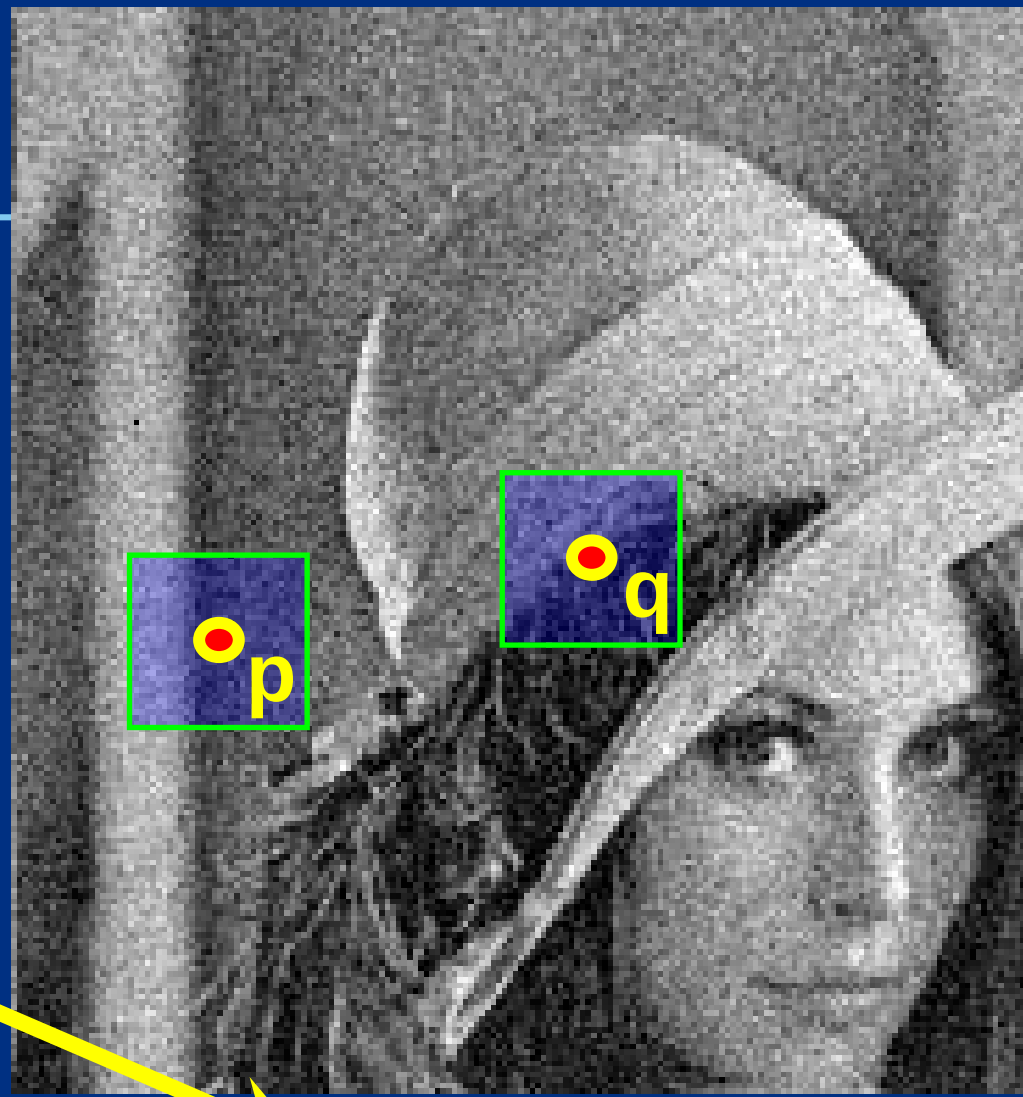
NL-Means Method: Buades (2005)

p, q neighbors define a vector distance;

$$\| V_p - V_q \|^2$$

Filter with this:

No spatial term!



$$NLMF\ [I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}\left(\| \mathbf{p} - \mathbf{q} \|\right) G_{\sigma_r}\left(\| \rho V_{\mathbf{p}} - \rho V_{\mathbf{q}} \|^2\right) I_{\mathbf{q}}$$

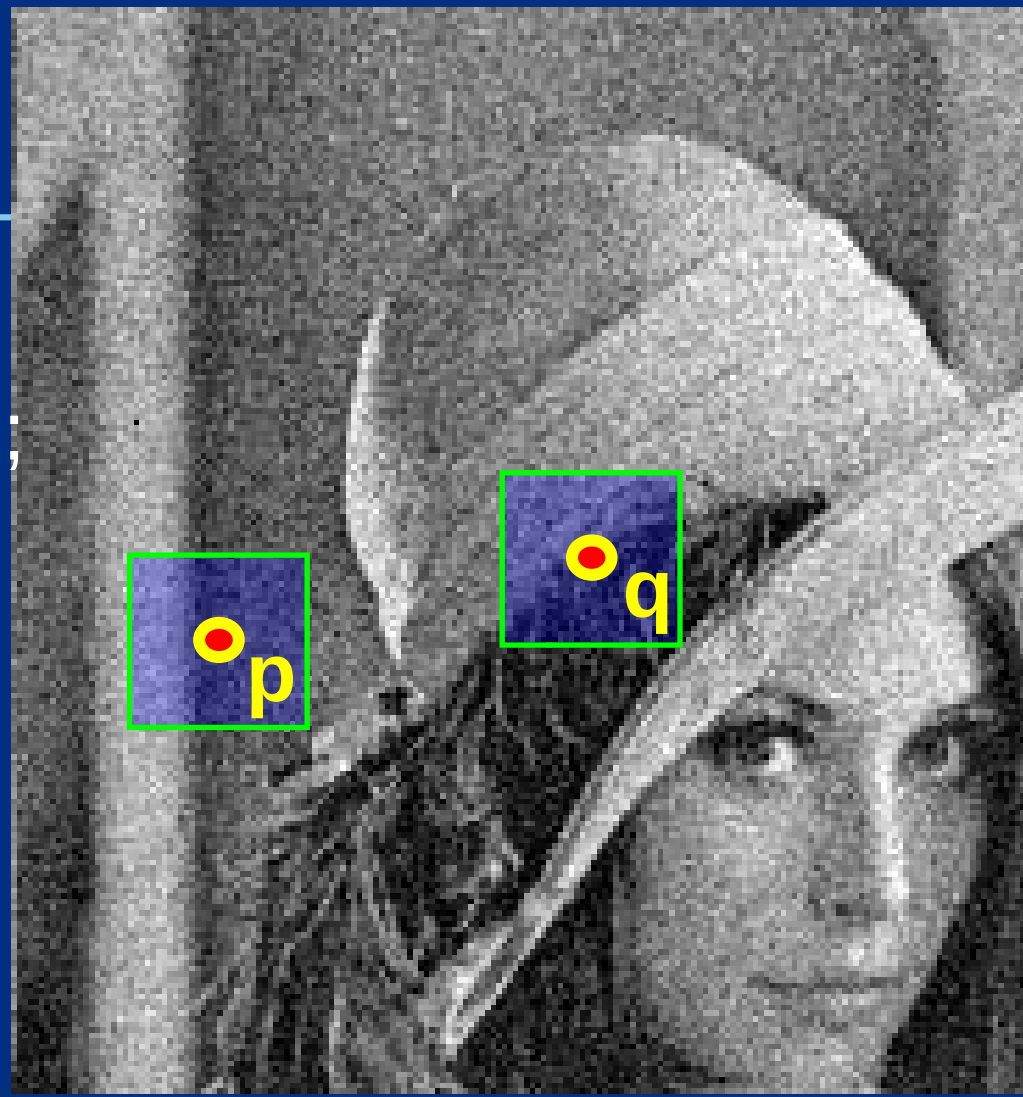
NL-Means Method: Buades (2005)

pixels **p, q** neighbors

Set a vector distance;

$$\| V_p - V_q \|^2$$

Vector Distance to p sets weight for each pixel q



$$NLMF\ [I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_r}\left(\| \vec{V}_{\mathbf{p}} - \vec{V}_{\mathbf{q}} \|^2\right) I_{\mathbf{q}}$$

NL-Means Filter (Buades 2005)

- Noisy source image:

NL-Means Filter (Buades 2005)

- Gaussian Filter

Low noise,

Low detail

NL-Means Filter (Buades 2005)

- Anisotropic Diffusion

(Note ‘stairsteps’: ~ piecewise constant)

NL-Means Filter (Buades 2005)

- Bilateral Filter

(better, but similar ‘stairsteps’:

NL-Means Filter (Buades 2005)

- NL-Means:

Sharp,

Low noise,

Few artifacts.

Many More Possibilities: EXPERIMENT!

- Bilateral goals are *subjective*;

  ‘Local smoothing within similar regions’
  ‘Edge-preserving smoothing’
  ‘Separate large structure & fine detail’
  ‘Eliminate outliers’
  ‘Filter within edges, not across them’

- It’s simplicity *invites new inventive answers.*

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