

# Domain Transform for Edge-Aware Image and Video Processing

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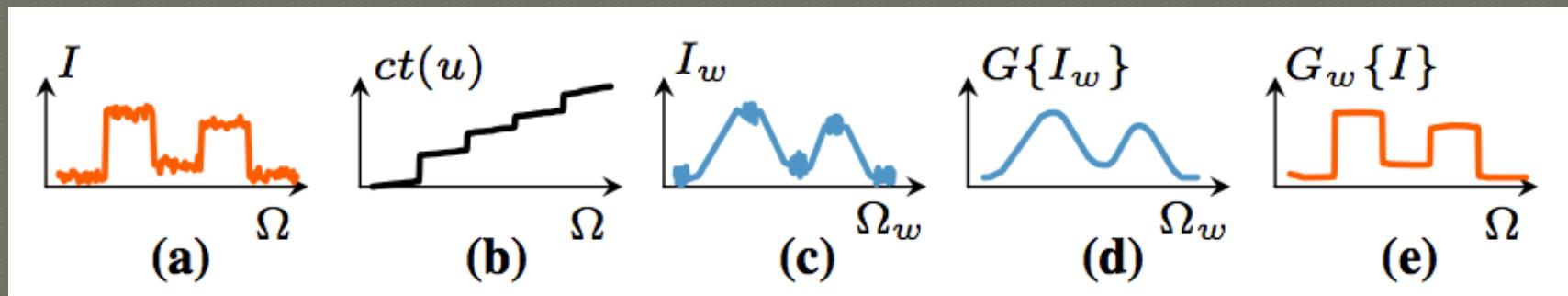
# Overview

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- A faster method of performing edge-preserving filtering on images
- Main idea: domain transform from image in  $R^5 (x,y,r,g,b)$  to lower dimension where distances are preserved ??
- Then, perform filtering on the transformed image

# Overview (continued)

- How the transformation will look:



# Images in $\mathbb{R}^5$

- 2D RGB image I:  $I : \Omega \subset \mathbb{R}^2 \rightarrow \mathbb{R}^3$
- I defines a 2D manifold  $M_I$  in  $\mathbb{R}^5$
- Let  $\hat{p} = (x_p, y_p, r_p, g_p, b_p) \in M_I$
- $\hat{p}$  has a corresponding pixel in I with:
  - Spatial coordinates  $p = (x_p, y_p)$ , and
  - Range coordinates  $I(p) = (r_p, g_p, b_p)$
- Let  $F(\hat{p}, \hat{q})$  be an edge-preserving filter in 5D
- Filtered image J is:

$$J(p) = \int_{\Omega} I(q) F(\hat{p}, \hat{q}) dq$$

# Example - Bilateral Filter

- $J$ , the image obtained when filtering  $I$  with  $F$  can be expressed as:

$$J(p) = \int_{\Omega} I(q) F(\hat{p}, \hat{q}) dq$$

- Bilateral filter kernel is given by:

$$F(\hat{p}, \hat{q}) = G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(\|I(p) - I(q)\|)$$

(  $p = (x_p, y_p)$  and  $I(p) = (r_p, g_p, b_p)$  )

# Problem Statement

● Does there exist:

- Transformation  $t : \mathbb{R}^5 \rightarrow \mathbb{R}^l$ ,  $l < 5$ , and
- Filter kernel  $H$  defined over  $\mathbb{R}^l$ , such that
- For any input image  $I$ , an equivalent result to the 5D edge-preserving kernel  $F$  is produced, i.e.:

$$J(p) = \int_{\Omega} I(q) F(\hat{p}, \hat{q}) dq = \int_{\Omega} I(q) H(t(\hat{p}), t(\hat{q})) dq$$

# Simplification: $\mathbb{R}^5 \rightarrow \mathbb{R}^2$

Instead of starting with  $t : \mathbb{R}^5 \rightarrow \mathbb{R}^l, l < 5$

let's try to find  $t : \mathbb{R}^2 \rightarrow \mathbb{R}$ , where

- $t$  preserves (in  $\mathbb{R}$ ) the original distances between points  $(x_i, I(x_i))$  given by some distance metric (e.g. Euclidean):

$$|t(x_i, I(x_i)) - t(x_j, I(x_j))| = \|(x_i, I(x_i)) - (x_j, I(x_j))\|$$

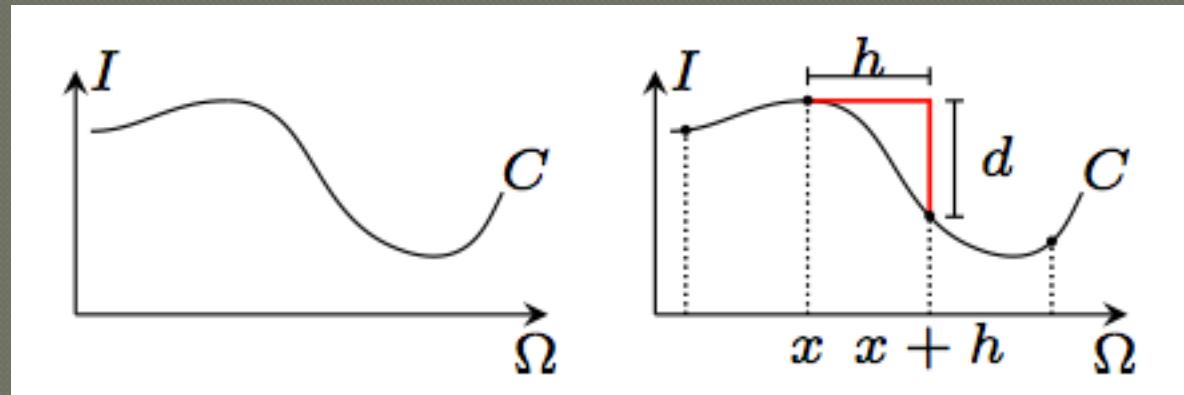
# Finding t

- Let  $ct(x) = t(\hat{x}) = t(x, I(x))$

- Transform must satisfy

$$ct(x + h) - ct(x) = h + |I(x + h) - I(x)|$$

in order to preserve L1 distances between neighboring pixels  $x$  and  $x + h$  (with sampling width  $h$ )



## Finding t (continued)

$$ct(x + h) - ct(x) = h + |I(x + h) - I(x)|$$

- Dividing by h and taking the limit as h approaches 0 gives:

$$ct'(x) = 1 + |I'(x)|$$

- Integrating both sides gives:

$$ct(u) = \int_0^u 1 + |I'(x)| dx, \quad u \in \Omega$$

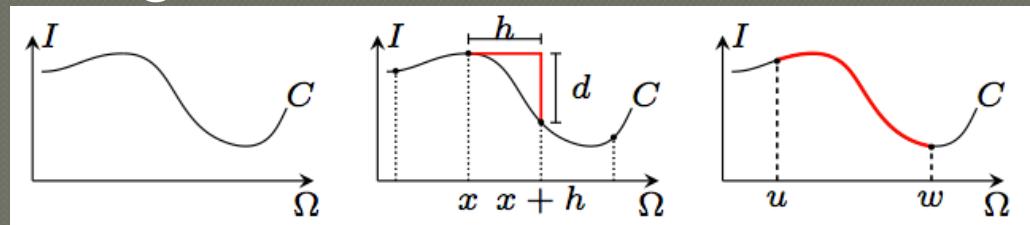
# Finding t (continued)

$$ct(u) = \int_0^u 1 + |I'(x)| dx, \quad u \in \Omega$$

- Then, distance between two points in new domain is given by:

$$ct(w) - ct(u) = \int_u^w 1 + |I'(x)| dx$$

the L1 arc length of curve C in the interval [u,w]



# Generalizing t - Multichannel

- Want to do this with RGB images, not just grayscale; so we want  $t : \mathbb{R}^4 \rightarrow \mathbb{R}$
- Change from this:

$$ct(u) = \int_0^u 1 + |I'(x)| \, dx, \quad u \in \Omega$$

- To this:

$$ct(u) = \int_0^u 1 + \sum_{k=1}^c |I'_k(x)| \, dx,$$

(sum over all  $c = 3$  color channels)

# Generalizing t – Multidimensional

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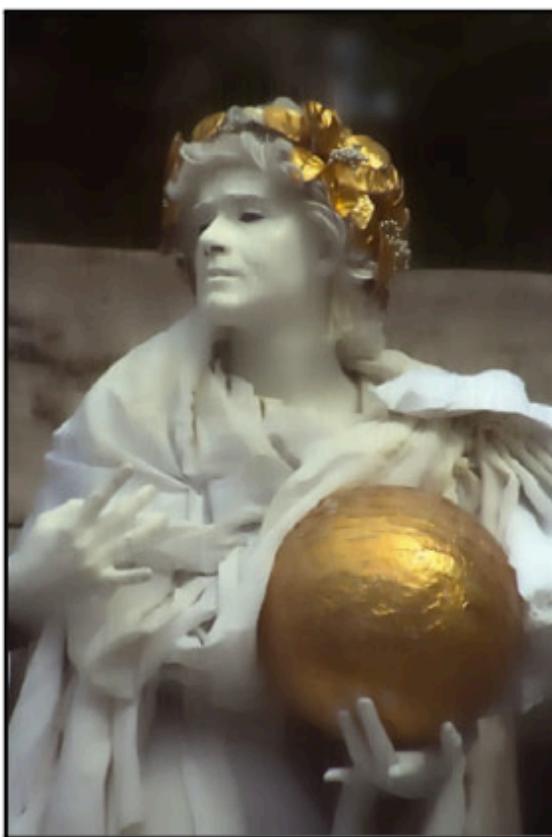
- Want to do this with 2D images, not just 1D signals
- Unfortunately, not possible in general
- So, instead we apply our current 1-dimensional t to rows/columns of image
  - First, along each row
  - Then, along each column
  - Iterate N times
  - Good N depends on the geometry of the image

# Generalizing t – Multidimensional (continued)

More iterations preserves edges somewhat better:



**(a) Input**



**(b) 1 itr.**



**(c) 3 itr.**

# Generalizing t – Spatial vs. Range Parameters

- Bilateral kernel has spatial vs. range parameters  $\sigma_s$  and  $\sigma_r$ :

$$F(\hat{p}, \hat{q}) = G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(\|I(p) - I(q)\|)$$

- We can encode these into ct by adding factor  $\sigma_s / \sigma_r$ :

$$ct(u) = \int_0^u 1 + \frac{\sigma_s}{\sigma_r} \sum_{k=1}^c |I'_k(x)| \ dx$$

# Filtering in the Transformed Domain

- Wanted  $t$  and  $H$  such that:

$$J(p) = \int_{\Omega} I(q) F(\hat{p}, \hat{q}) dq = \int_{\Omega} I(q) H(t(\hat{p}), t(\hat{q})) dq$$

- Found  $t$
- $H$  can be any filter whose response decreases with distance at least as fast as  $F$ 's
- Choices of  $H$ : Normalized Convolution, Interpolated Convolution, Recursive Filtering

# Normalized Convolution

- One of three filters the paper describes

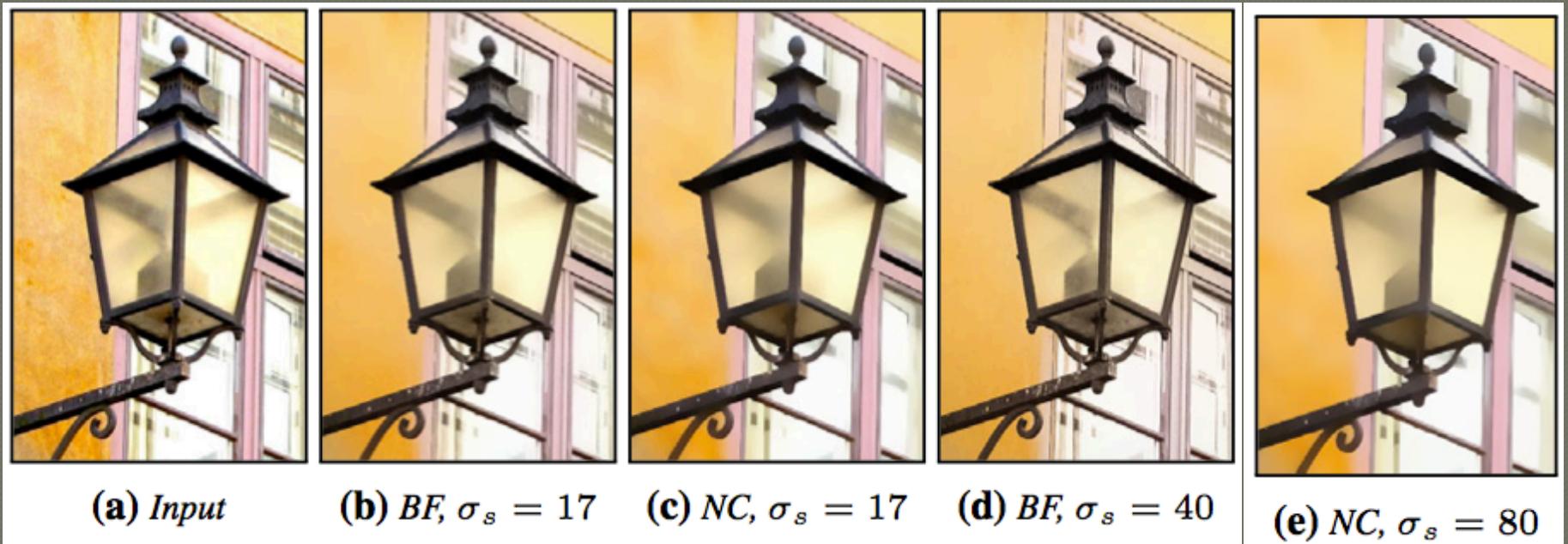
$$J(p) = (1/K_p) \sum_{q \in D(\Omega)} I(q) H(t(\hat{p}), t(\hat{q}))$$

$$H(t(\hat{p}), t(\hat{q})) = \delta\{|t(\hat{p}) - t(\hat{q})| \leq r\}$$

$$r = \sigma_H \sqrt{3}$$

- Parallelizable – fast GPU implementation

# Results - Smoothing Quality



# Results - Performance

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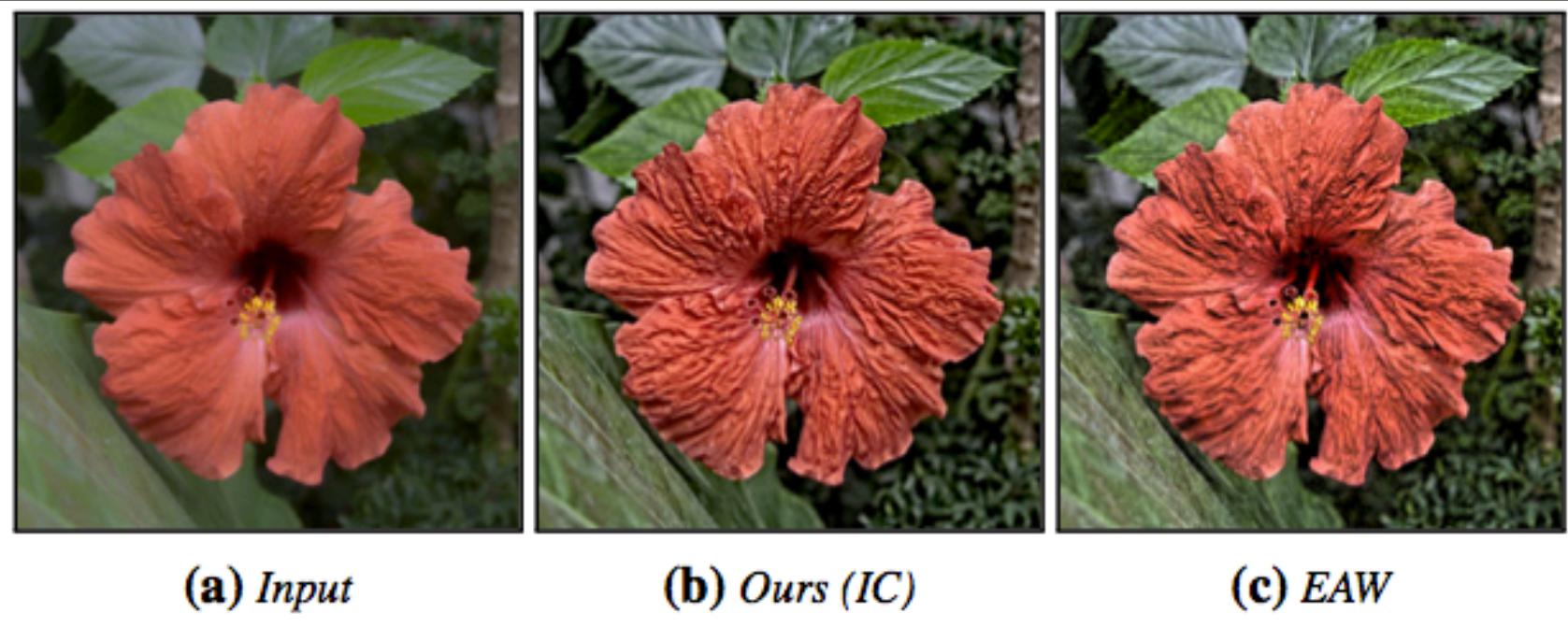
- Filtering on CPU - NC w/ 3 iterations

- 1 megapixel: 0.16 seconds
- 10 megapixels: 1.6 seconds
- 3.3x speedup with quad-core CPU
- Vs. CTBF: 10 seconds with 1/3 the work (single color channel instead of all 3)

- Filtering on GPU

- 1 megapixel: 0.007 seconds
- Speedup of 23x vs. single core CPU implementation
- Vs. WLS: 1 second for grayscale image

# Results – Fine Details



**Figure 12:** Fine detail manipulation. (a) Input image. (b) Our result.  $J_1$  was obtained with the IC filter ( $\sigma_s = 20$  and  $\sigma_r = 0.08$ ). (c) EAW result by Fattal [2009].

# Results – Real-Time

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- Input:

[http://www.youtube.com/watch?  
v=HsAW9sh\\_IW0&hd=1](http://www.youtube.com/watch?v=HsAW9sh_IW0&hd=1)

- Output (1080p video filtered in real time):

[http://www.youtube.com/watch?  
v=lTy9W5mWG\\_0&hd=1](http://www.youtube.com/watch?v=lTy9W5mWG_0&hd=1)