BIL 717
Image Processing
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Modern Image Smoothing

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A little bit of history

- Gaussian Filtering / linear diffusion - the most widely used method

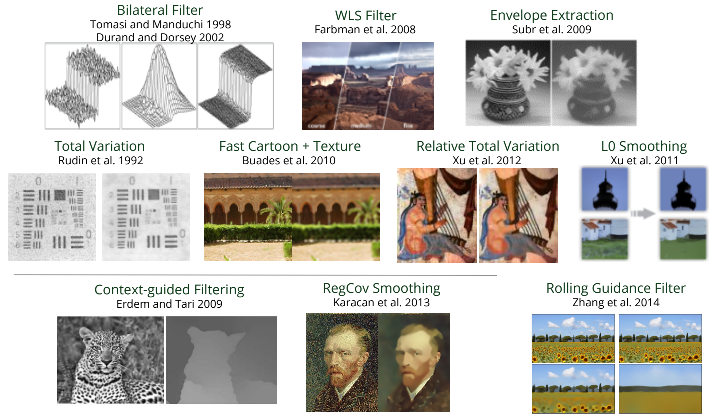
- mid 80's – unified formulations – a breakthrough!
  - methods that combine smoothing and edge detection (Geman & Geman'84, Mumford & Shah'89, Perona & Malik'90)

A little bit of (personal) history

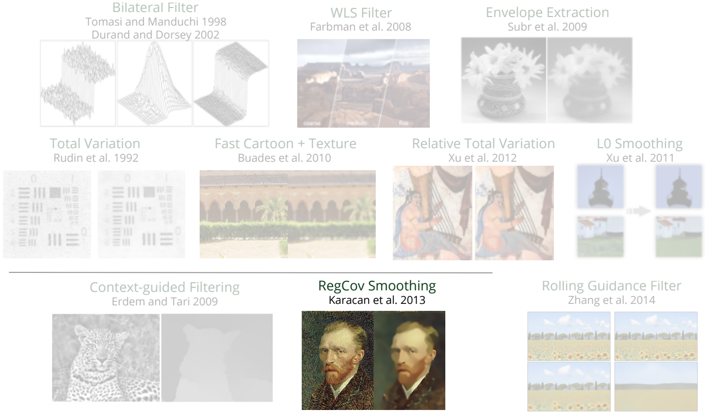
Standard unified formulations (nonlinear filters) fail to capture some details, e.g. due to texture!

- mid 80's – unified formulations – a breakthrough!
  - methods that combine smoothing and edge detection (Geman & Geman'84, Mumford & Shah'89, Perona & Malik'90)

Some seminal works



Some seminal works



Context-guided filtering

- Contextual knowledge extracted from local image regions guides the regularization process.
  - E. Erdem, A. Sancar-Yilmaz, and S. Tari, "Mumford-Shah Regularizer with Spatial Coherence", In SSVM 2007
  - E. Erdem and S. Tari, "Mumford-Shah Regularizer with Contextual Feedback", JMIV 2009

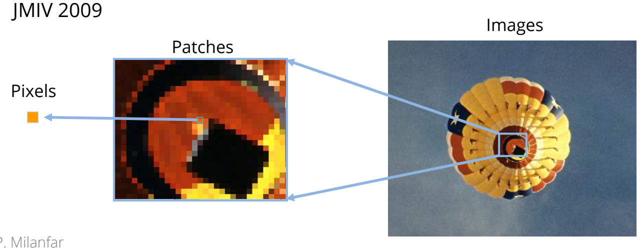


Image Credit: P. Milanfar

Structure-Texture Decomposition

- Decomposing an image into structure and texture components

Input Image

Structure-Texture Decomposition

- Decomposing an image into structure and texture components

Structure Component

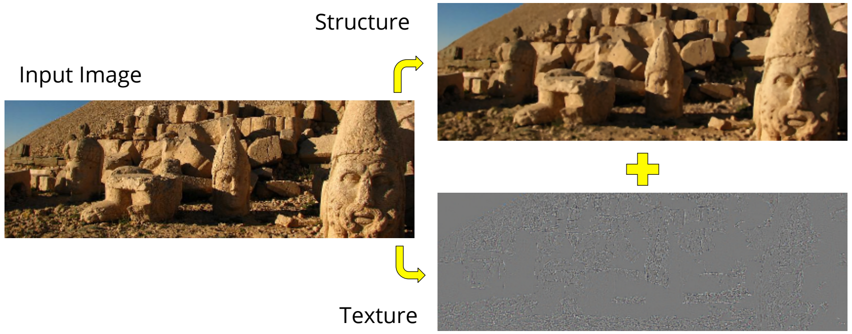
Structure-Texture Decomposition

- Decomposing an image into structure and texture components

Texture Component

Structure-Texture Decomposition

- Decomposing an image into structure and texture components

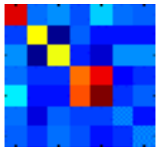


Region Covariances as Region Descriptors

Tuzel et al., ECCV 2006

$F(x,y)=\phi(I,x,y)$

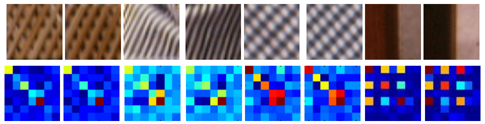
$$F(x,y) = \left[I(x,y) \quad \left|\frac{\partial I}{\partial x}\right| \quad \left|\frac{\partial I}{\partial y}\right| \quad \left|\frac{\partial^2 I}{\partial x^2}\right| \quad \left|\frac{\partial^2 I}{\partial y^2}\right| \quad x \quad y \right]^T$$



$$\mathbf{C}_R = \frac{1}{n-1} \sum_{i=0}^{n} (\mathbf{z}_k - \mu)(\mathbf{z}_k - \mu)^T$$

Motivation

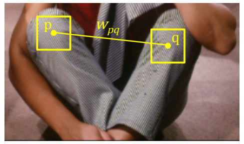
- Region covariances capture local structure and texture information.
- Similar regions have similar statistics.



RegCov Smoothing - Formulation

$$I = S + T$$

$$S(\mathbf{p}) = \frac{1}{Z_\mathbf{p}} \sum_{\mathbf{q} \in N(\mathbf{p},r)} w_{\mathbf{pq}} I(\mathbf{q})$$



- Structure-texture decomposition via smoothing
- Smoothing as weighted averaging
- Different kernels (w_{pq}) result in different types of filters.
- Three novel patch-based kernels for structure texture decomposition.

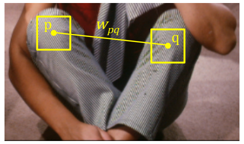
- L. Karacan, A. Erdem, E. Erdem, “Structure Preserving Image Smoothing via Region Covariances”, ACM TOG 2013 (SIGGRAPH Asia 2013)

Model 1

- Depends on sigma-points representation of covariance matrices (Hong et al.,CVPR’09)

$\mathbf{C} = \mathbf{L}\mathbf{L}^T$ *Cholesky Decomposition* $\mathcal{S} = \{\mathbf{s}_i\}$ *Sigma Points*

$$\mathbf{s}_i = \begin{cases} \alpha\sqrt{d}\mathbf{L}_i & \text{if } 1 \le i \le d \\ -\alpha\sqrt{d}\mathbf{L}_i & \text{if } d+1 \le i \le 2d \end{cases}$$



Final representation

$$\Psi(\mathbf{C}) = (\mu, \mathbf{s}_1, \ldots, \mathbf{s}_d, \mathbf{s}_{d+1}, \ldots, \mathbf{s}_{2d})^T$$

Resulting kernel function

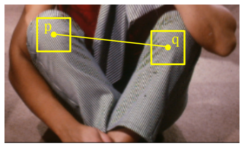
$$w_{\mathbf{pq}} \propto \exp\left(-\frac{\|\Psi(\mathbf{C_p}) - \Psi(\mathbf{C_q})\|^2}{2\sigma^2}\right)$$

Model 2

- An alternative way is to use statistical similarity measures.
- A Mahalanobis-like distance measure to compare to image patches.

$$d(\mathbf{p},\mathbf{q}) = \sqrt{(\mu_\mathbf{p} - \mu_\mathbf{q})\mathbf{C}^{-1}(\mu_\mathbf{p} - \mu_\mathbf{q})^T}$$

$$\mathbf{C} = \mathbf{C_p} + \mathbf{C_q}$$

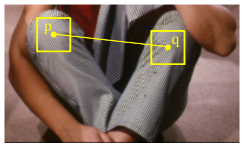


Resulting kernel $w_{\mathbf{pq}} \propto \exp\left(-\frac{d(\mathbf{p},\mathbf{q})^2}{2\sigma^2}\right)$

Model 3

resulted from a discussion with Rahul Narain (Berkeley University)

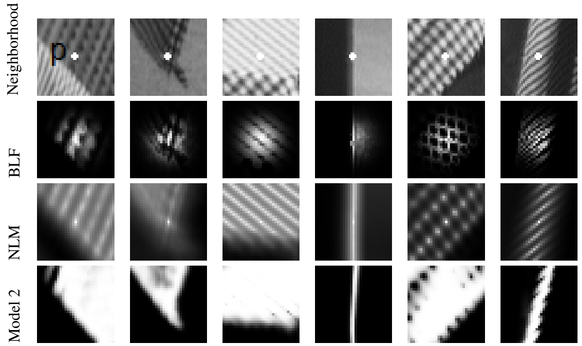
- We use Kullback-Leibler(KL)-Divergence measure from probability theory.
- A KL-Divergence form is used to calculate statistical distance between two multivariate normal distribution

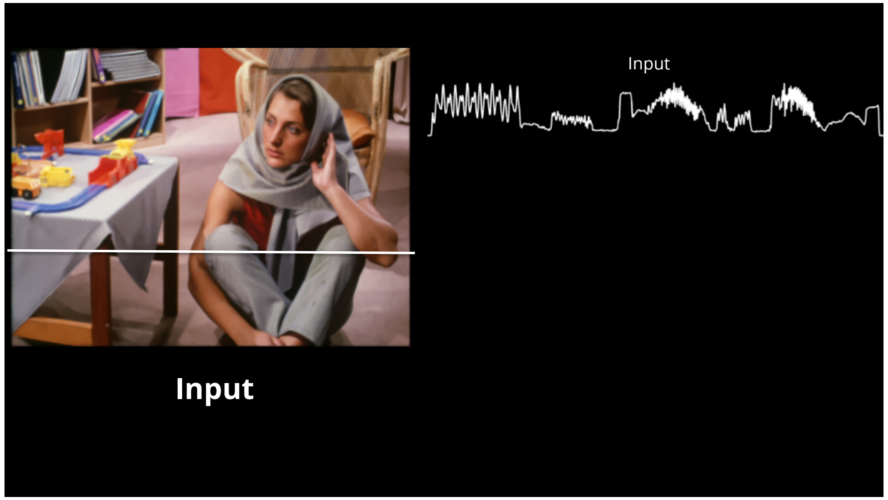


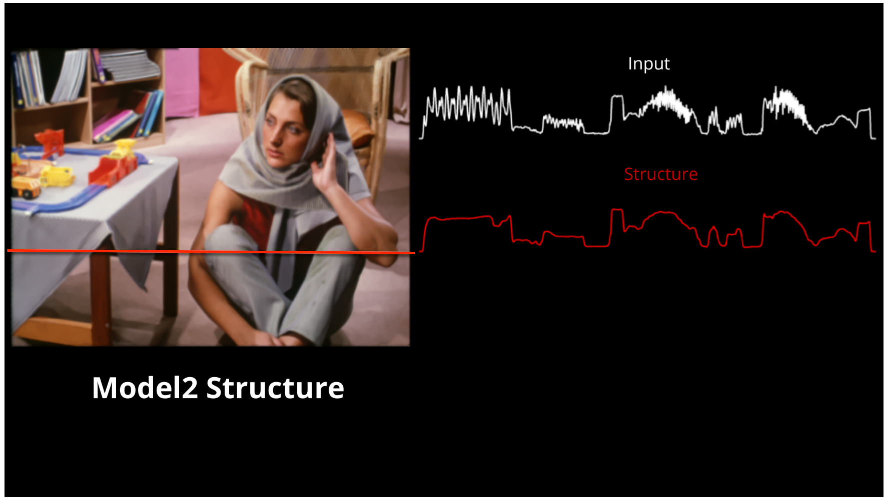
$$d_{KL}(\mathbf{p},\mathbf{q}) = \frac{1}{2}\left(tr(\mathbf{C_q}^{-1}\mathbf{C_p}) + (\mu_p - \mu_q)^T\mathbf{C_q}^{-1}(\mu_p - \mu_q) - k - ln\left(\frac{\det \mathbf{C_p}}{\det \mathbf{C_q}}\right)\right)$$

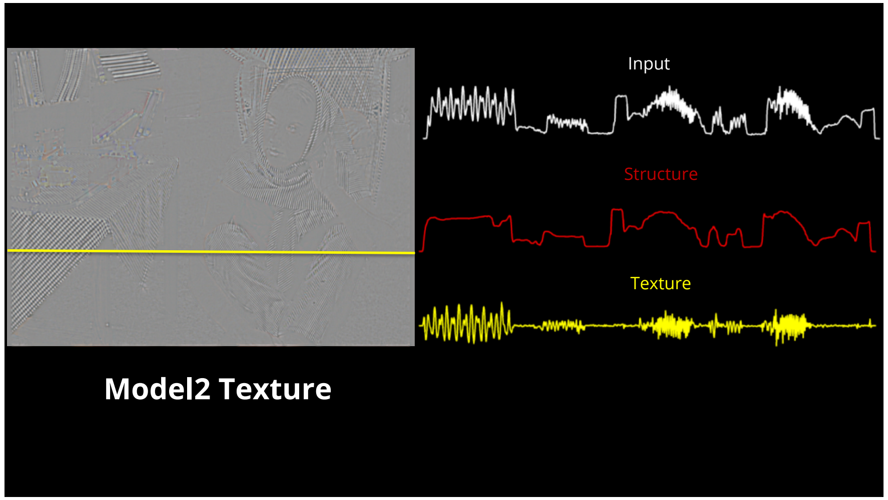
Resulting kernel $w_{pq} \propto \frac{d_{KL}(\mathbf{p},\mathbf{q})}{2\sigma^2}$

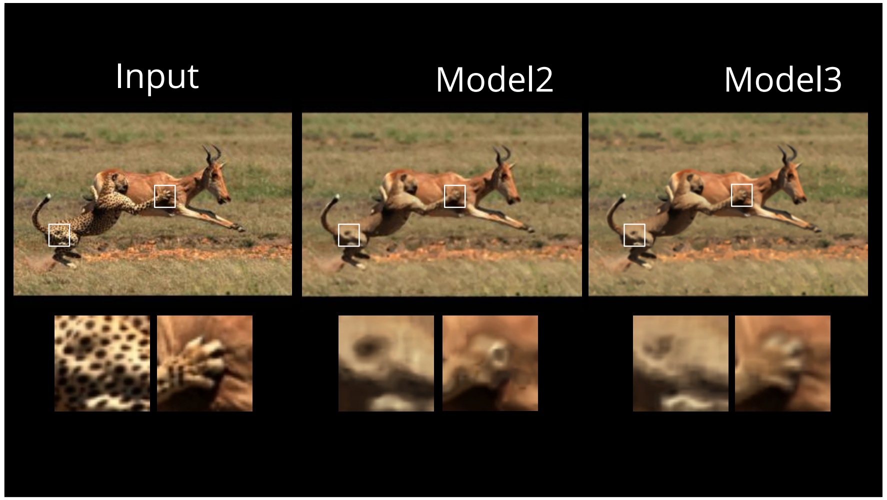
Smoothing Kernels






Input
Structure
Model2 Structure


Input
Structure
Texture
Model2 Texture


Input
Model2
Model3


Input

TV
Rudin et al.
1992

BLF
1998

WLS
Farbman et al.
2008

Envelope Extraction
Subr et al.
2009


Buades et al.
2010

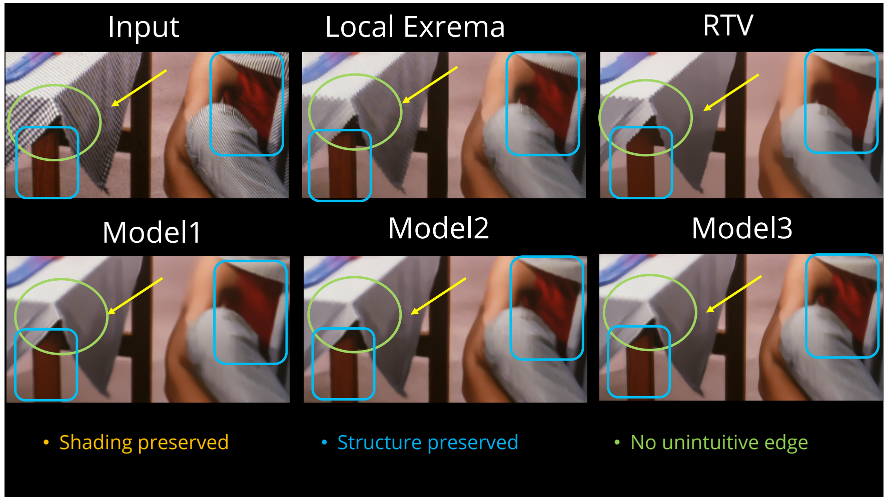

L0
Xu et al.
2011

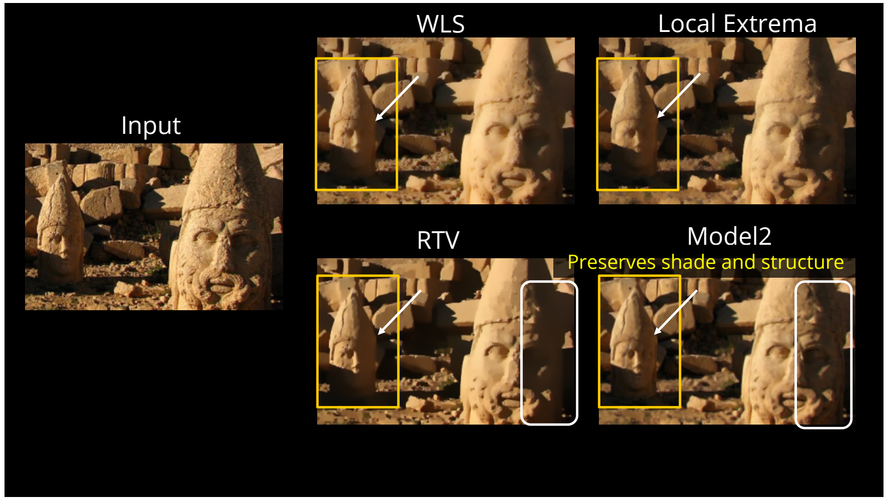

RTV
Xu et al.
2012

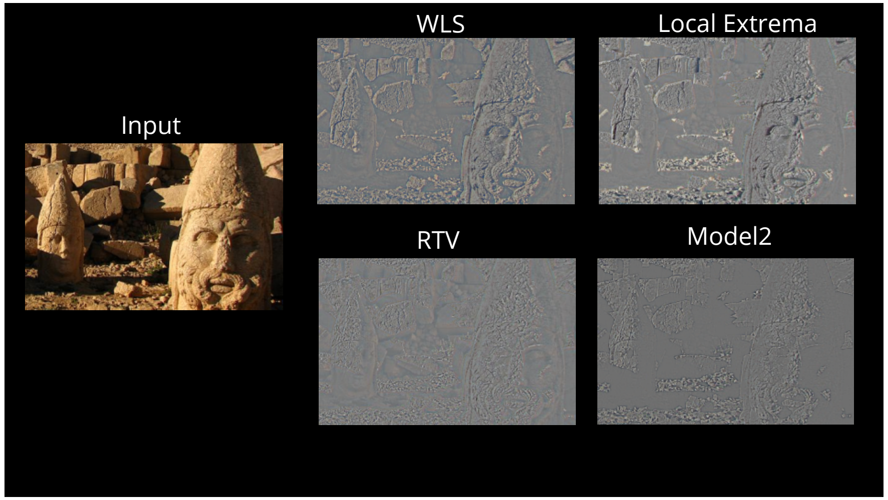

Model 1


Model 2


Model 3

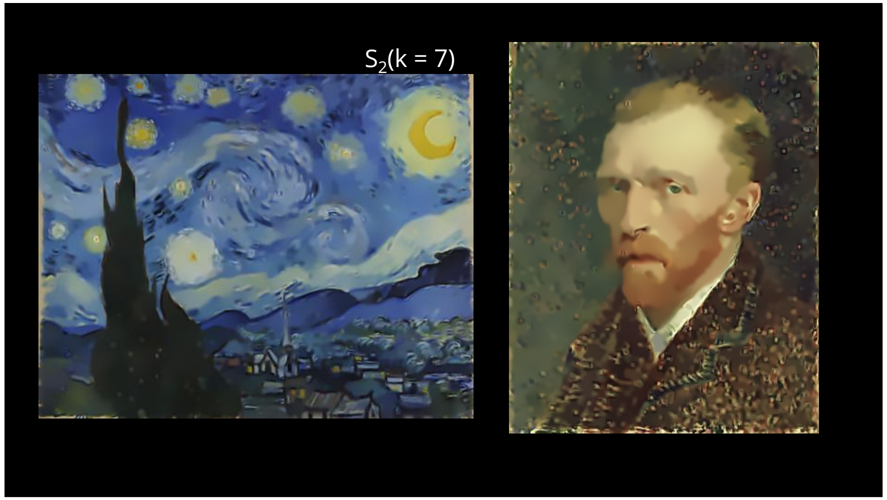

Input
Local Exrema
RTV
Model1
Model2
Model3
• Shading preserved
• Structure preserved
• No unintuitive edge

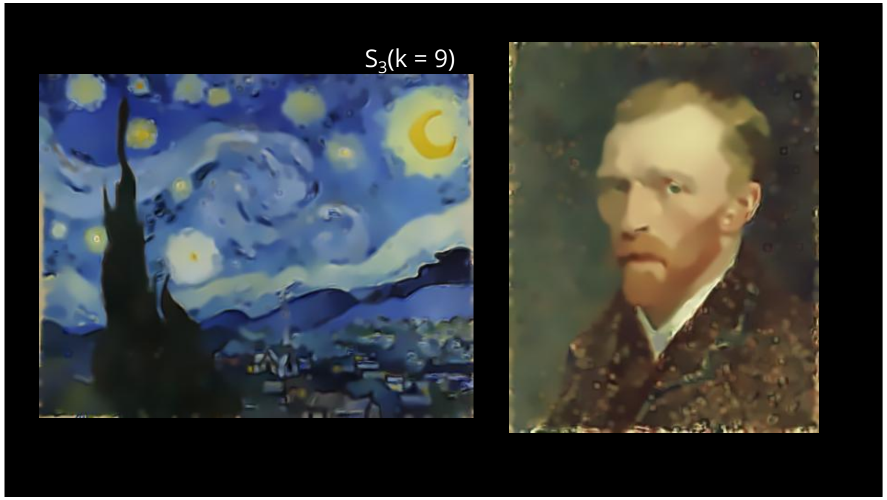

Input
WLS
Local Extrema
RTV
Model2
Preserves shade and structure

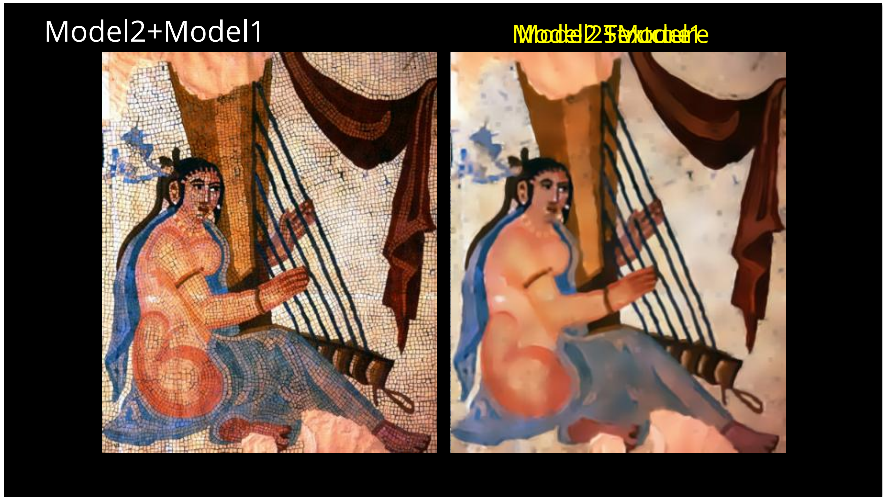

Input
WLS
Local Extrema
RTV
Model2

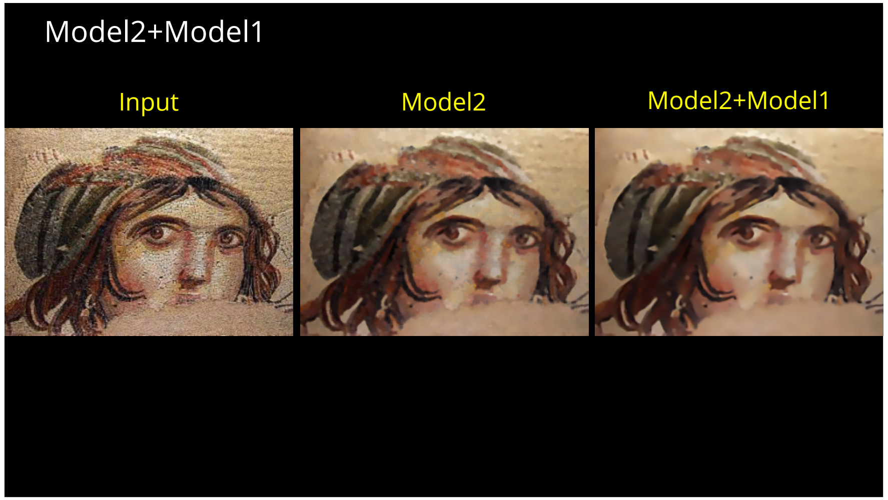

Multiscale decomposition

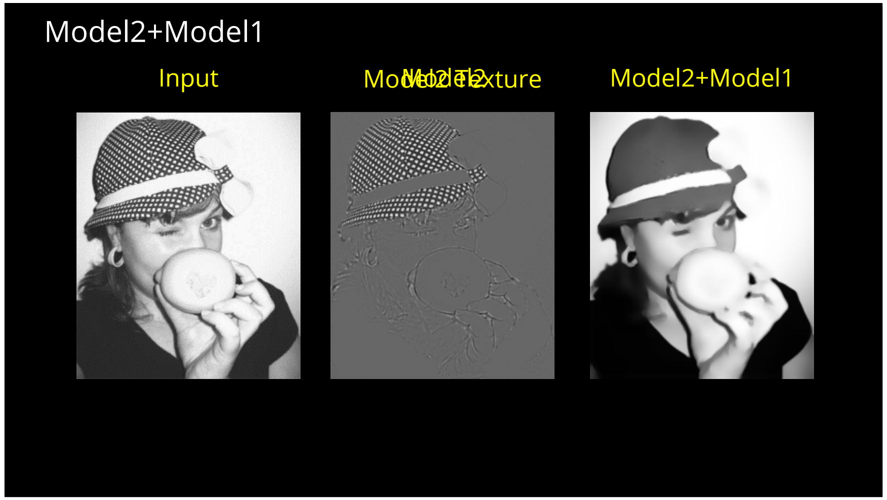

$S_1(k = 5)$


$S_2(k = 7)$


$S_3(k = 9)$

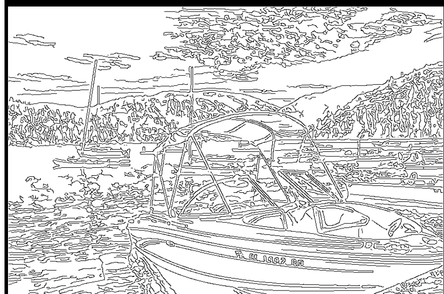

Model2+Model1


Model2+Model1
Input
Model2
Model2+Model1


Model2+Model1
Input
Model2+Model1

Edge Detection

Canny edges of original image



Canny edges of smoothed image

Image Abstraction

Detail Boosting

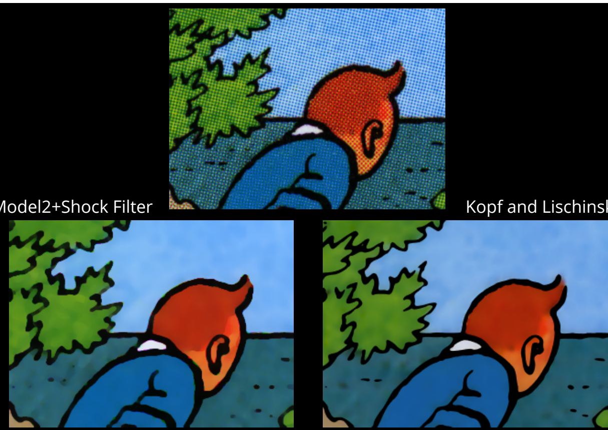
Image Composition

Inverse Halftoning

Smoothed

Shock filter
on the smooth image

Model2



Model2+Shock Filter

Kopf and Lischinski 2012

Image Retargeting

Input

Smoothed

Extracted Seams

Avidan and Shamir 2007

Retargeting Results

Avidan and Shamir 2007

Where we are going

- Linear filtering
- Nonlinear filtering (unified formulations)
- Pixels to Patches (context is more important than content)
- New patch representations may reveal new smoothing behaviors
- Better the smoothing, better the applications!
- Clearly, we have a long way to go to solve the problem of image smoothing!