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!
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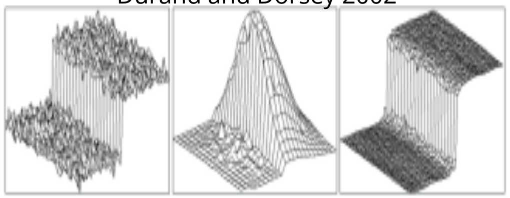
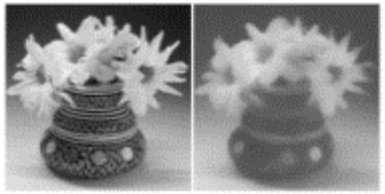
Some seminal works

Bilateral Filter
Tomasi and Manduchi 1998
Durand and Dorsey 2002

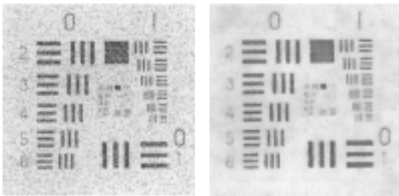


WLS Filter
Farbman et al. 2008

Envelope Extraction
Subr et al. 2009



Total Variation
Rudin et al. 1992



Fast Cartoon + Texture
Buades et al. 2010

Relative Total Variation
Xu et al. 2012

L0 Smoothing
Xu et al. 2011

Context-guided Filtering
Erdem and Tari 2009

RegCov Smoothing
Karacan et al. 2013

Rolling Guidance Filter
Zhang et al. 2014

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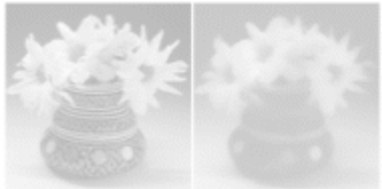

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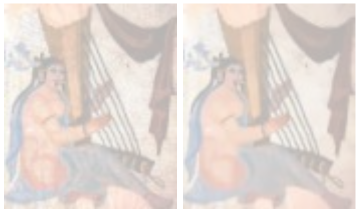
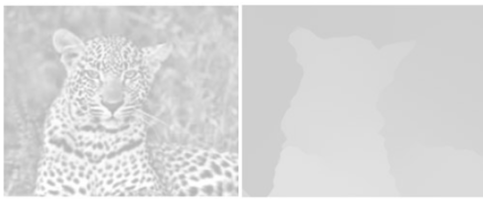


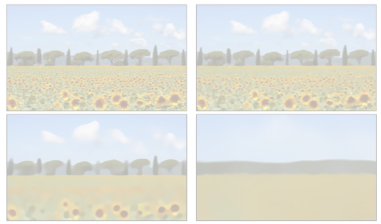
L0 Smoothing
Xu et al. 2011

Context-guided Filtering
Erdem and Tari 2009



RegCov Smoothing
Karacan et al. 2013

Rolling Guidance Filter
Zhang et al. 2014



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

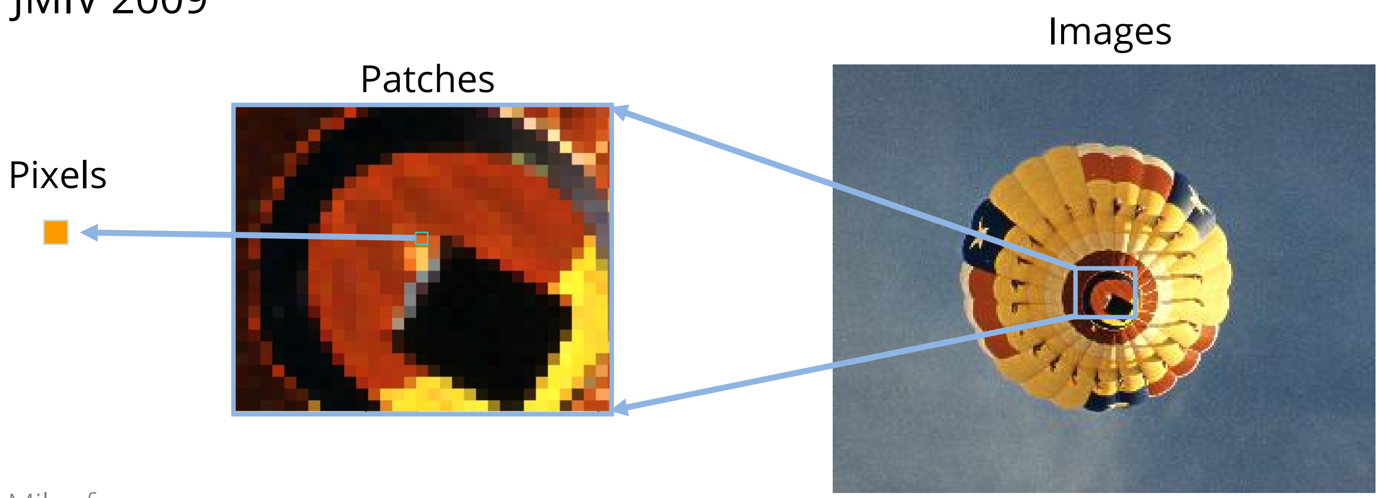


Image Credit: P. Milanfar

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

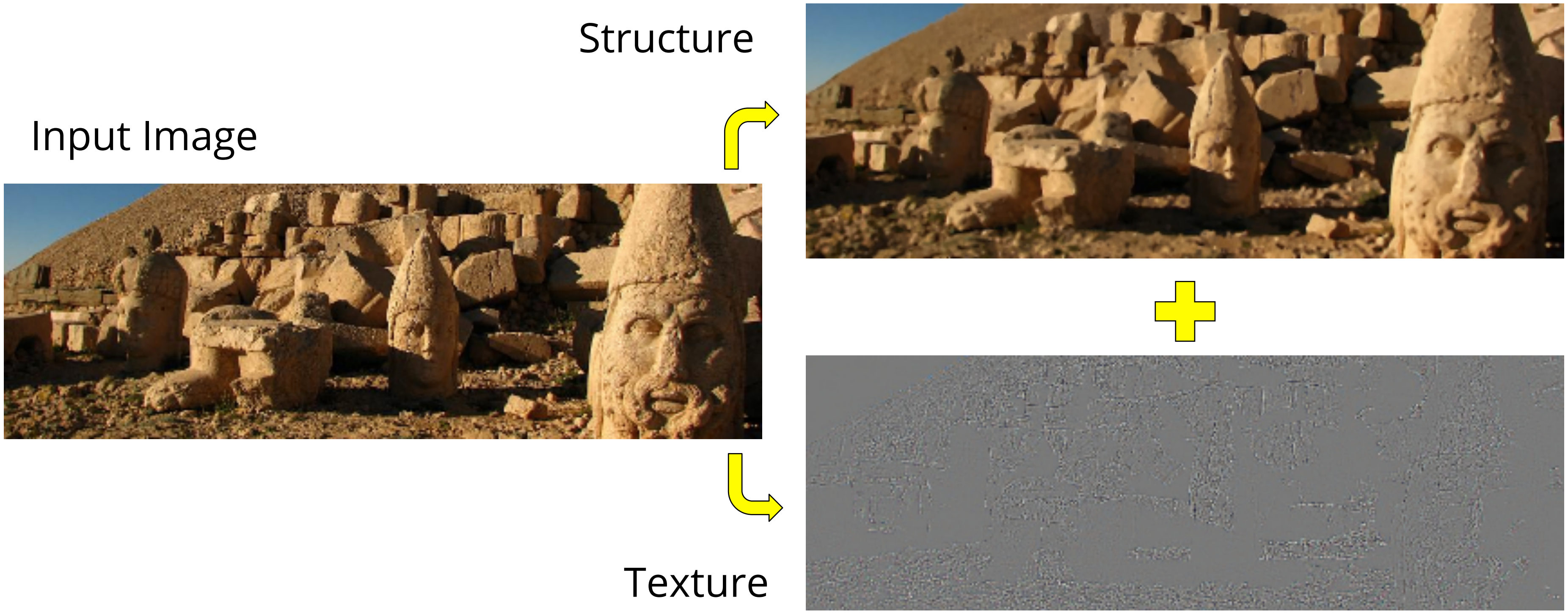
Structure-Texture Decomposition

- Decomposing an image into structure and texture components

Texture Component

Structure-Texture Decomposition

- Decomposing an image into structure and texture components

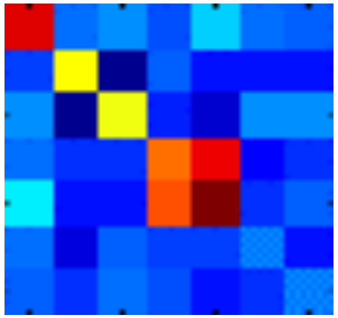


Region Covariances as Region Descriptors

Tuzel et al., ECCV 2006

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

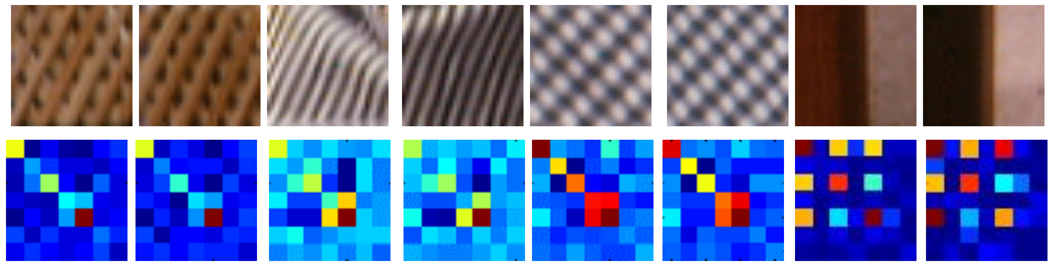
$$F(x,y) = \left[I(x,y) \quad \left|\frac{\partial I}{\partial x}\right| \quad \left|\frac{\partial I}{\partial y}\right| \quad \left|\frac{\partial^2 I}{\partial x^2}\right| \quad \left|\frac{\partial^2 I}{\partial y^2}\right| \quad x \quad y \right]^T$$



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

Motivation

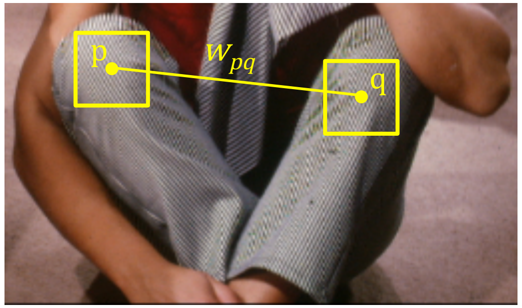
- Region covariances capture local structure and texture information.
- Similar regions have similar statistics.



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.

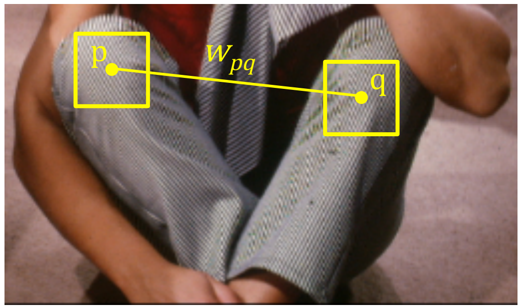
- L. Karacan, A. Erdem, E. Erdem, “Structure Preserving Image Smoothing via Region Covariances”, ACM TOG 2013 (SIGGRAPH Asia 2013)

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*

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



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

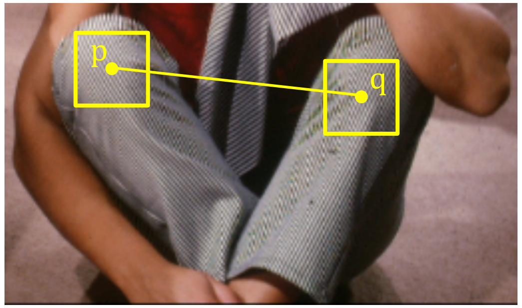
$$w_{\mathbf{pq}} \propto \exp\left(-\frac{\|\Psi(\mathbf{C_p}) - \Psi(\mathbf{C_q})\|^2}{2\sigma^2}\right)$$

Model 2

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

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

$$\mathbf{C} = \mathbf{C}_\mathbf{p} + \mathbf{C}_\mathbf{q}$$

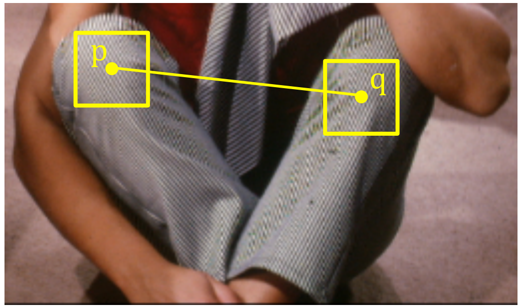


Resulting kernel $w_{\mathbf{pq}} \propto \exp\left(-\frac{d(\mathbf{p},\mathbf{q})^2}{2\sigma^2}\right)$

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

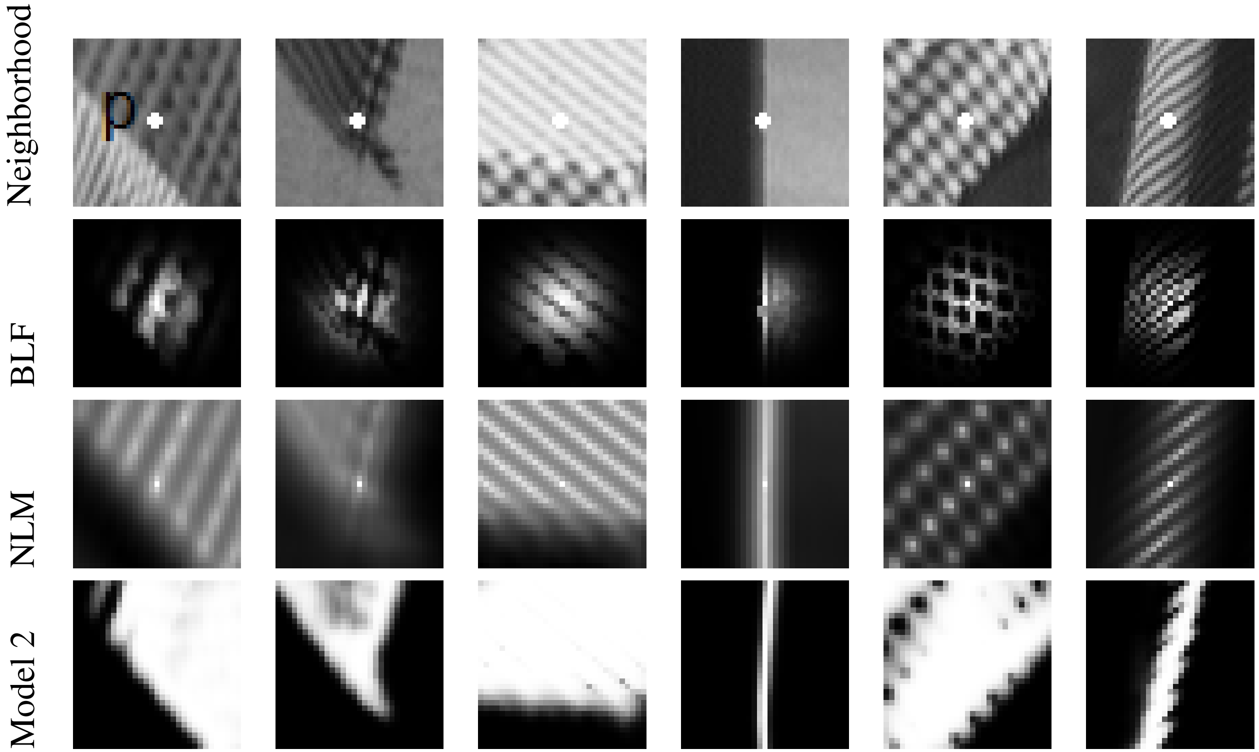


$$d_{KL}(\mathbf{p},\mathbf{q}) = \frac{1}{2}\left(tr(\mathbf{C_q}^{-1}\mathbf{C_p}) + (\mu_p - \mu_q)^T \mathbf{C_q}^{-1}(\mu_p - \mu_q) - k - ln\left(\frac{\det \mathbf{C_p}}{\det \mathbf{C_q}}\right)\right)$$

Resulting kernel

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

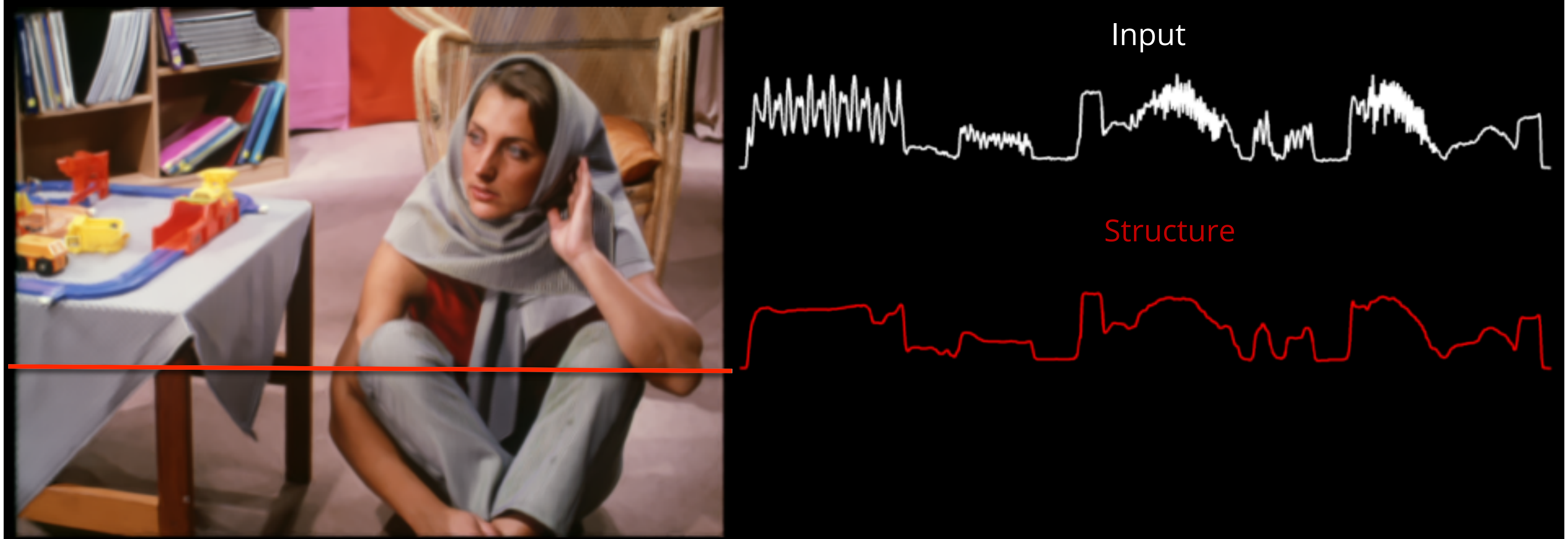
Smoothing Kernels



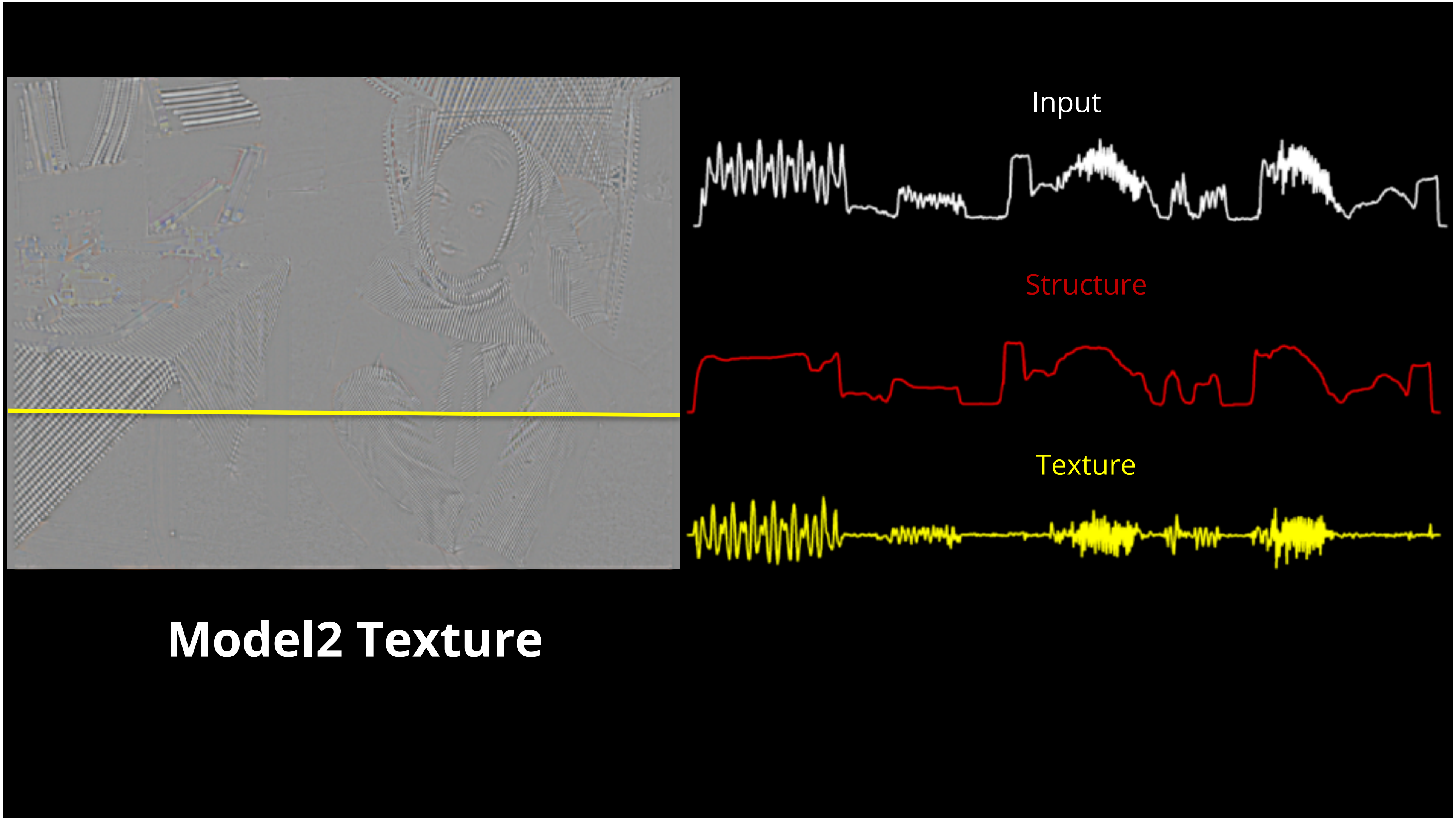
Input

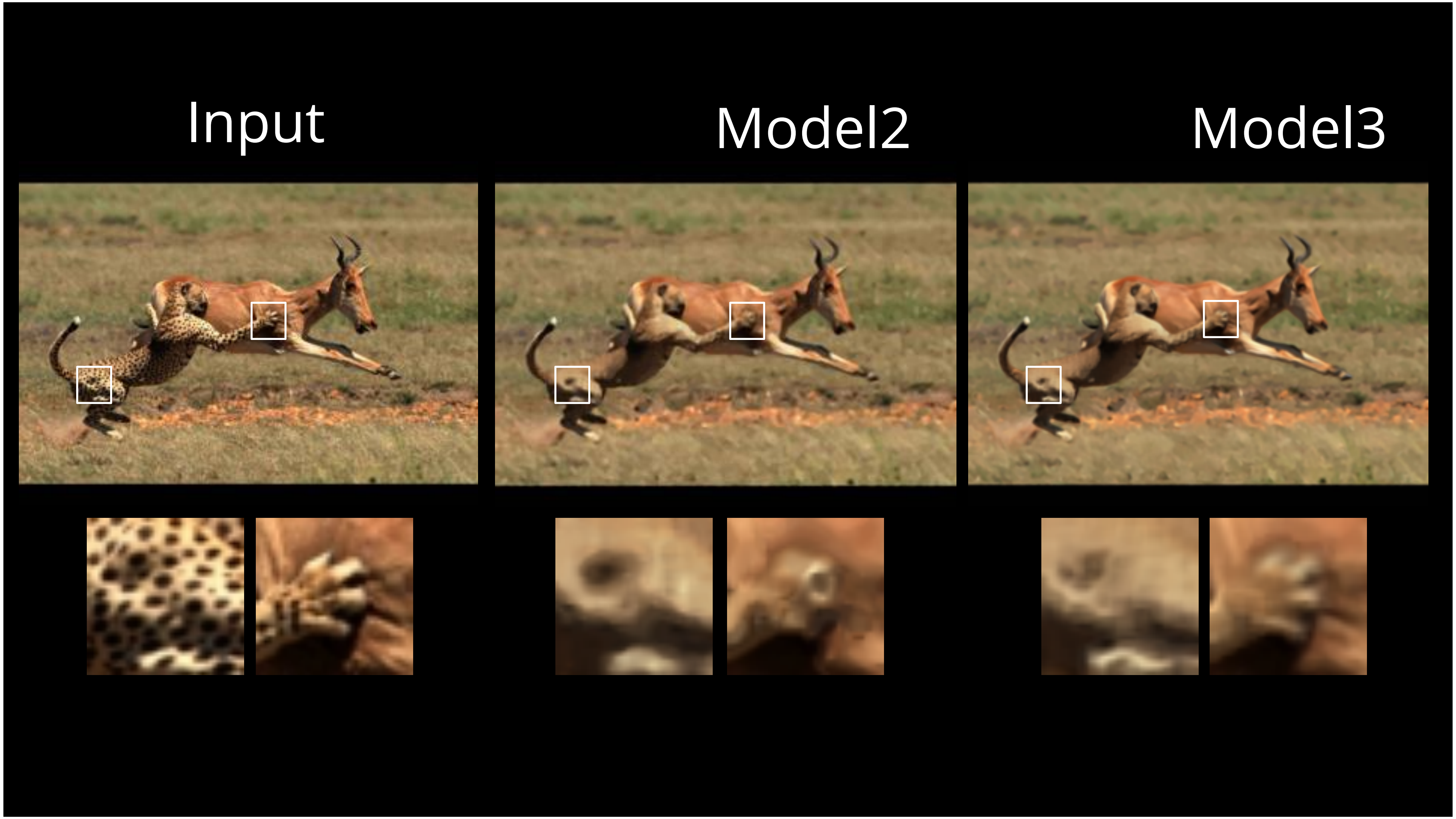

Model1
Model2
Model3

Input



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

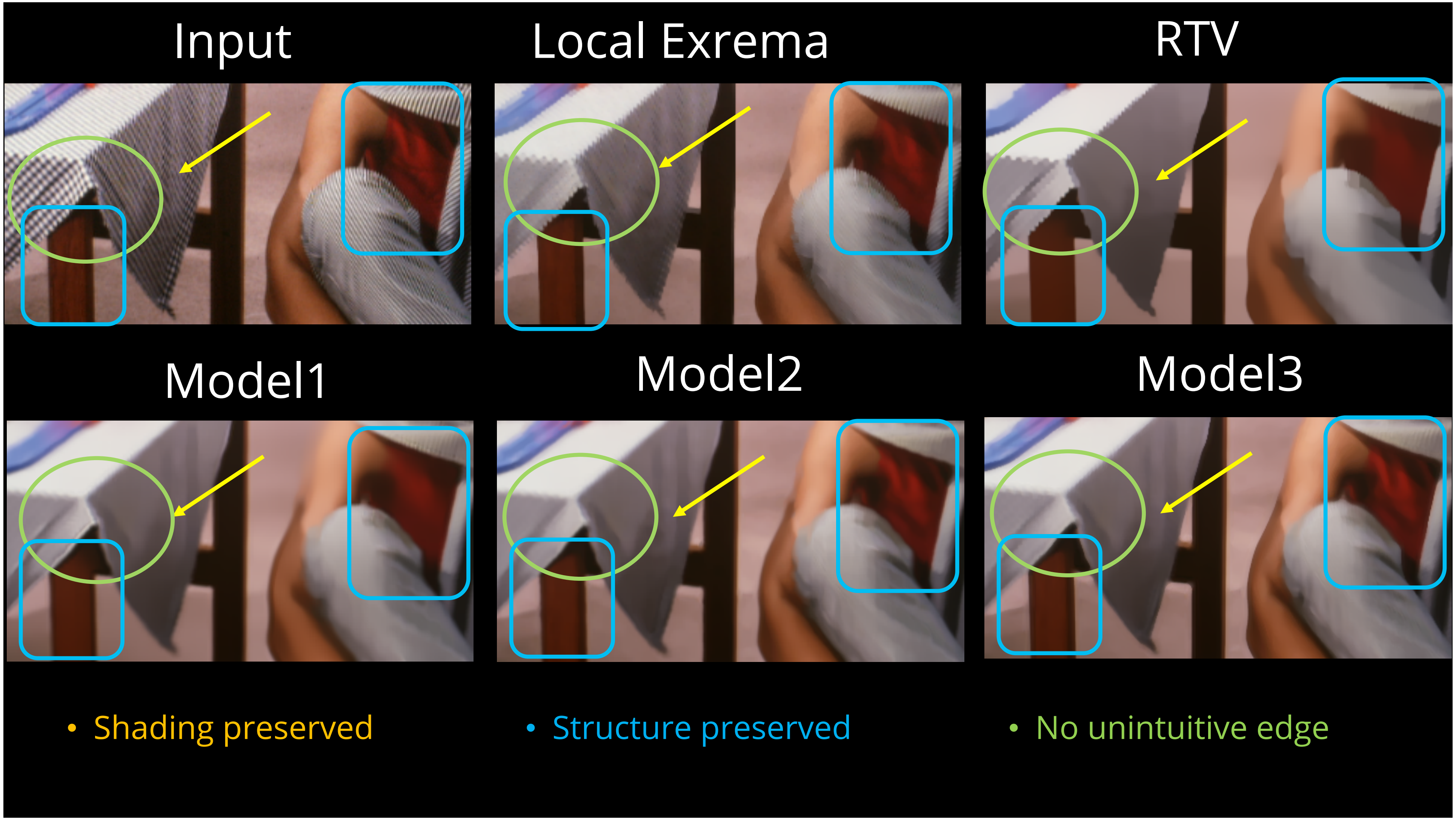
Xu et al.

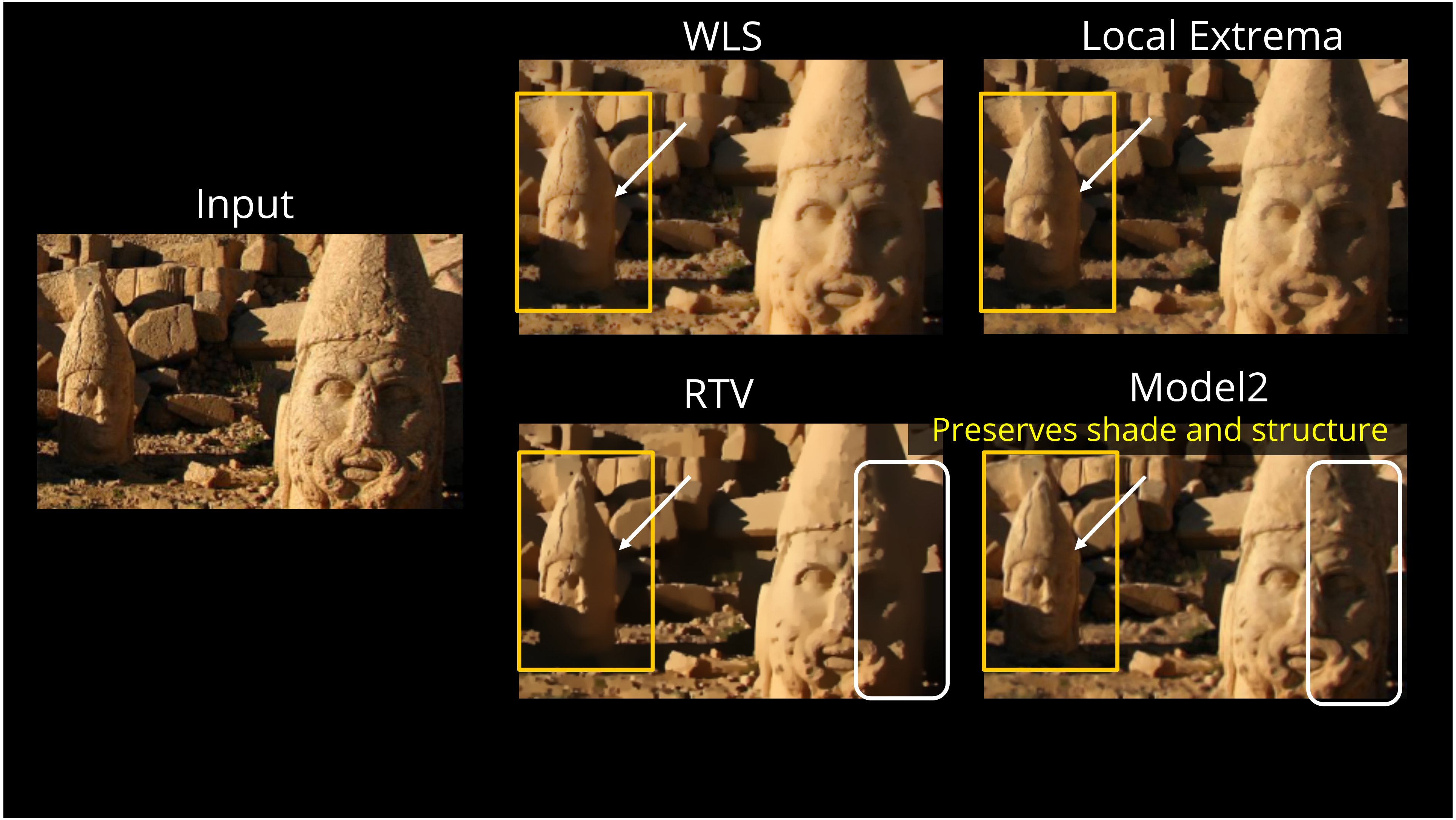
2012

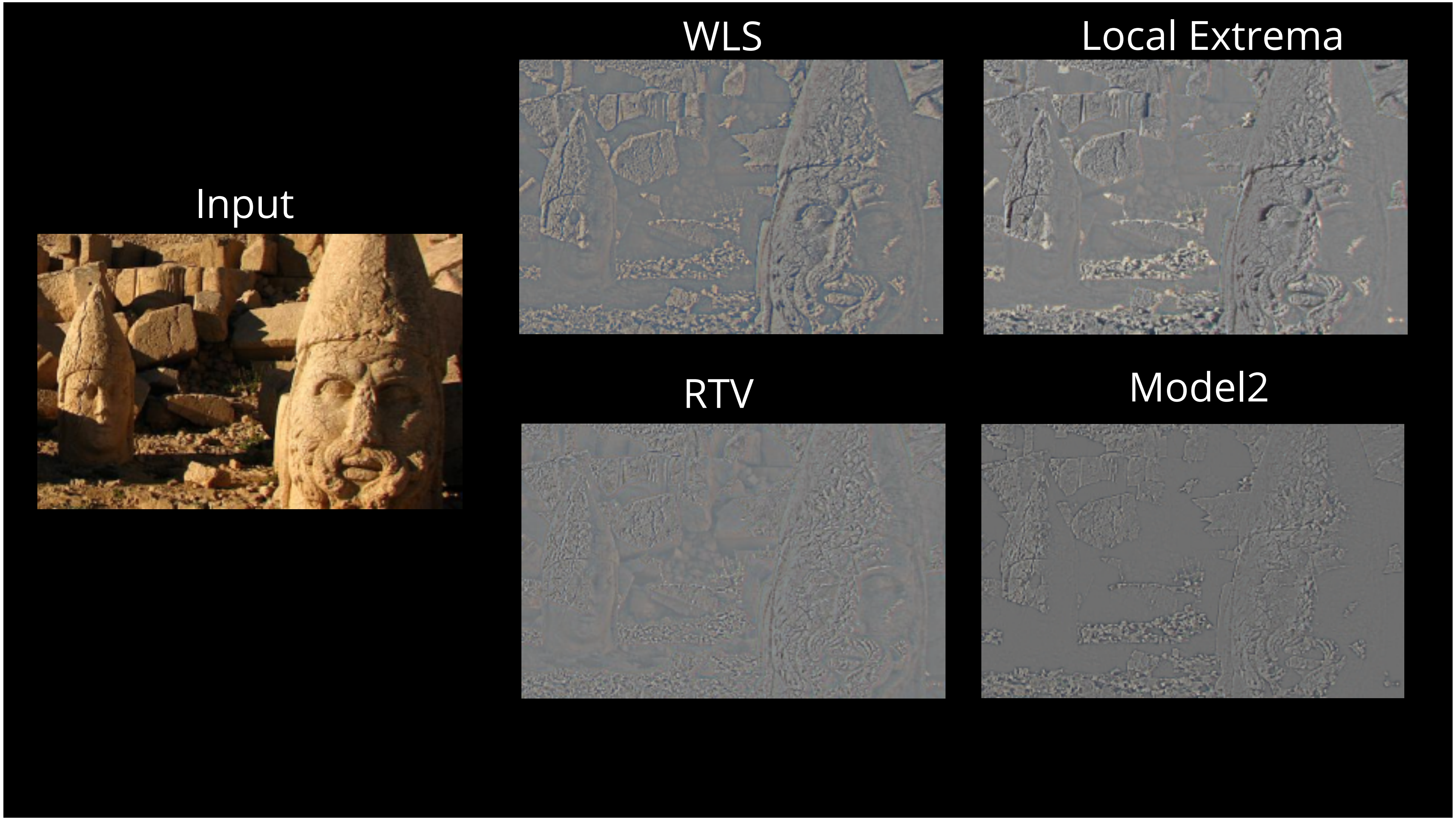
Model 1

Model 2

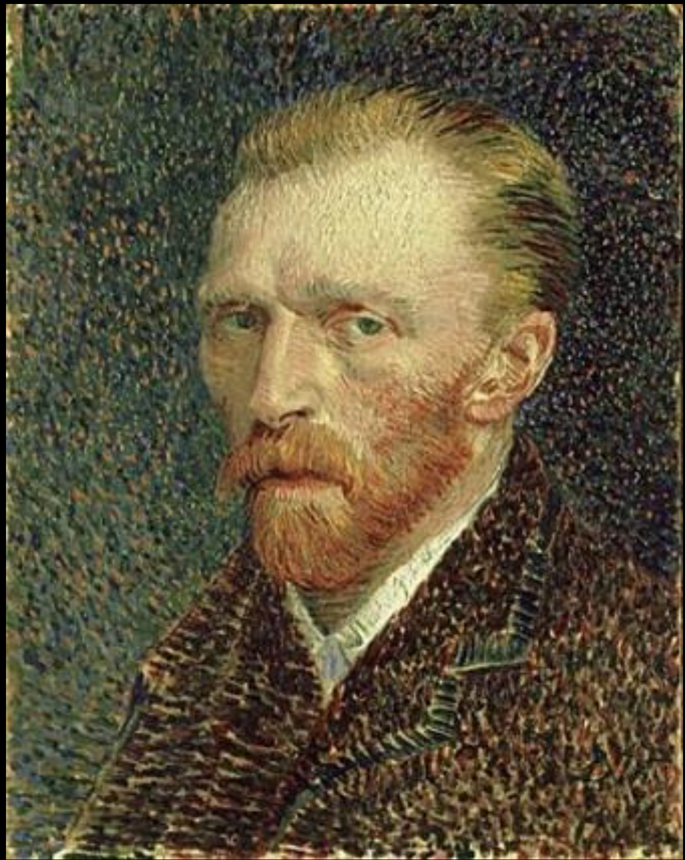
Model 3


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

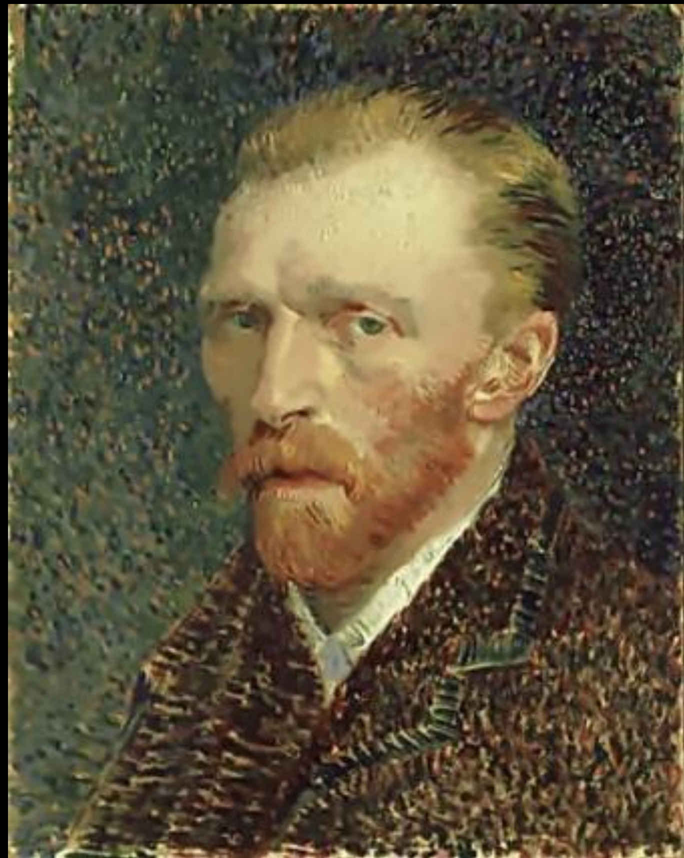

Input
WLS
Local Extrema
RTV
Model2
Preserves shade and structure


Input
WLS
Local Extrema
RTV
Model2

Multiscale decomposition

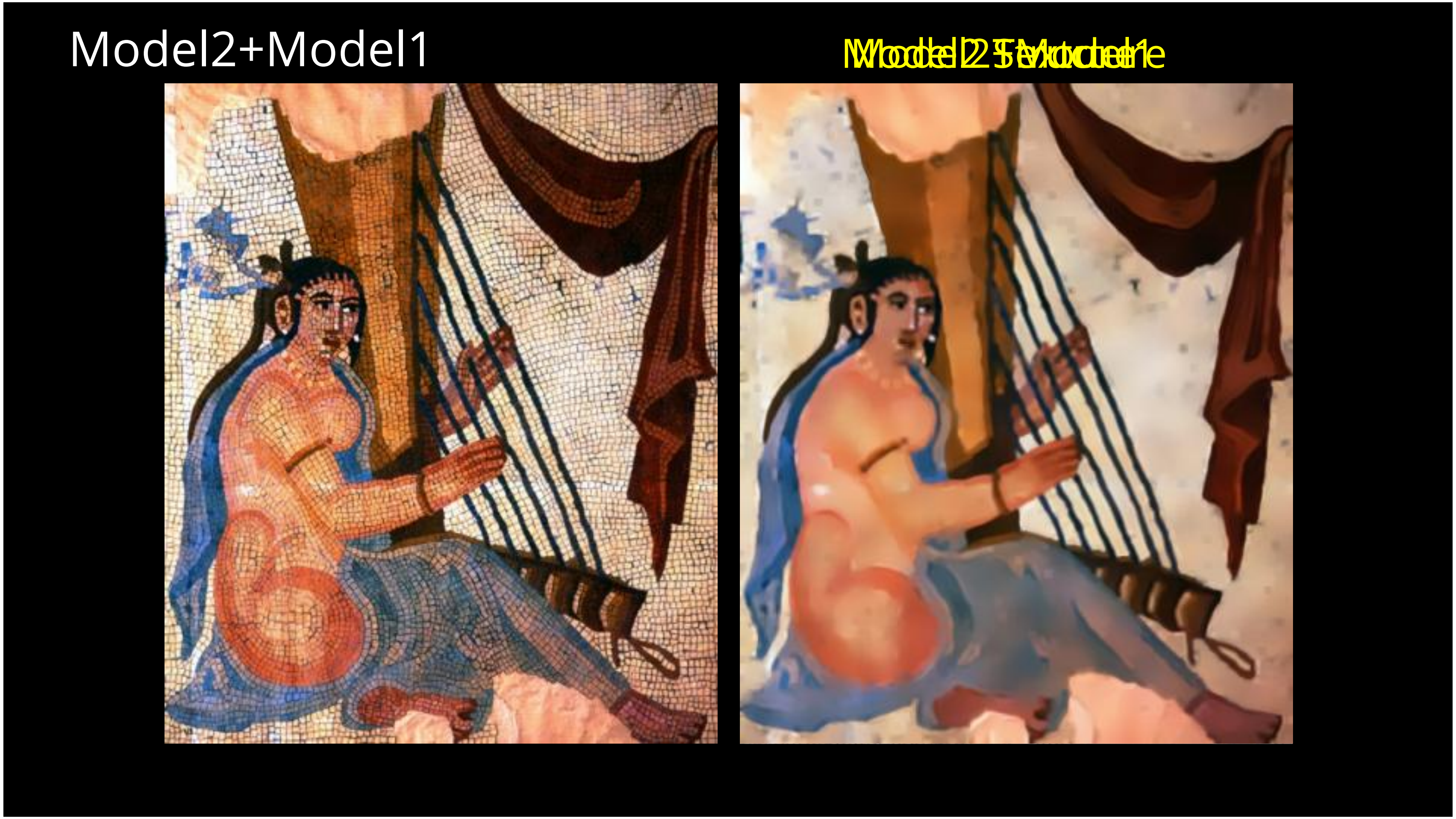


$S_1(k = 5)$



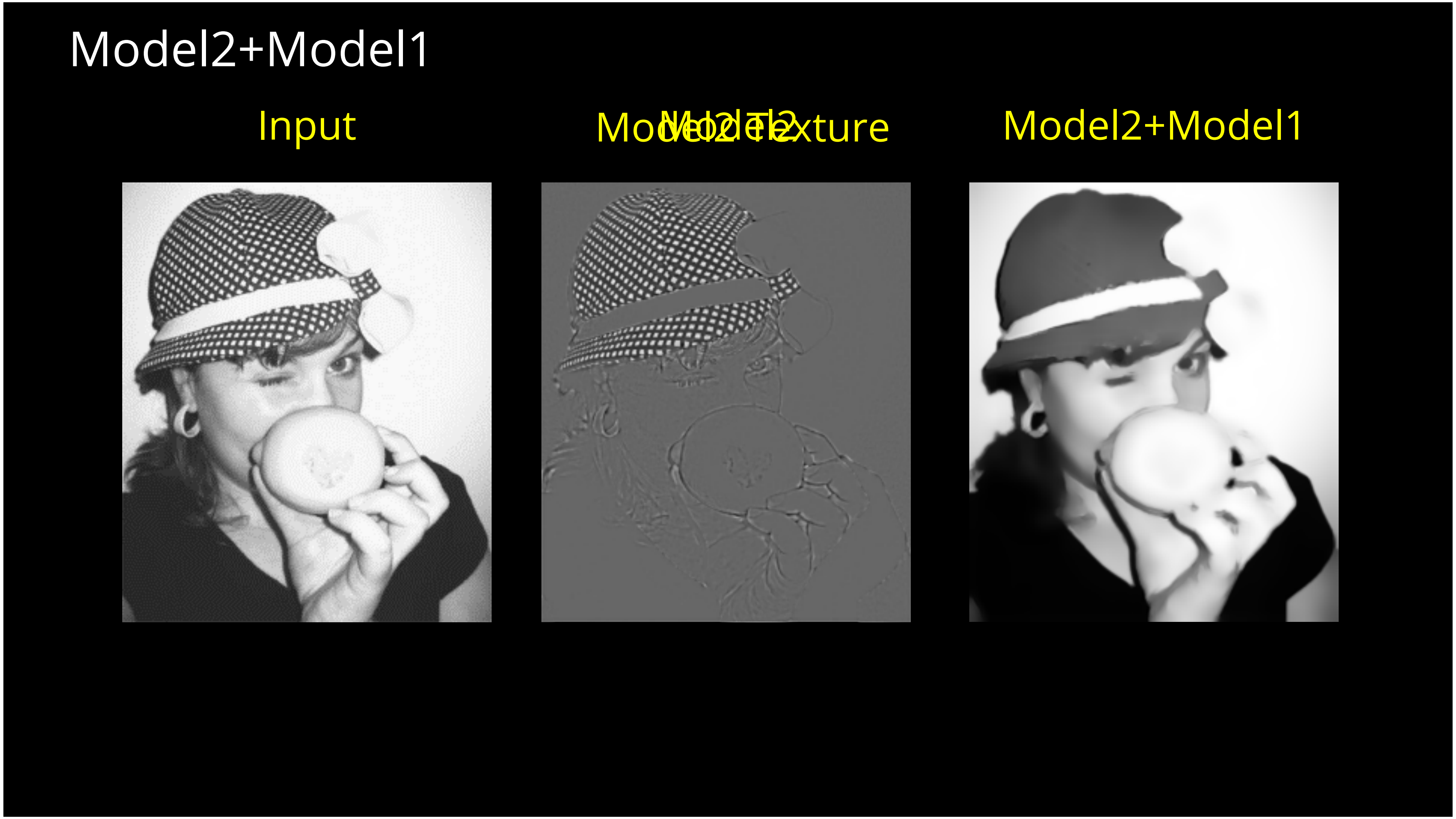
$S_2(k = 7)$

$S_3(k = 9)$


Model2+Model1

Model2+Model1

Input | Model2 | Model2+Model1

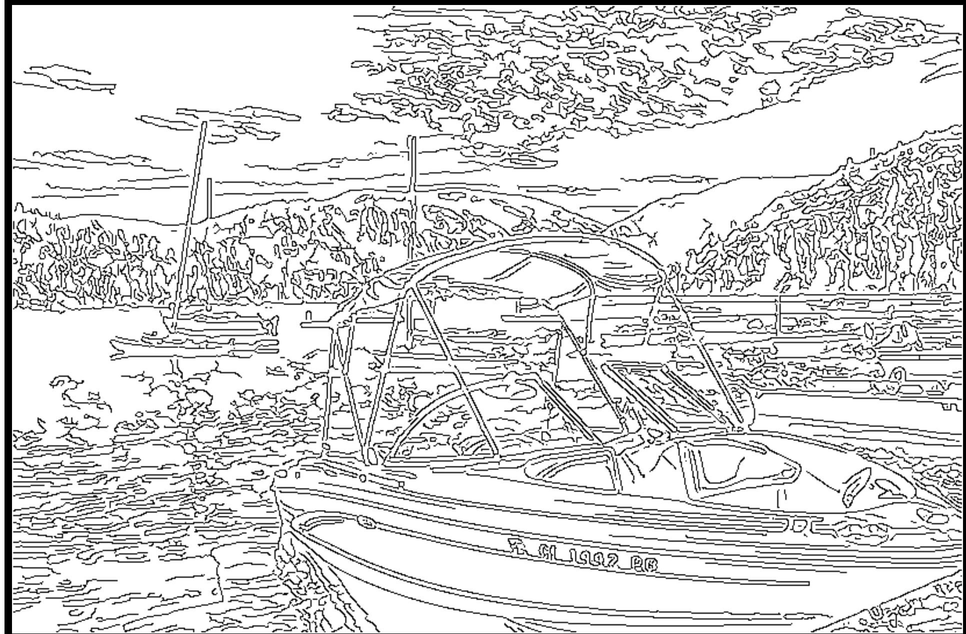

Model2+Model1
Input
Model2
Model2 Texture
Model2+Model1

Edge Detection


CF 1442 RB

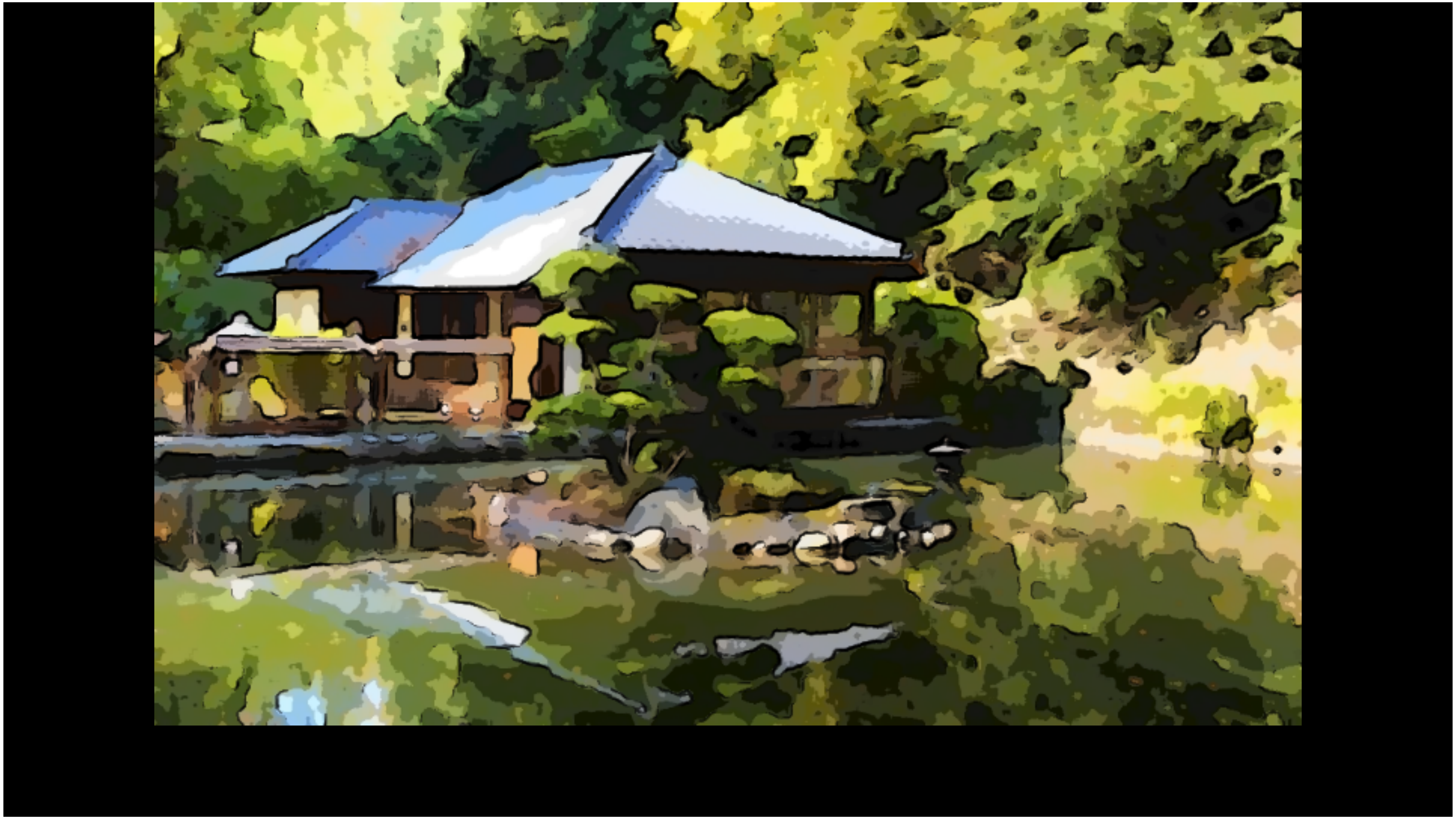

CF 1442 RB

Canny edges of original image



Canny edges of smoothed image

Image Abstraction



Detail Boosting

Image Composition

[redacted]

Inverse Halftoning

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!