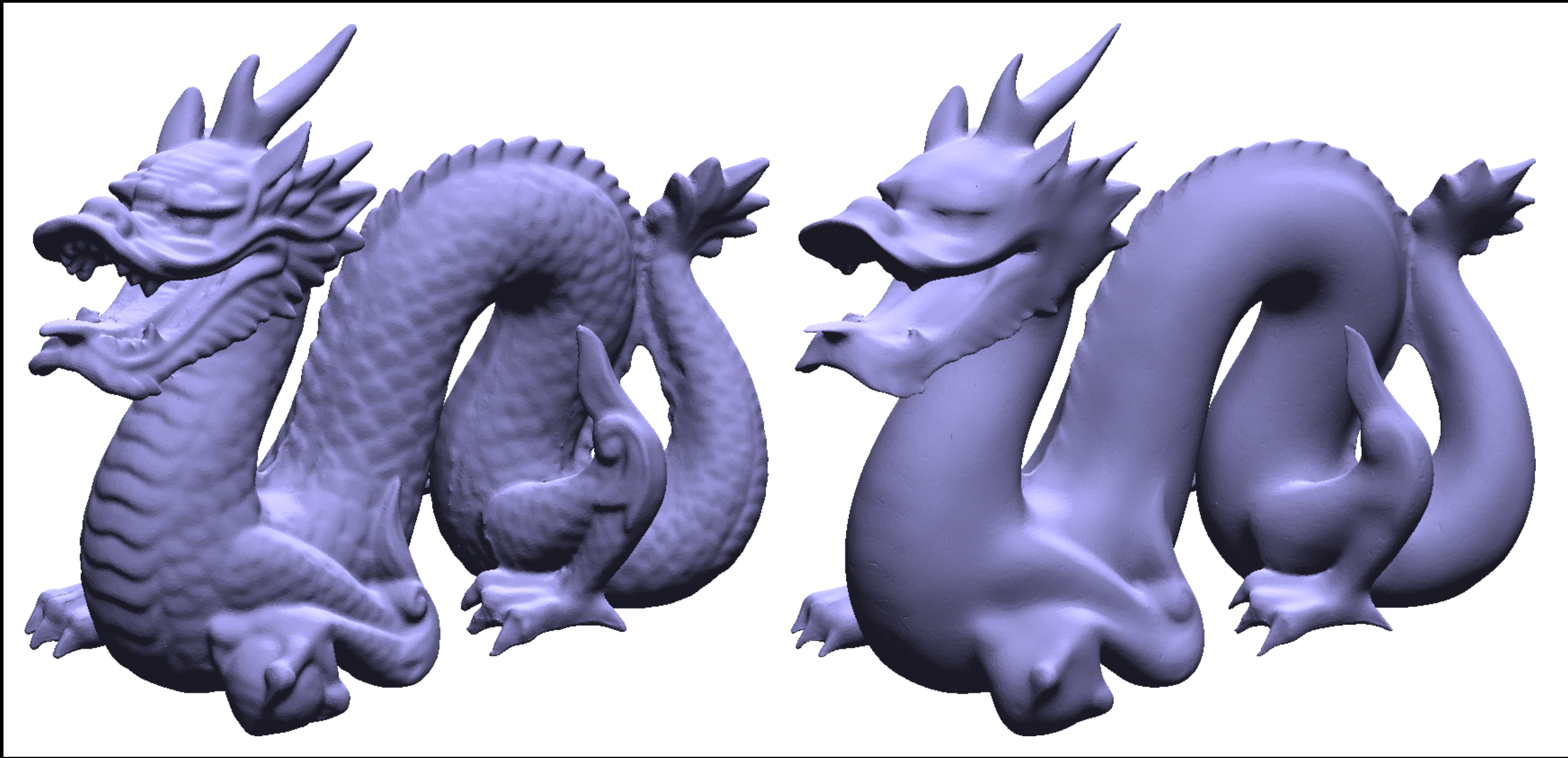
Non-Iterative, Feature-Preserving Mesh Smoothing



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Why Smooth?

3D scanners are noisy...

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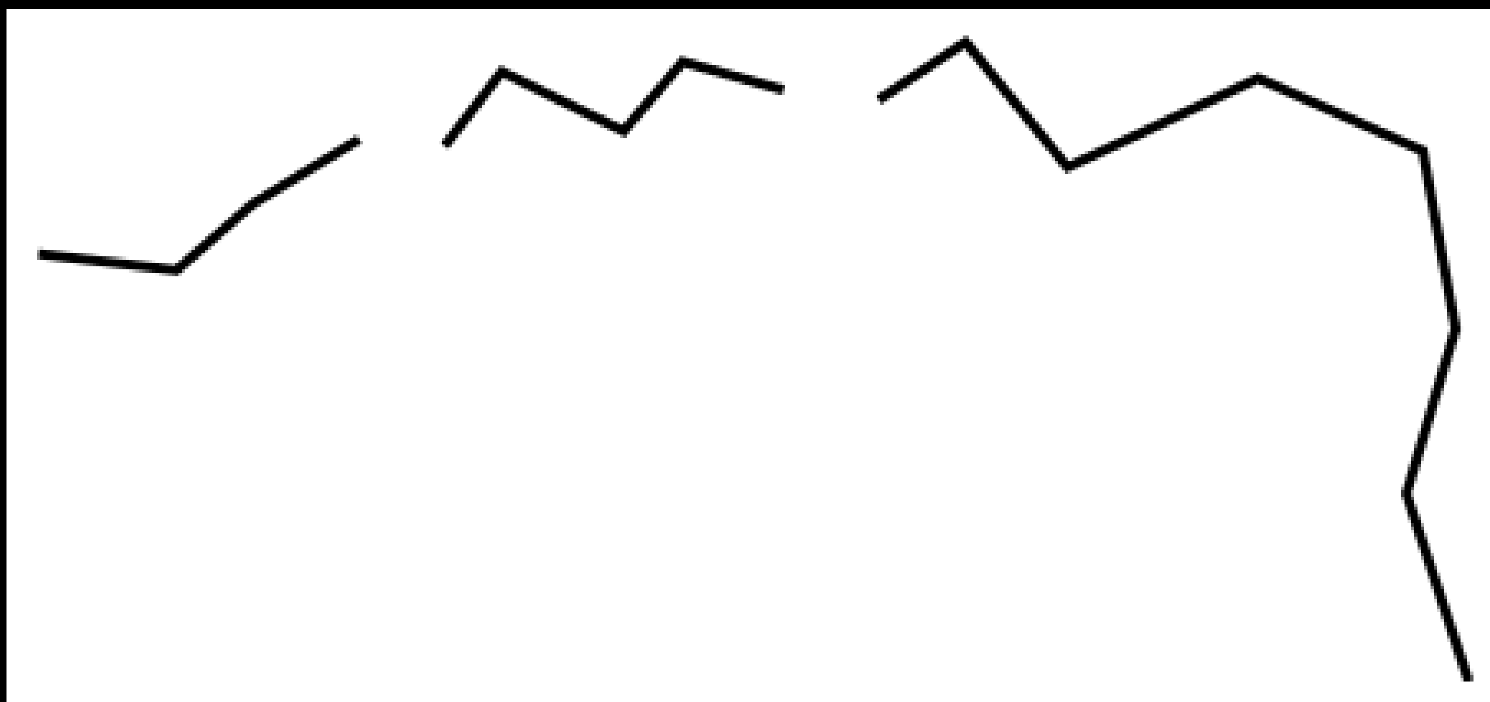
Why Smooth?

3D scanners are noisy...

and have dropouts...

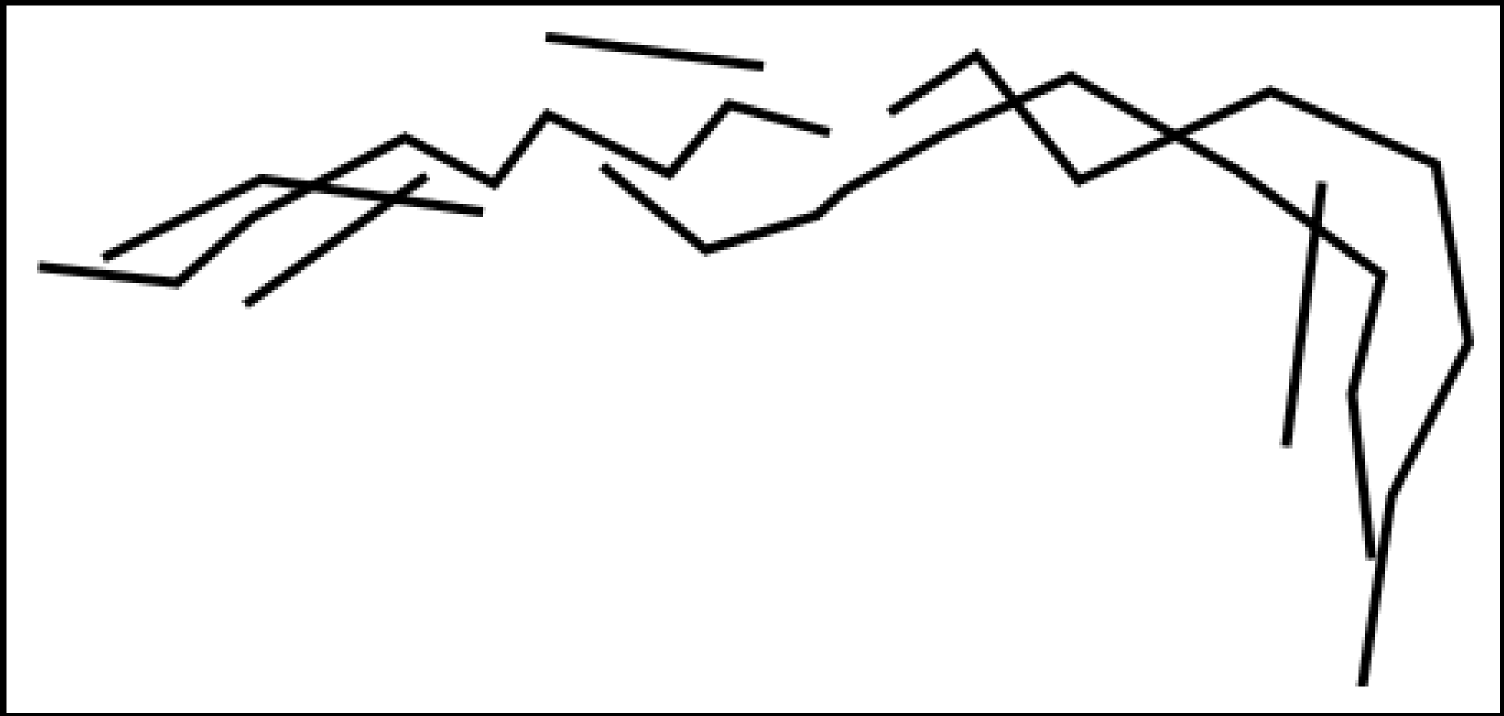


Why Smooth?

3D scanners are noisy...

and have dropouts...

and usually require multiple scans.



Goals

Fast smoothing of meshes

Robust

- Geometrically: preserve features
- Topologically: no connectivity information

Simple to implement

Goals

Fast smoothing of ~~meshes~~ polygon soups

Robust

- Geometrically: preserve features
- Topologically: no connectivity information

Simple to implement

Previous Work on Smoothing

Fast Mesh Smoothing

- Taubin 1995; Desbrun et al. 1999

Feature Preserving

- Clarenz et al. 2000; Desbrun et al. 2000; Meyer et al. 2002; Zhang and Fiume 2002; Bajaj and Xu 2003

Diffusion on Normal Field

- Taubin 2001; Belyaev and Ohtake 2001; Ohtake et al. 2002; Tasdizen et al. 2002

Wiener Filtering of Meshes

- Peng et al. 2001; Alexa 2002; Pauly and Gross 2001 (points)

Approach

We cast feature-preserving filtering as a robust estimation problem on vertex positions.

Extend Bilateral Filter to 3D.

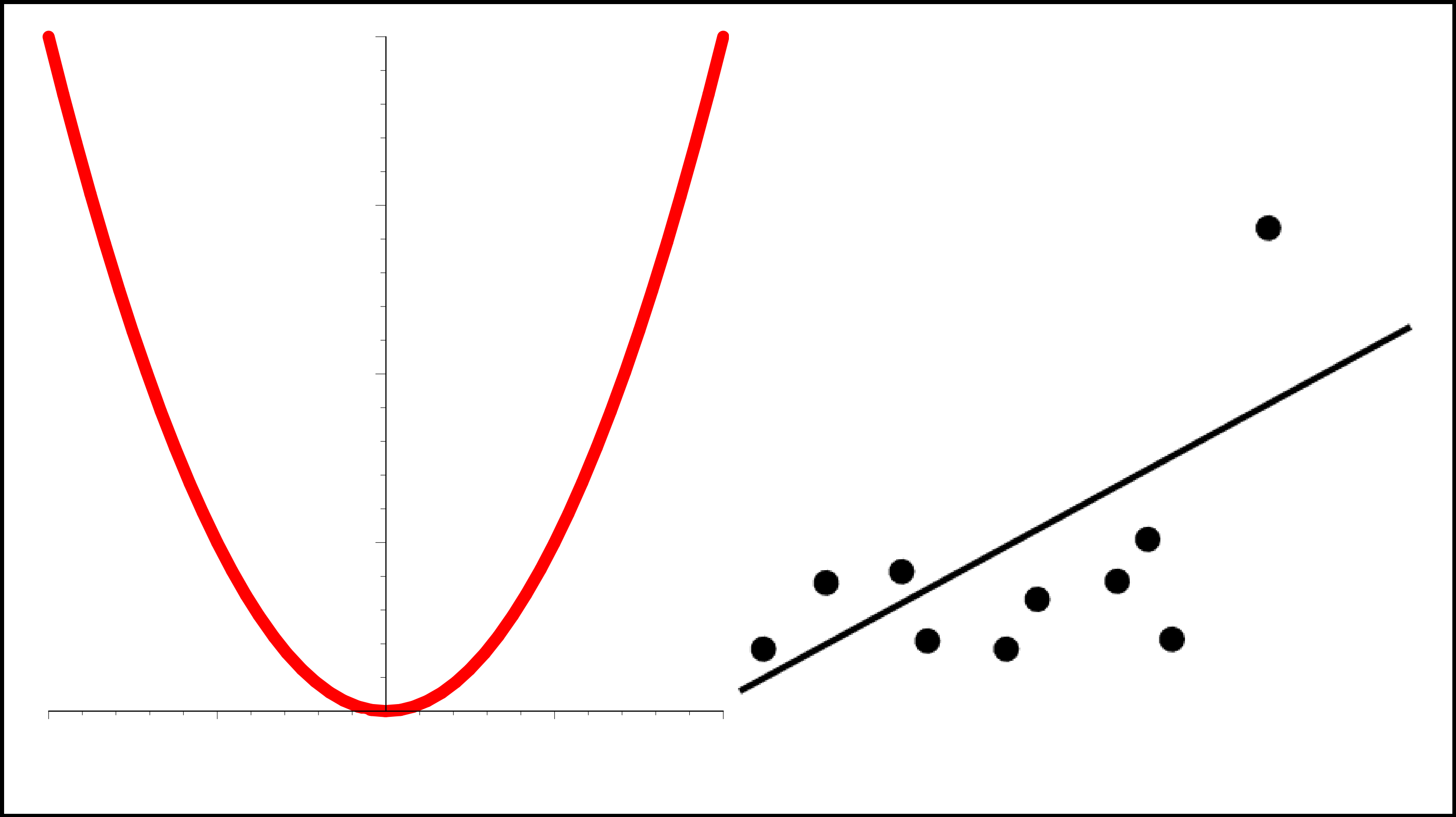
- Smith and Brady 1997; Tomasi and Manduchi 1998

Use first-order *predictors* based on facets of model.

Single pass.

Non-Robust Estimation

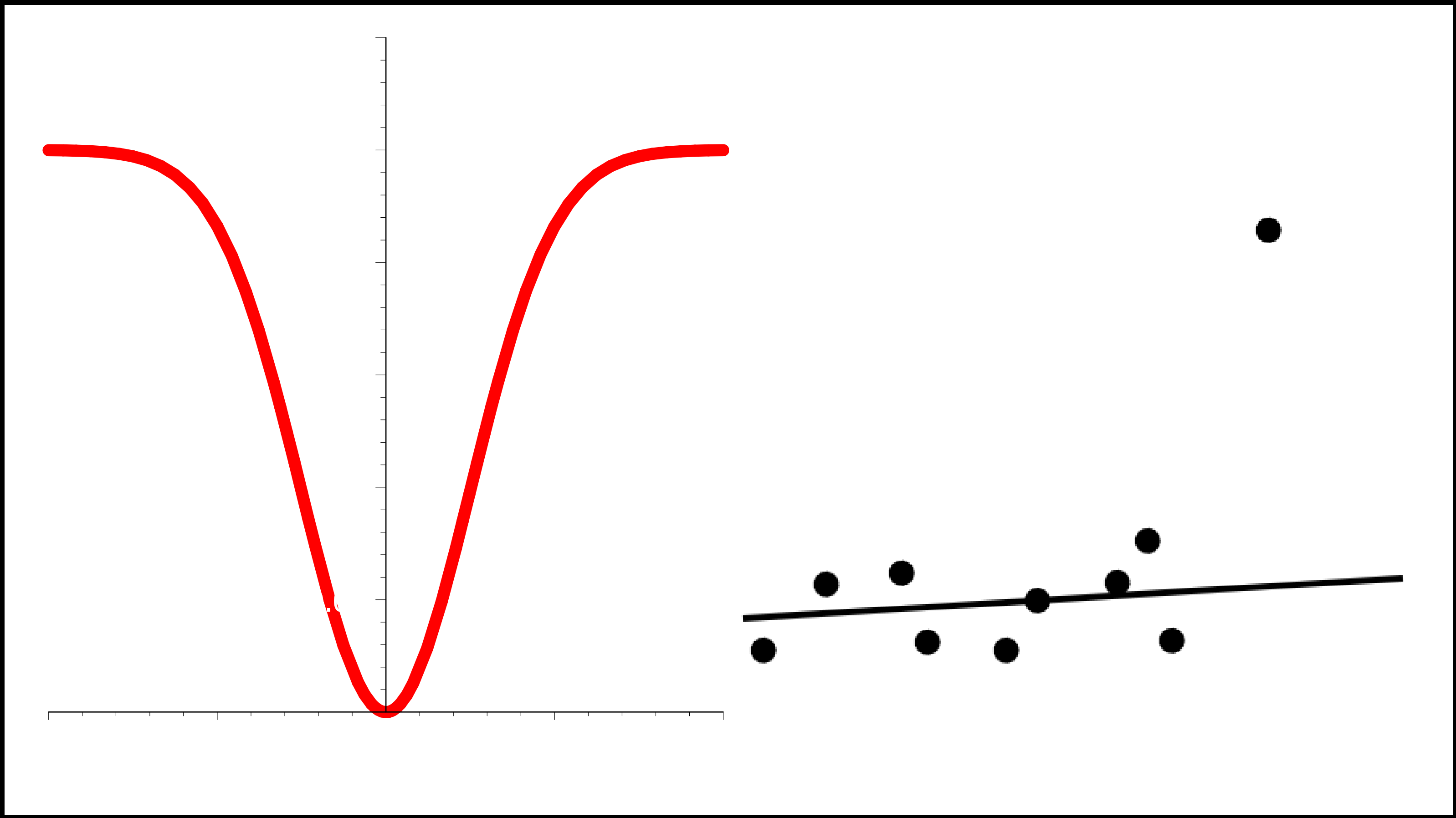
Least Squares Error Norm



Outliers have unlimited influence on estimate.

Robust Estimation

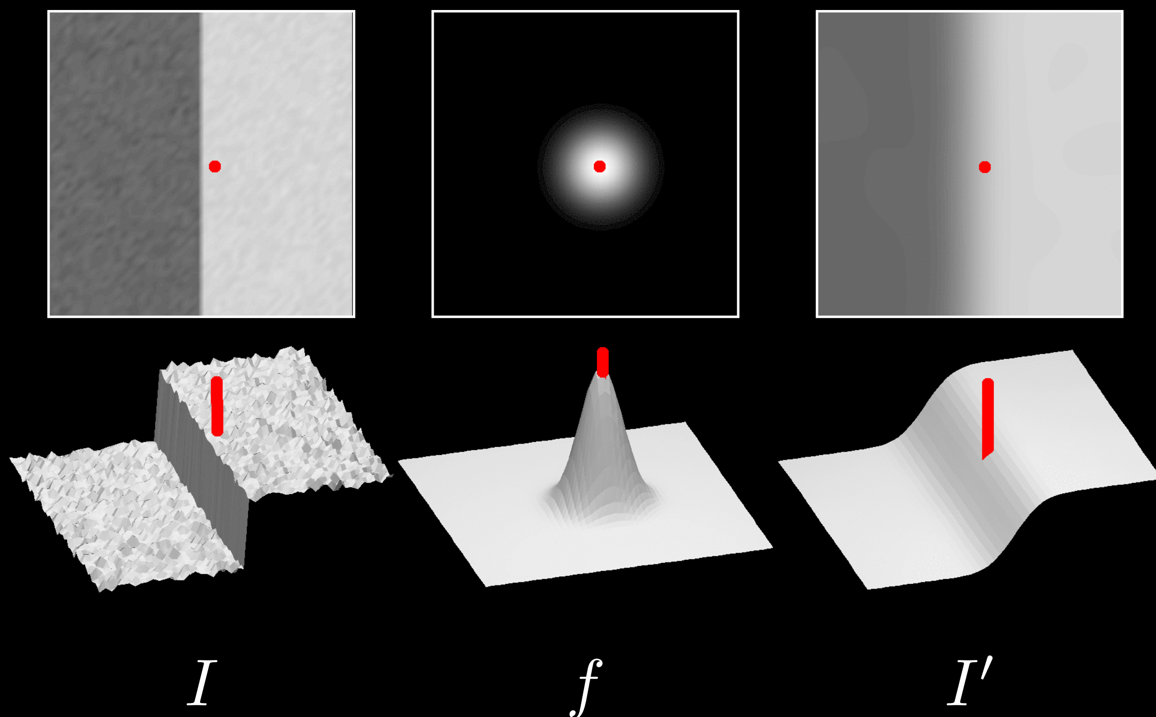
Robust Error Norm



Outliers have bounded influence on estimate.

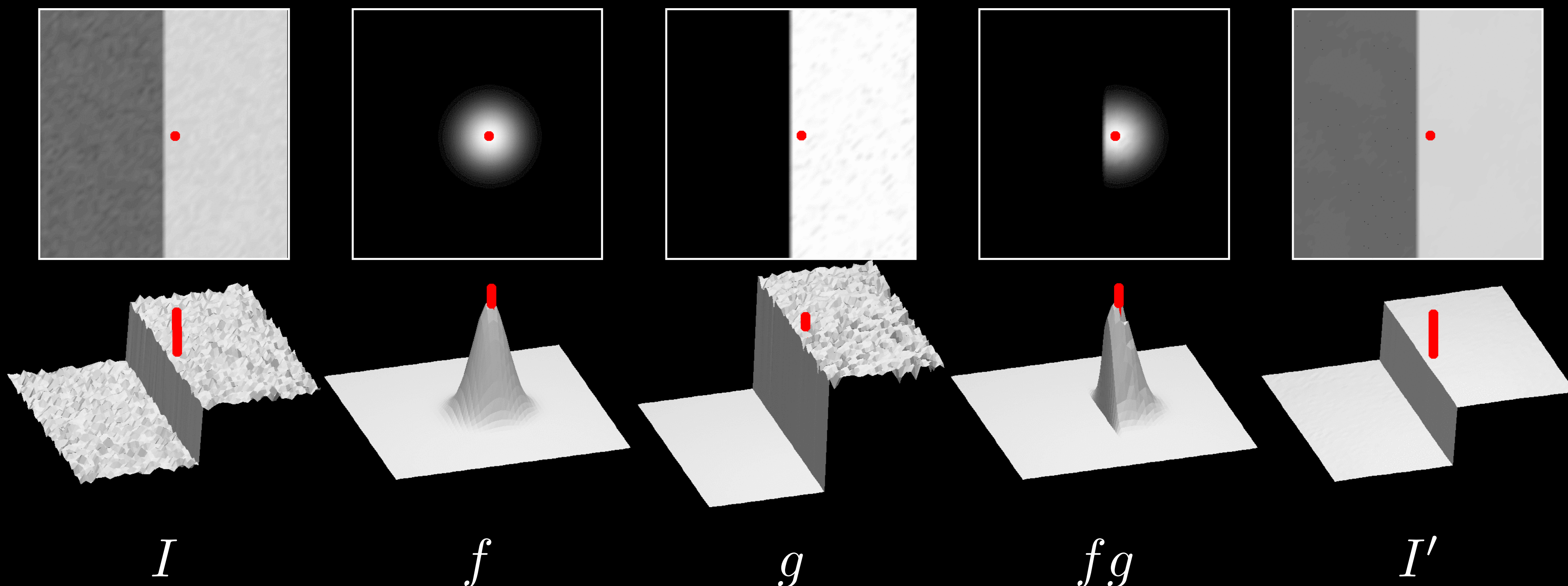
Gaussian Filter (Non-robust)

$$I'_s = \sum_p \overbrace{I(p)}^{\text{image}} \; \overbrace{f(s-p)}^{\text{spatial}}$$



Bilateral Filter (Robust)

$$I'_s = \frac{1}{k_s} \sum_p \overbrace{I(p)}^{\text{image}} \; \overbrace{f(s-p)}^{\text{spatial}} \; \overbrace{g(I_s - I_p)}^{\text{influence}}$$



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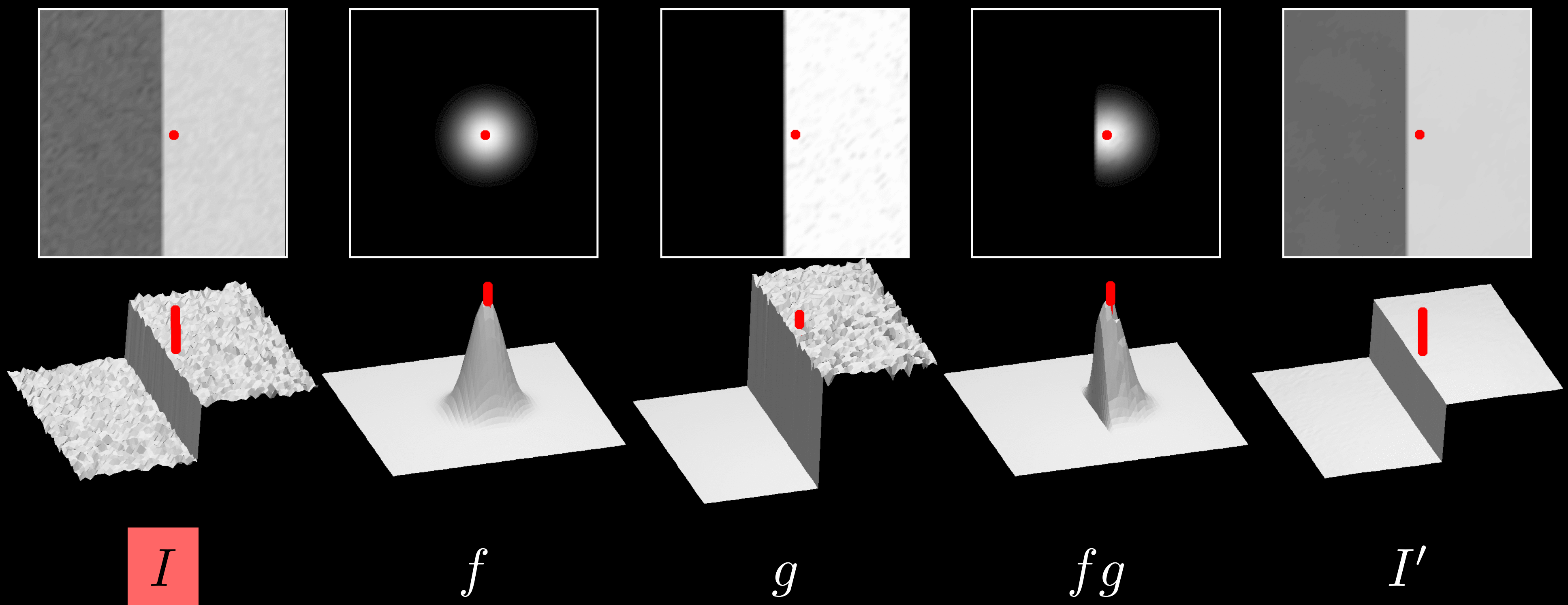

Jones, Durand, Desbrun

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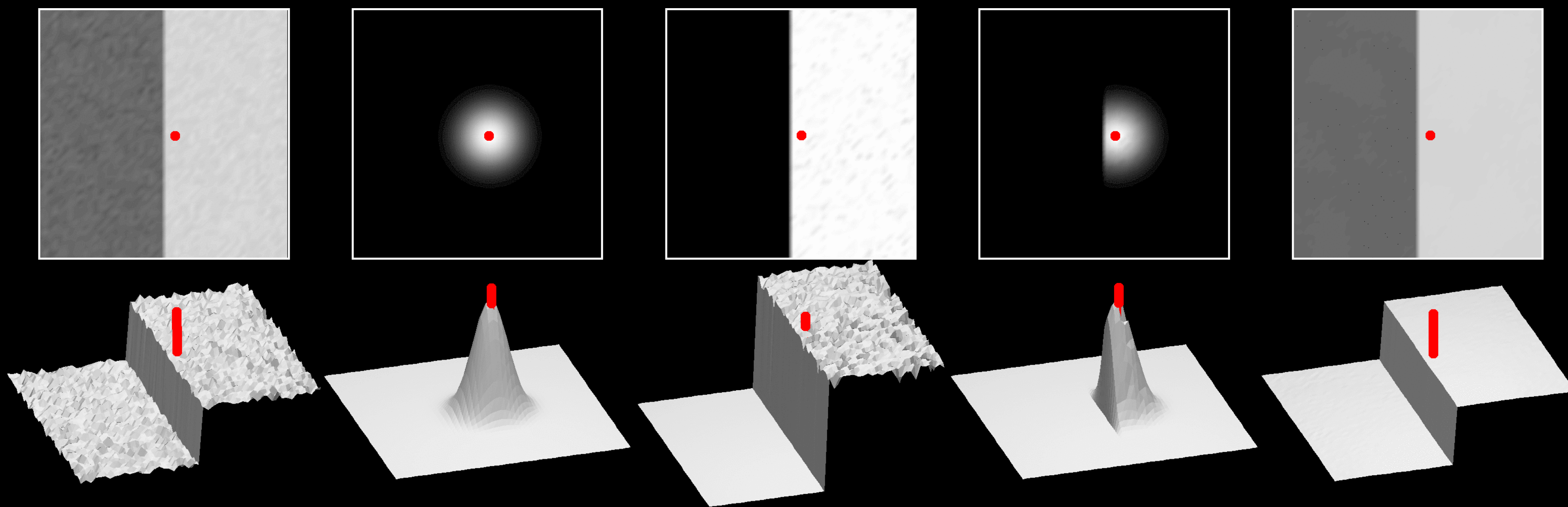

I f g fg I'

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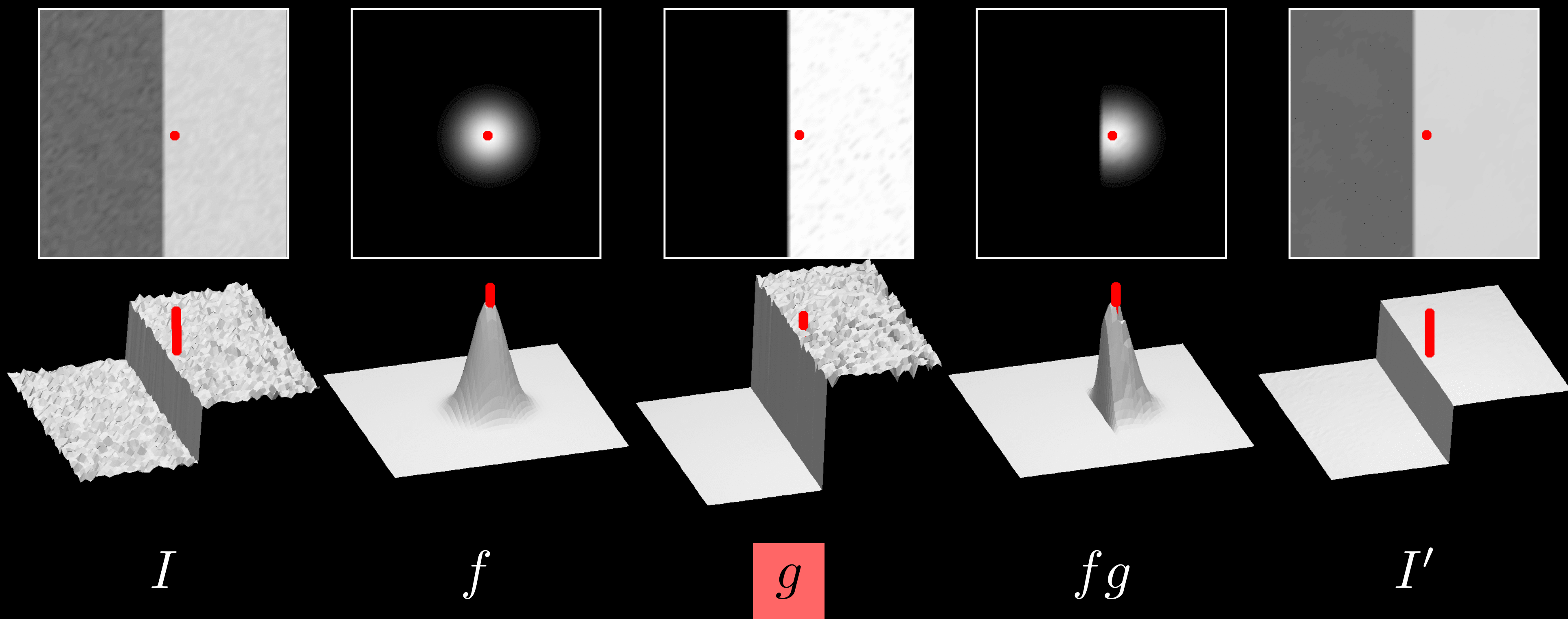

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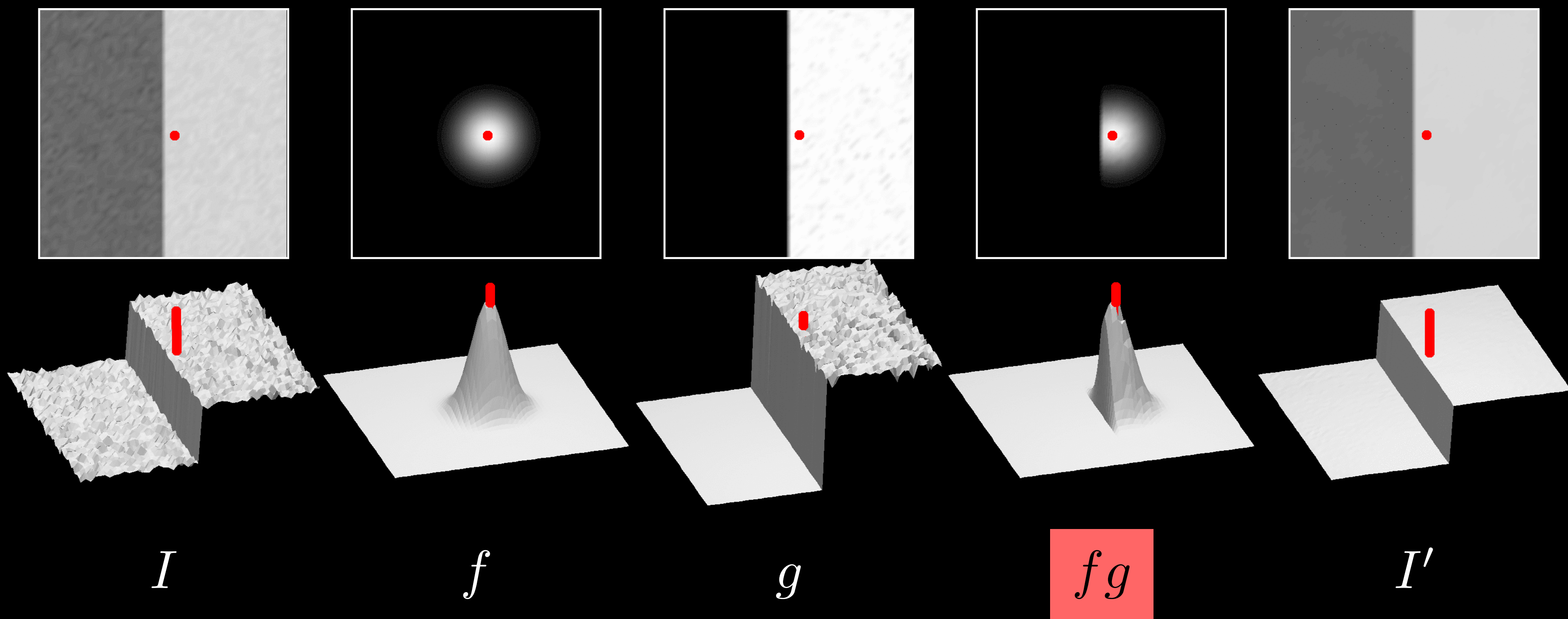

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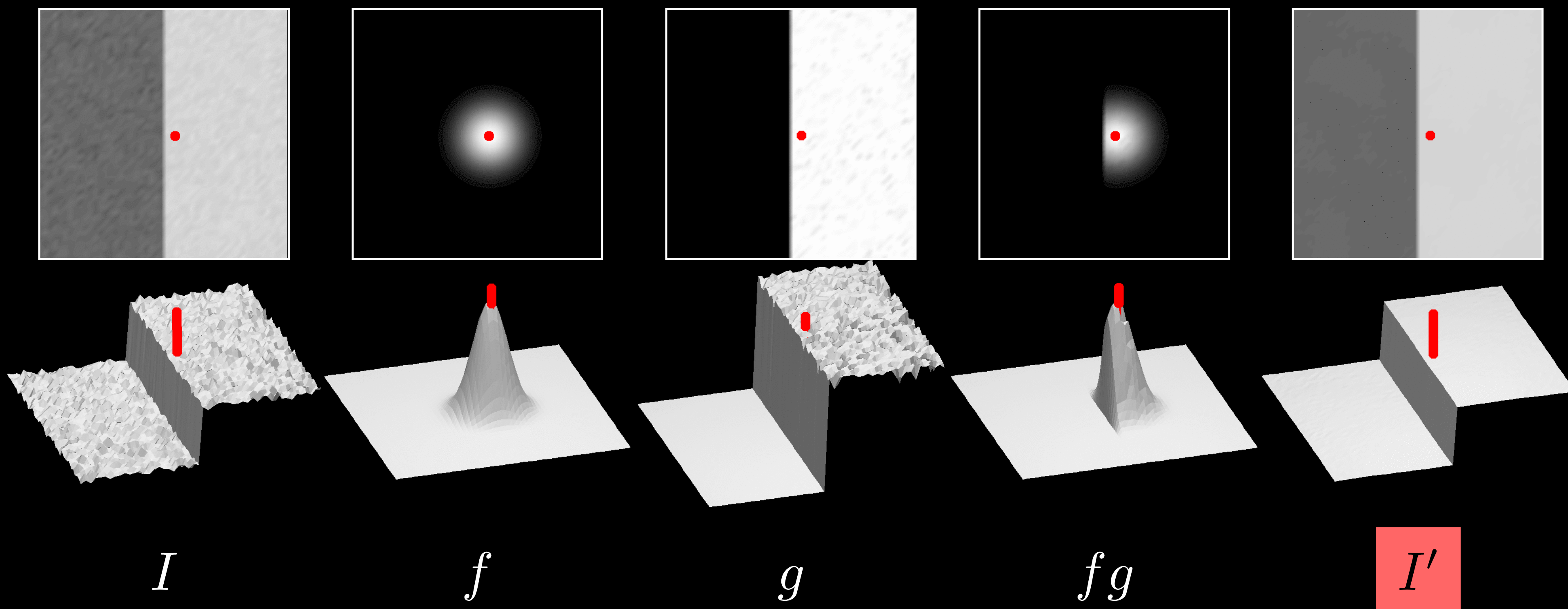
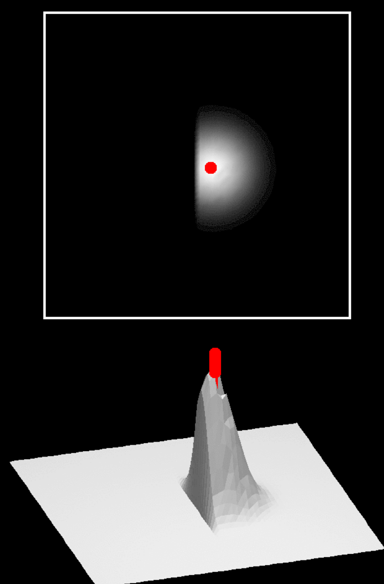


Jones, Durand, Desbrun

Bilateral Filter (Robust)

$$I'_s = \frac{1}{\color{red}{k_s}} \sum_p \overbrace{I(p)}^{\text{image}} \; \overbrace{f(s-p)}^{\text{spatial}} \; \overbrace{g(I_s - I_p)}^{\text{influence}}$$

$$k_s = \sum_p f(s-p)\; g(I_s - I_p)$$



Bilateral Filter

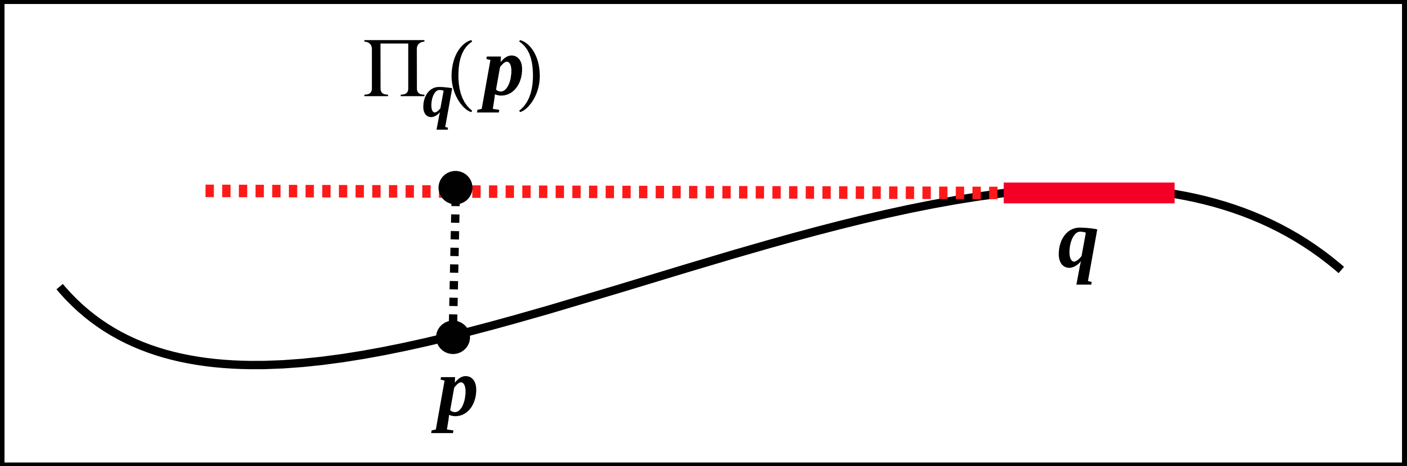
Left: Jones and Jones 2003 Right: Bilaterally filtered.

Extending the Bilateral Filter to Meshes

How to separate location and signal in a 3D model?

- Forming local frames requires a connected mesh.

Instead, use first-order predictors based on facets:

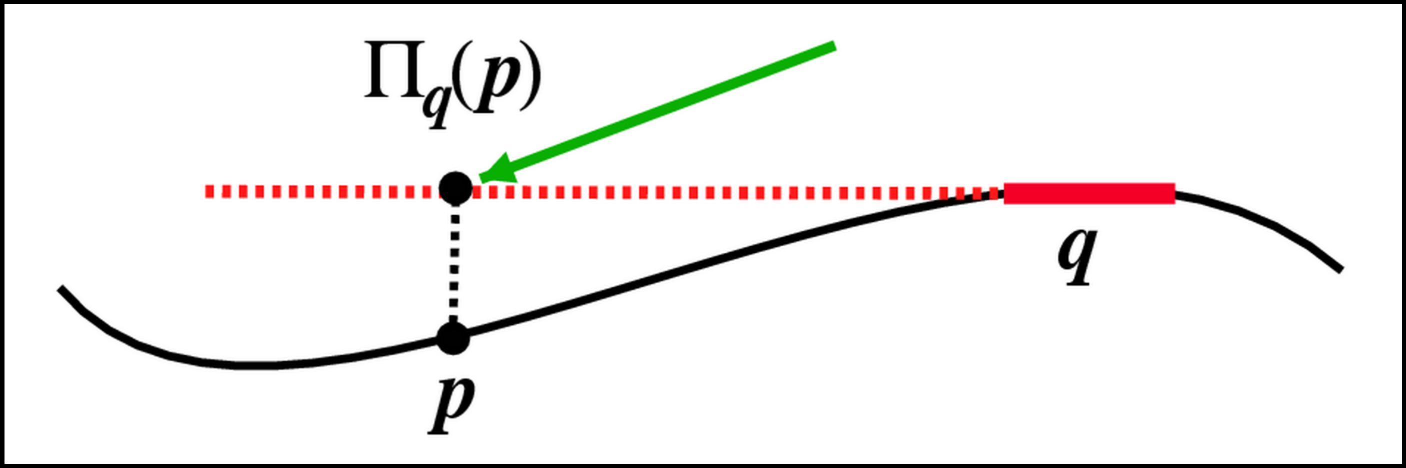


No connectivity required between facets.

Bilateral Filter for Meshes

Estimate p', the new position for a vertex p

$$p' = \frac{1}{k(p)} \sum_{q \in S} \overbrace{\Pi_q(p)}^{\text{prediction}} \; \overbrace{f(||c_q - p||)}^{\text{spatial}} \; \overbrace{g(||\Pi_q(p) - p||)}^{\text{influence}} \; \overbrace{a_q}^{\text{area}}$$



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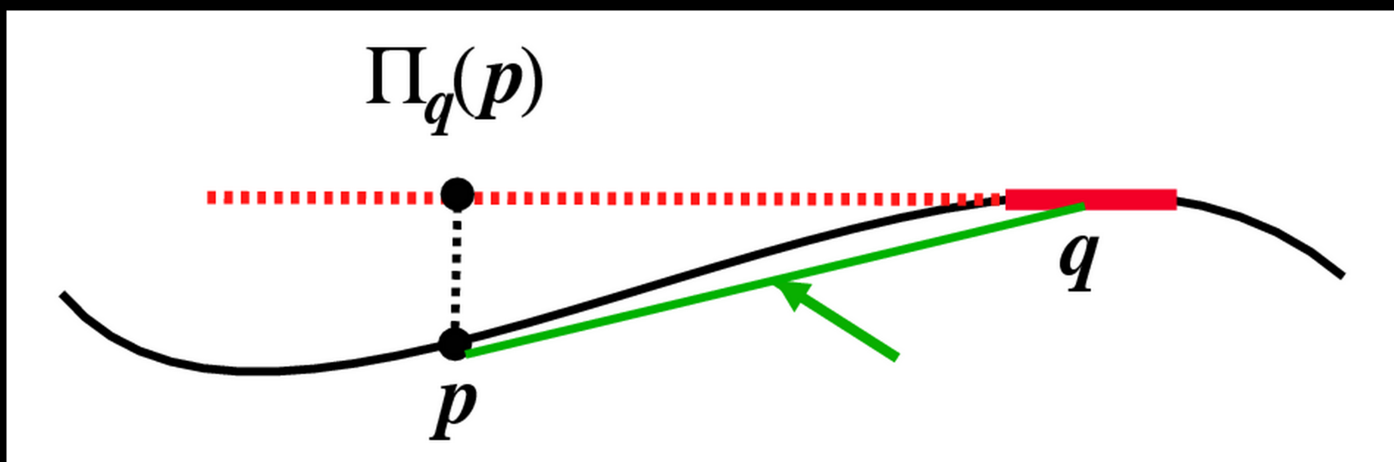

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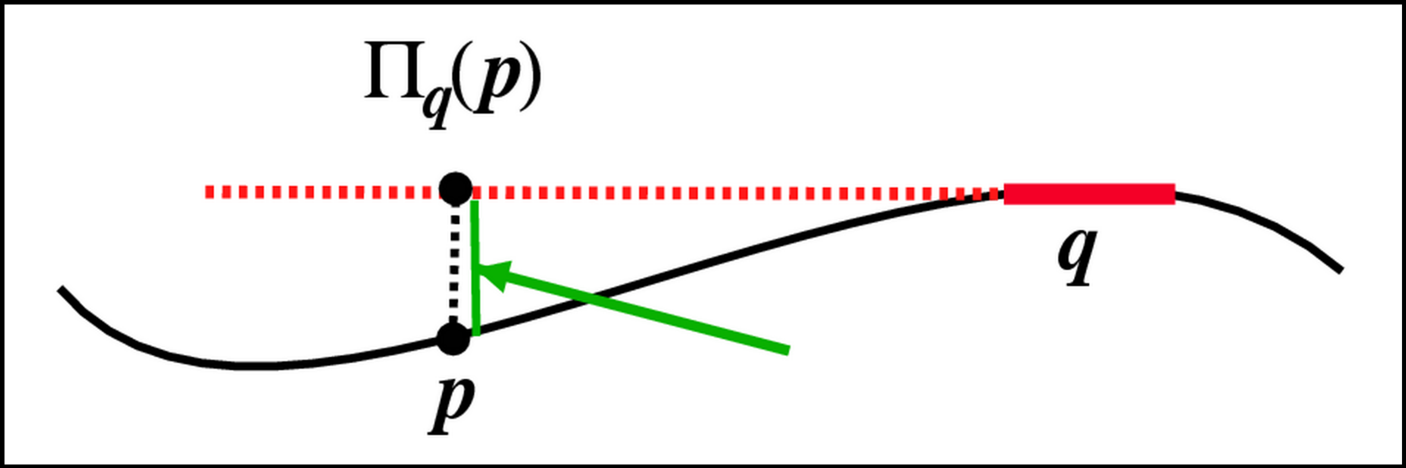

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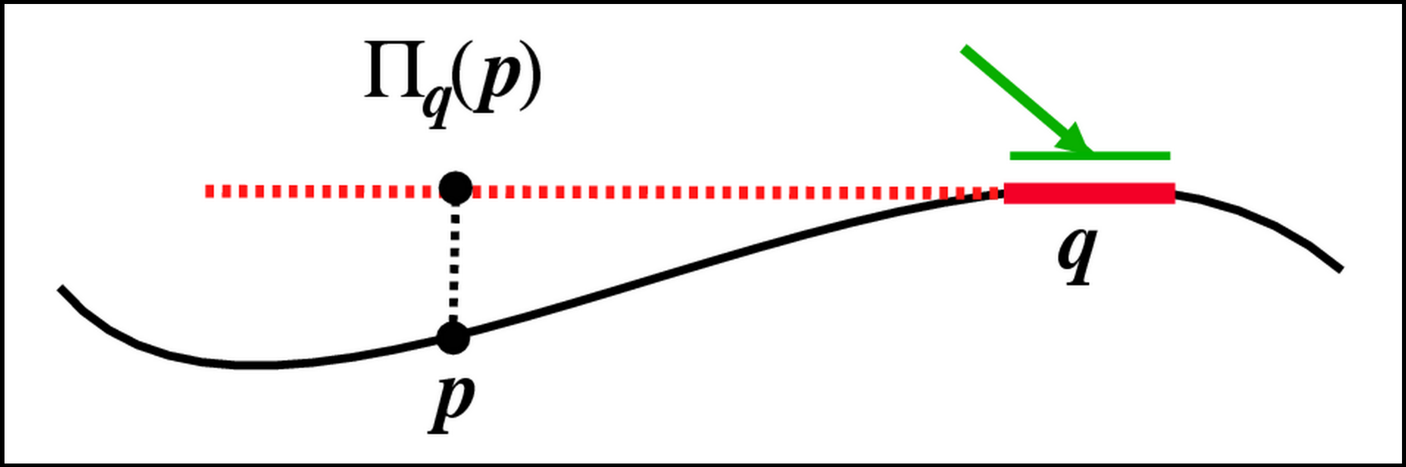
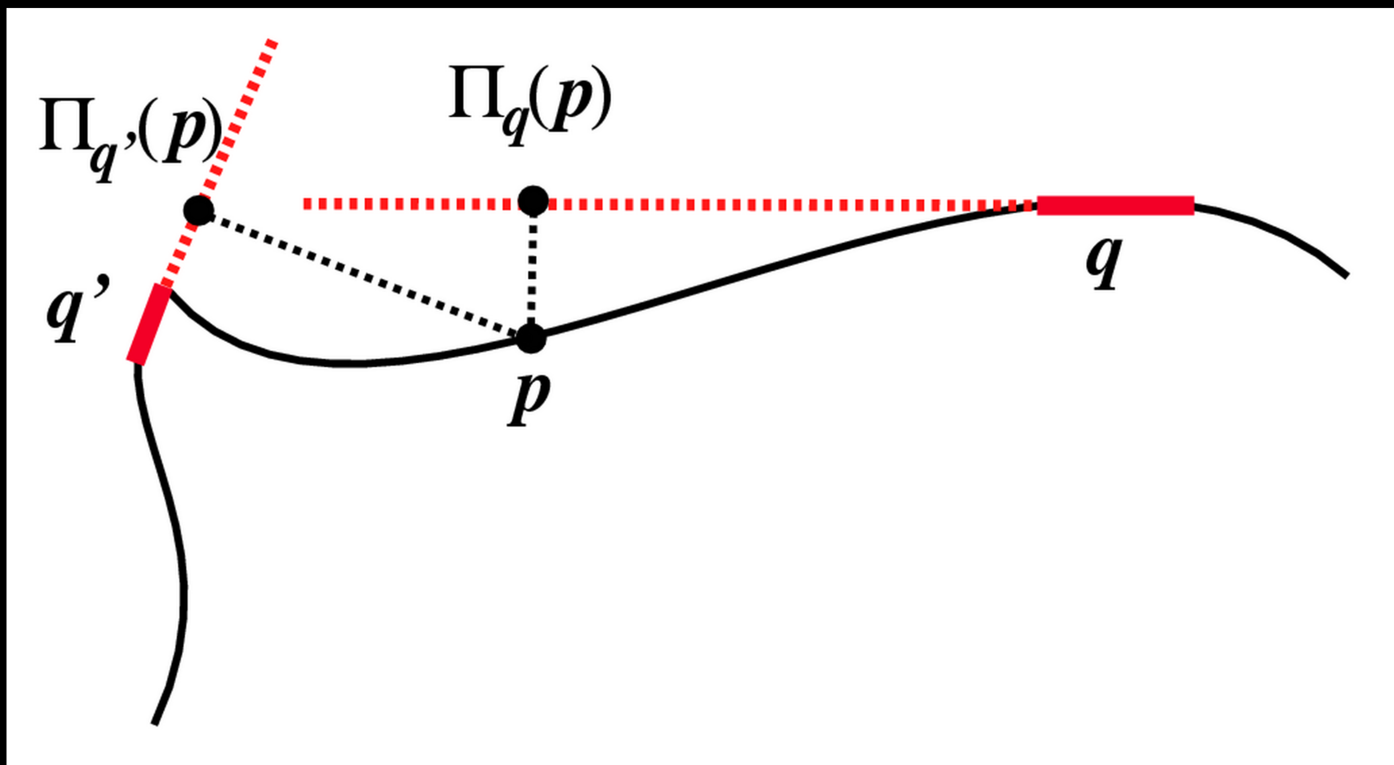


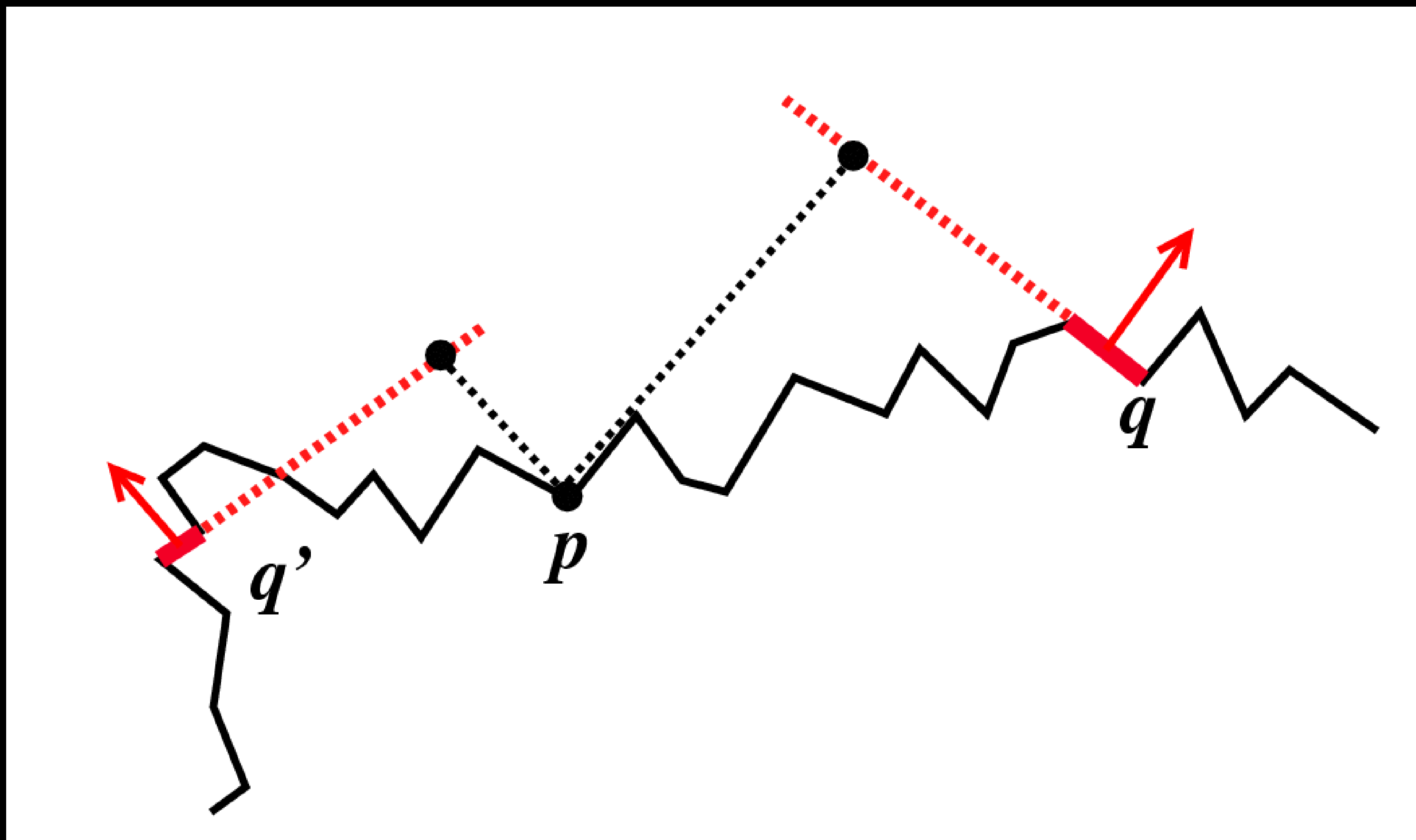
Why we expect it to work

Predictions across corners are ‘‘outliers’’.



Dealing with Noise

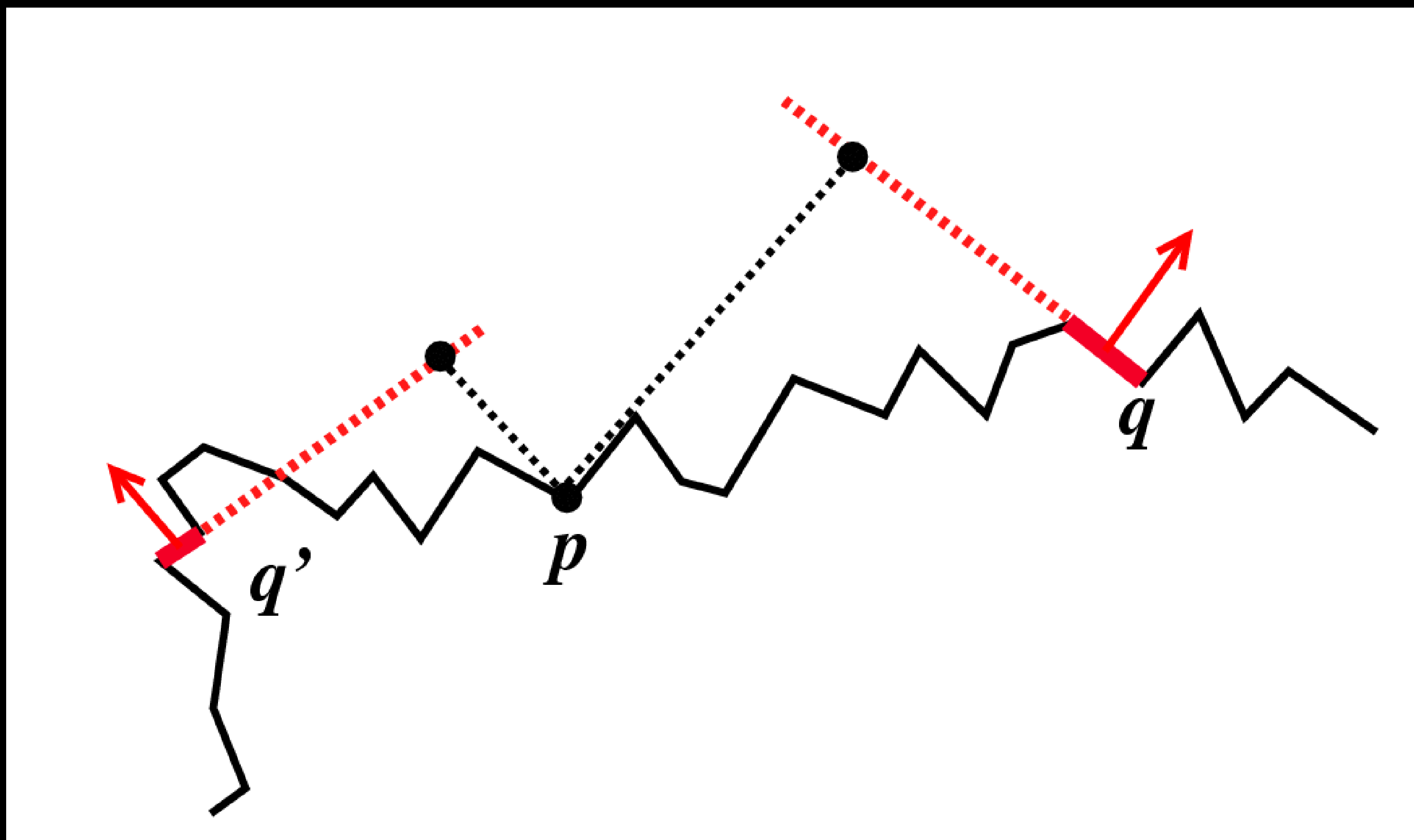
Noise has a nonlinear effect on predictions.



Dealing with Noise

Noise has a nonlinear effect on predictions.

We must *mollify* (pre-smooth) normals.



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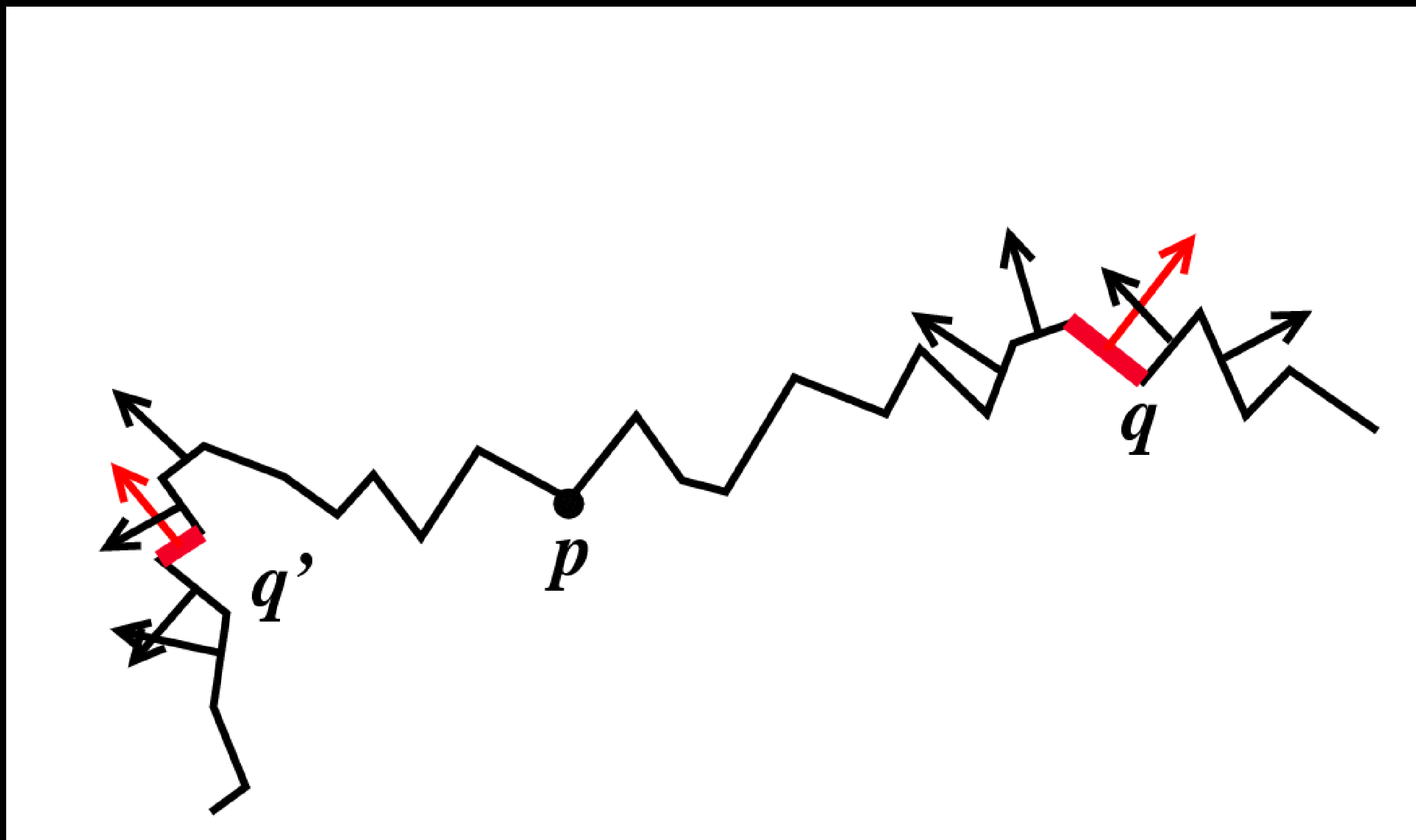

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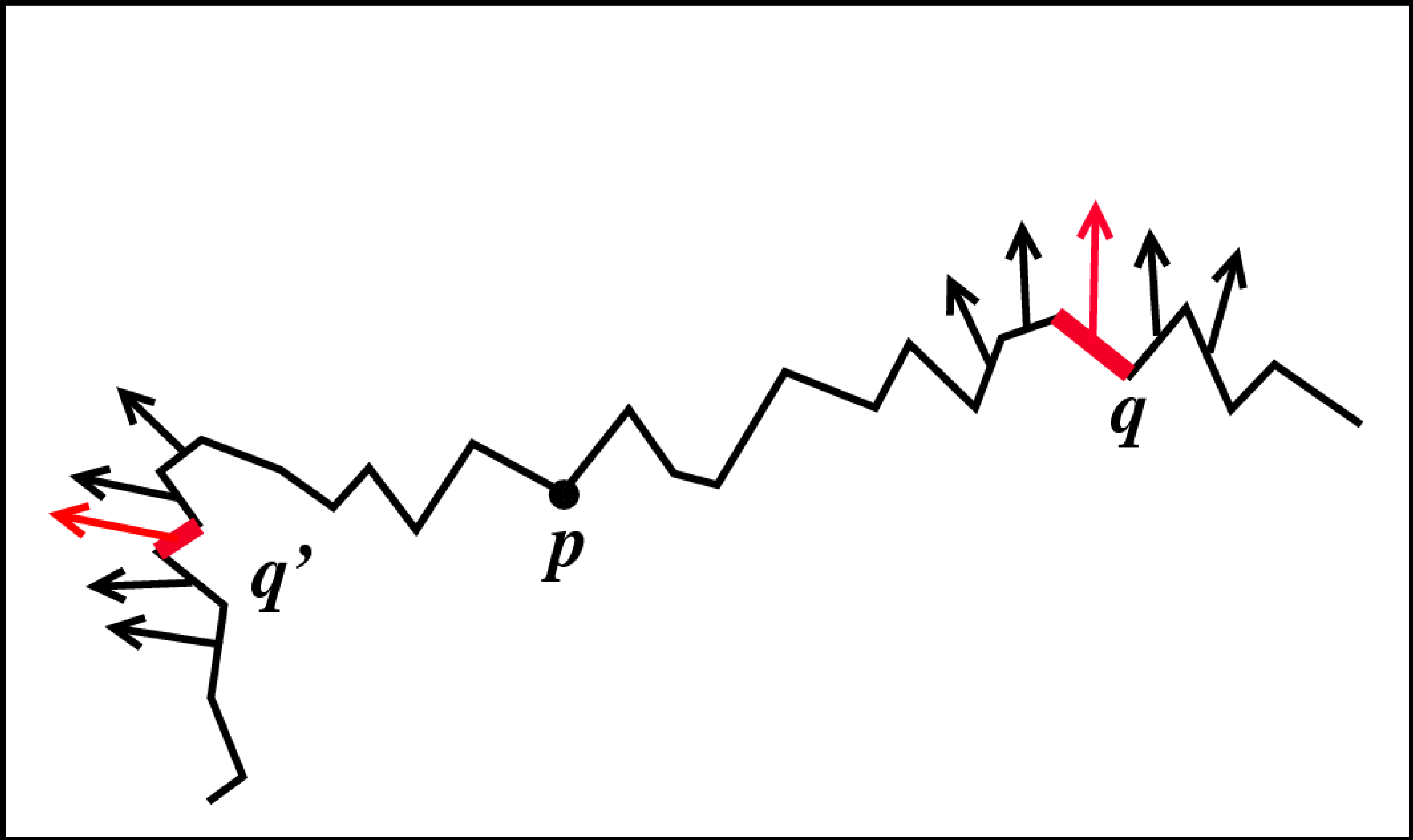

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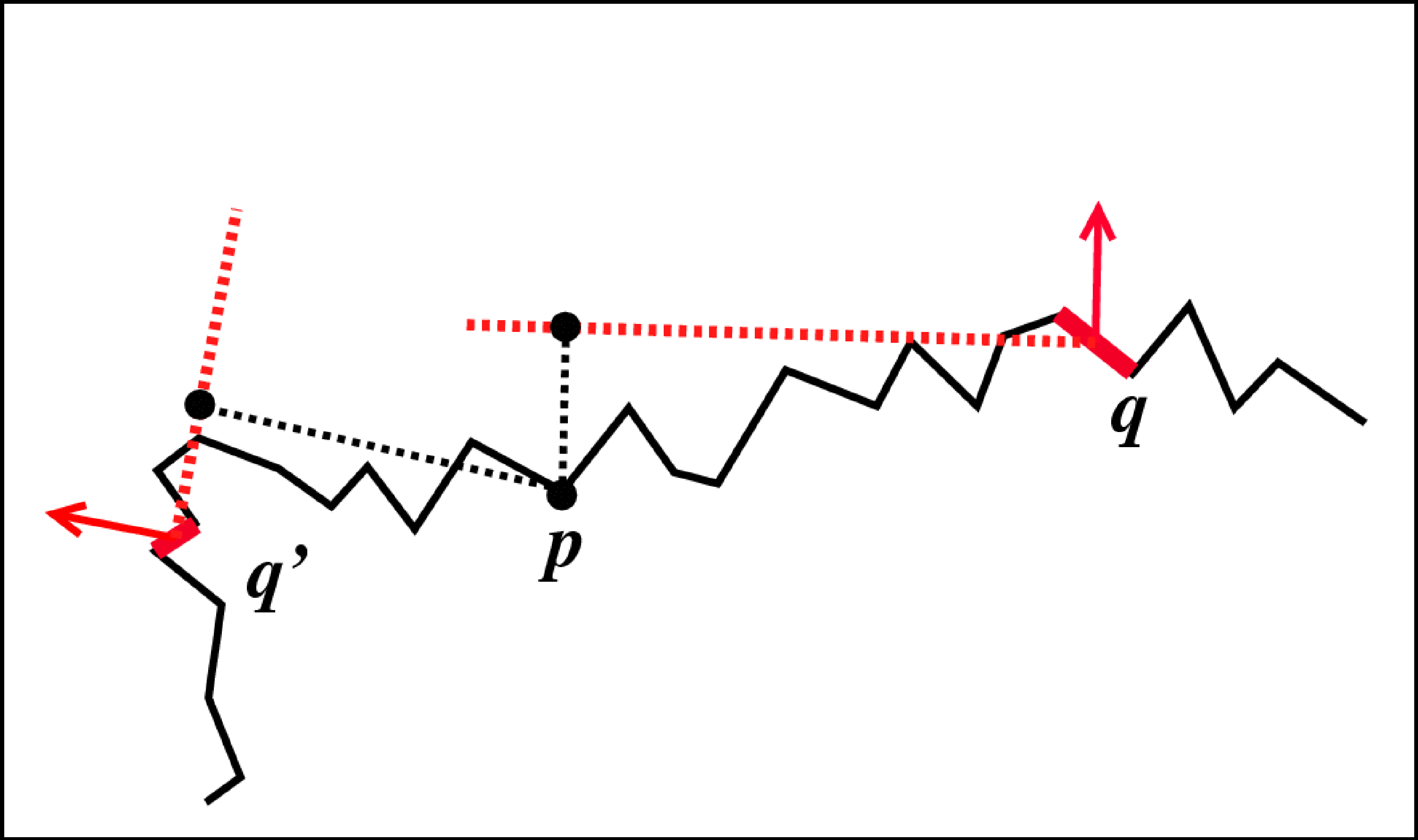


Implementation

3K vertices / second (typical), 1.4 GHz Athlon.

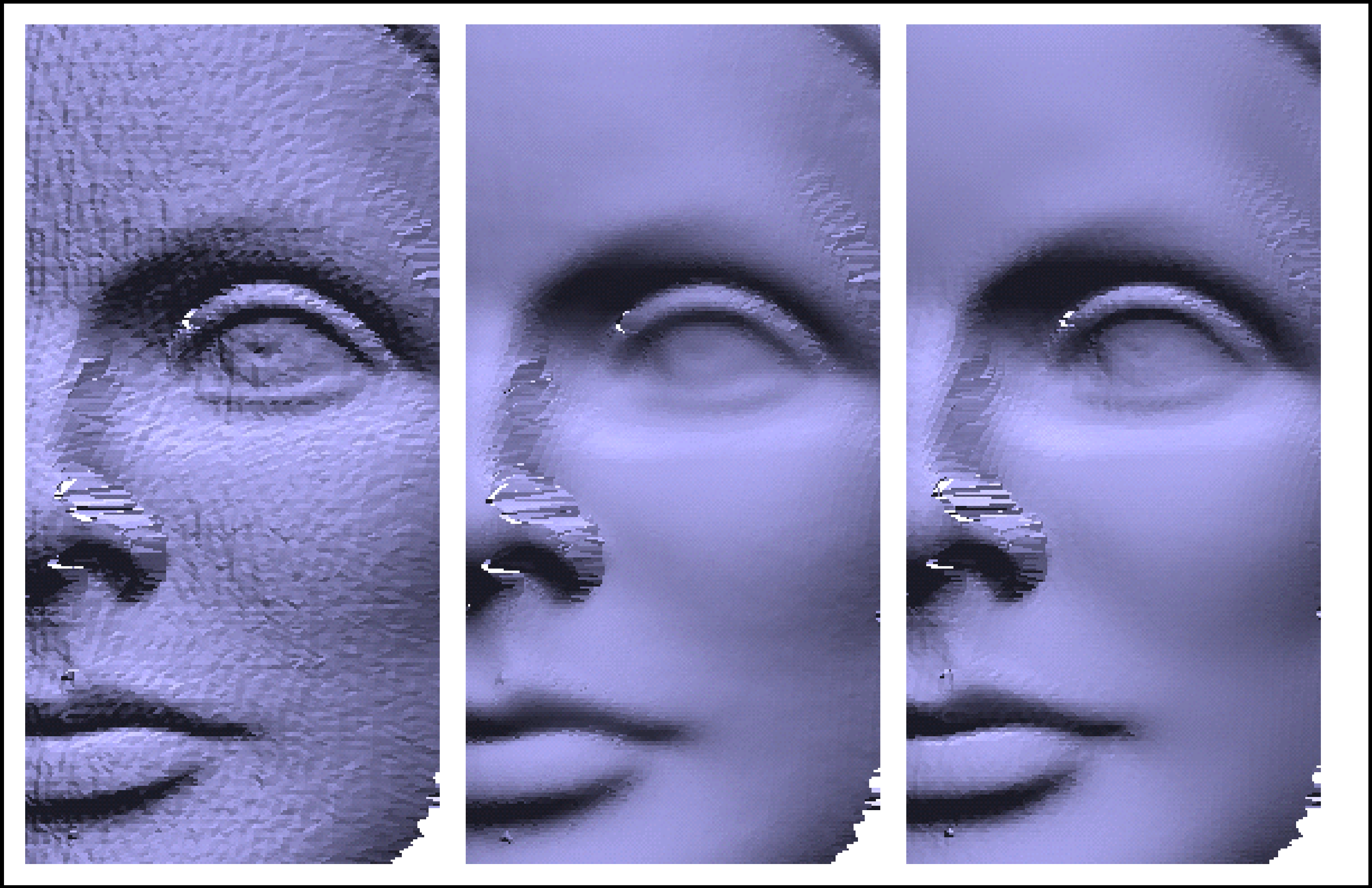
Gaussians for f and g.

Optimizations

- Cutoff at twice spatial filter radius.
- Binning for spatially coherent computation.

Data and non-optimized code available online.

Results - Smoothing



Original Desbrun 1999 Our result

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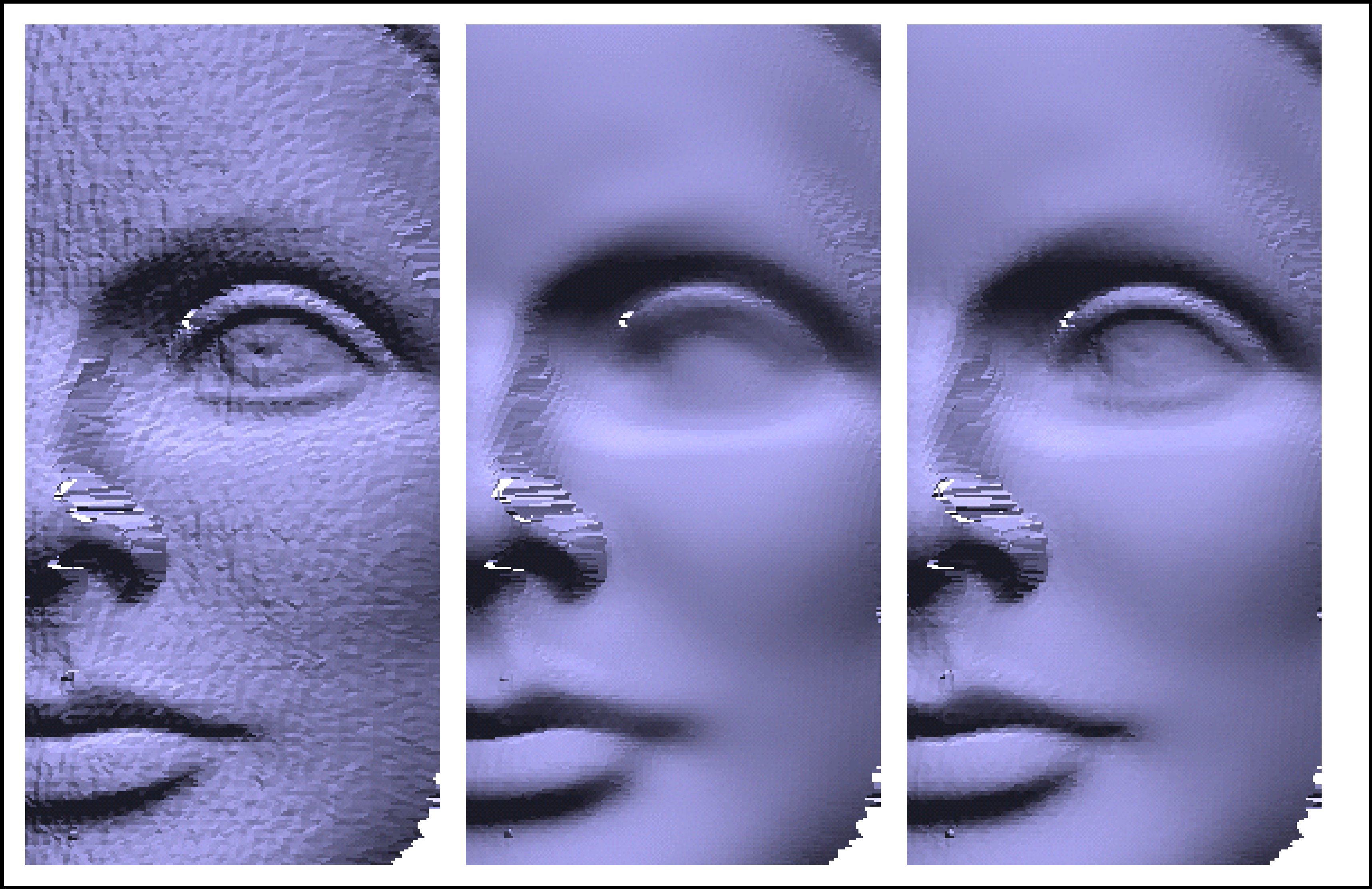
Results - Effect of g

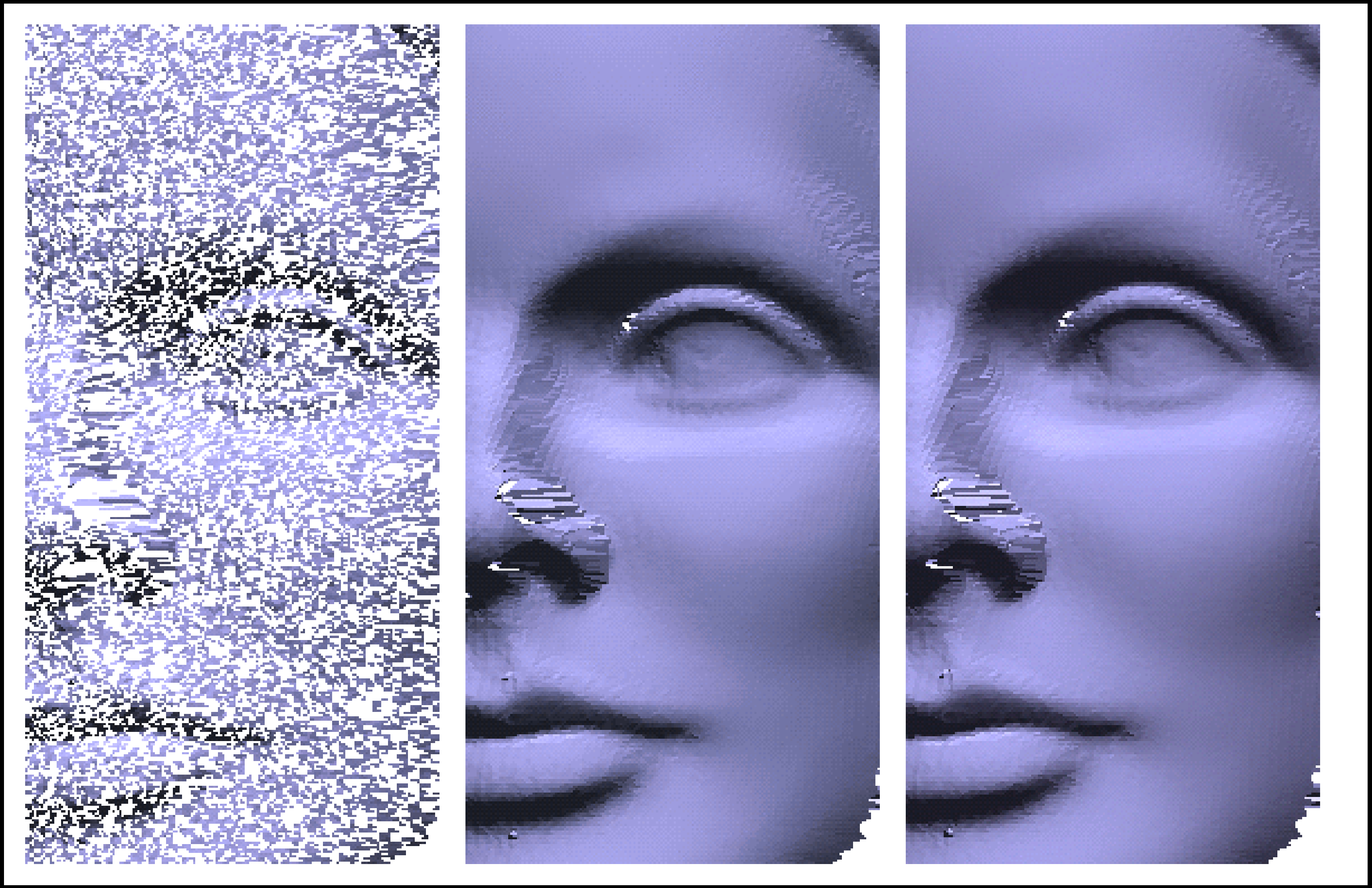


Original Without g Our result

Results - Effect of Mollification

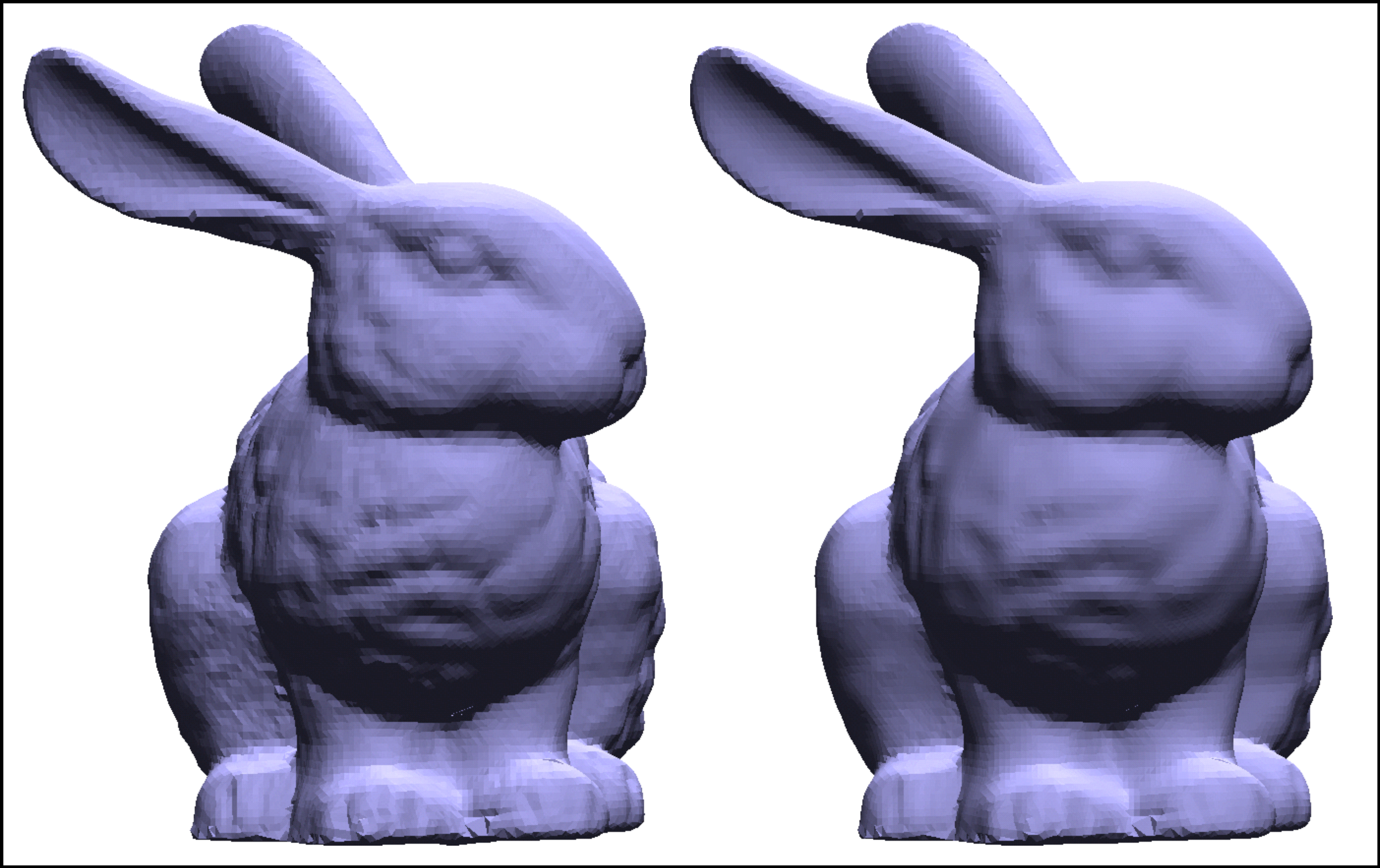
Original Without mollification Our result

Results - Connectivity



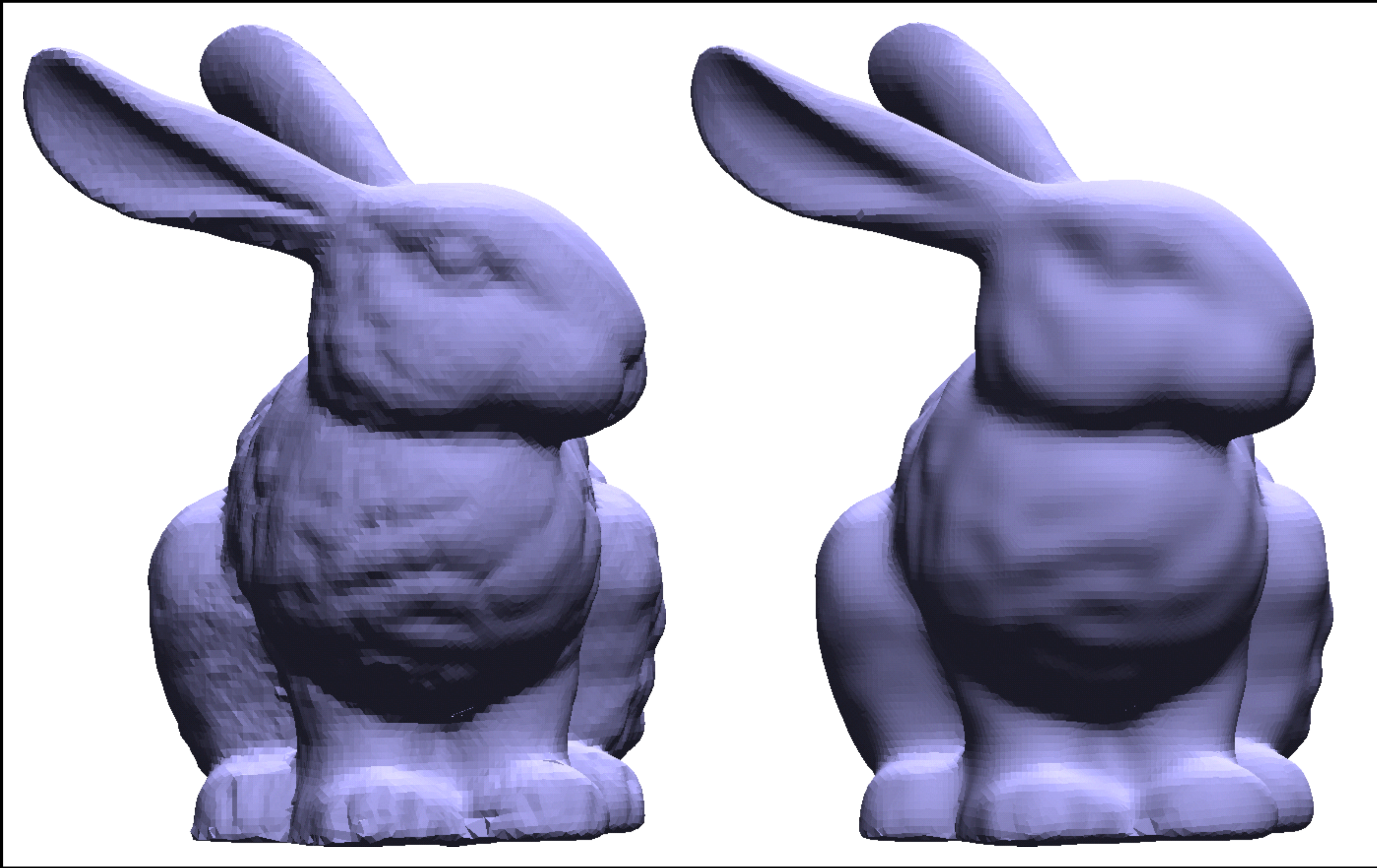
50% Original   Smoothed   All predictors

Results - Varying width of f and g



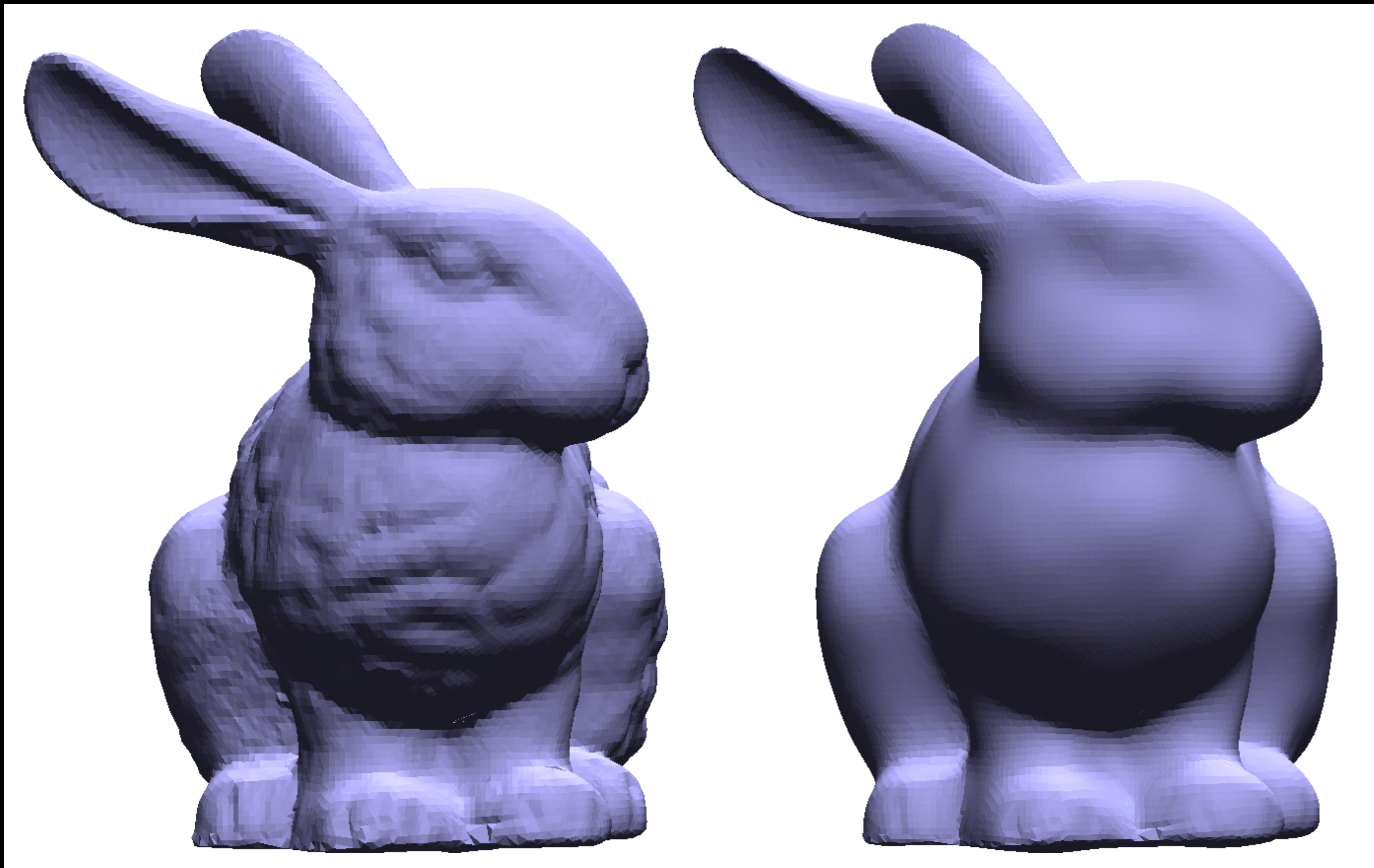
Original　　　　Narrow spatial and influence

Results - Varying width of f and g



Original Narrow spatial and wide influence

Results - Varying width of f and g



Original Wide spatial and influence

SIGGRAPH 2003
SAN DIEGO

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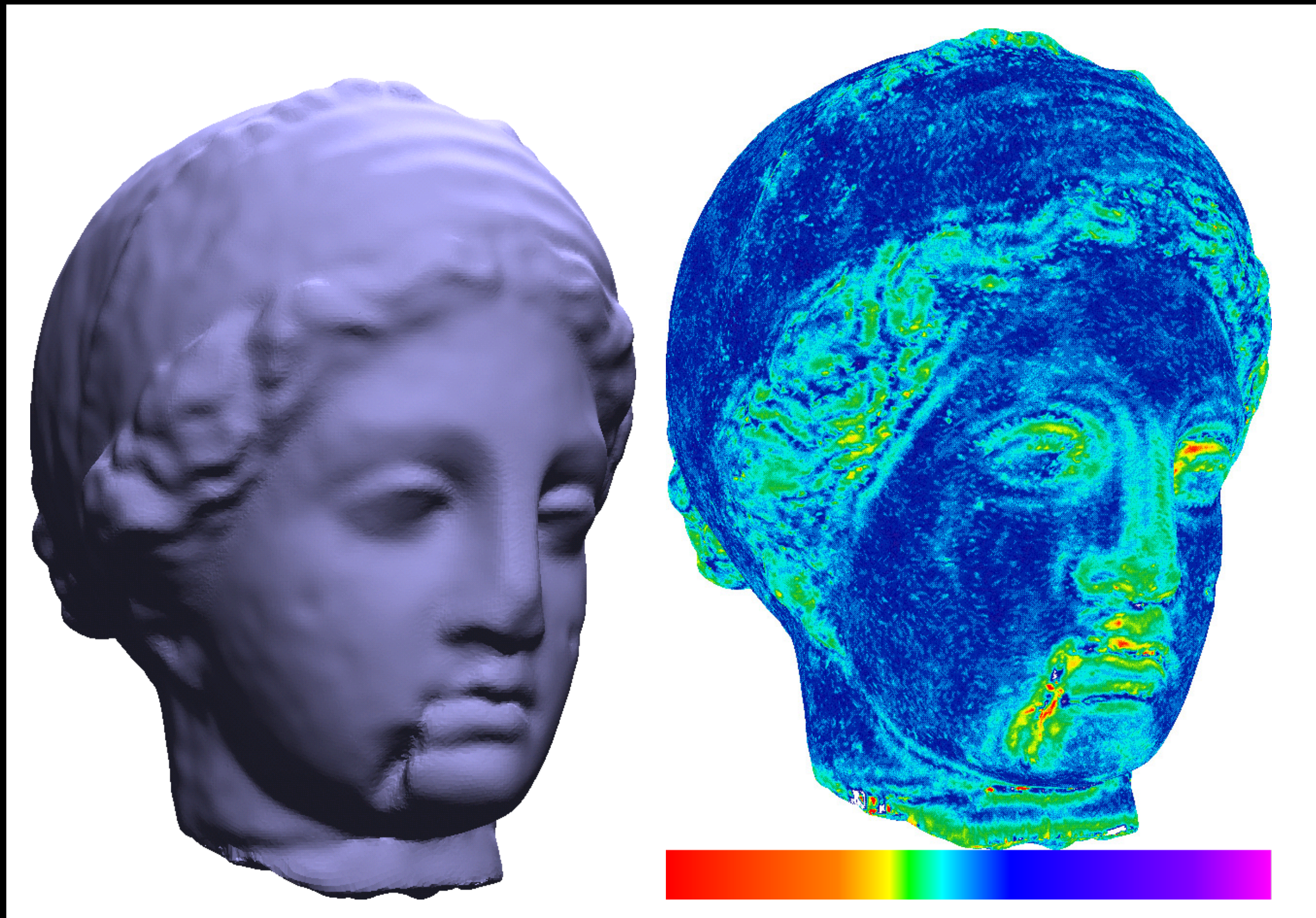
Normalization factor k as "Confidence"

Normalization term $k(p)$ is sum of weights, and is a measure of *confidence* in the estimation at p.

$$p' = \frac{1}{k(p)} \sum_{q \in S} \Pi_q(p)\ f(||c_q - p||)\ g(||\Pi_q(p) - p||)\ a_q$$

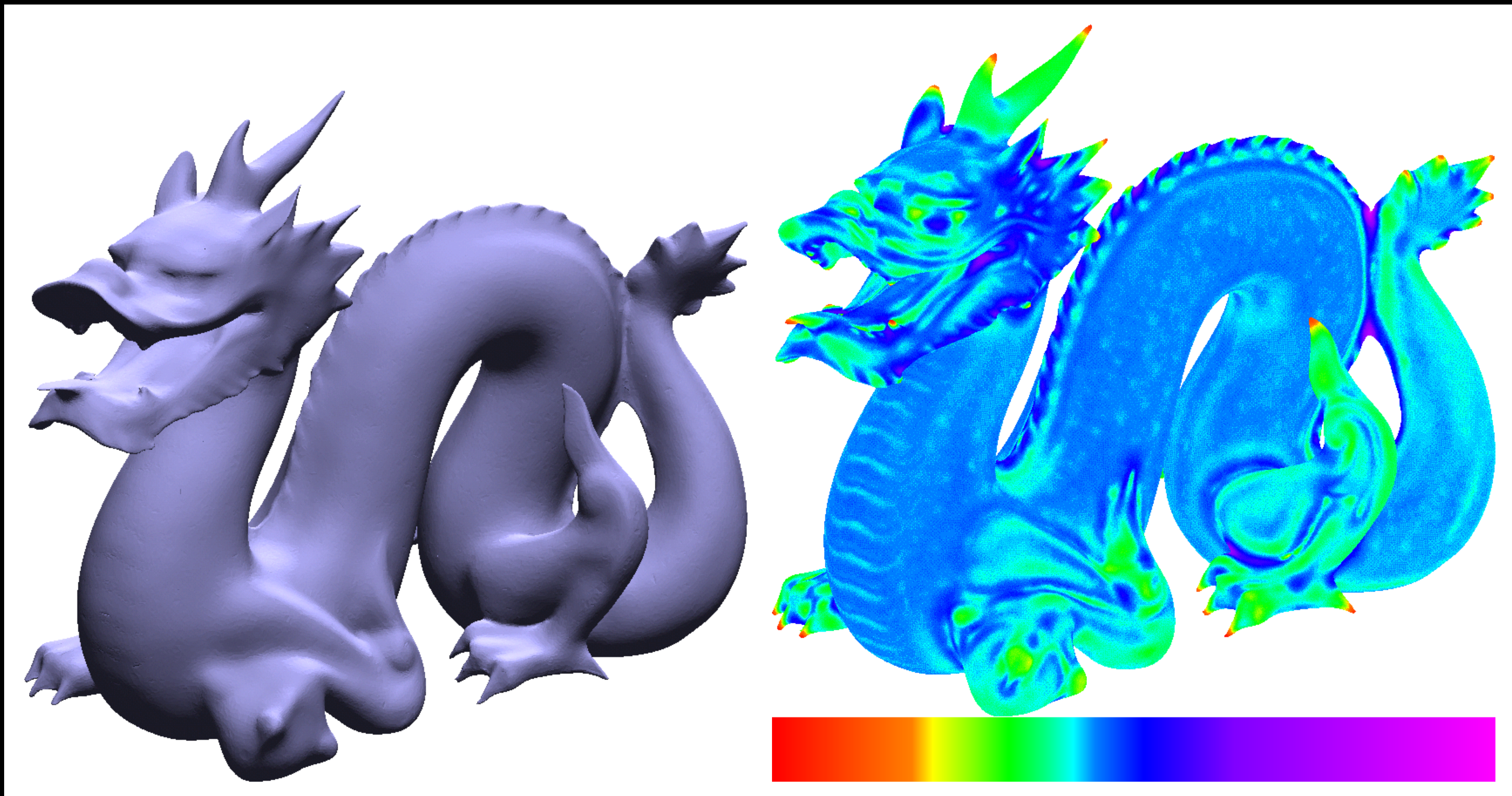
$$k(p) = \sum_{q \in S} f(||c_q - p||)\ g(||\Pi_q(p) - p||)\ a_q$$

Results - k as Confidence



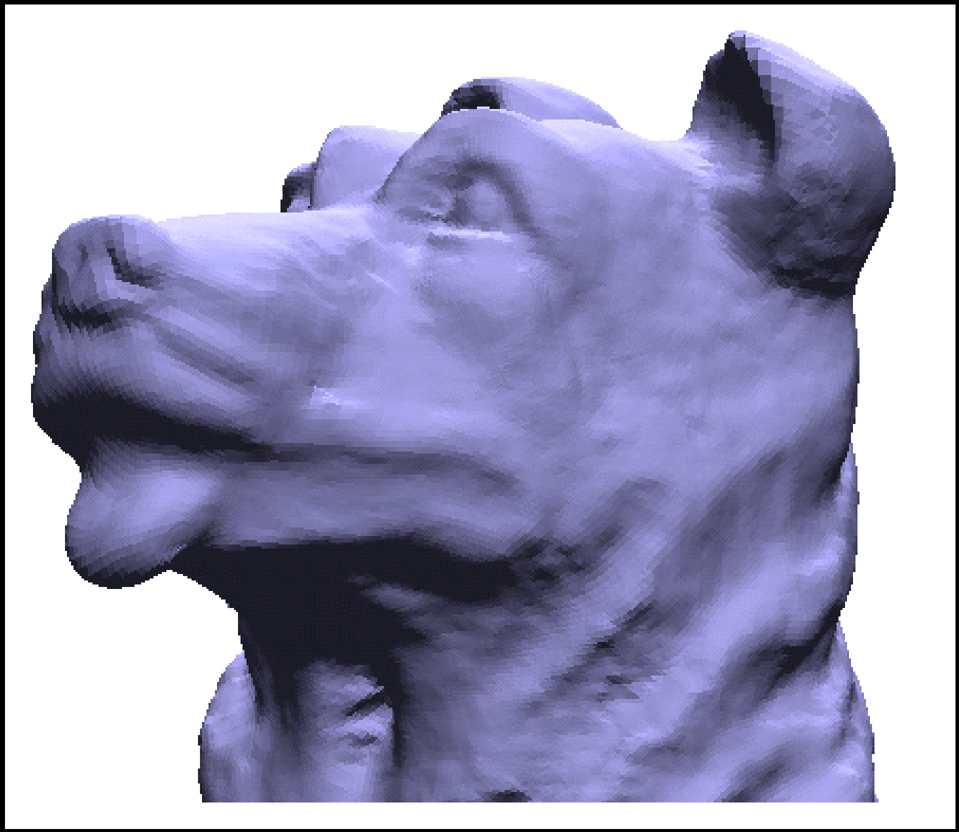
Low High

Results - k as Confidence



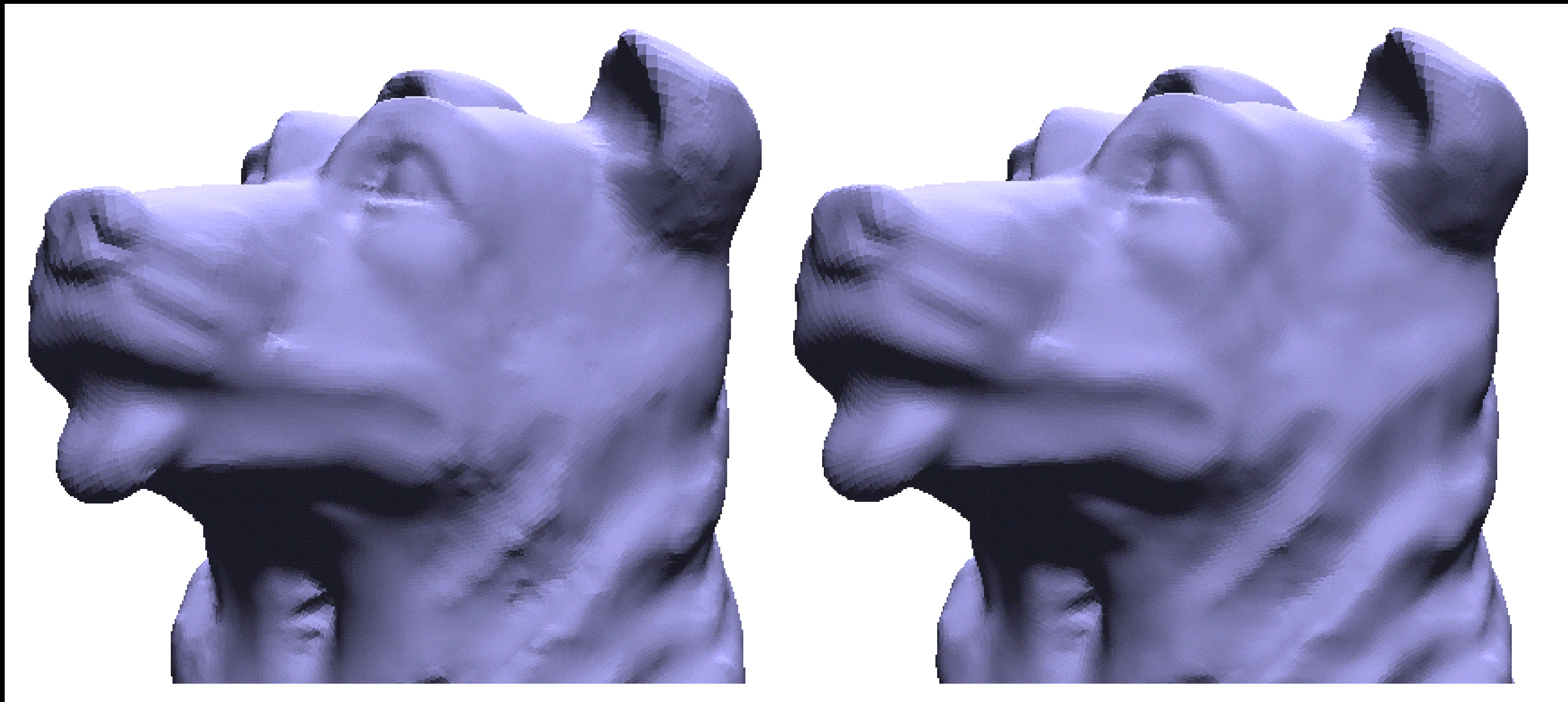
Low High

Results - vs Wiener Filtering



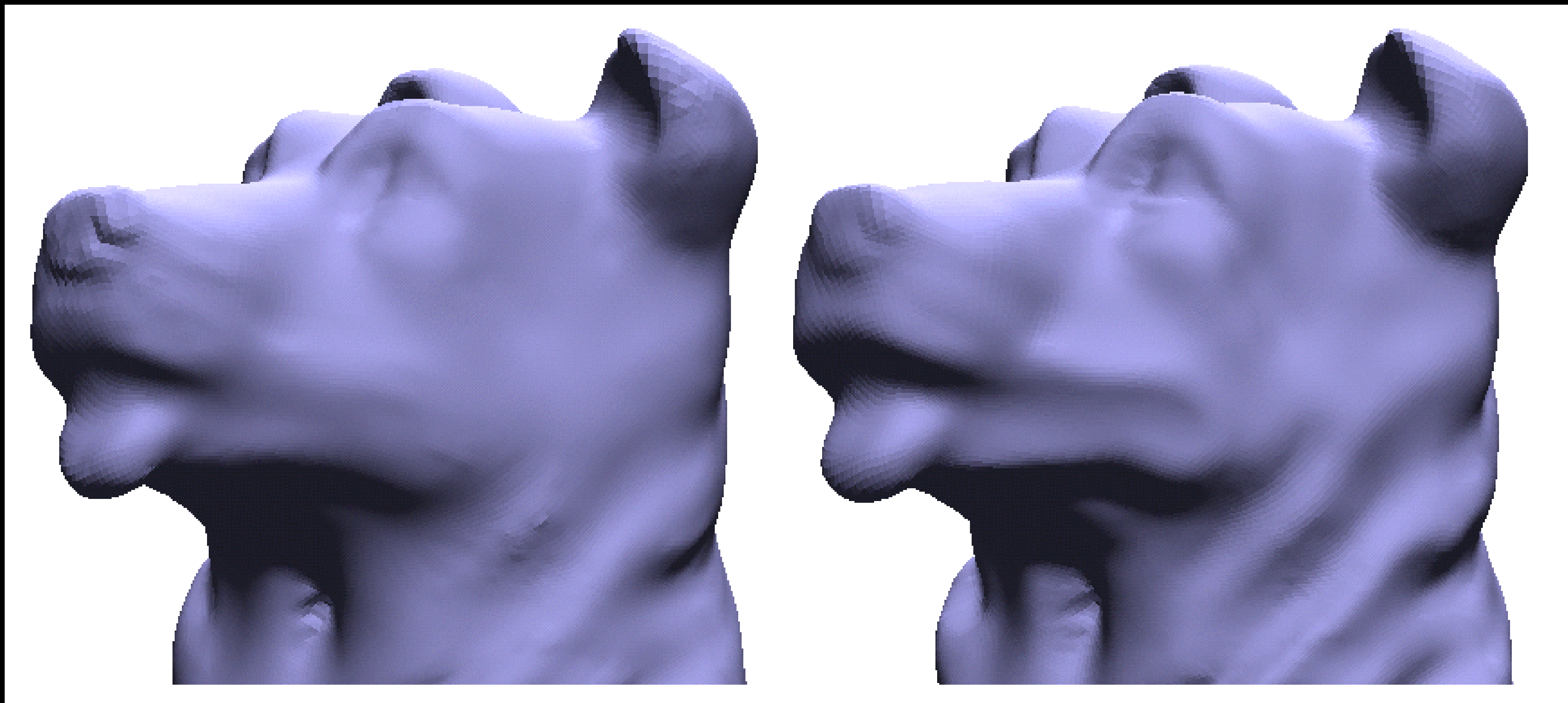
Original

Results - vs Wiener Filtering (Low Noise)



Peng et al. 2001 Our result

Results - vs Wiener Filtering (High Noise)

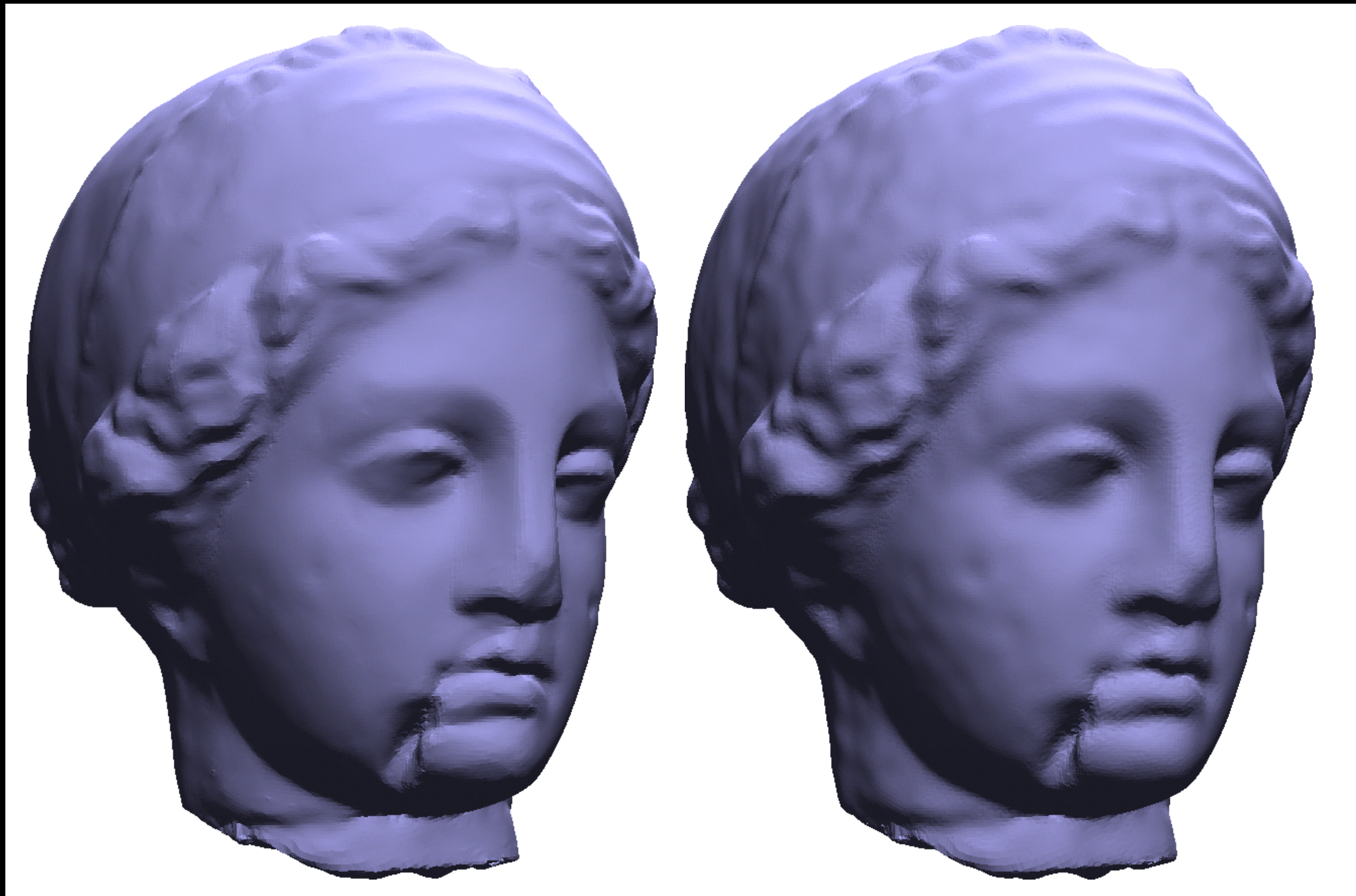


Peng et al. 2001 | Our result

Results - vs Anisotropic Diffusion

Original

Results - vs Anisotropic Diffusion



Clarenz et al. 2000 Our result

Similar Methods

Bilateral Mesh Denoising, Fleishman et al. 2003 (next talk)

- Iterative
- Local frame
- No mollification
- Different predictor

Trilateral Filter, Cloudhury and Tumblin 2003 (EGSR)

- Images and Meshes
- Mollify normals, then vertices
- Different predictor

Future Work

Extend to other types of data (point models, volume data).

Using k to steer further processing.

Iterative application.

Conclusions

Fast, feature preserving filter.

Simple to implement.

Applicable to polygon soups.

Take-home message:

- Robust estimation for smoothing.
- Points across features are outliers.
- First-order predictors remove connectivity requirements.

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