Smooth Shape-Aware Functions with Controlled Extrema

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INTERACTIVE GEOMETRY LAB

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

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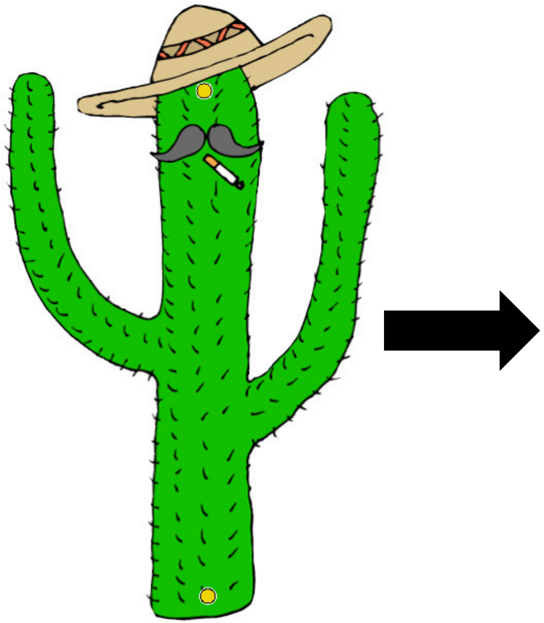
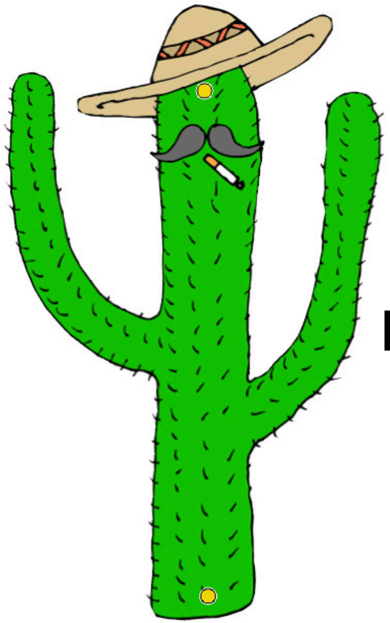
Real-time deformation relies on smooth, shape-aware functions

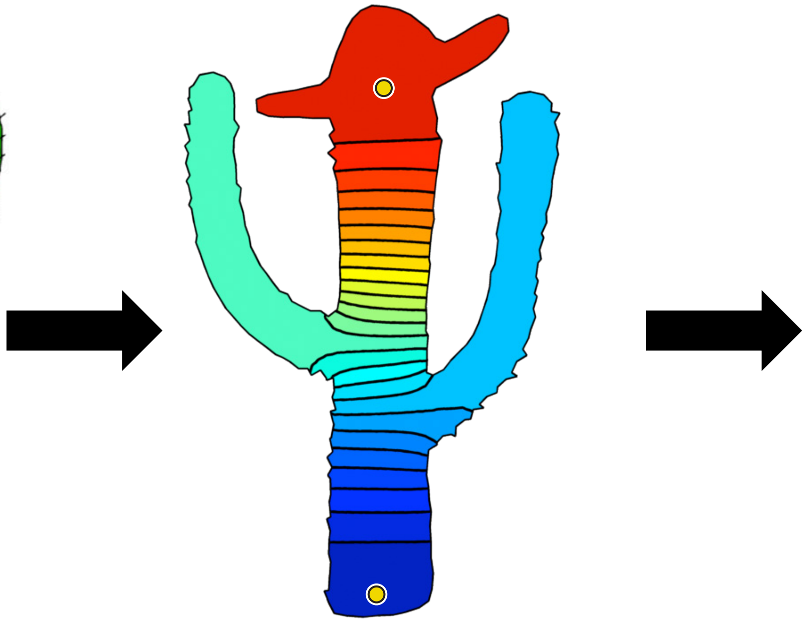
input shape + handles



Real-time deformation relies on smooth, shape-aware functions

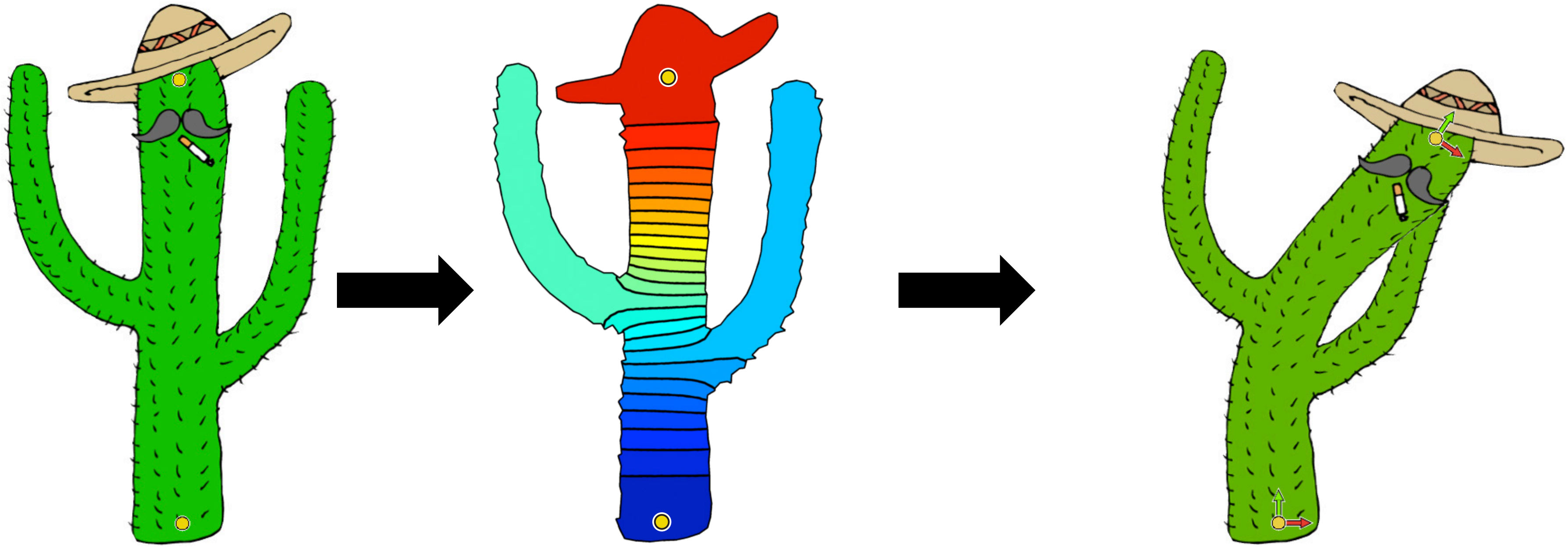
precompute weight functions





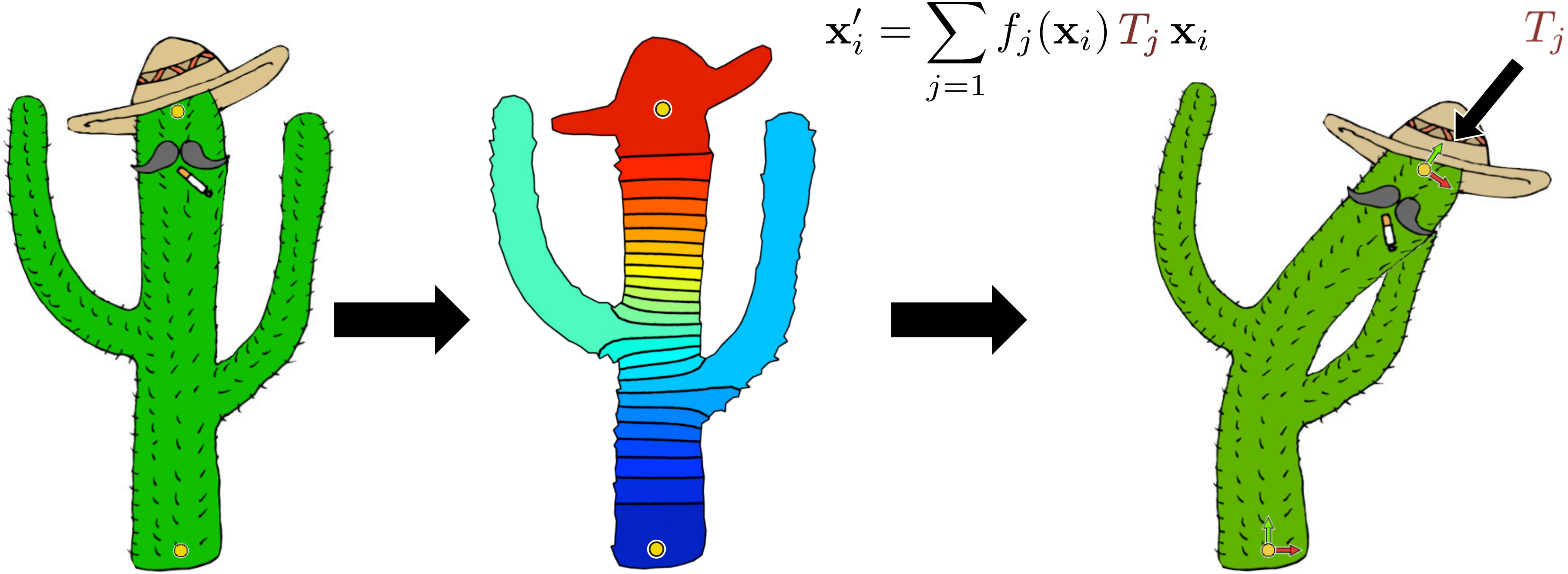
Real-time deformation relies on smooth, shape-aware functions

deform handles → deform shape



Real-time deformation relies on smooth, shape-aware functions

$$\mathbf{x}'_i = \sum_{j=1}^{H} f_j(\mathbf{x}_i)\, T_j\, \mathbf{x}_i$$



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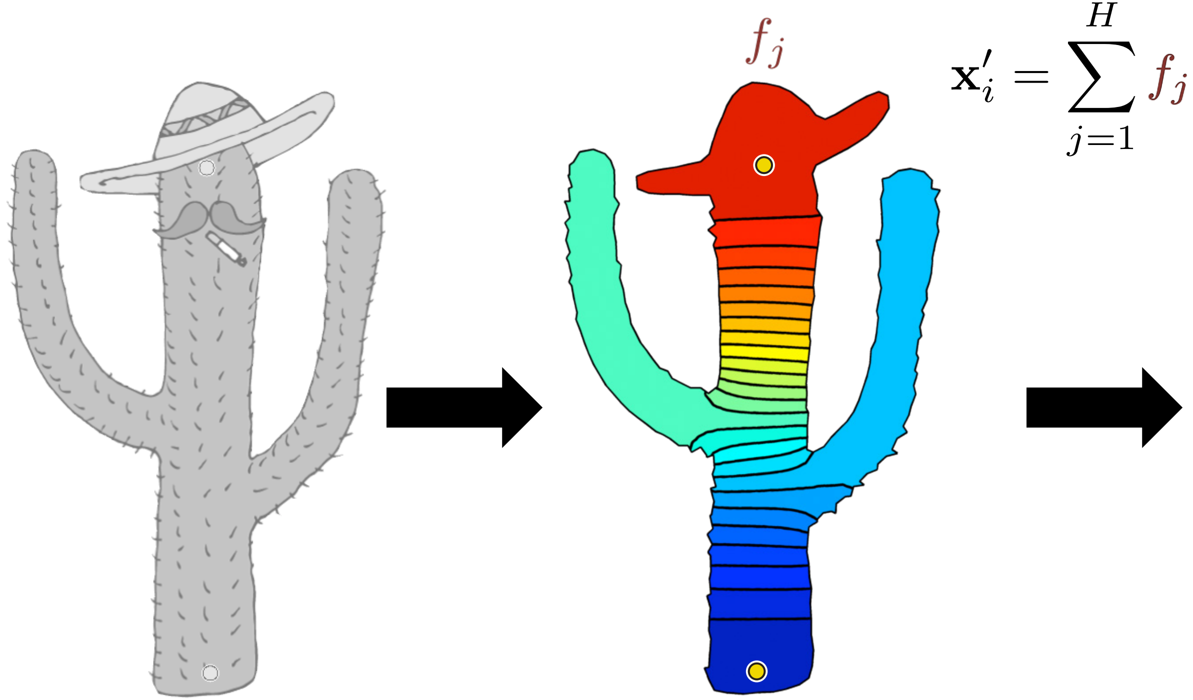

$$\mathbf{x}'_i = \sum_{j=1}^{H} f_j(\mathbf{x}_i)\, T_j\, \mathbf{x}_i$$

Spurious extrema cause distracting artifacts

unconstrained Δ^2
[Botsch & Kobbelt 2004]

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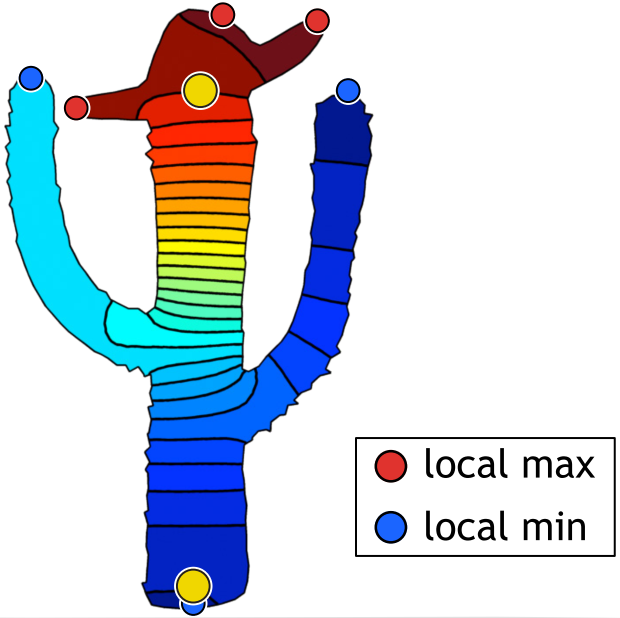

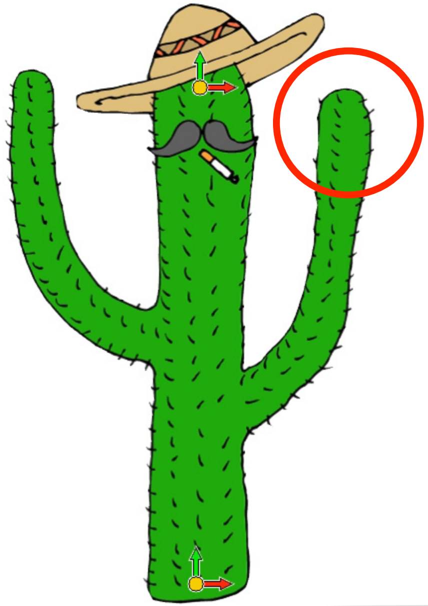

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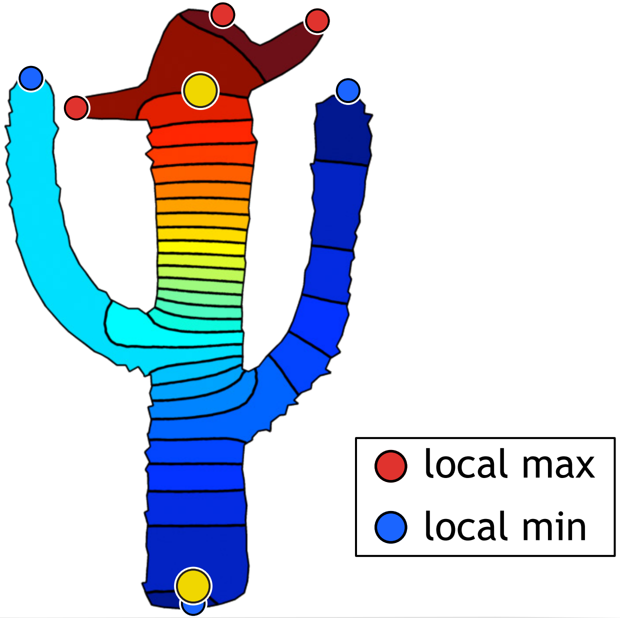
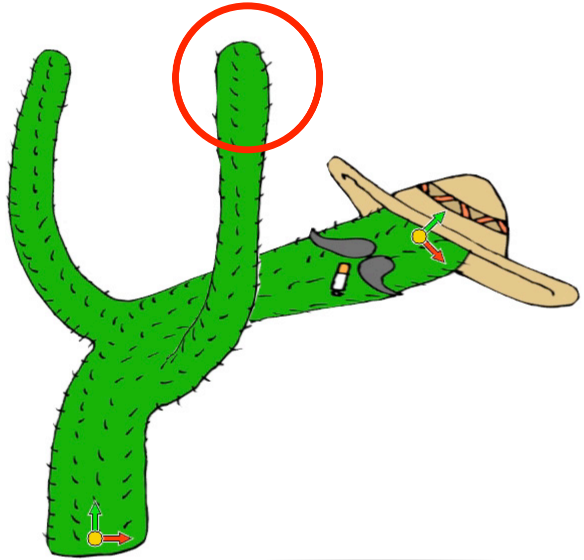
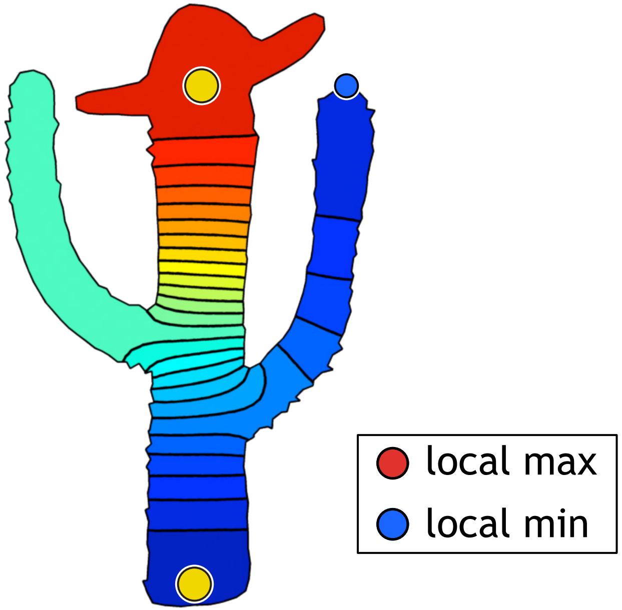




Bounds help, but don't solve problem

bounded Δ^2
[Jacobson et al. 2011]



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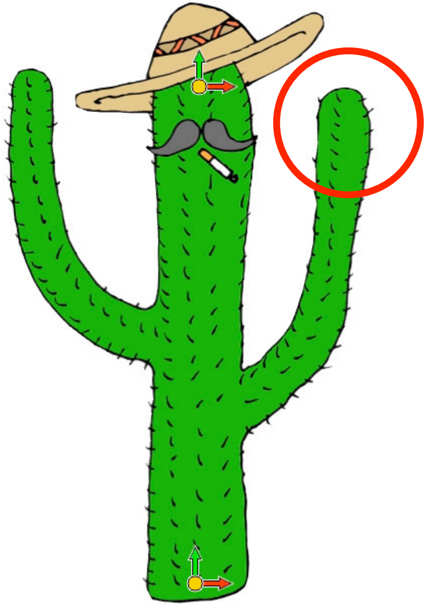

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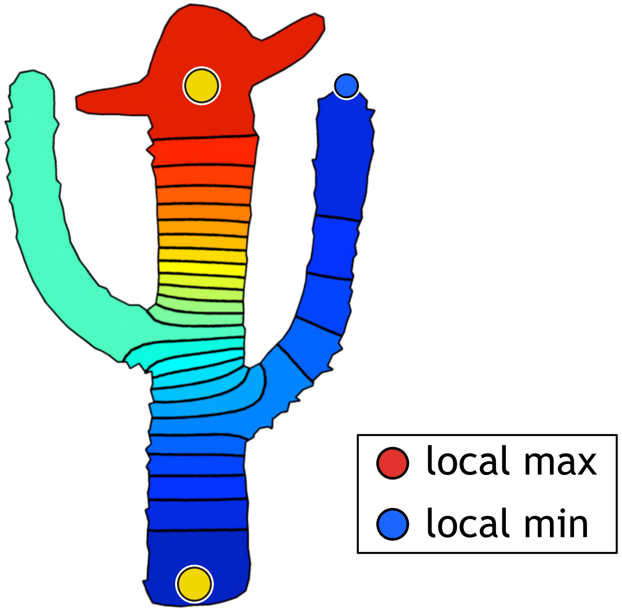
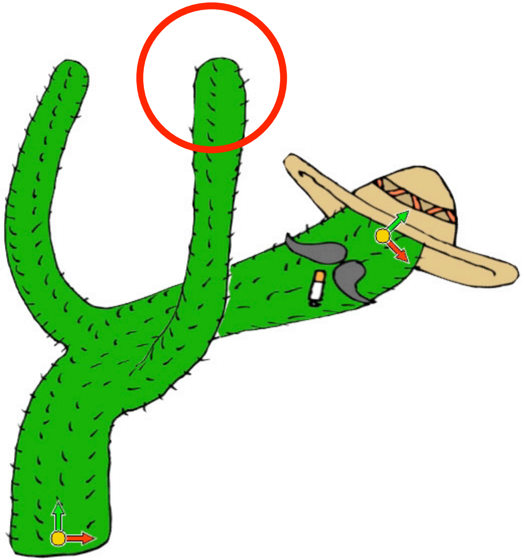
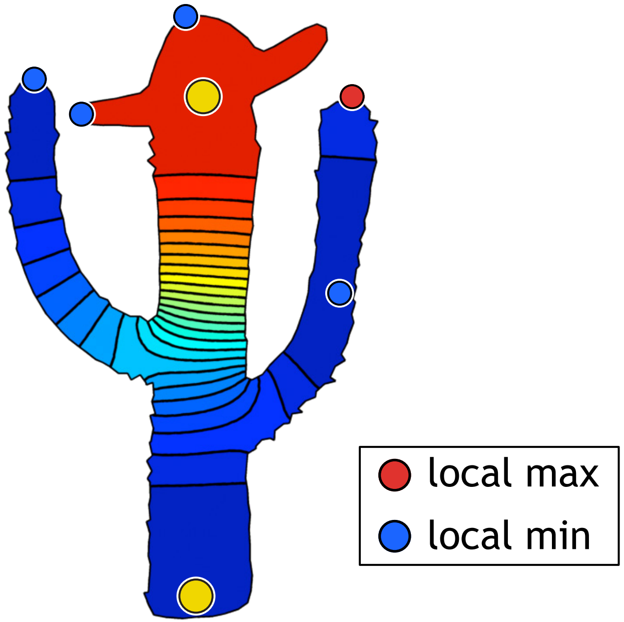




Gets worse with higher-order smoothness

bounded Δ^4
[Jacobson et al. 2011]



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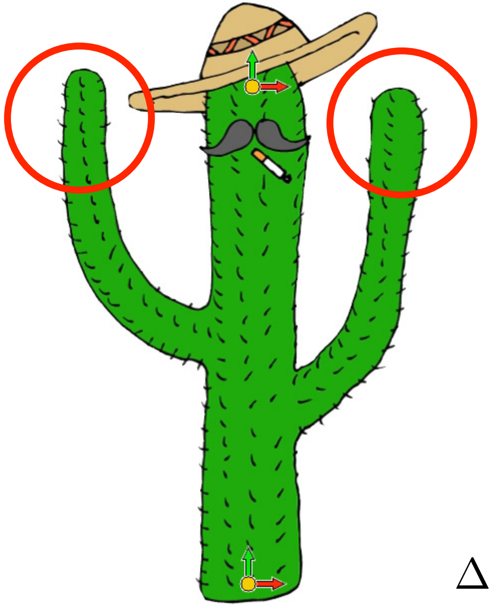

$\Delta^k,\ k > 2$ *oscillate too much*

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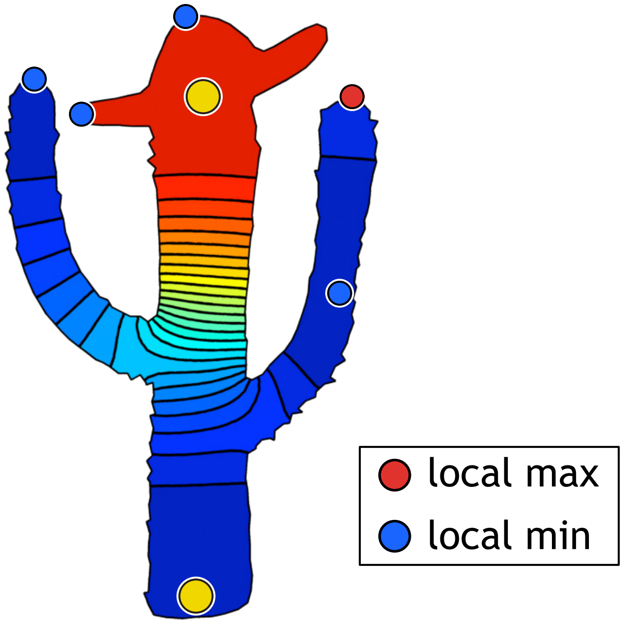

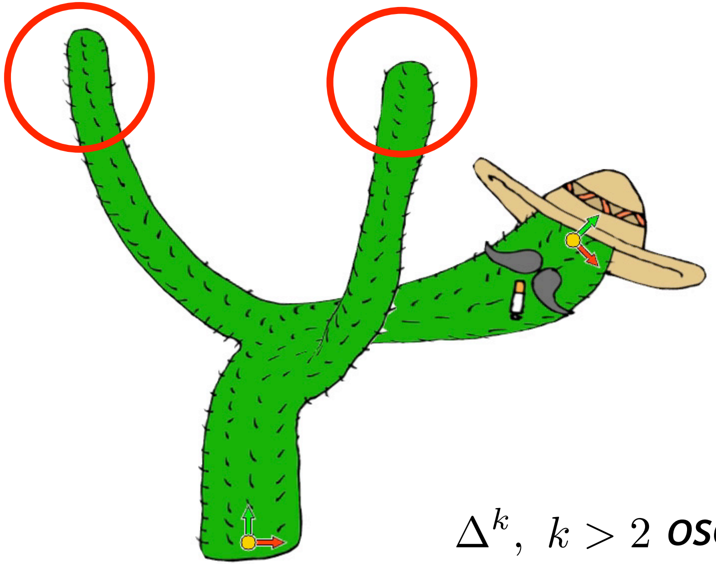

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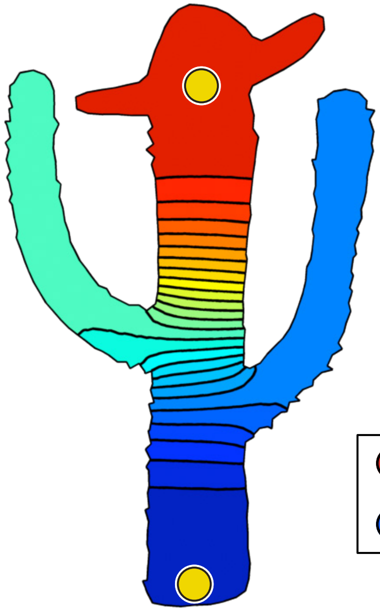
We *explicitly* prohibit spurious extrema

our Δ^4



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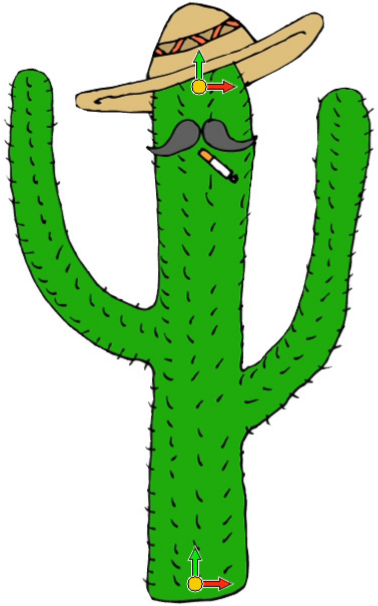

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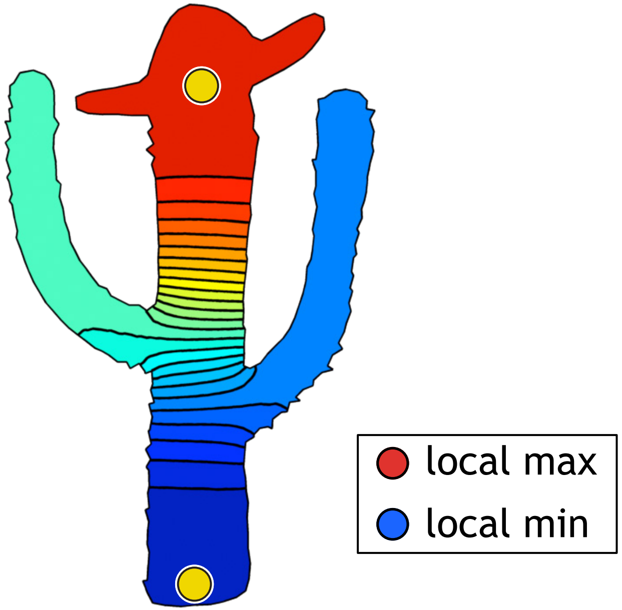

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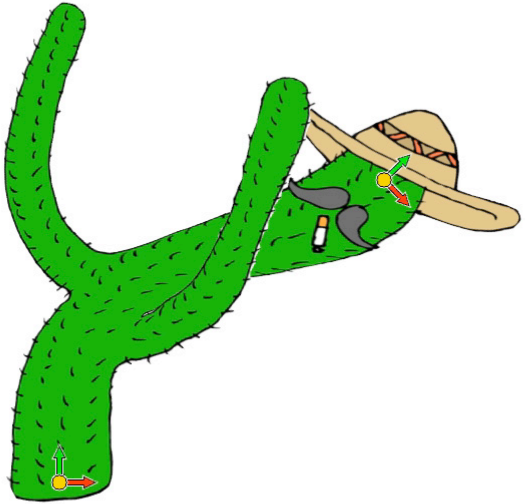

Same functions used for color interpolation

$$\mathbf{x}_i' = \sum_{j=1}^{H} f_j(\mathbf{x}_i)\, T_j\, \mathbf{x}_i$$

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Same functions used for color interpolation

$$\mathbf{c}_i = \sum_{j=1}^{H} f_j(\mathbf{x}_i)\,\mathbf{c}_j$$

Same functions used for color interpolation

unconstrained Δ^2
[Finch et al. 2011]

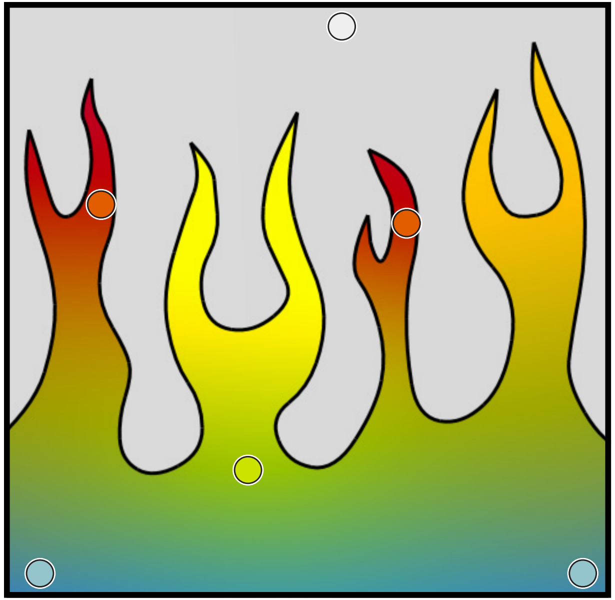

Image courtesy Mark Finch

$$\mathbf{c}_i = \sum_{j=1}^{H} f_j(\mathbf{x}_i)\mathbf{c}_j$$

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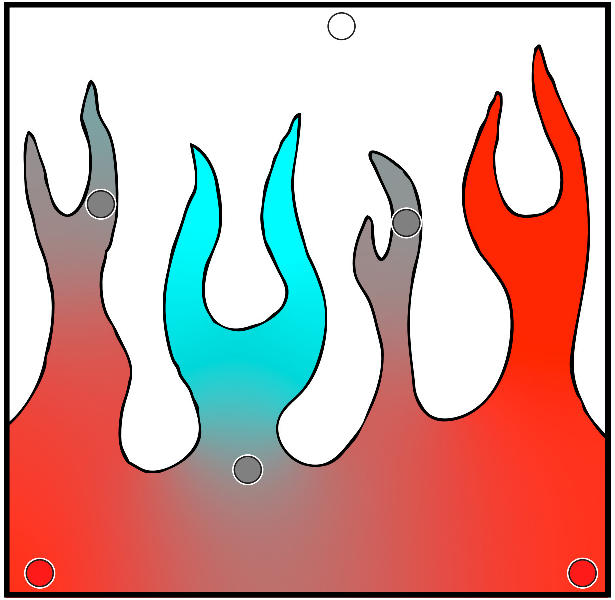

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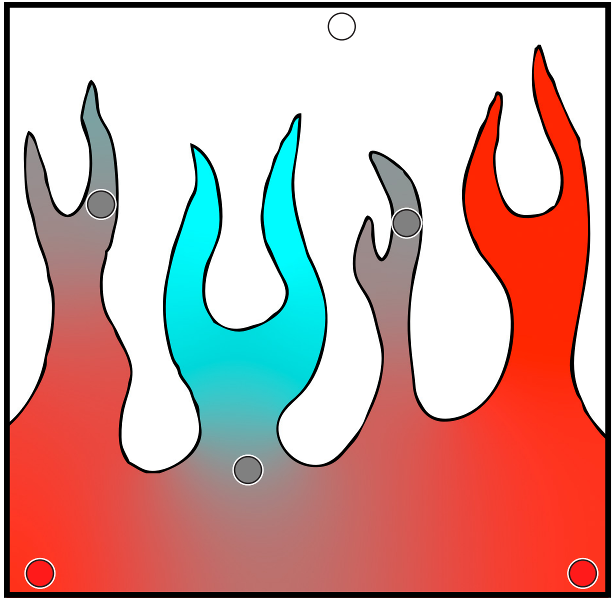

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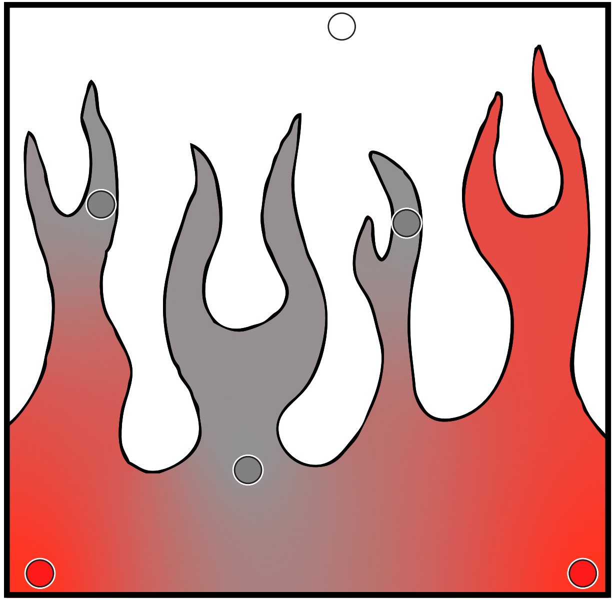

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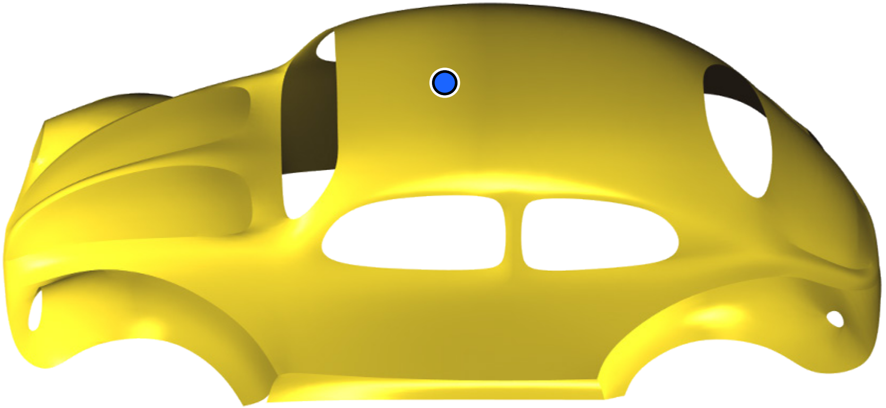
Want same control when smoothing data



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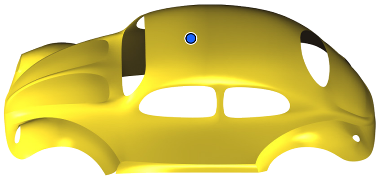

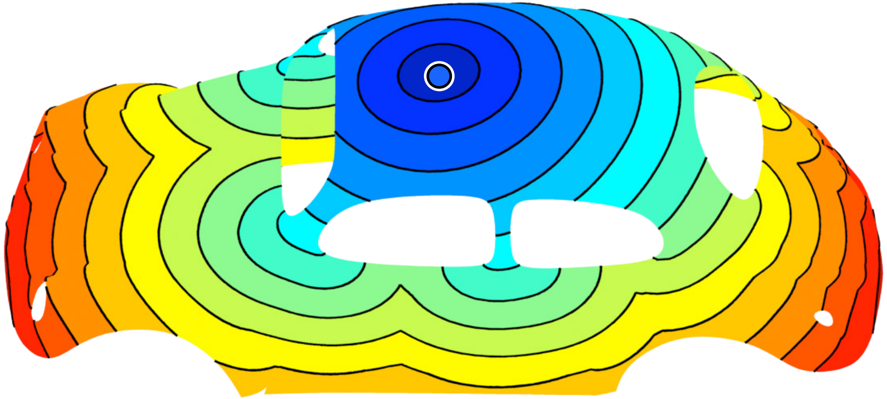

Exact, but sharp geodesic

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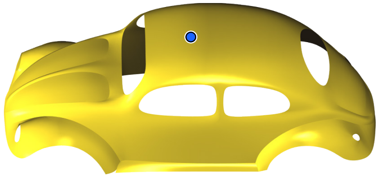

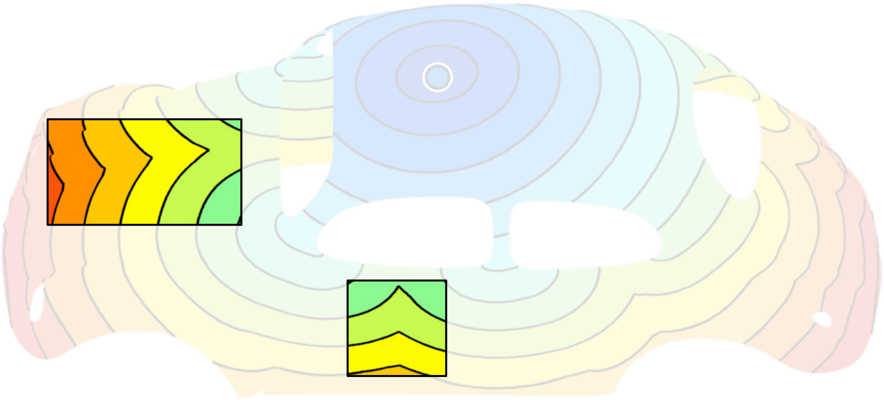

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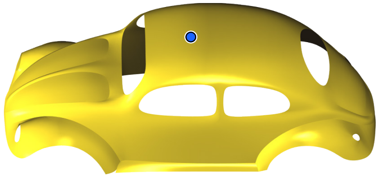

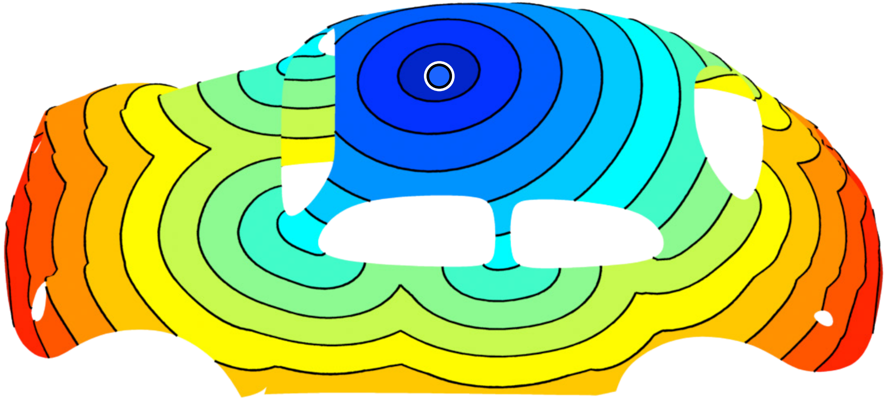

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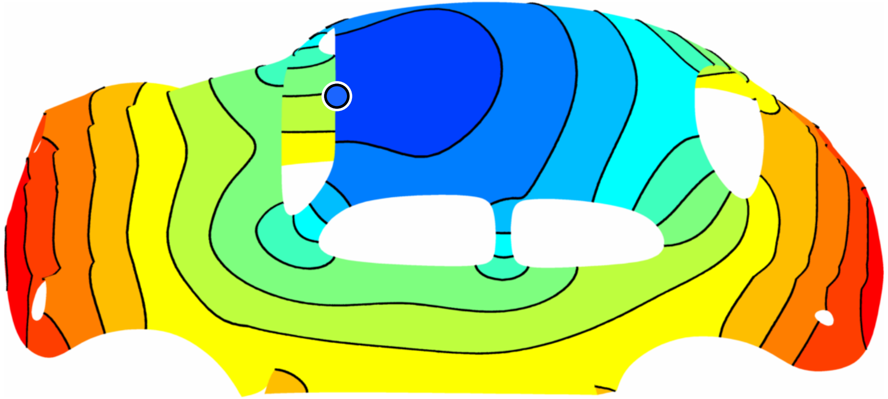
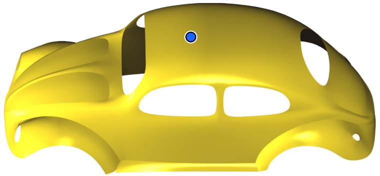
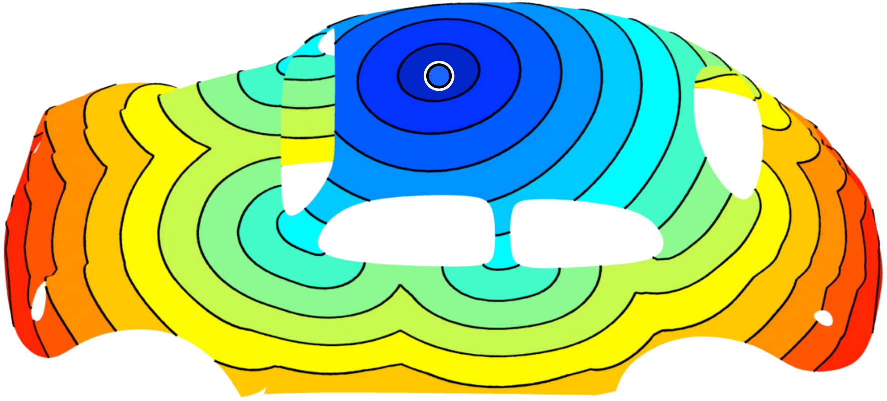


Smooth, but extrema are lost

Want same control when smoothing data





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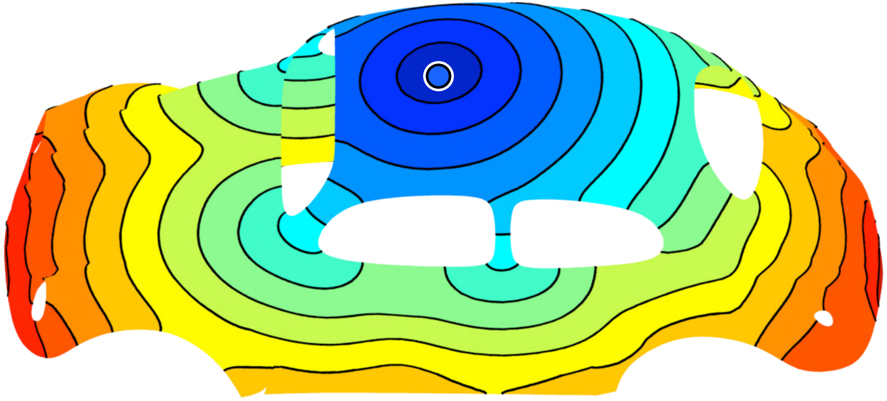


Smooth *and* maintain extrema

Ideal discrete problem is intractable

$$\arg\min_{f} \; E(f)$$

Interpolation functions:

$$E_L(f) = \int_{\mathcal{M}} \|\nabla^k f\|^2 dV, \quad k = 2, 3, \ldots$$

Ideal discrete problem is intractable

$$\arg\min_{f} \; E(f)$$

Data smoothing:

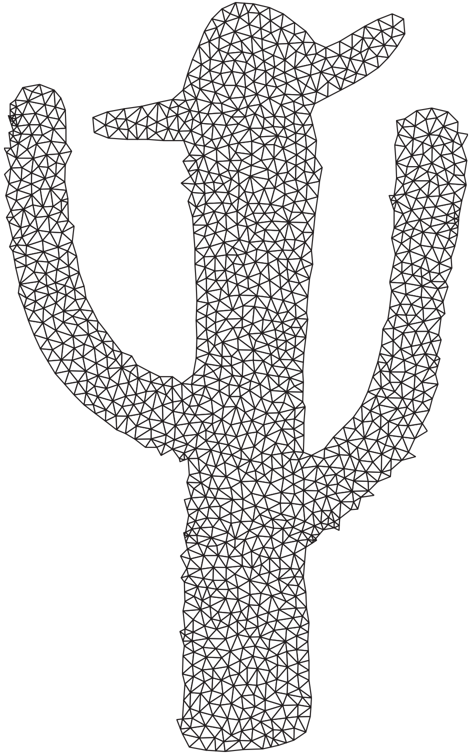
$$E_L(f) = \int_{\mathcal{M}} \|\nabla^k f\|^2 dV, \quad k = 2, 3, \ldots$$

$$E_D(f) = \sum_{i \in \mathcal{M}} \|h_i - f_i\|^2$$

$$E(f) = \gamma_L E_L(f) + \gamma_D E_D(f)$$

Ideal discrete problem is intractable

$$\arg\min_{f} \; E(f)$$

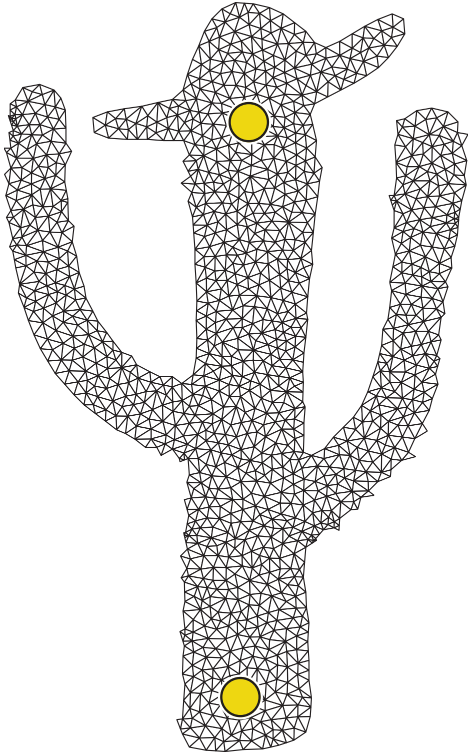


Ideal discrete problem is intractable

$$\arg\min_f \; E(f)$$

$$\text{s.t.} \quad f_{\max} = known$$

$$f_{\min} = known$$



Ideal discrete problem is intractable

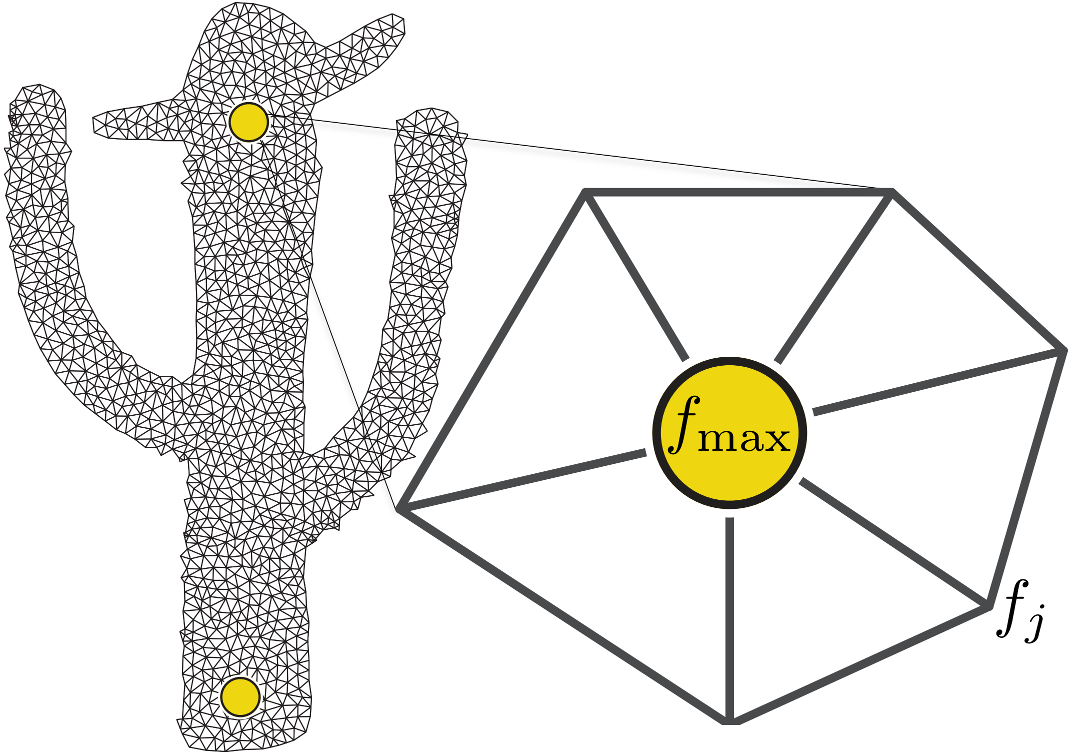
$$\arg\min_{f} \; E(f)$$

s.t. $f_{\max} = known$

$f_{\min} = known$

linear $f_j < f_{\max}$

$f_j > f_{\min}$



Ideal discrete problem is intractable

$$\arg\min_{f} \; E(f)$$

s.t.

$$f_{\max} = known$$

$$f_{\min} = known$$

linear

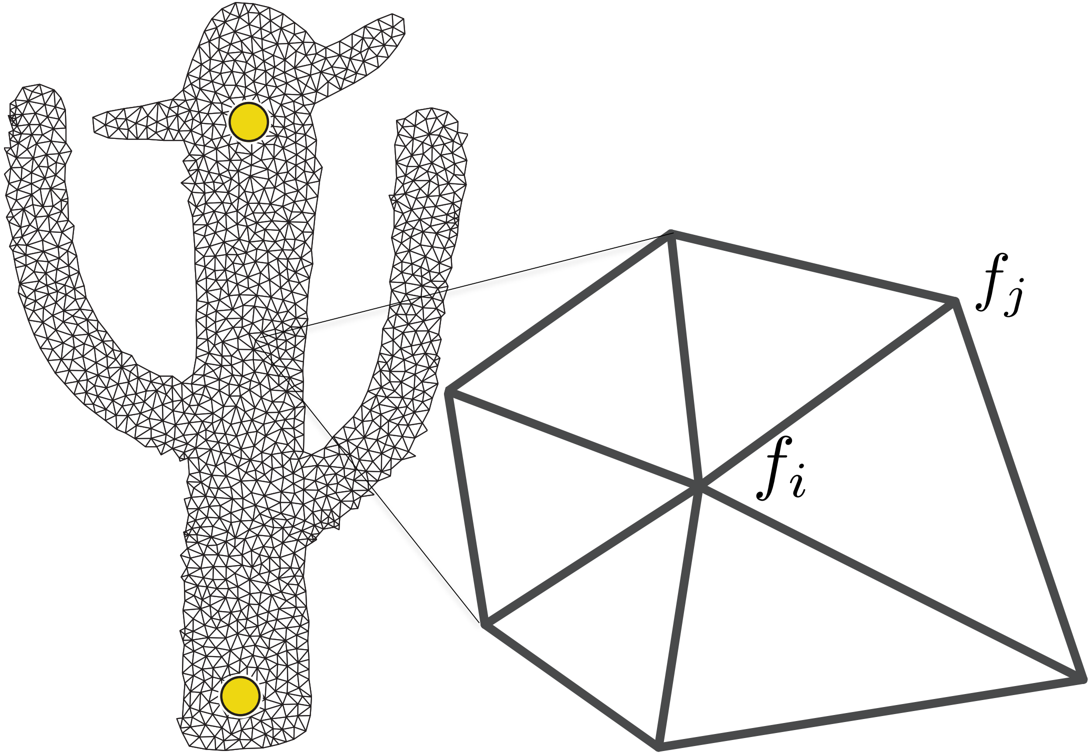
$$f_j < f_{\max}$$

$$f_j > f_{\min}$$

nonlinear

$$f_i > \min_{j \in \mathcal{N}(i)} f_j$$

$$f_i < \max_{j \in \mathcal{N}(i)} f_j$$



Assume we have a feasible solution

$$\arg\min_f \; E(f)$$

$$\text{s.t.} \quad f_{\max} = known$$

$$f_{\min} = known$$

linear

$$f_j < f_{\max}$$

$$f_j > f_{\min}$$

nonlinear

$$f_i > \min_{j \in \mathcal{N}(i)} f_j$$

$$f_i < \max_{j \in \mathcal{N}(i)} f_j$$

"Representative function" u

$$u_j < u_{\max}$$

$$u_j > u_{\min}$$

handles

$$u_i > \min_{j \in \mathcal{N}(i)} u_j$$

$$u_i < \max_{j \in \mathcal{N}(i)} u_j$$

interior

Assume we have a feasible solution

"Representative function" $\mathcal{U}$

handles	$u_j < u_{\max}$ $u_j > u_{\min}$
interior	$u_i > \min\limits_{j \in \mathcal{N}(i)} u_j$ $u_i < \max\limits_{j \in \mathcal{N}(i)} u_j$

Copy "monotonicity" of representative

$$\arg\min_f \; E(f)$$

$$\text{s.t.} \quad f_{\max} = known$$

$$f_{\min} = known$$

$$(f_i - f_j)(u_i - u_j) > 0 \qquad \text{linear} \qquad \forall (i,j) \in \mathcal{E}$$

At least one edge in either direction per vertex

Rewrite as conic optimization

QP

$$\begin{aligned} \underset{\mathbf{f}}{\text{minimize}} \quad & \frac{1}{2}\|\mathbf{F}\,\mathbf{f}\|^2 + \mathbf{c}^\mathsf{T}\mathbf{f} + \text{const} \\ \text{subject to} \quad & \mathbf{A}_{leq}^\mathsf{T}\mathbf{f} \leq \mathbf{b}_{leq}, \\ & \mathbf{f} \leq \mathbf{u}_f, \quad \mathbf{f} \geq \mathbf{l}_f \end{aligned}$$

Conic

$$\begin{aligned} \underset{\left[\begin{array}{ccc}\mathbf{f}^\mathsf{T} & \mathbf{t}^\mathsf{T} & v\end{array}\right]}{\text{minimize}} \quad & \left[\begin{array}{ccc}\mathbf{c}^\mathsf{T} & 0 & 1\end{array}\right] \left[\begin{array}{c}\mathbf{f} \\ \mathbf{t} \\ v\end{array}\right] + \text{const} \\ \text{subject to} \quad & \left[\begin{array}{ccc}\mathbf{F} & -\mathbf{I} & 0 \\ \mathbf{A}_{leq}^\mathsf{T} & 0 & 0\end{array}\right] \left[\begin{array}{c}\mathbf{f} \\ \mathbf{t} \\ v\end{array}\right] \geq \left[\begin{array}{c}0 \\ -\infty\end{array}\right] \\ & \left[\begin{array}{ccc}\mathbf{F} & -\mathbf{I} & 0 \\ \mathbf{A}_{leq}^\mathsf{T} & 0 & 0\end{array}\right] \left[\begin{array}{c}\mathbf{f} \\ \mathbf{t} \\ v\end{array}\right] \leq \left[\begin{array}{c}0 \\ \mathbf{b}_{leq}\end{array}\right] \\ & \left[\begin{array}{c}\mathbf{f} \\ \mathbf{t} \\ v\end{array}\right] \leq \left[\begin{array}{c}\mathbf{u}_f \\ \infty \\ \infty\end{array}\right] \\ & \left[\begin{array}{c}\mathbf{f} \\ \mathbf{t} \\ v\end{array}\right] \geq \left[\begin{array}{c}\mathbf{l}_f \\ -\infty \\ 0\end{array}\right] \\ & 2v \geq \sum_i t_i^2 \end{aligned}$$

Optimize with MOSEK

We always have harmonic representative

$$\arg\min_u \ \frac{1}{2}\int_\Omega \|\nabla u\|^2 dV$$

We always have harmonic representative

$$\arg\min_u \ \frac{1}{2}\int_\Omega \|\nabla u\|^2 dV$$

$$\text{s.t.} \quad u_{\max} = 1$$

We always have harmonic representative

$$\arg\min_{u} \ \frac{1}{2}\int_{\Omega} \|\nabla u\|^2 dV$$

$$\text{s.t.} \qquad u_{\max} = 1$$

$$\text{s.t.} \qquad u_{\min} = 0$$

We always have harmonic representative

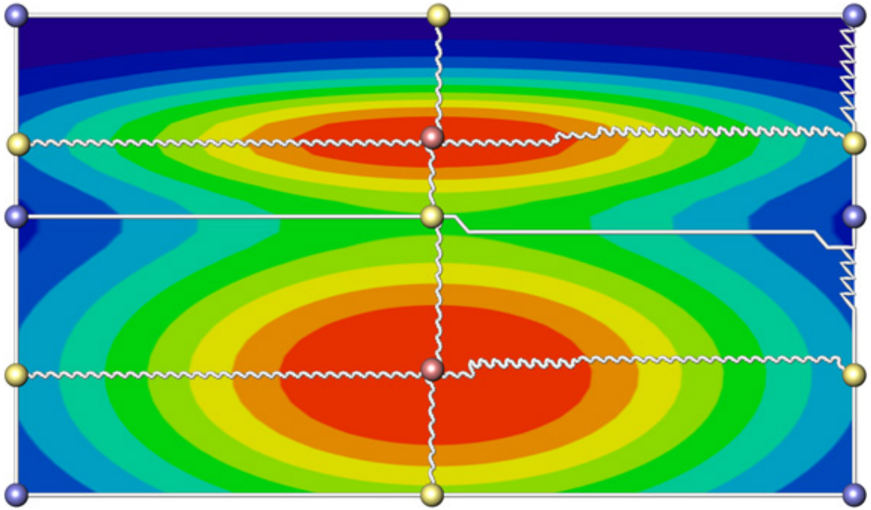
$$\mathop{\arg\min}_{u} \ \frac{1}{2}\int_{\Omega} \|\nabla u\|^2 dV$$

$$\text{s.t.} \quad u_{\max} = 1$$

$$\text{s.t.} \quad u_{\min} = 0$$

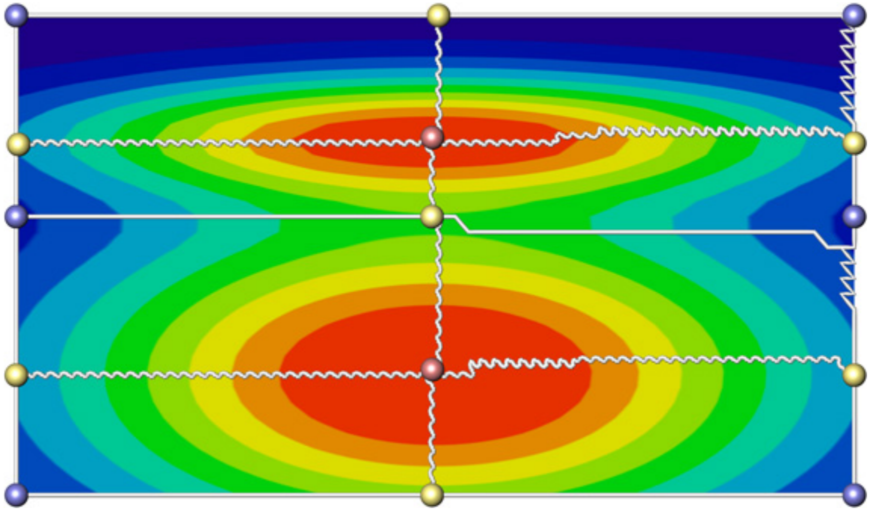
Works well when no input function exists

Data energy may fight harmonic representative



Anisotropic input data

Data energy may fight harmonic representative



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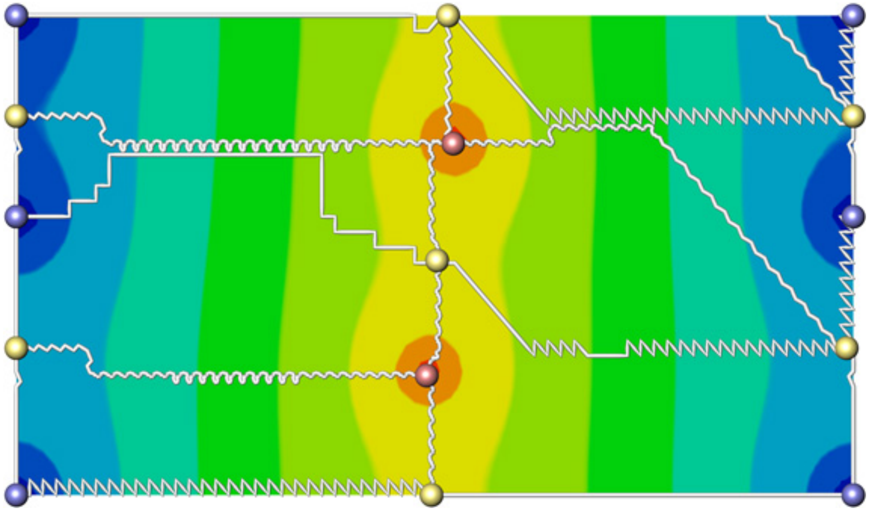

Harmonic representative

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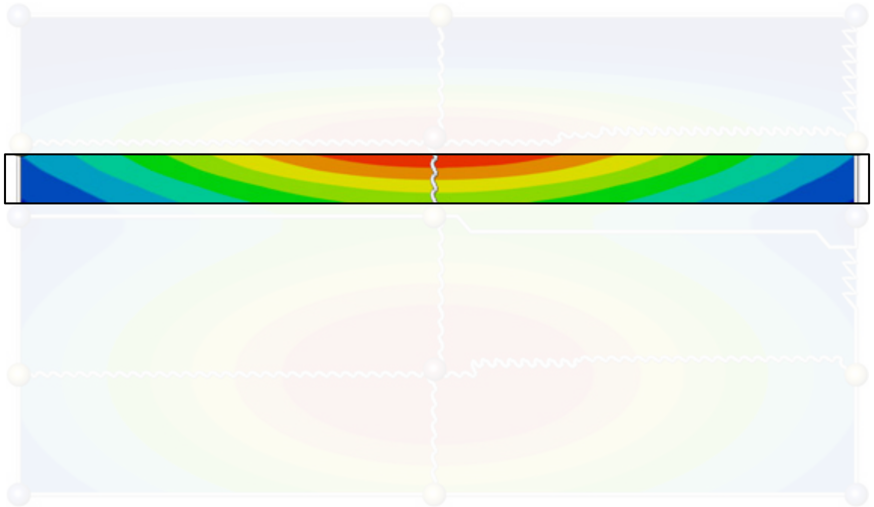

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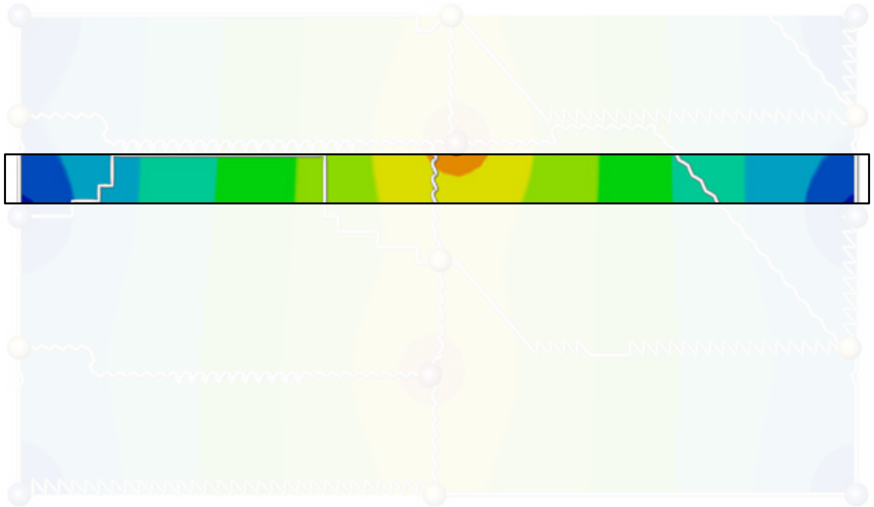

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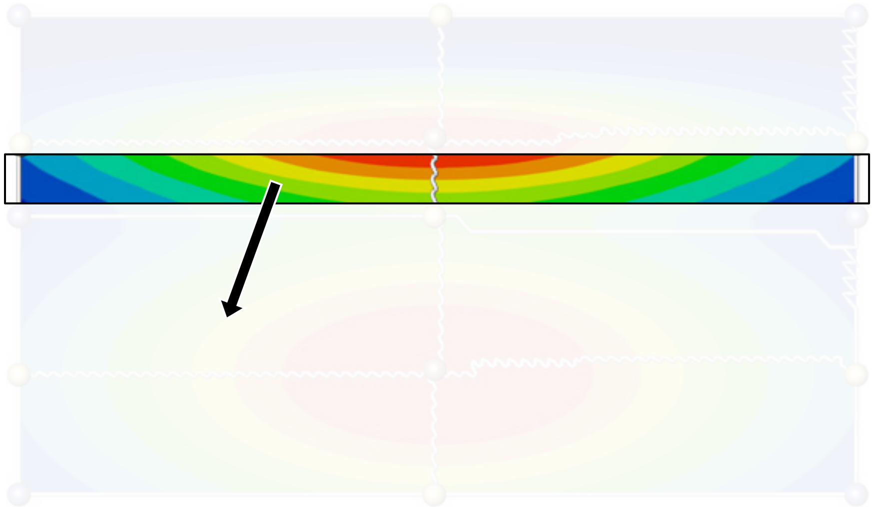

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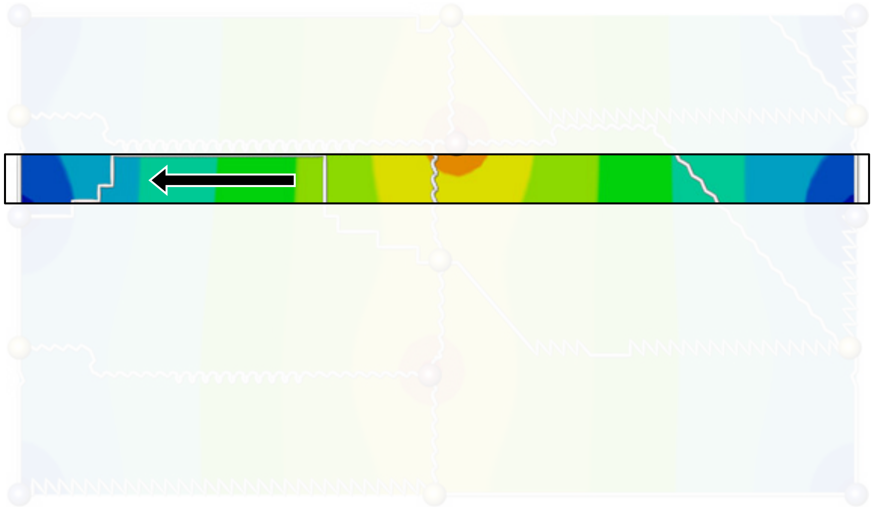
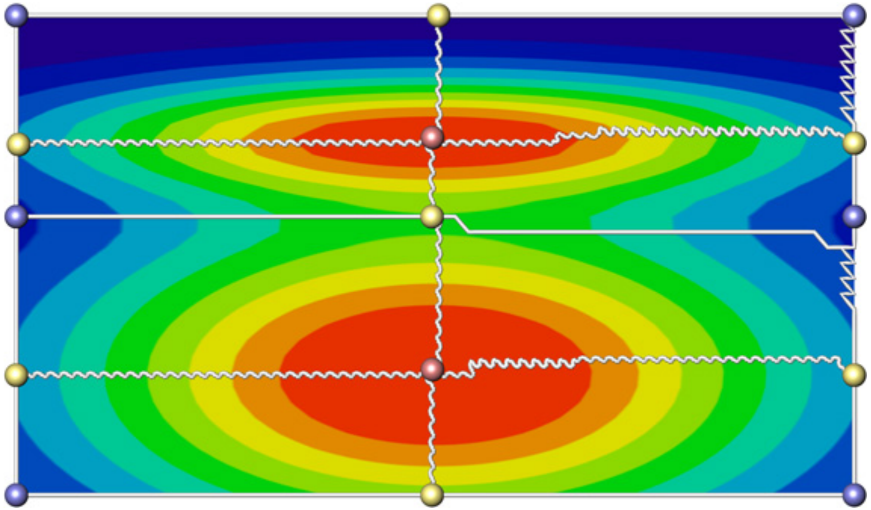
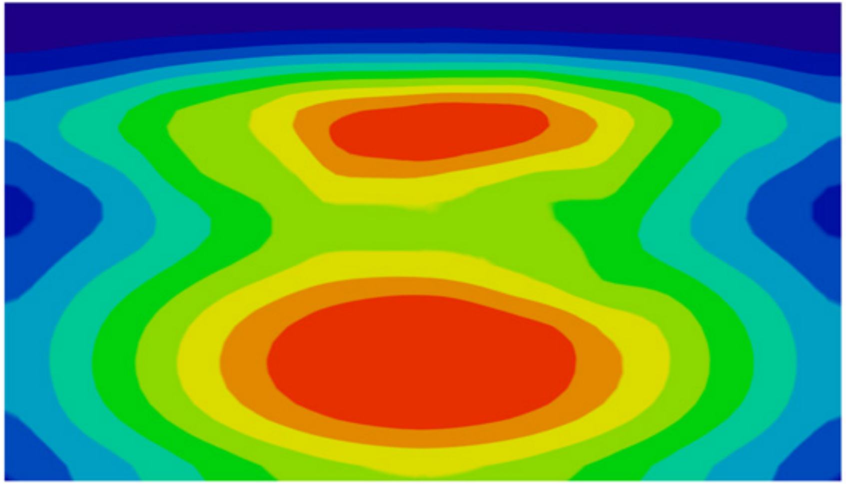


Harmonic representative

Data energy may fight harmonic representative

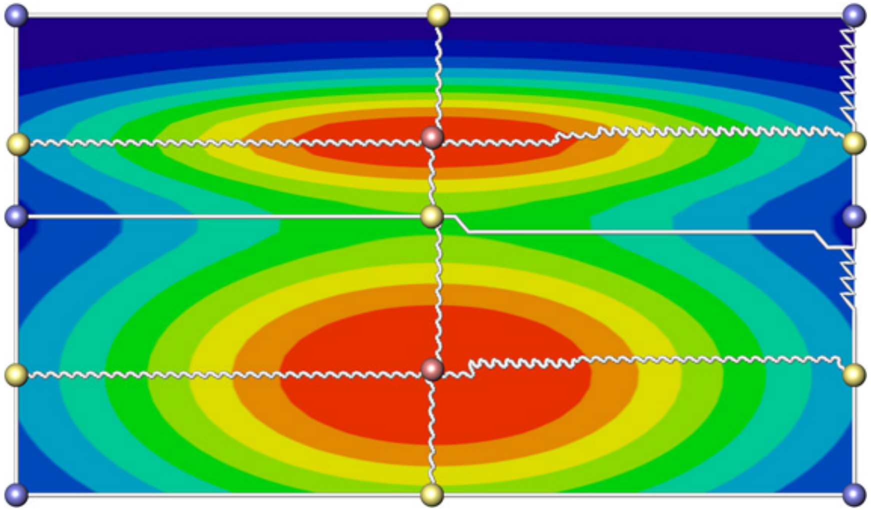


Anisotropic input data



Resulting solution with large γ_D

If data exists, copy topology, too



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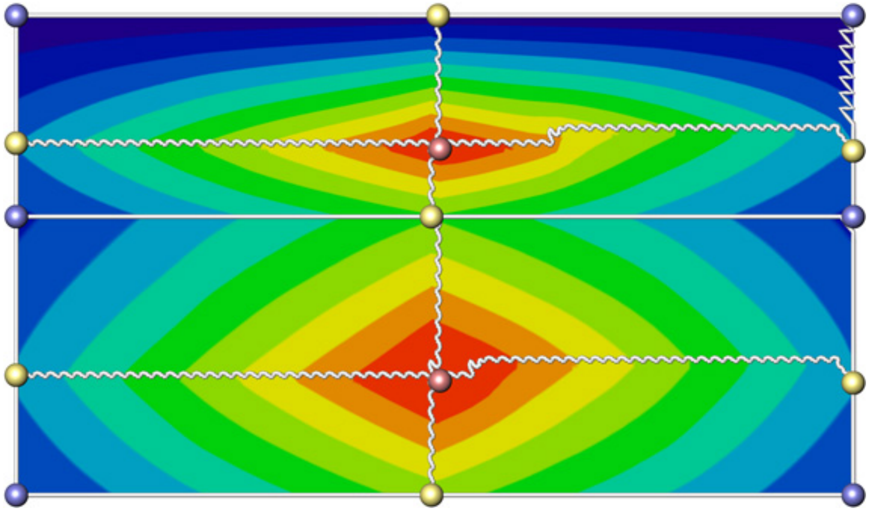

[Weinkauf et al. 2010] representative

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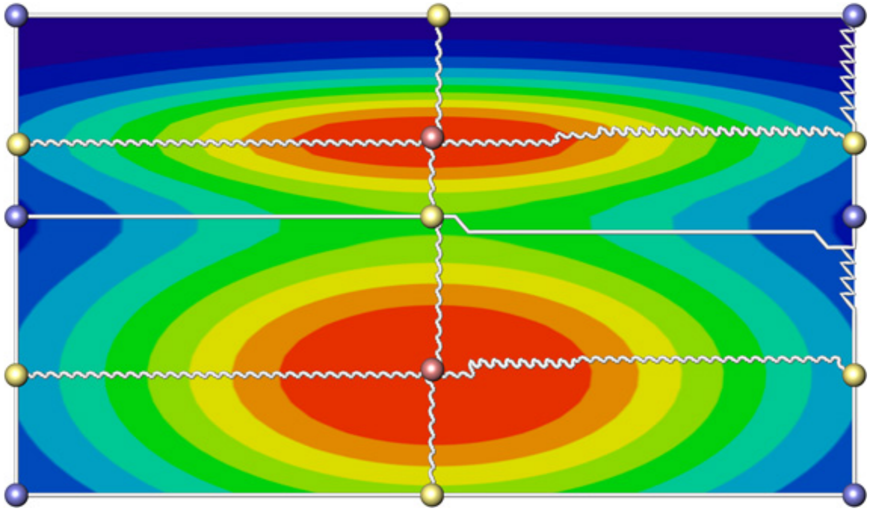

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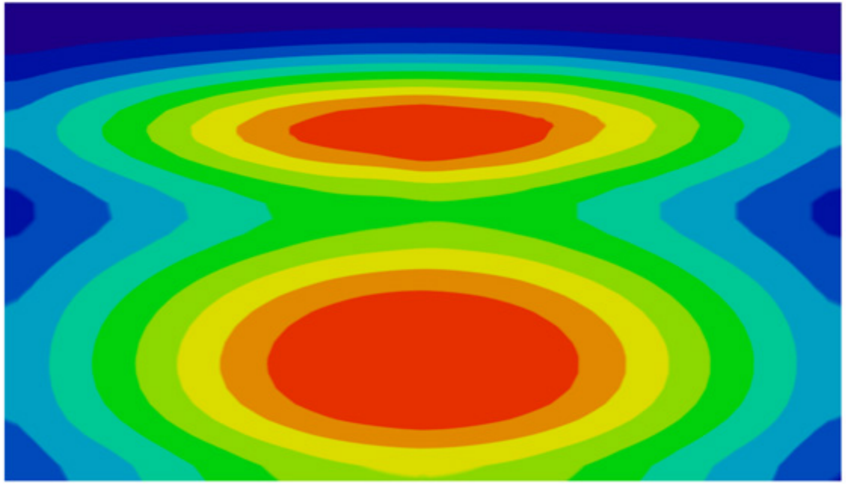

Resulting solution with large γ_D

Final algorithm is simple and efficient

- *Data smoothing*: topology-aware representative
  - Morse-smale + linear solve ~milliseconds

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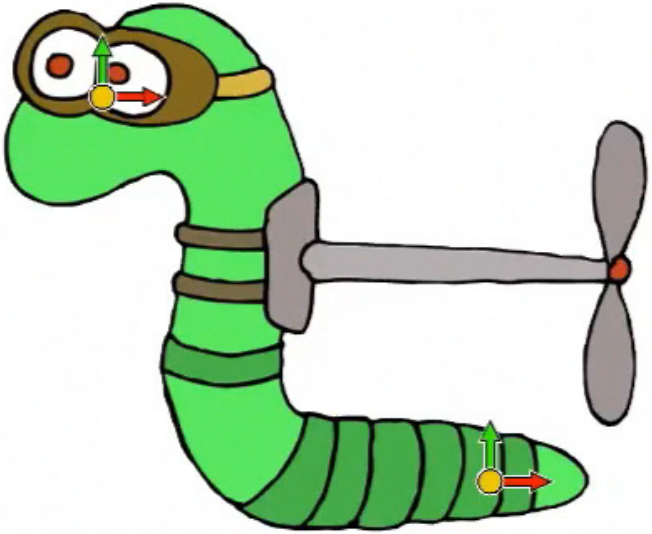
Interpolation: functions are **precomputed**

We preserve troublesome appendages

Bounded Δ^2



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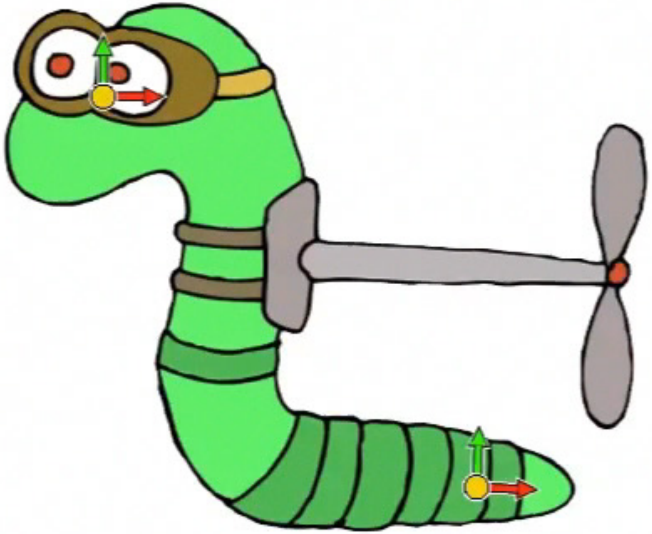

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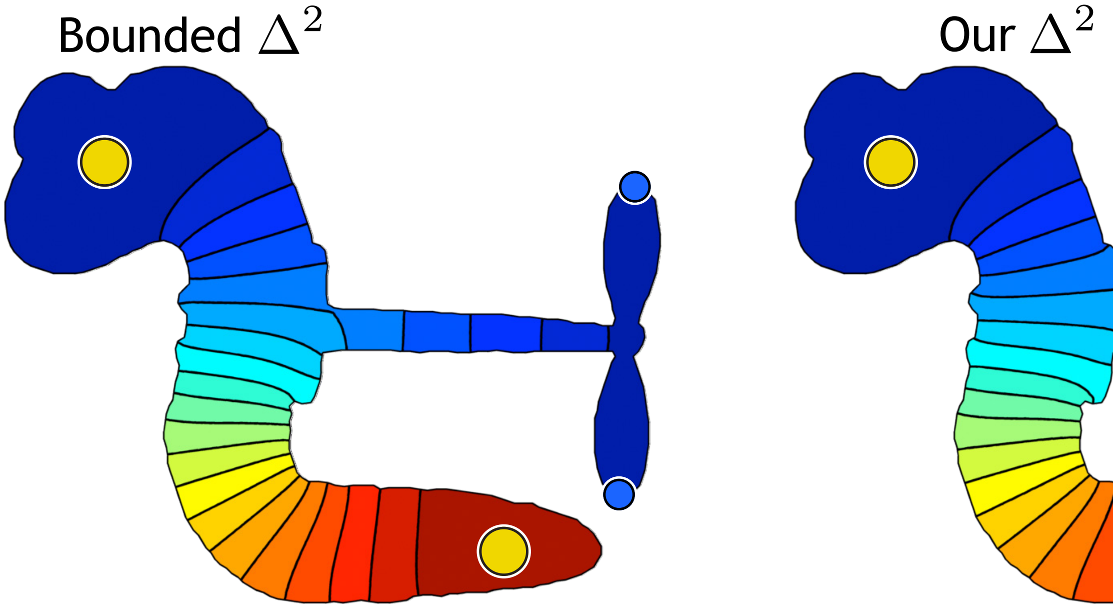

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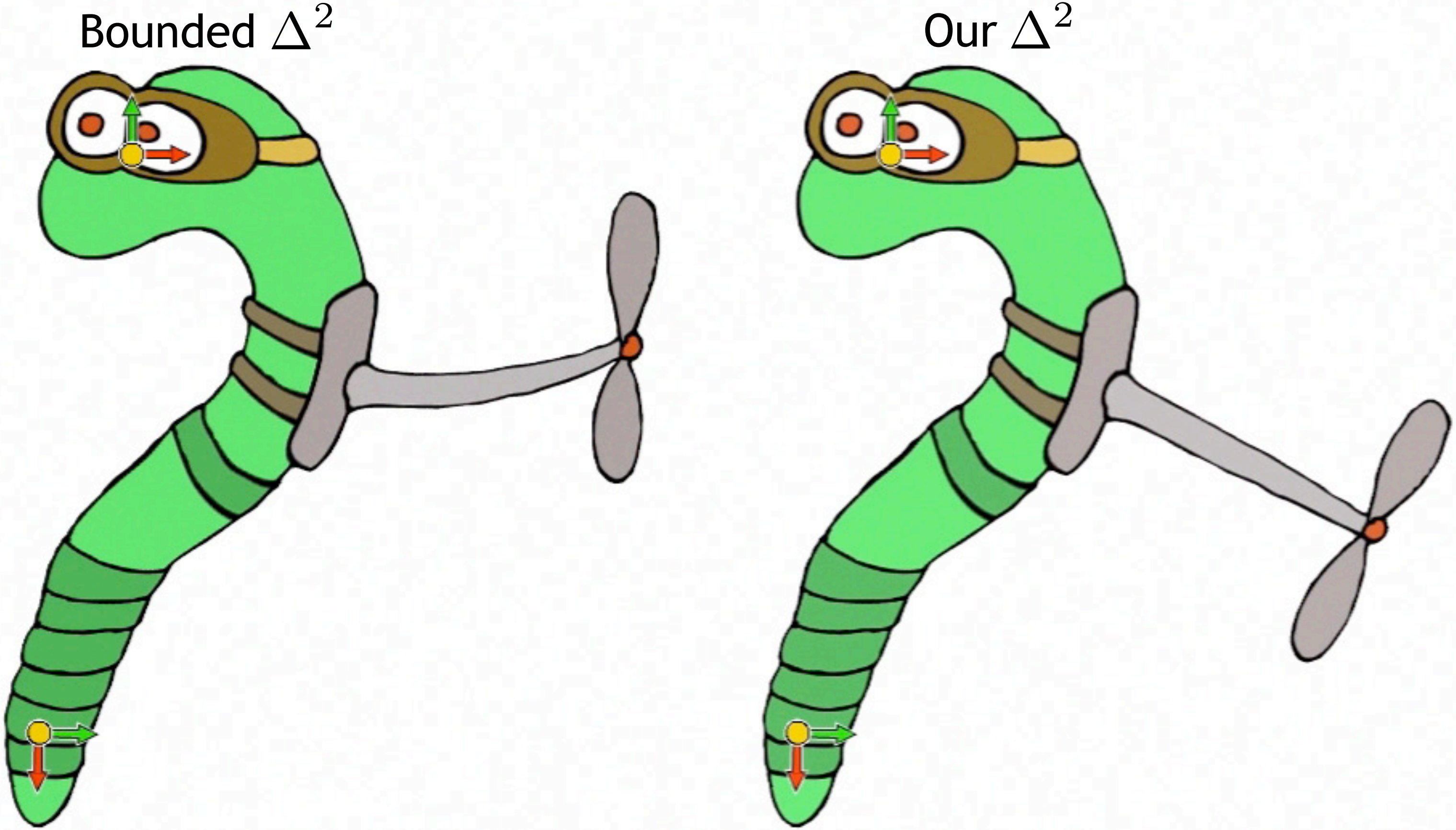
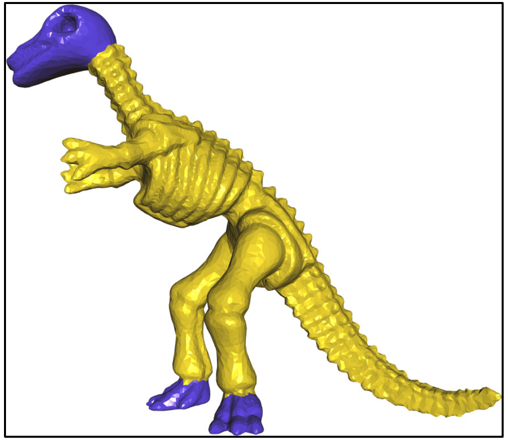
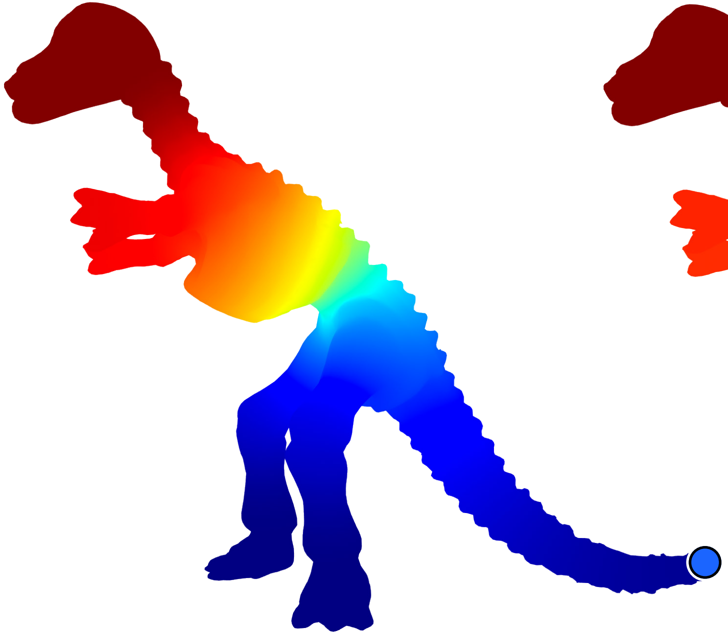
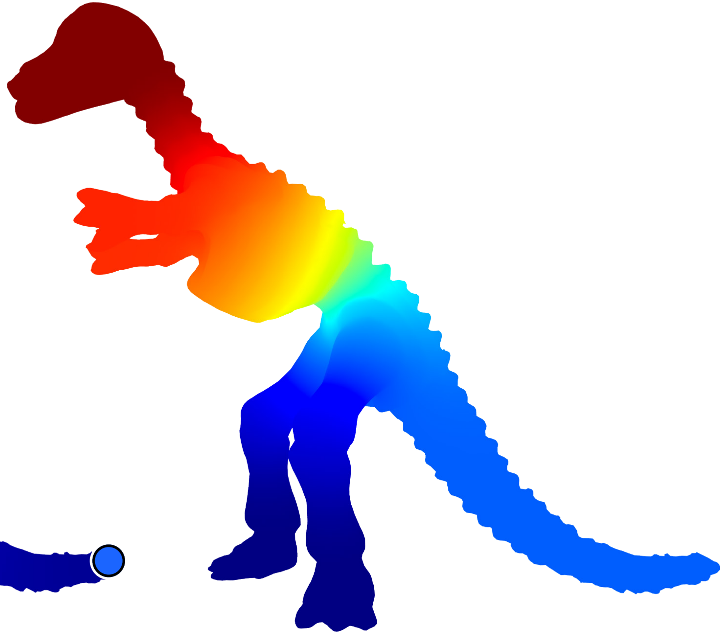


Our weights attach appendages to body



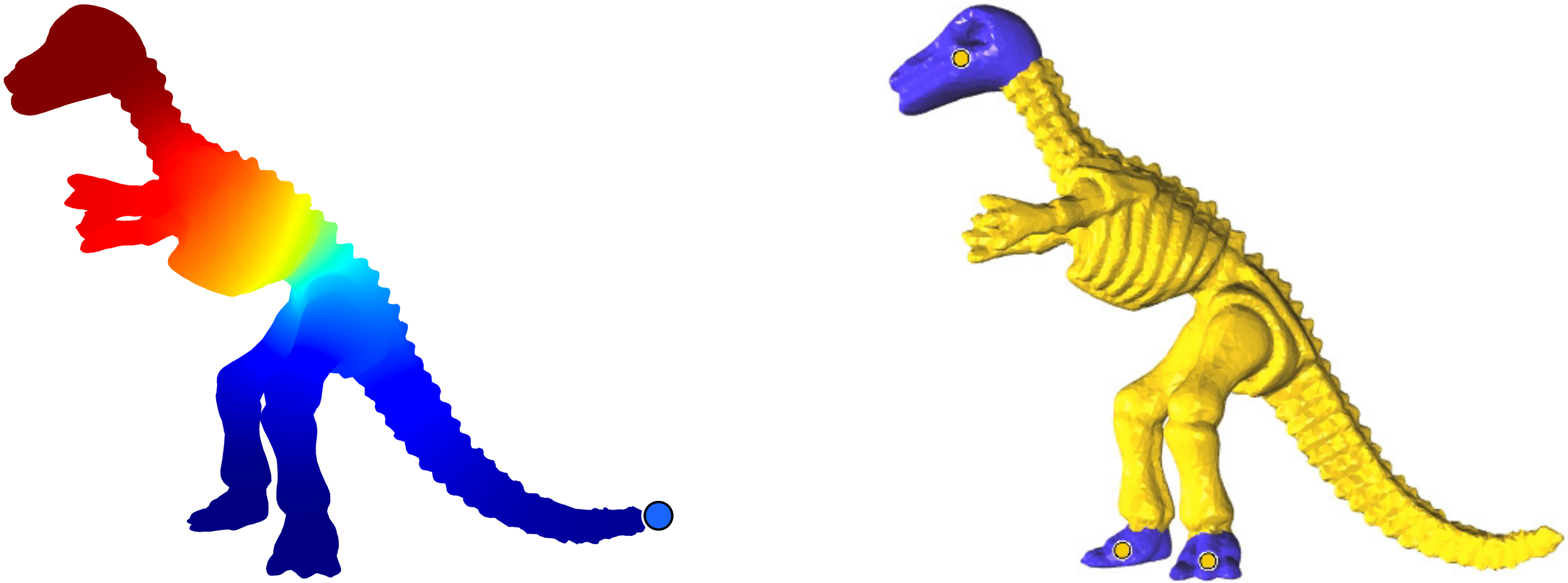


[Botsch & Kobbelt 2004, Jacobson et al. 2011]



Our method

Extrema glue appendages to far-away handles



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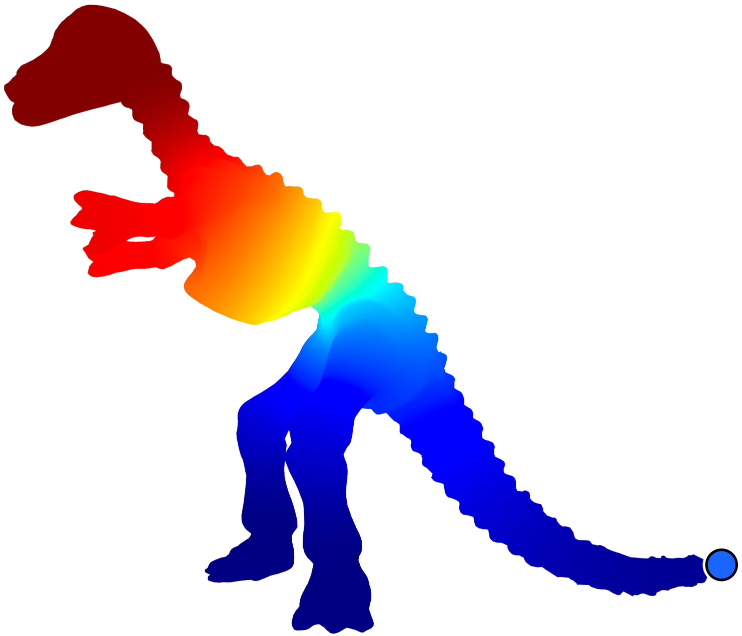

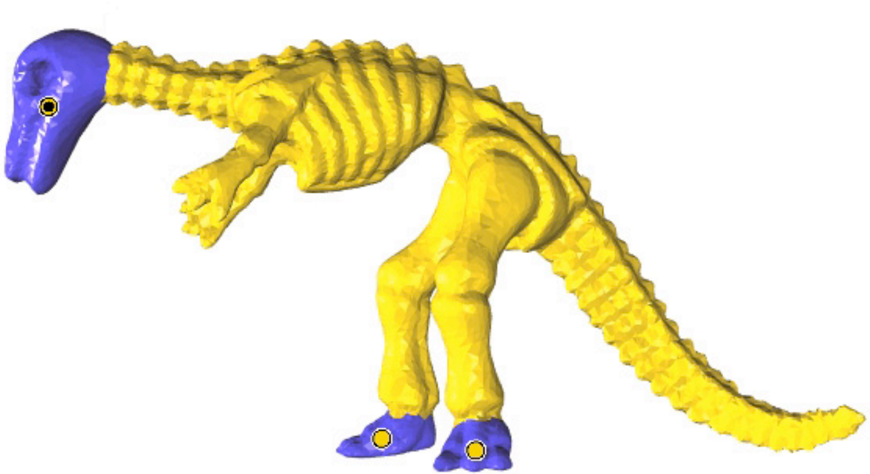

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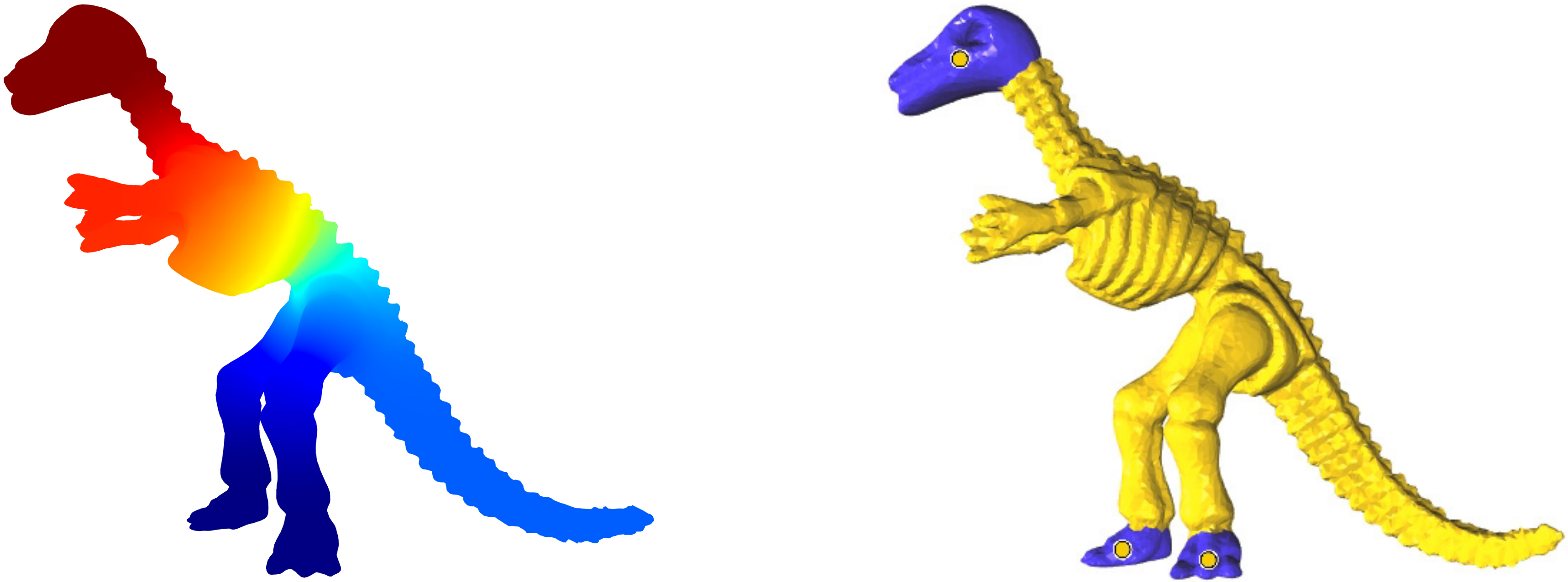

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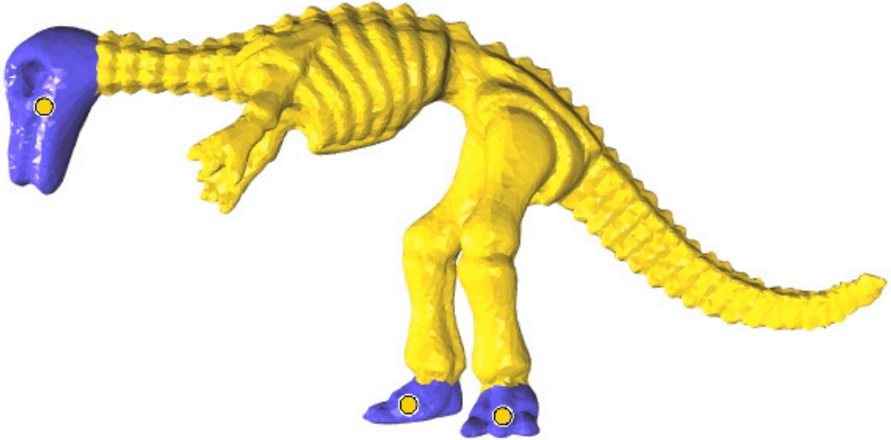
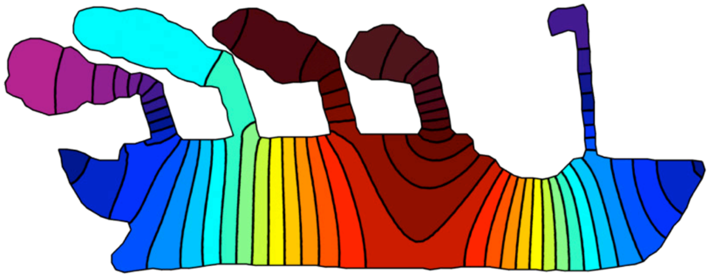


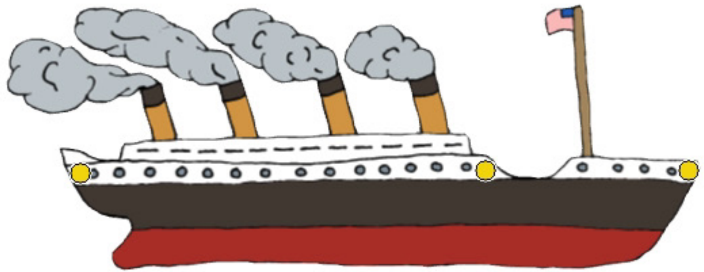
Our method

Extrema distort small features

Unconstrained Δ^2 [Botsch & Kobbelt 2004]



weight of middle point



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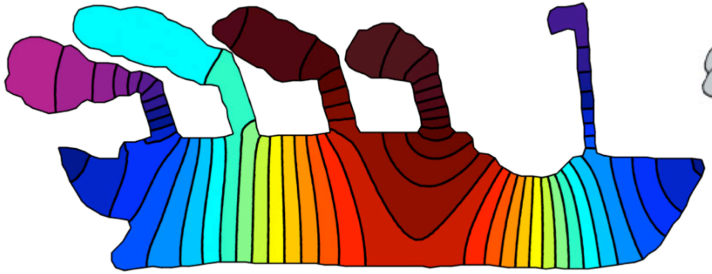

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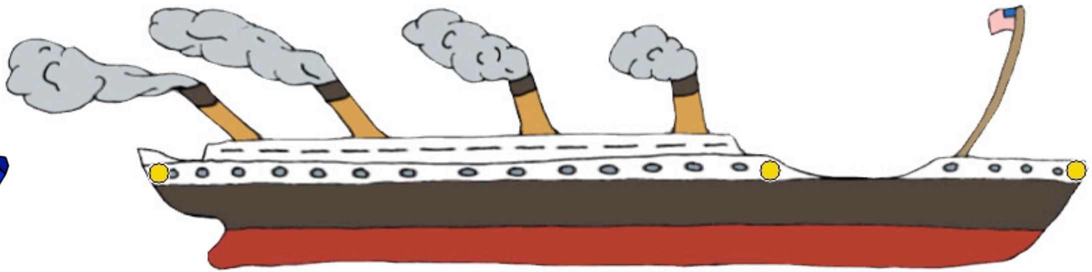

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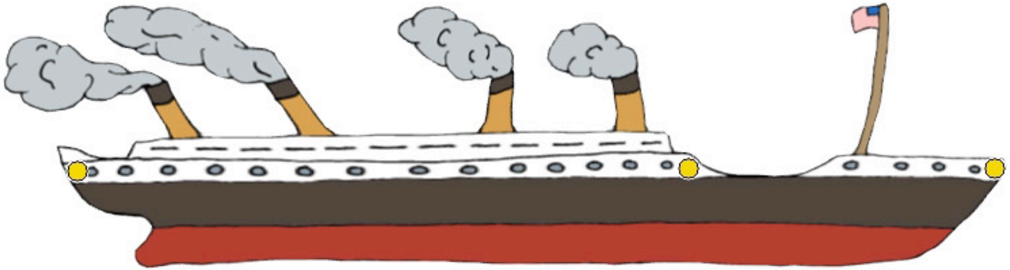
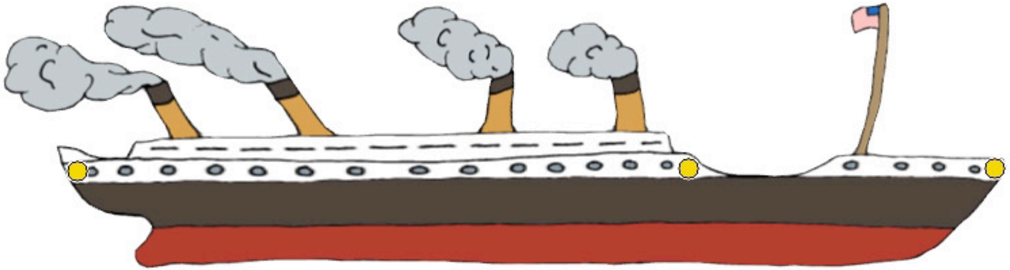


"Monotonicity" helps preserve small features

Bounded Δ^2 [Jacobson et al. 2011]



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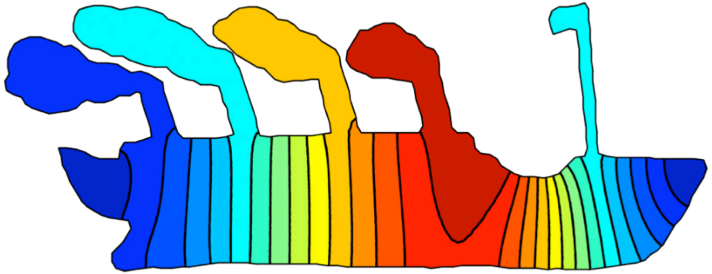
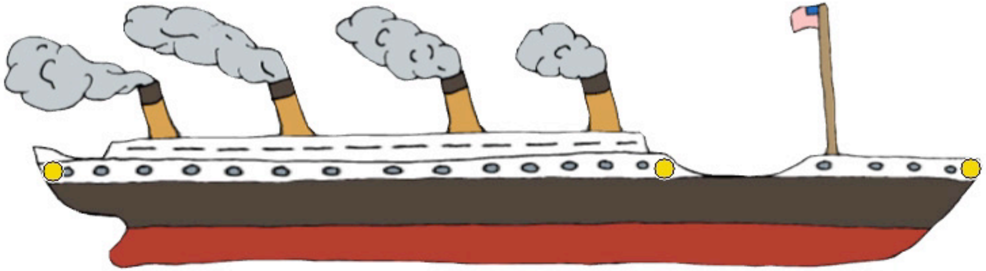
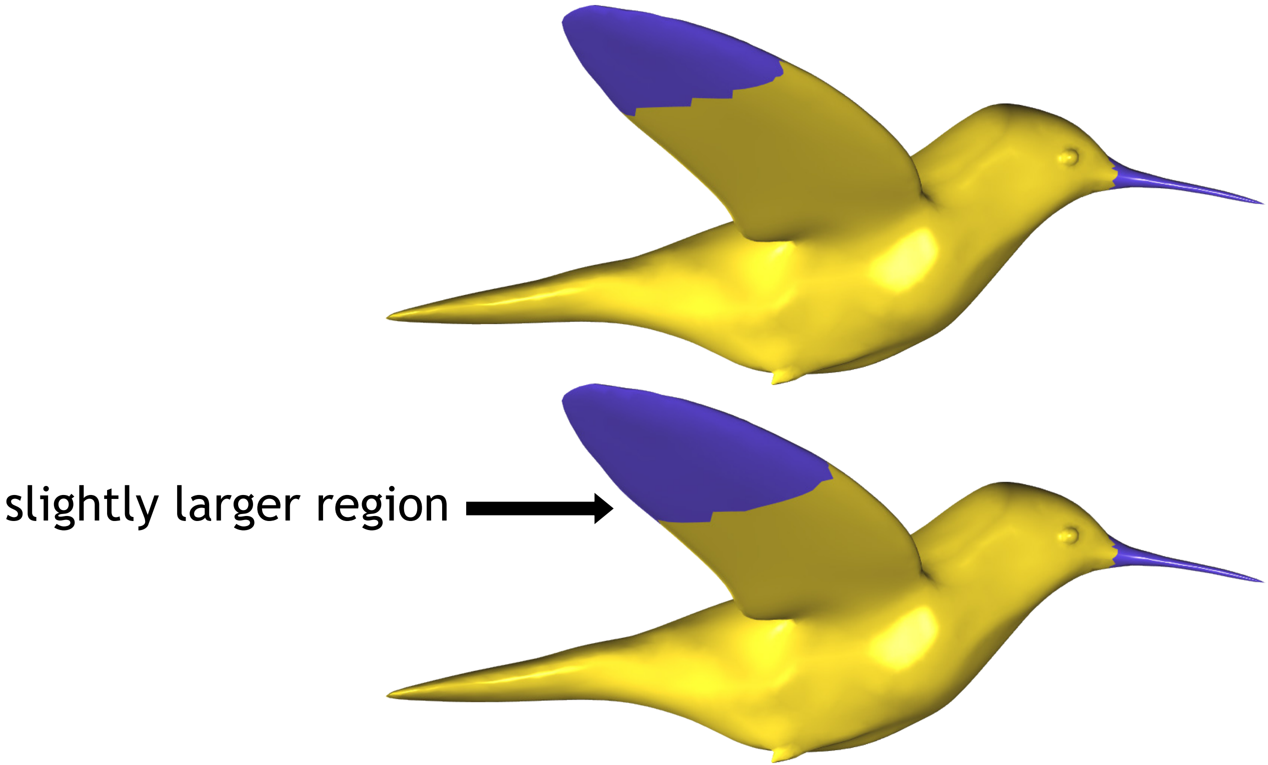




Spurious extrema are unstable, may “flip”



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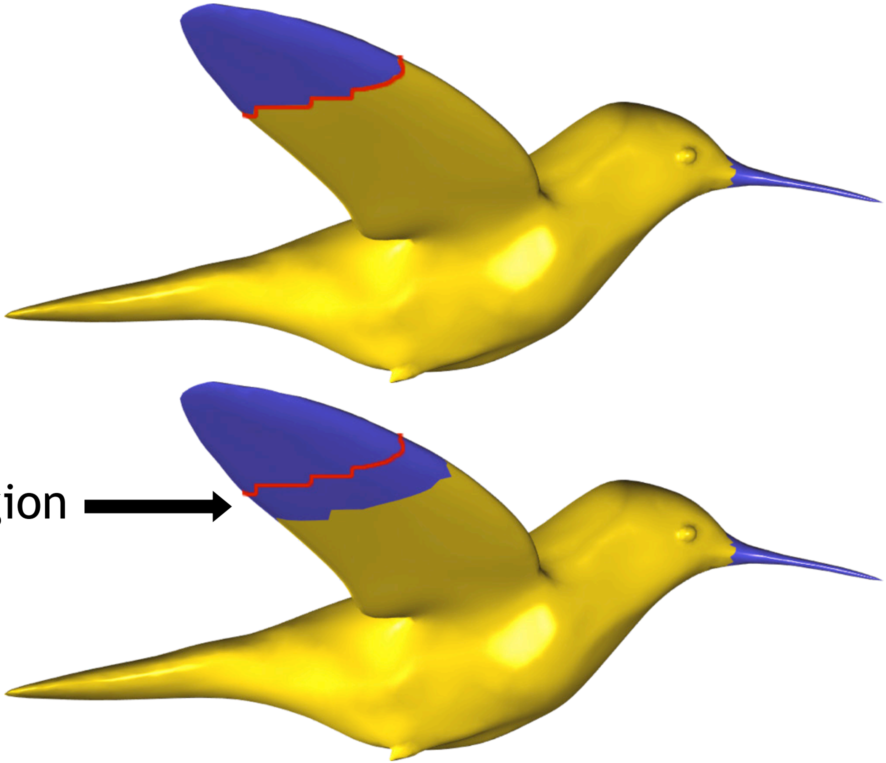

slightly larger region

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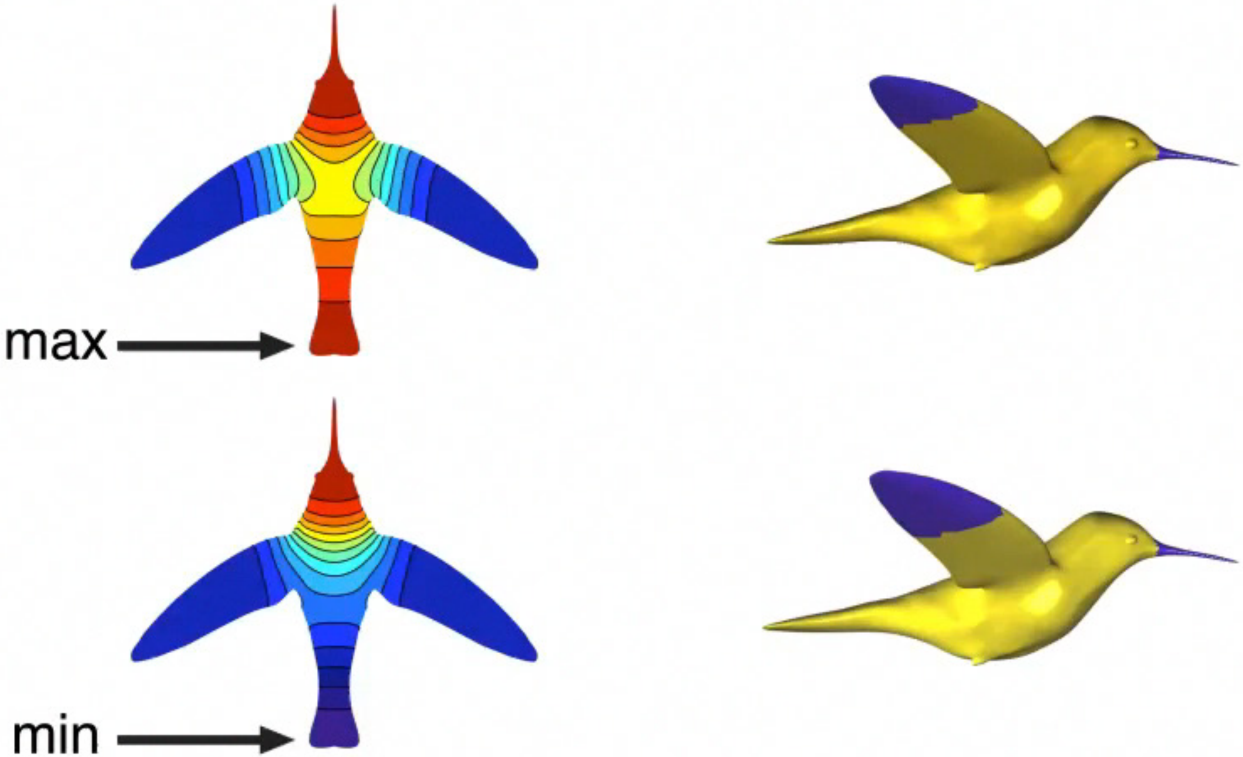

Unconstrained Δ^3 [Botsch & Kobbelt, 2004]

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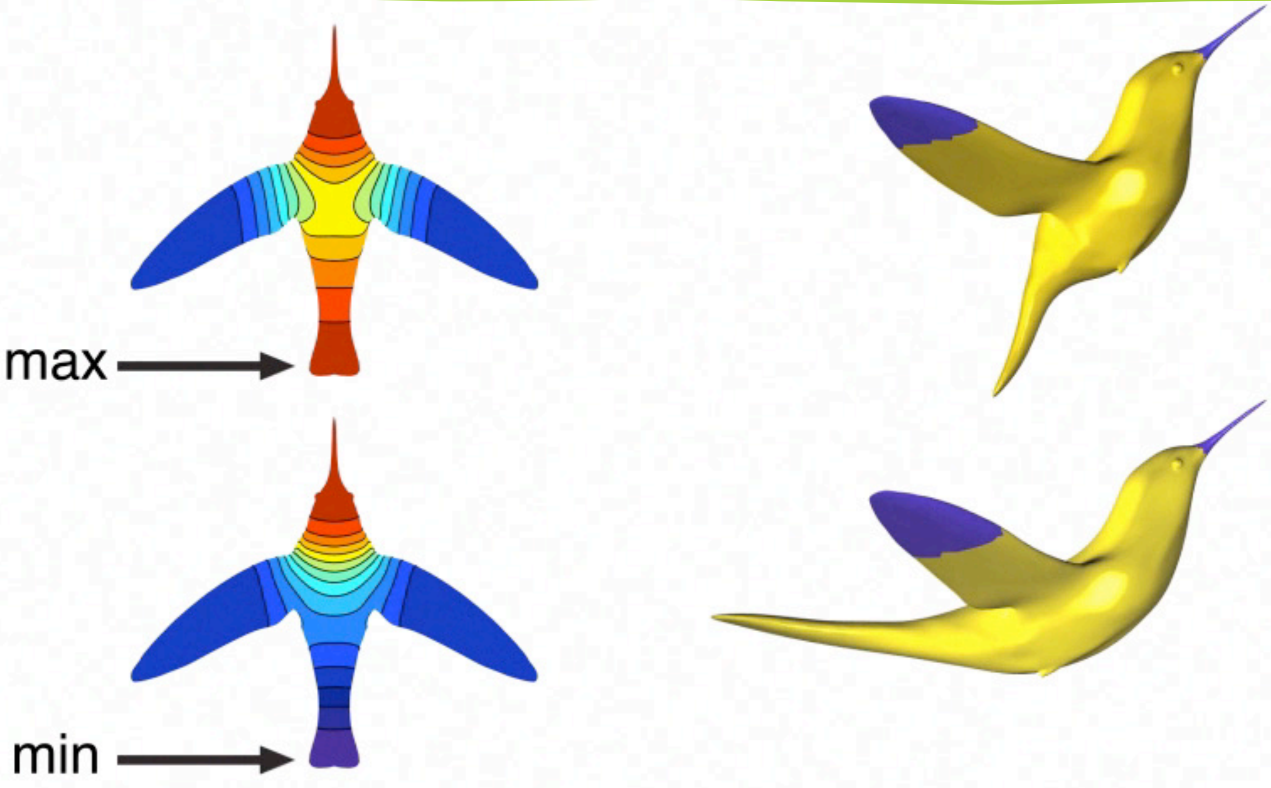

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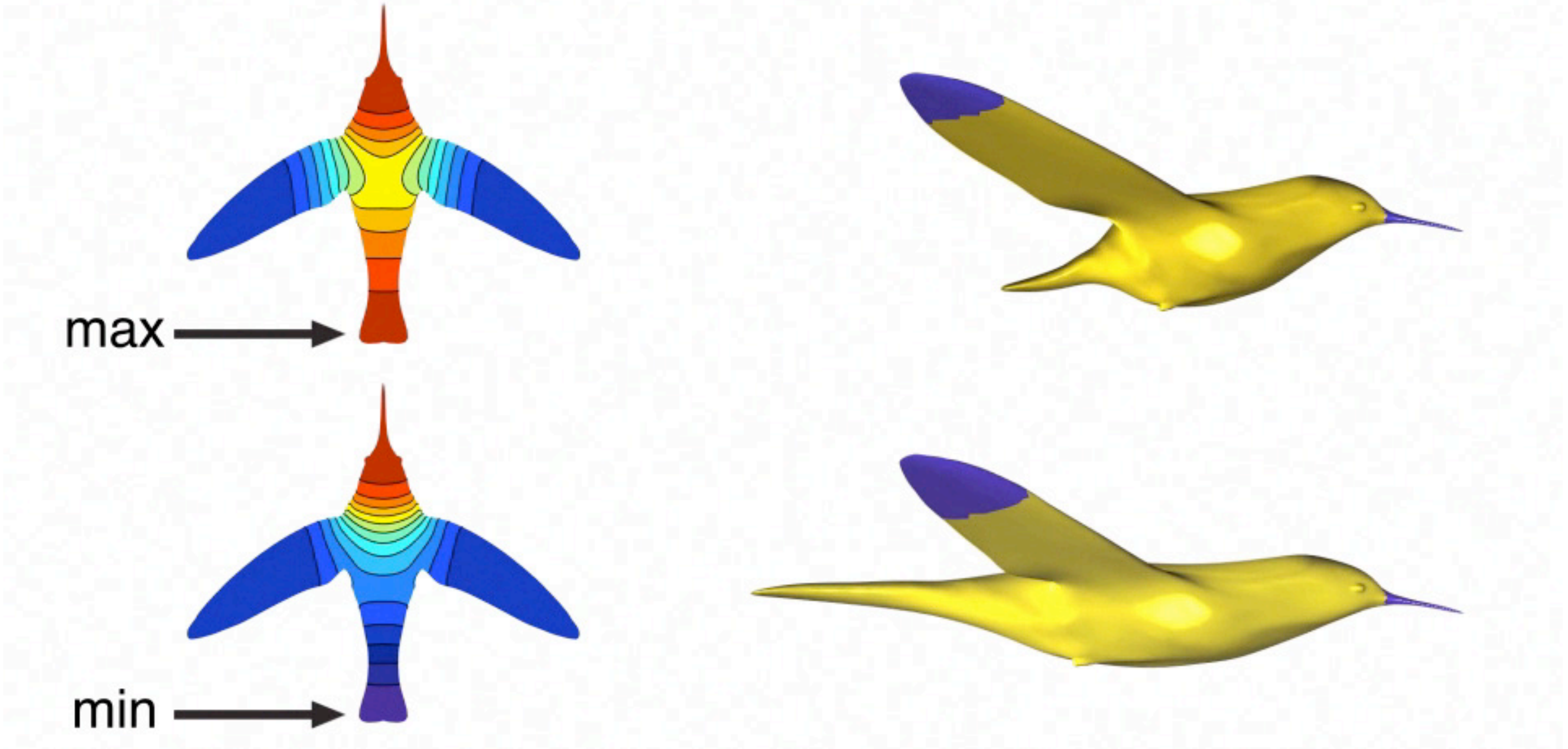

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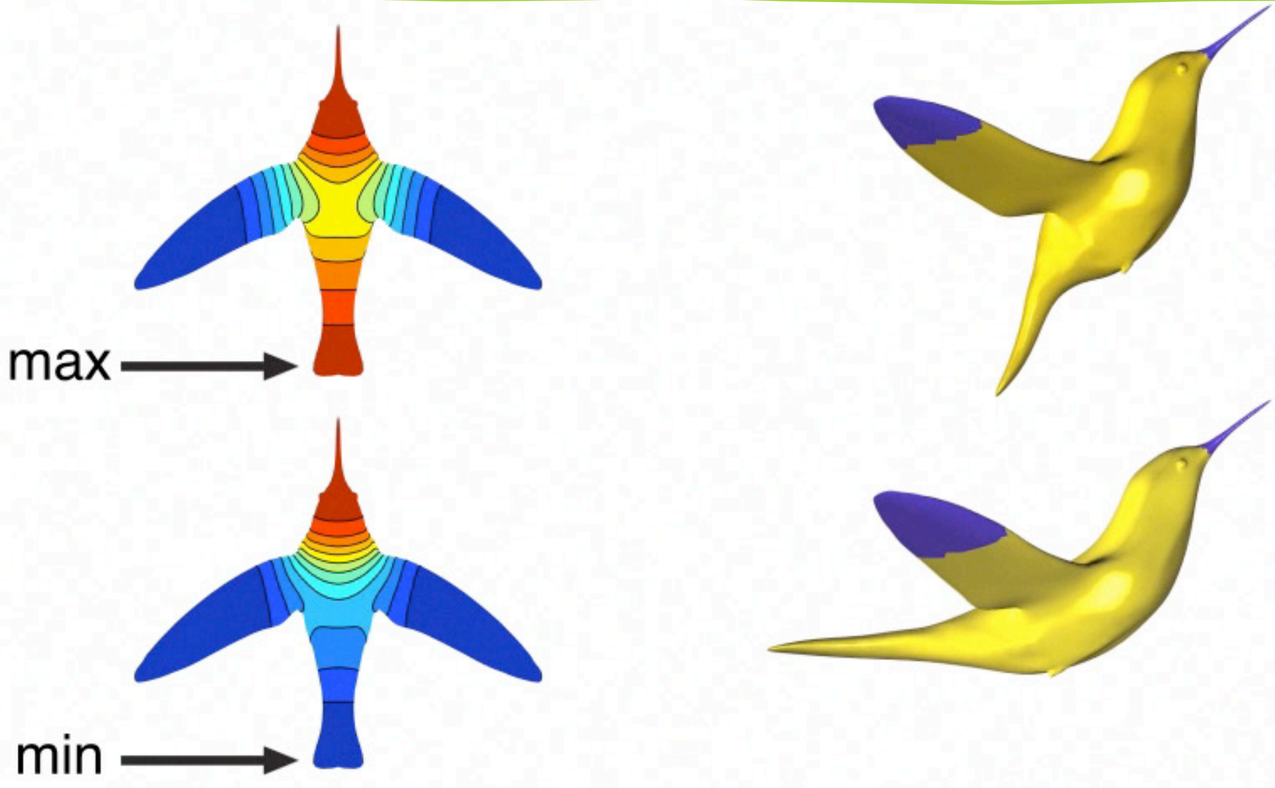

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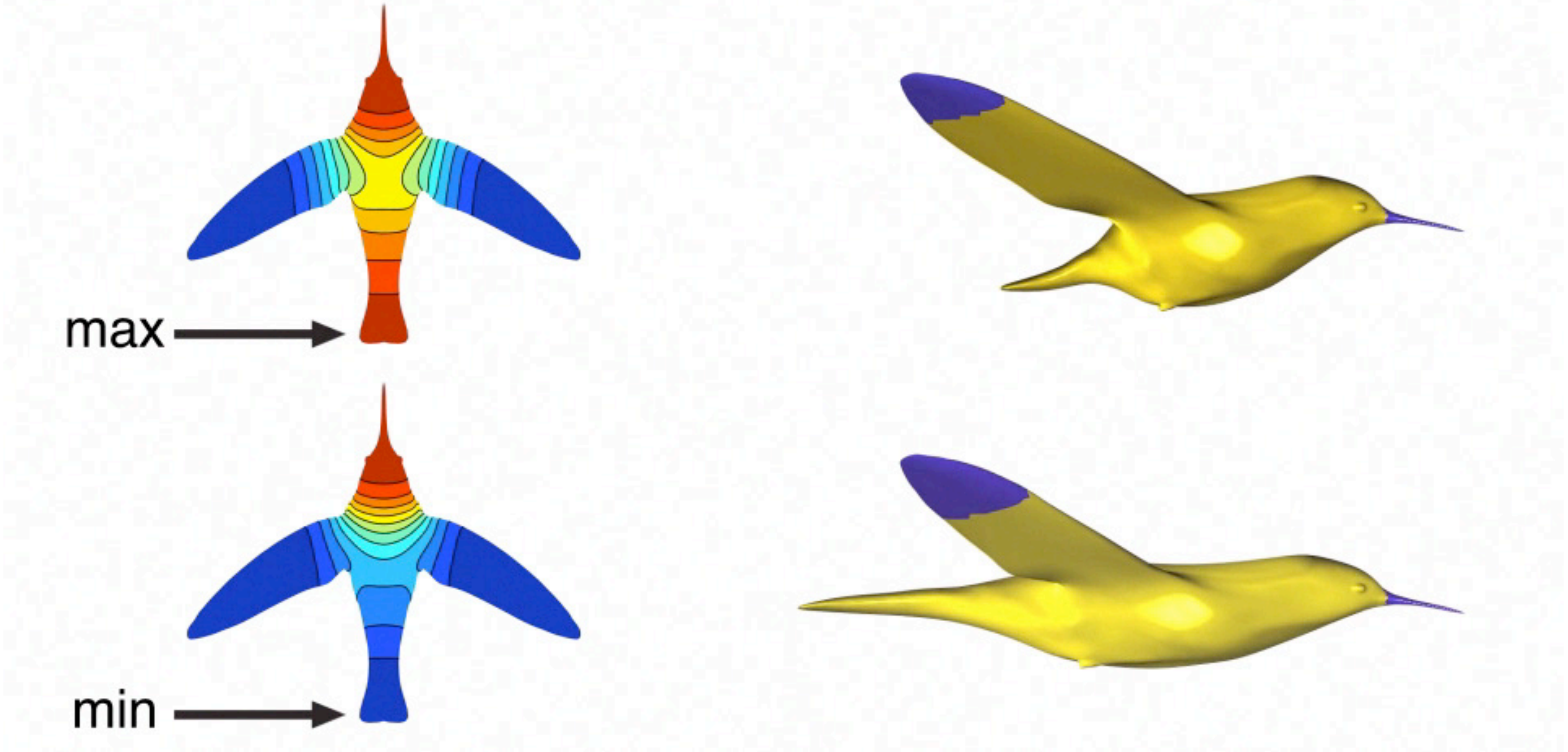
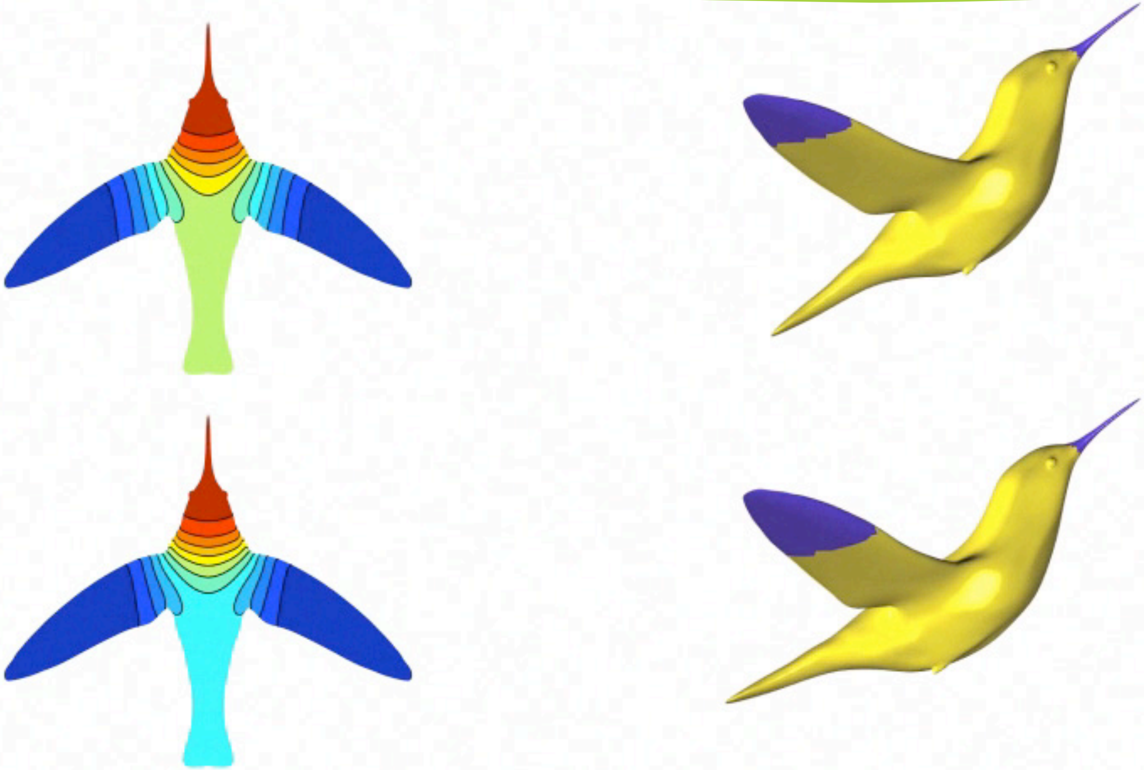


Bounded Δ^3

Lack of extrema leads to more stability



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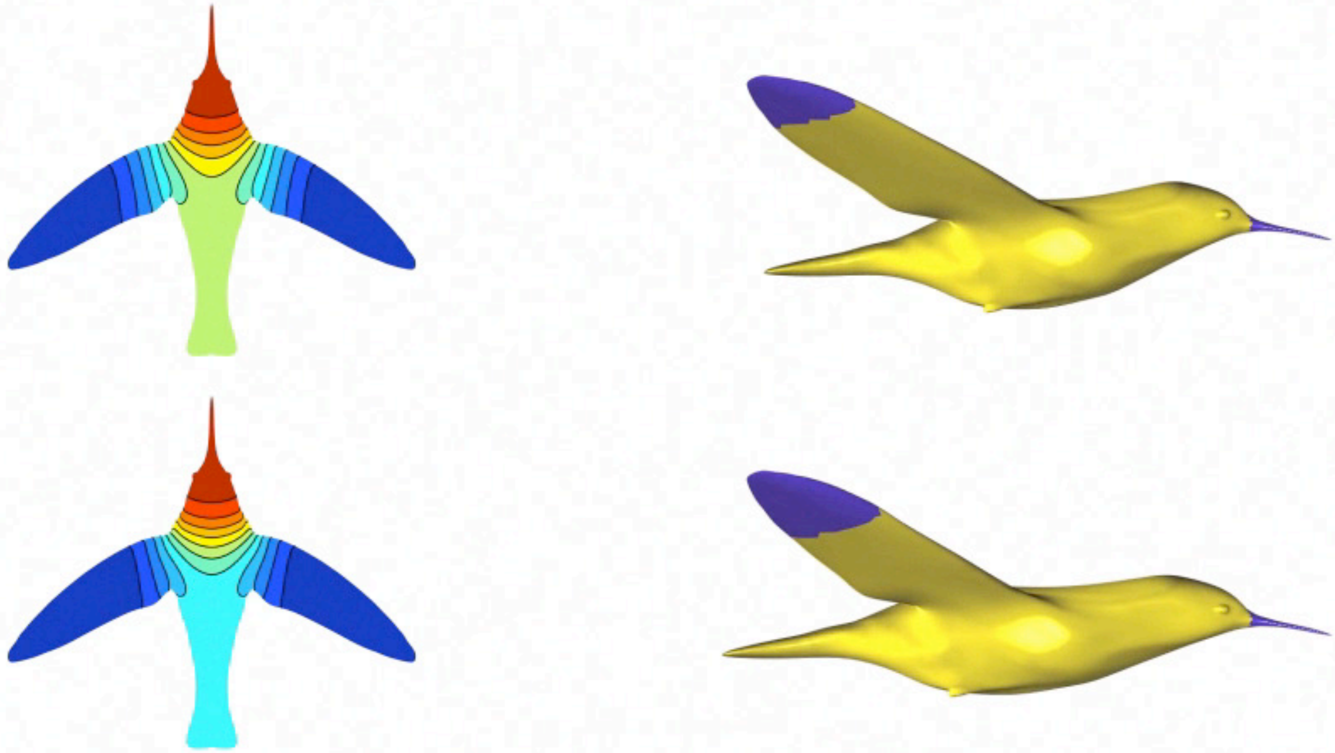
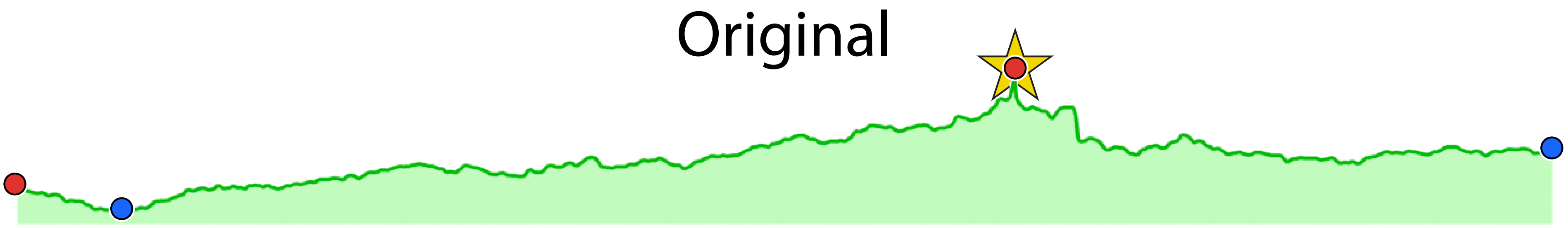


Our Δ^3

Even control continuity at extrema



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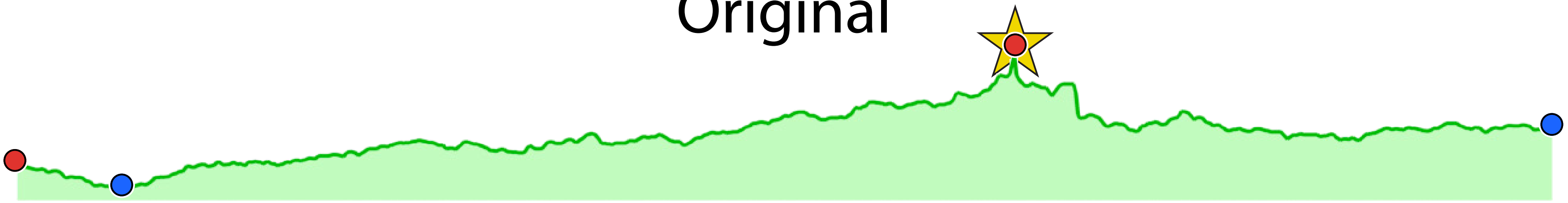
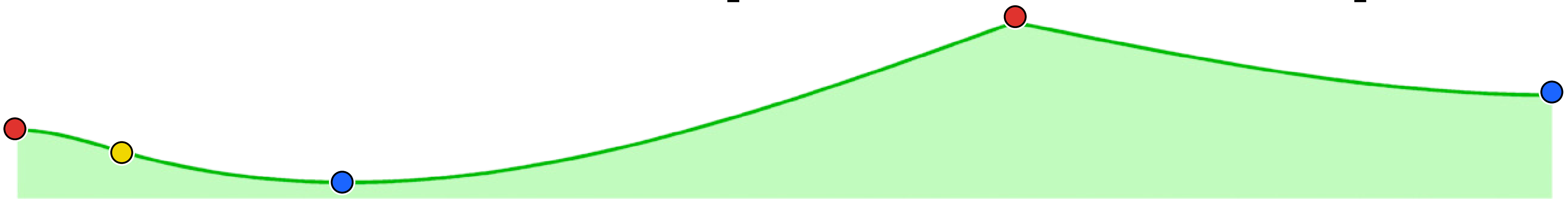
Original



Direct extension of [Botsch & Kobbelt 2004]



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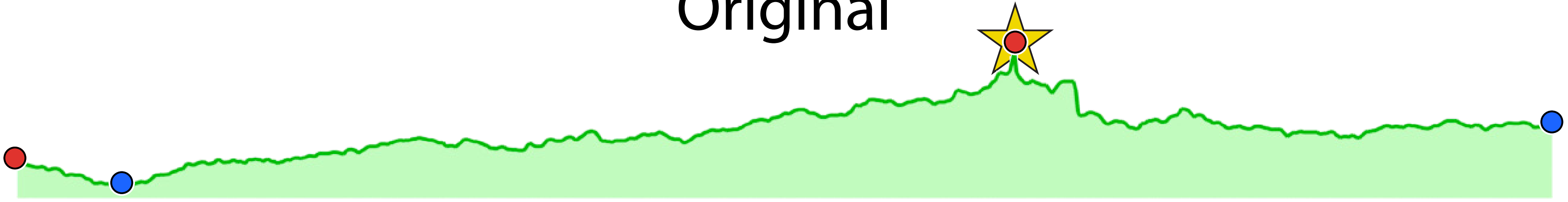

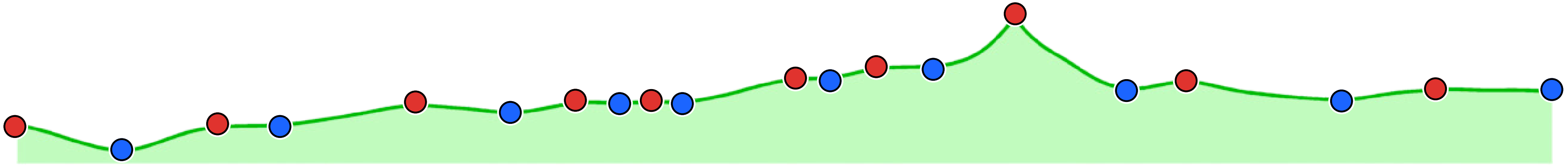

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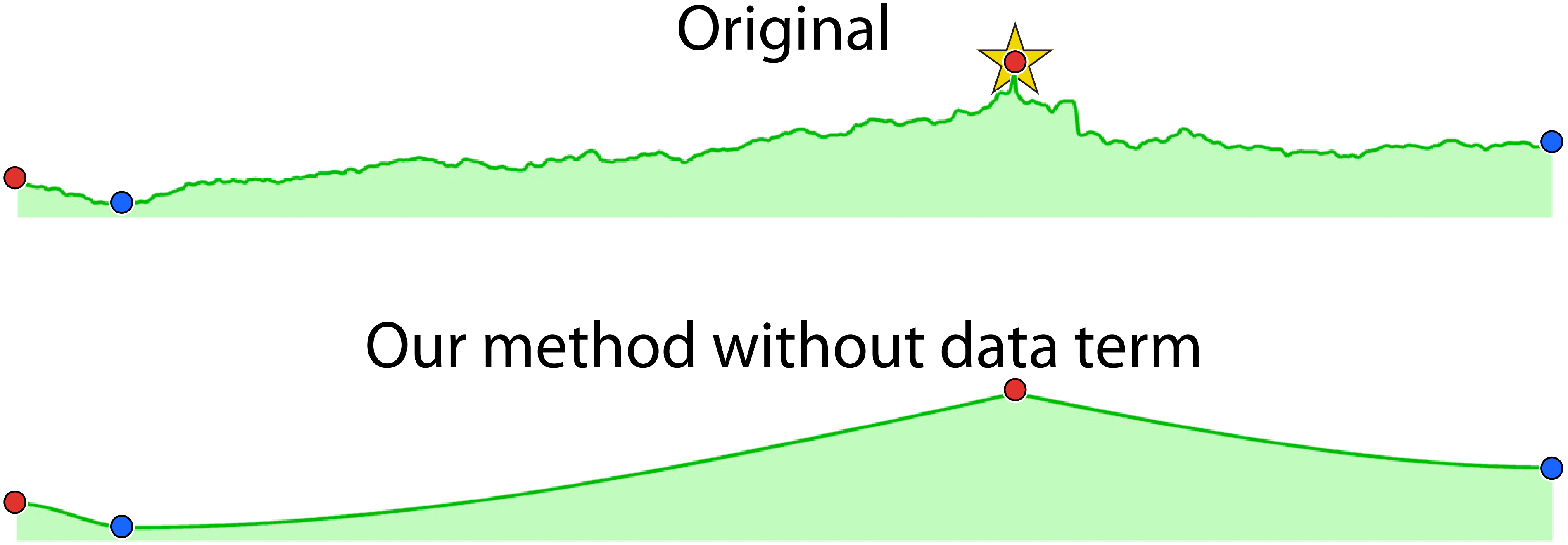

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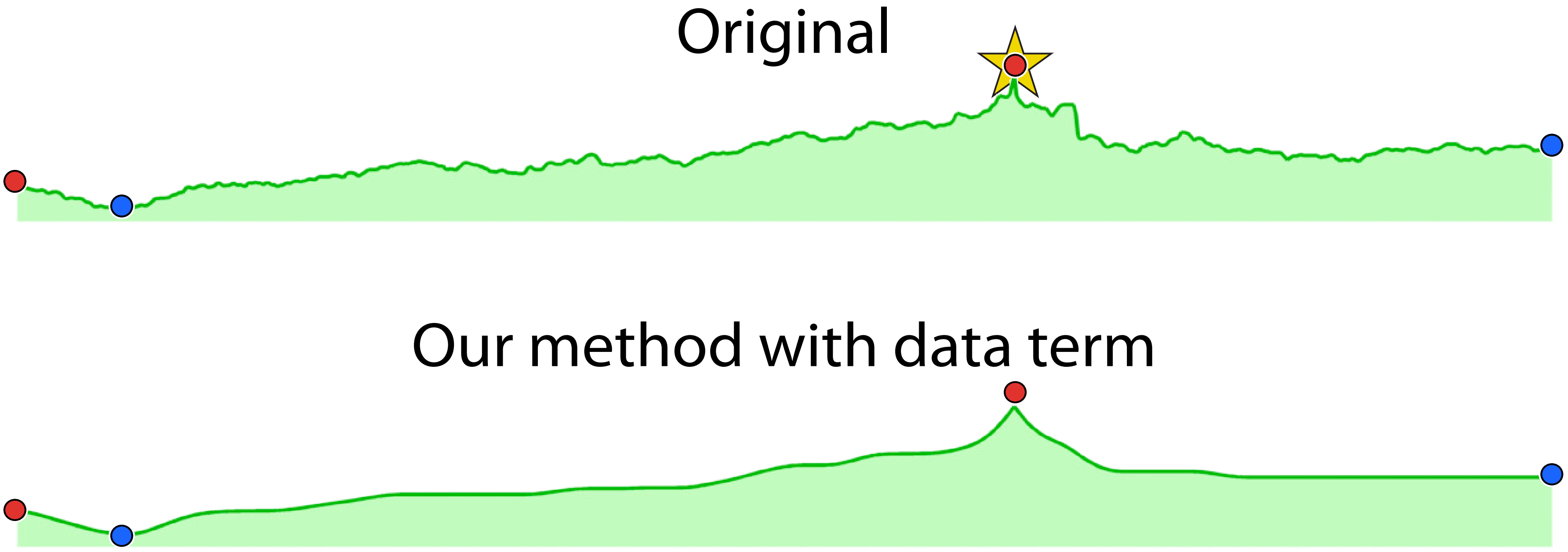
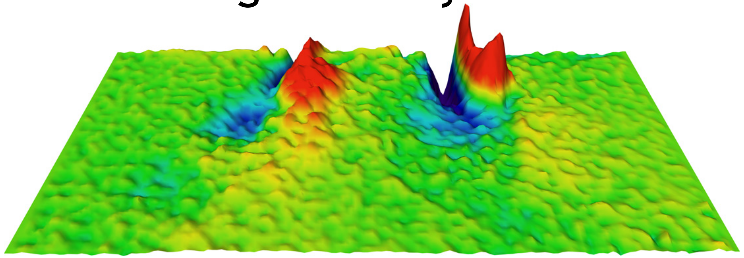


Reproduces results of Weinkauf et al. 2010…

Original noisy data



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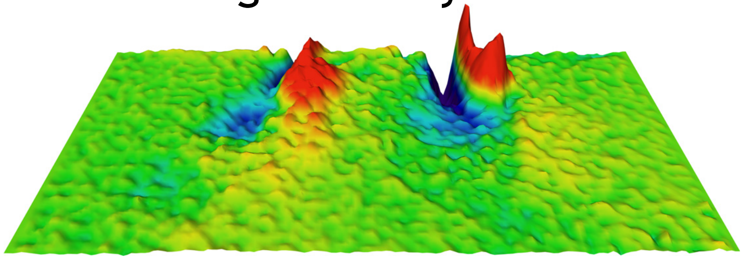

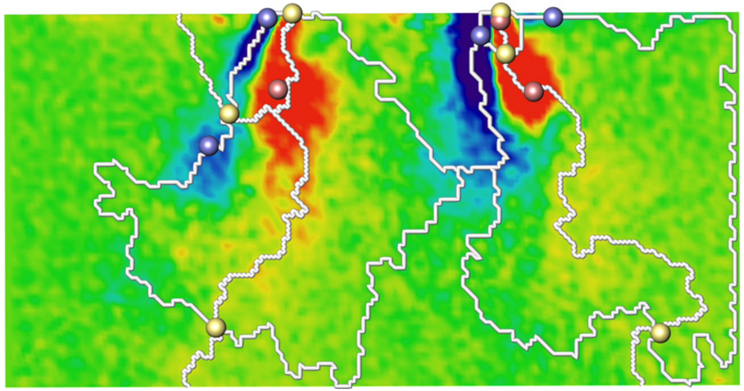

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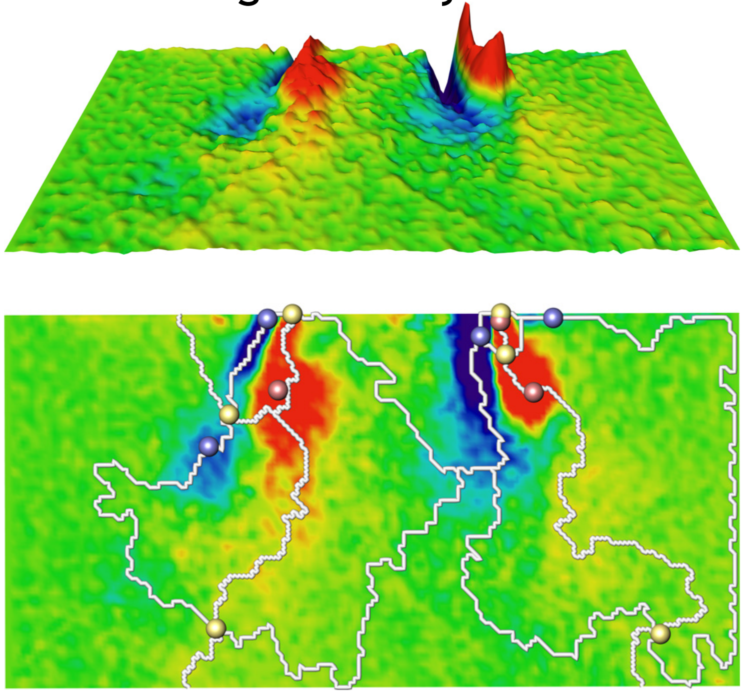
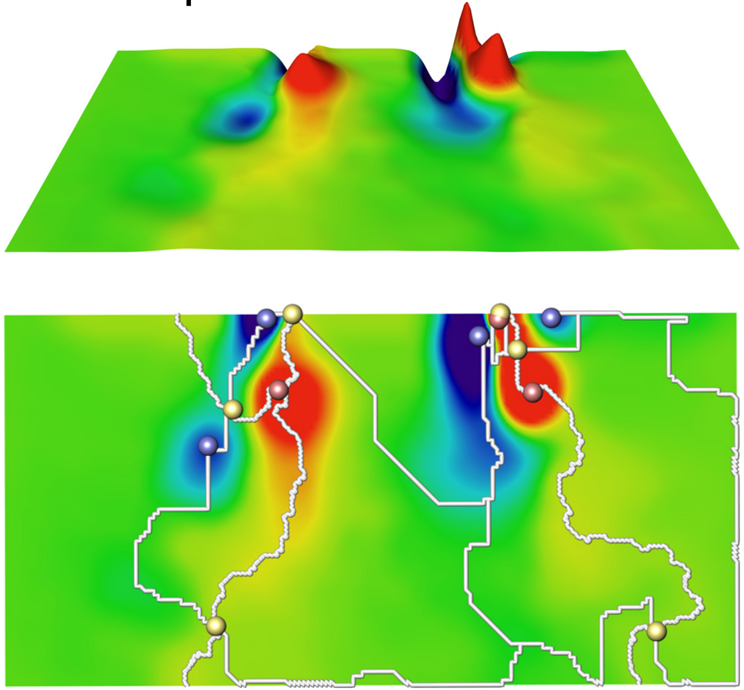


Simplified and smoothed



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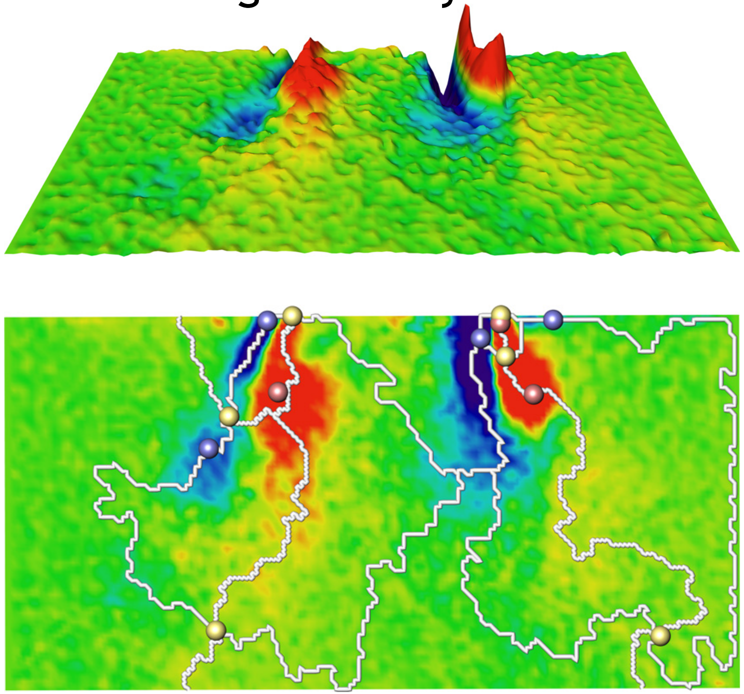

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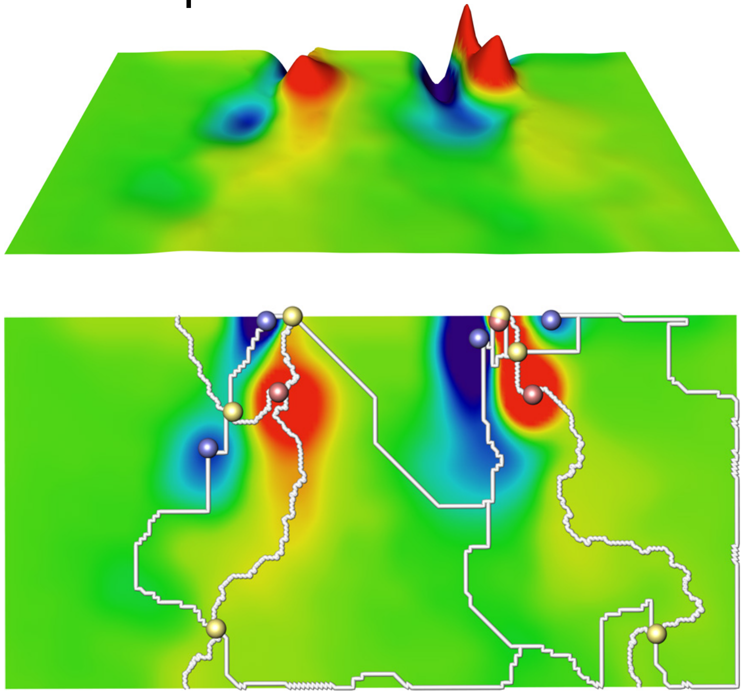
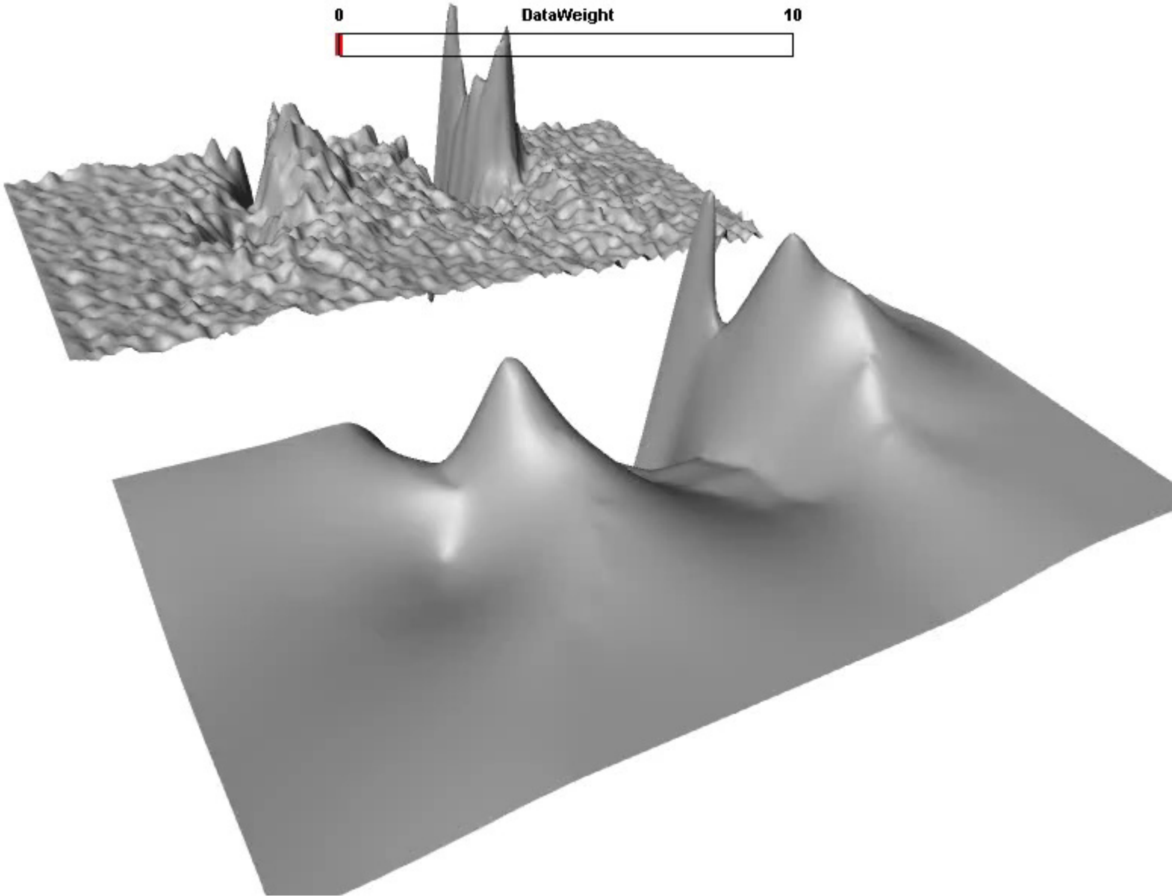


… but 1000 times faster

30K vertices
5 seconds per solve



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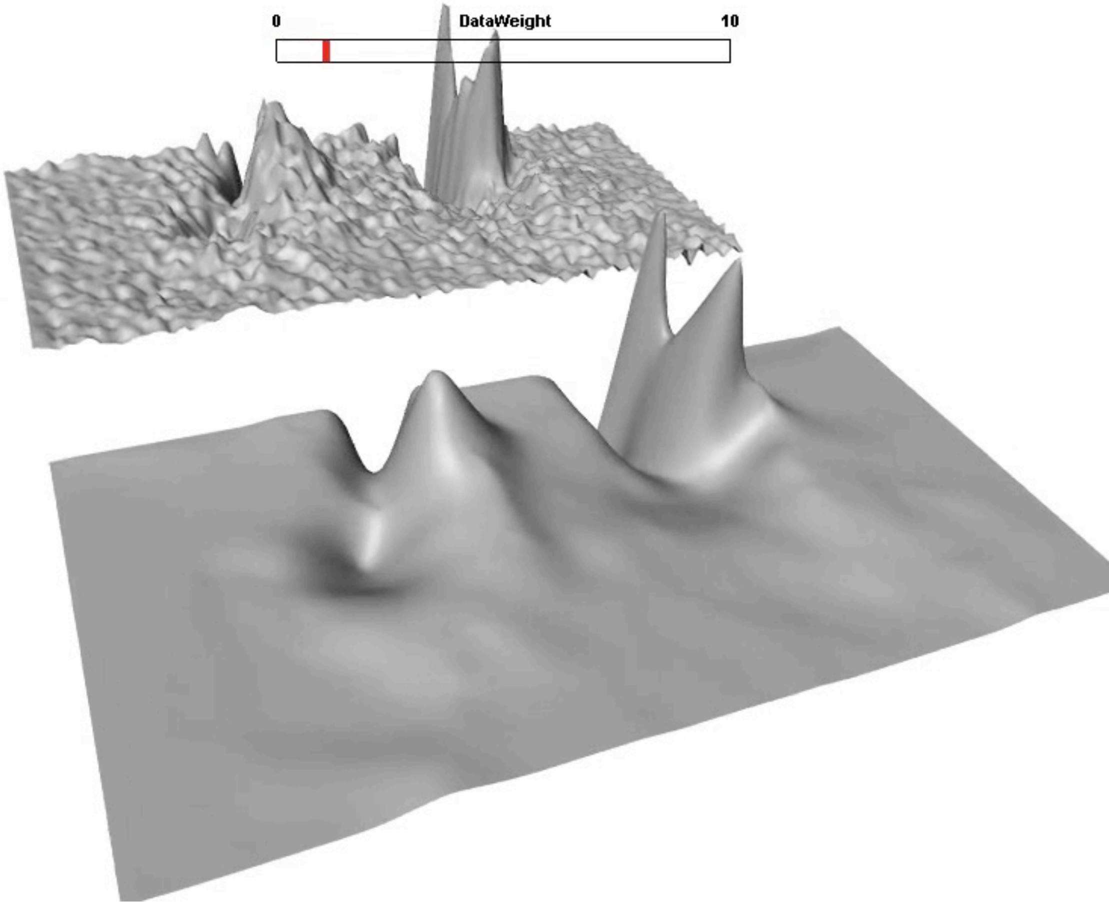

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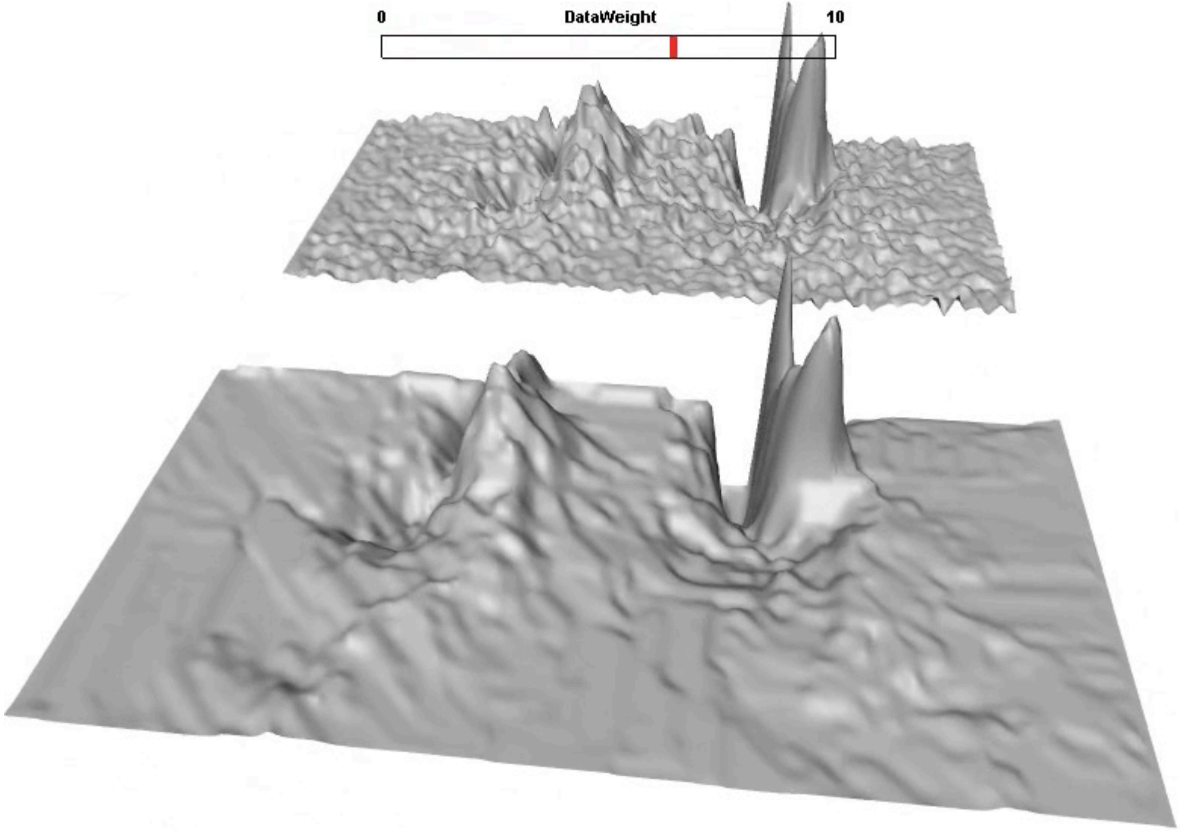

Conclusion: Important to control extrema

- Copy “monotonicity” of harmonic functions
- *Reduces* search-space, but optimization is tractable

Future work and discussion

- Larger, but still tractable subspace?
  - Consider all valid harmonic functions?

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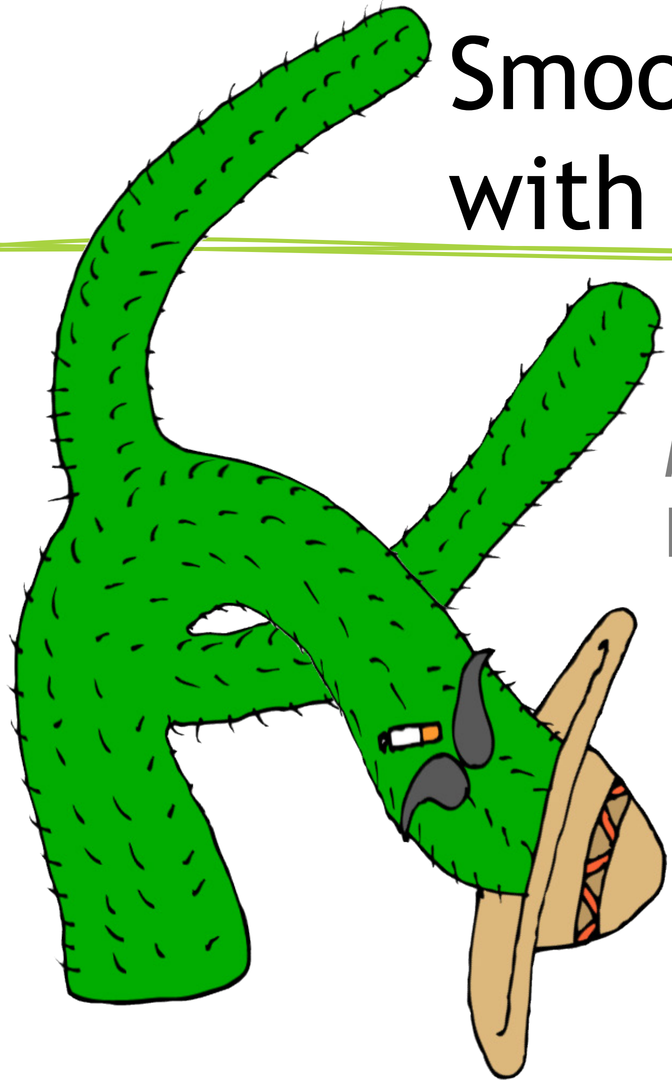
  - Consider all valid harmonic functions?
- Continuous formulation?

Acknowledgements

We thank Kenshi Takayama for his valuable feedback. This work was supported in part by an SNF award 200021_137879 and by a gift from Adobe Systems.

Smooth Shape-Aware Functions with Controlled Extrema



MATLAB Demo:
http://igl.ethz.ch/projects/monotonic/

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Tino Weinkauf
Olga Sorkine