

Efficient Guidance of Underpowered Vehicles in Time-Varying Flow Fields

Blane Rhoads

Ph.D. Defense

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Motivation: underwater gliders

Pro: range, duration, stealth

Con: 0.9-1.4 kph

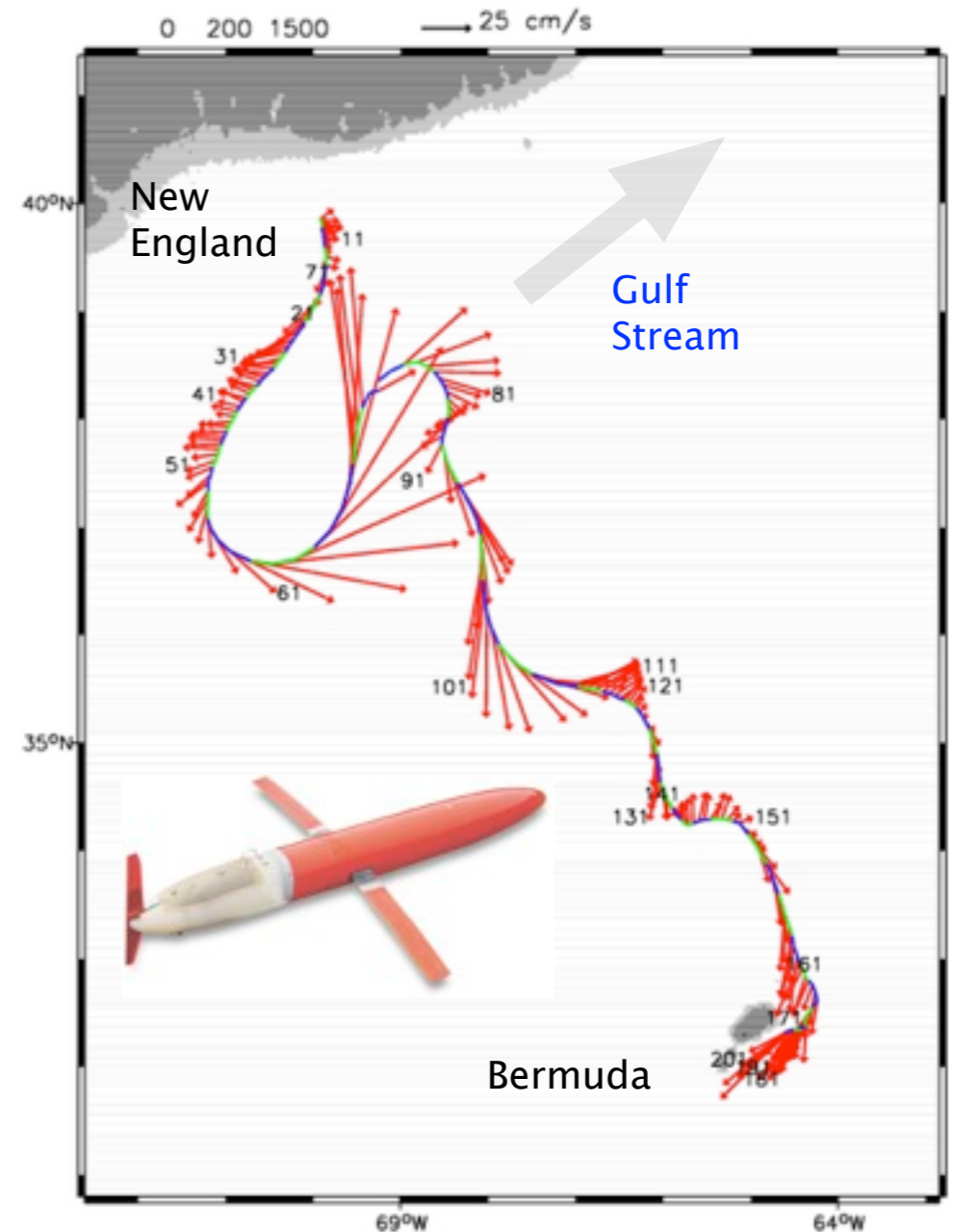
$$\dot{\mathbf{x}} = \mathbf{v}(\mathbf{x}, t) + \mathbf{u}$$

2D, time-
varying flow
field

Velocity relative
to flow

“... a methodology to exploit available estimates of the flow field is of significant interest.”

[Leonard, et al. 2007]



Actual 50-day trajectory (blue) and currents (red) [spray.ucsd.edu]

Overview

- Minimum time
 - Forward Lagrangian
 - Backward Lagrangian (briefly)
- Minimum energy
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 - Alternate perspective on minimum energy control
 - Simple greedy control

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Minimum time control

$$\min_{t_f, \mathbf{u}} \int_{t_0}^{t_f} (1) dt \quad \text{subject to:}$$

$$\dot{\mathbf{x}} = \mathbf{v}(\mathbf{x}, t) + \mathbf{u}$$

2D, time-
varying flow
field

Velocity relative
to flow

$$\mathbf{x}(t_0) = \mathbf{x}_0$$

$$\mathbf{x}(t_f) = \mathbf{x}_f$$

$$t_f \in [t_0, t_0 + T_{\max}]$$

$$|\mathbf{u}| \leq s$$

Time-to-go T solves Hamilton Jacobi Bellman (HJB) PDE:

$$\frac{\partial T}{\partial t} + \min_{\mathbf{u}} \{ (\mathbf{v} + \mathbf{u}) \cdot \nabla T + 1 \} = 0 \quad T(\mathbf{x}_f, t) = 0$$

Feedback control law:
$$\mathbf{u} = -s \frac{\nabla T}{|\nabla T|}$$

Why is this problem difficult?

- Time-dependence in \mathbf{v}
... a third dimension
- Spatial complexity in \mathbf{v}
... many locally optimal trajectories
... “**shocks**”
= discontinuities in ∇T and thus in \mathbf{u}
(or “*cusps*” in T).
- $|\mathbf{v}| > s$ (i.e. flow is “strong” or vehicle is “underpowered”)
... lack of local *controllability/reachability*
... “**discontinuities**”
= discontinuities in T itself.

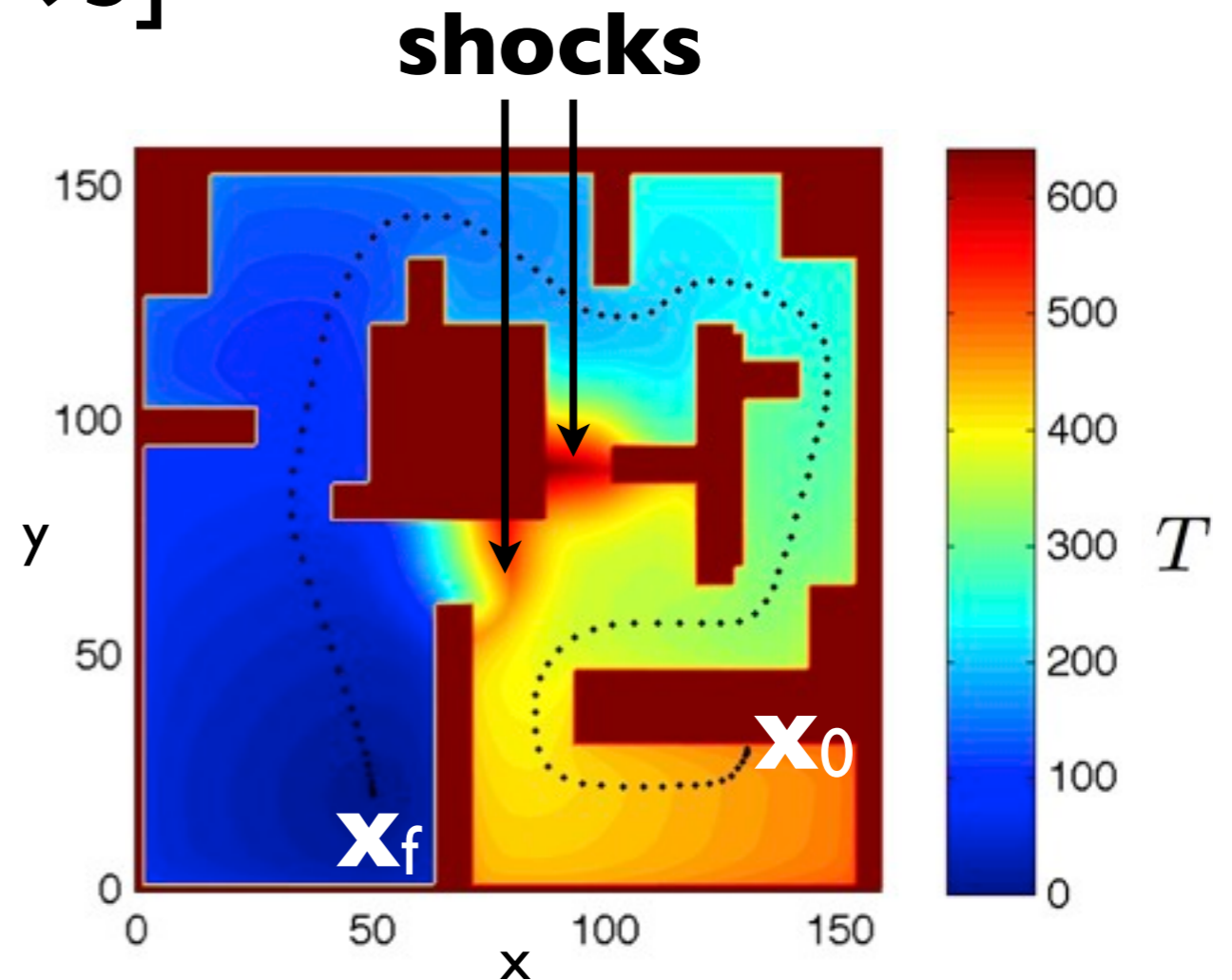
Benchmark for $\mathbf{v}(\mathbf{x},t) = 0$:
 Fast Marching (FM) method
 [Sethian '96, Tsitsiklis '95]

HJB = Eikonal:

$$s |\nabla T| = 1$$

Boundary
 condition:

$$T(\mathbf{x}_f) = 0$$



Front tracking method. Computes T
 one grid point at a time, in order.

Benchmark for $\mathbf{v}(\mathbf{x},t) = \mathbf{v}(\mathbf{x})$: Ordered Upwind Methods (OUMs) [Sethian & Vladmirsky '01]

Generalization of FM method to
 “anisotropic” (direction-dependent) front speeds.

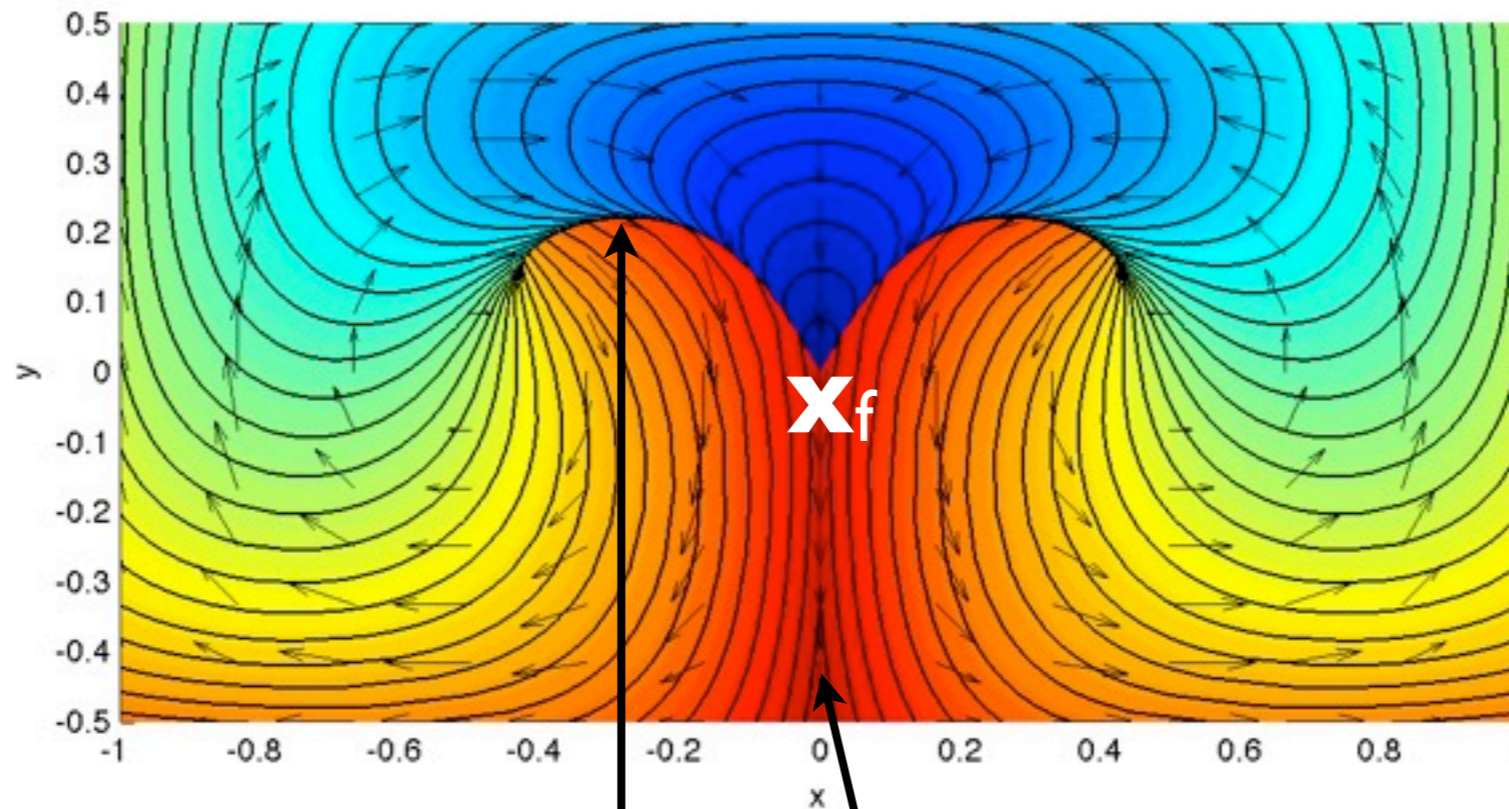
HJB:

$$\underbrace{\left(s - \mathbf{v}(\mathbf{x}) \cdot \frac{\nabla T}{|\nabla T|} \right)}_{\text{speed of front}} |\nabla T| = 1$$

speed of front

Limitation: Can't handle $|\mathbf{v}| > s$.

Alternative (for $|\mathbf{v}| > s$): Lagrangian (“marker particle”) front tracking method



[Rhoads, et al (2010)]

discontinuity

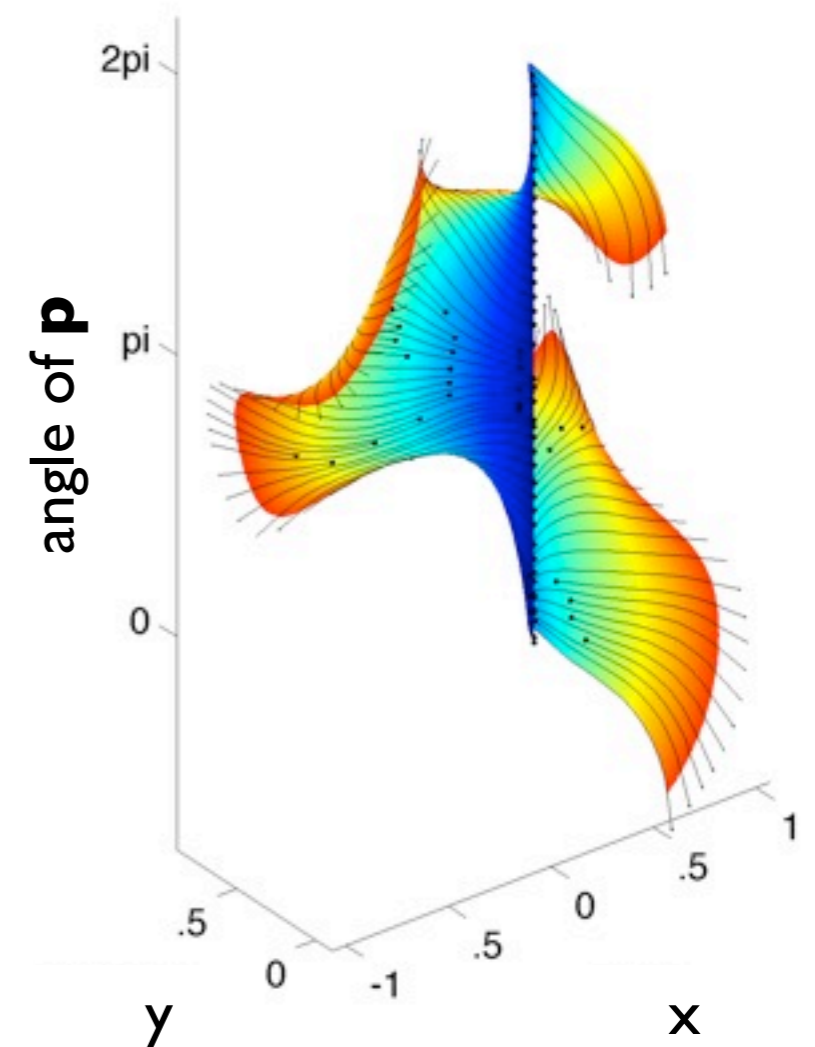
shock

(which happens to
coincide with separatrix)

Key to Lagrangian method: track state \mathbf{x}
and costate \mathbf{p} (vector normal to front)

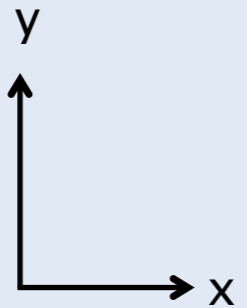
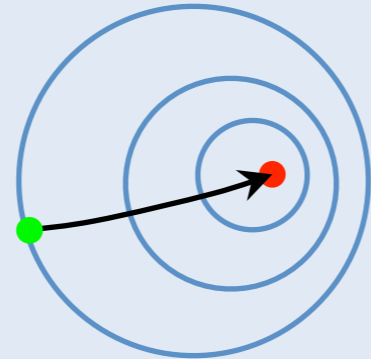
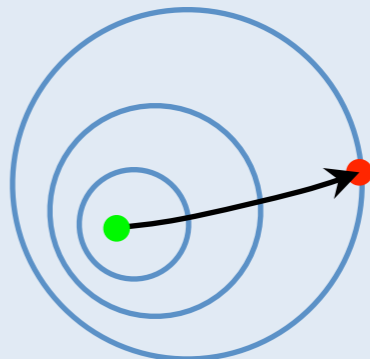
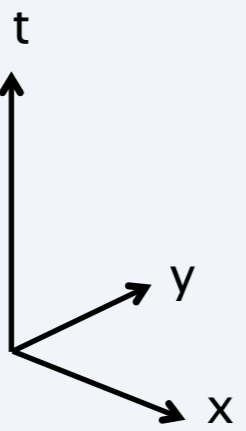
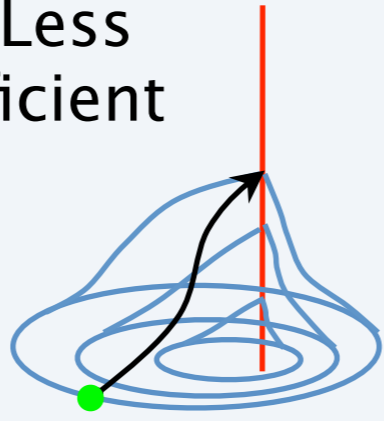
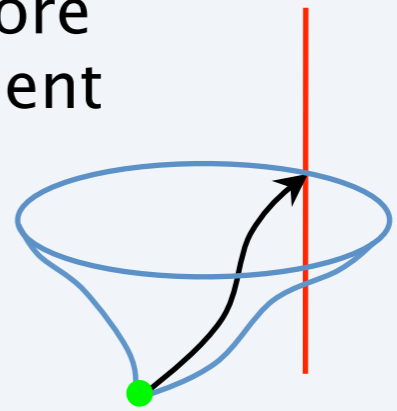
$$\dot{\mathbf{p}} = -\nabla \mathbf{v}^T \mathbf{p}$$

Special property of minimum
time control: It's sufficient to
track the *angle* of \mathbf{p} .

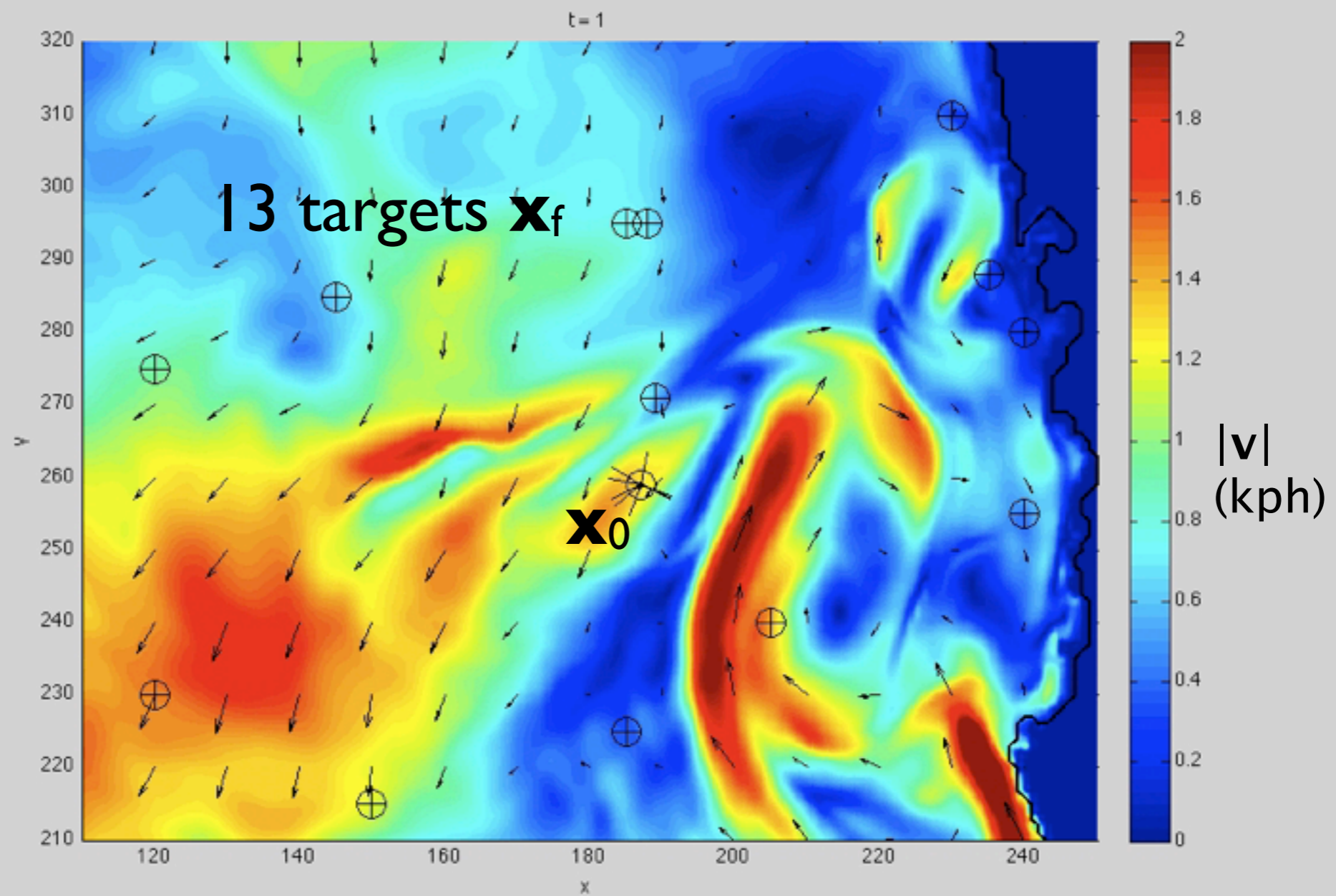


See also [Nishida, et al (2007)], [Holzhuter (2004)], [Osinga, Hauser (2006)],
[Mahoney, et al (2012)], [Mitchell, Mahoney (2012)]

Extends to forward &/or time-varying cases

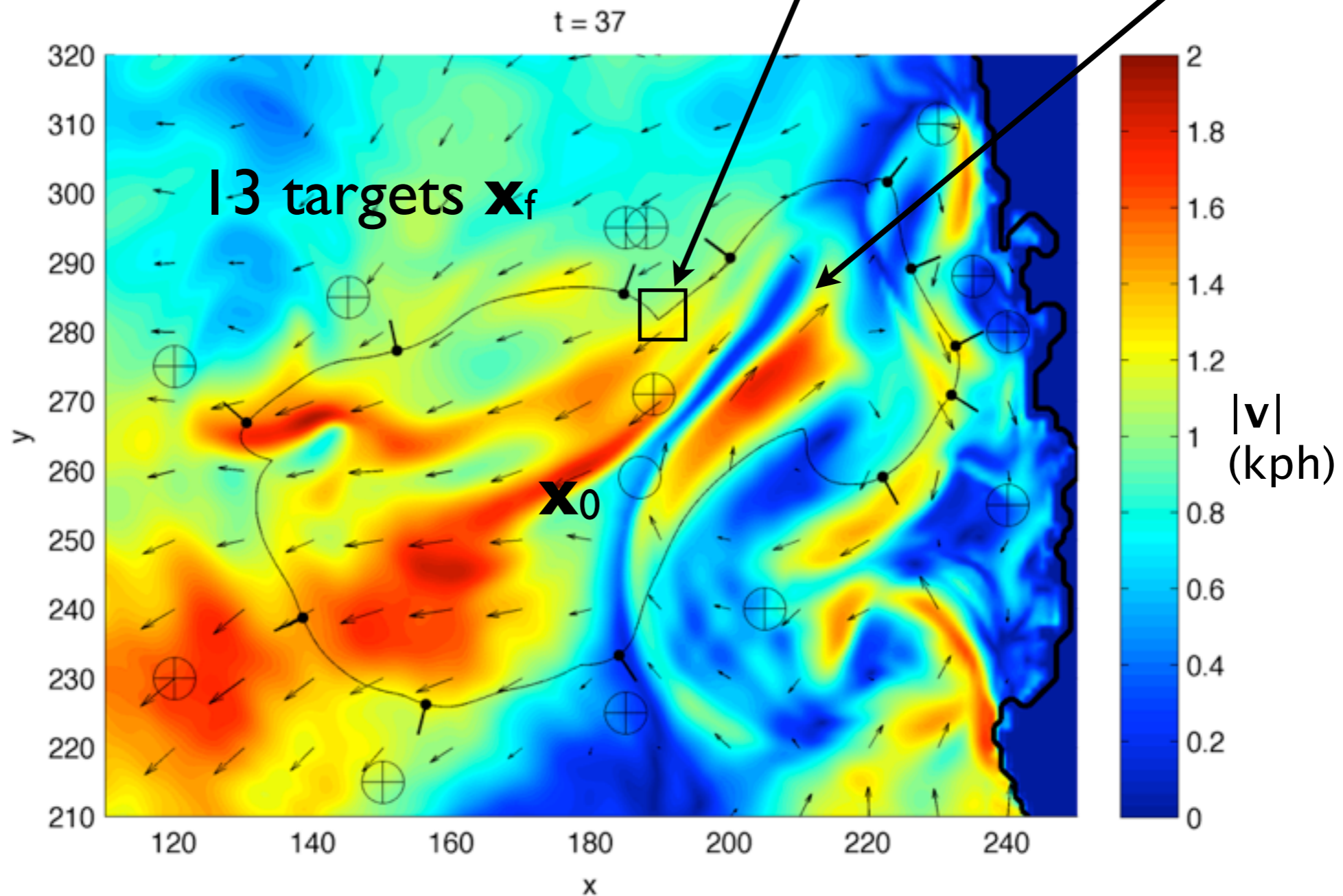
legend: \mathbf{x}_0 ● \mathbf{x}_f ●	backward: “controllability” feedback, but...	forward: “reachability” no feedback, but...
time-invariant case; $\mathbf{v}(\mathbf{x},t) = \mathbf{v}(\mathbf{x})$ 		
time-varying case 	... Less efficient  [Rhoads, et al (2010)]	... More efficient  [Rhoads, et al (2013)]

Ex: Adriatic Sea ($s = 0.9$ kph, $T_{\max} = 54$ h)



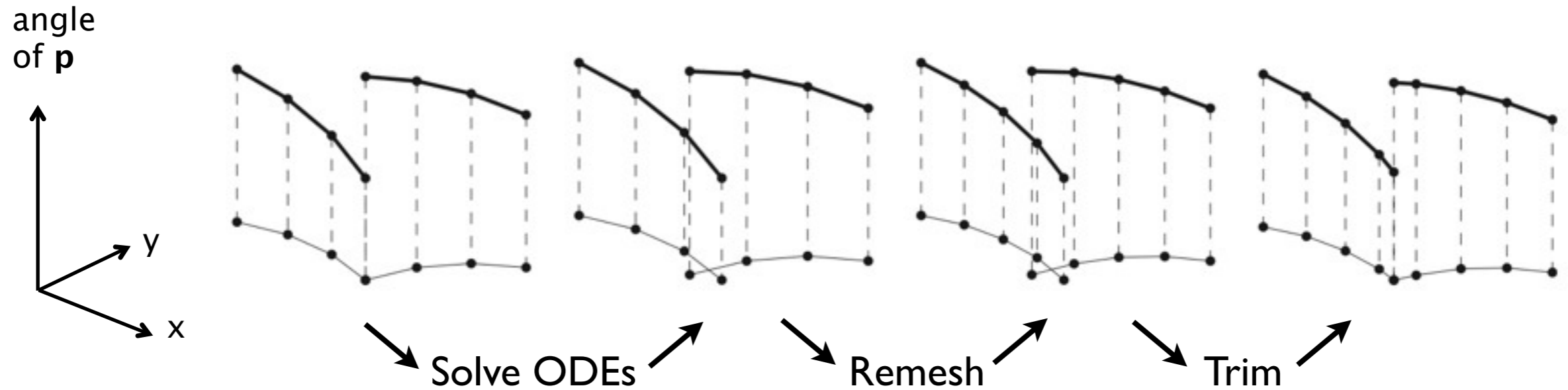
Movie of “reachability” front [Rhoads, et. al, 2013]

Two key challenges: *shocks* (cusps) and *stretching*



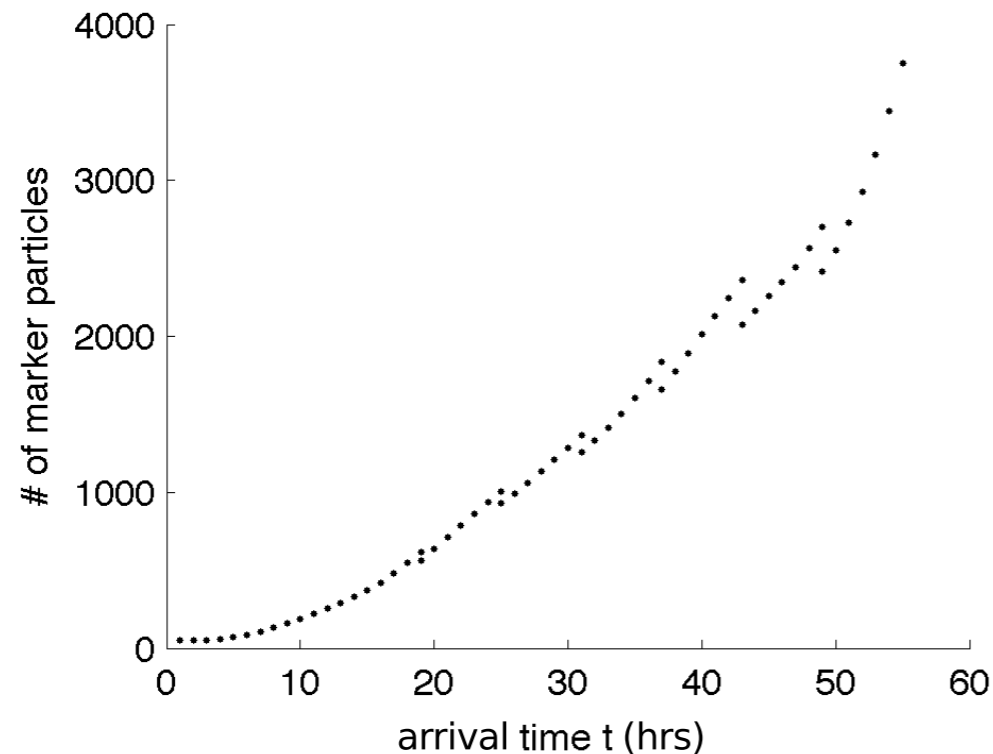
Snapshot of "reachability" front [Rhoads, et. al, 2013]

Two key ingredients: *trimming* and *remeshing*

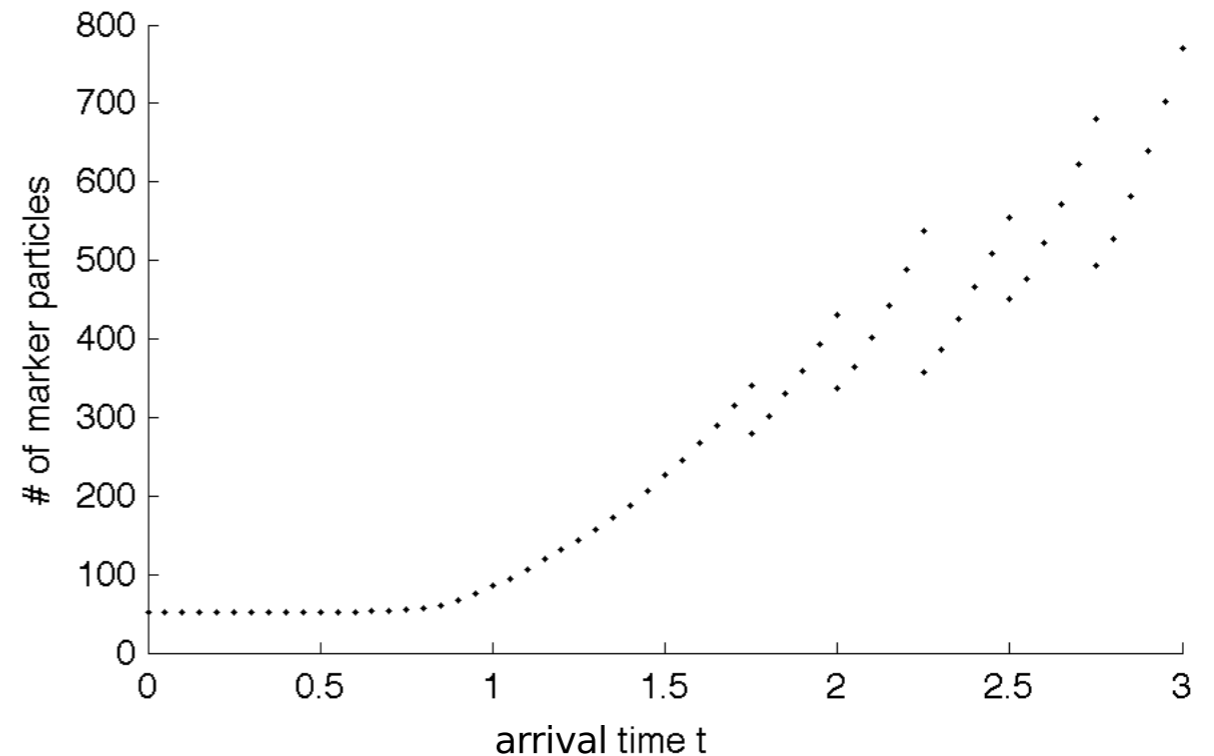


Eulerian alternative: Level Set Methods
[Lolla et al ('12)] (same application)

Trimming increases algorithmic complexity but decreases computational complexity.



Present example (Adriatic)

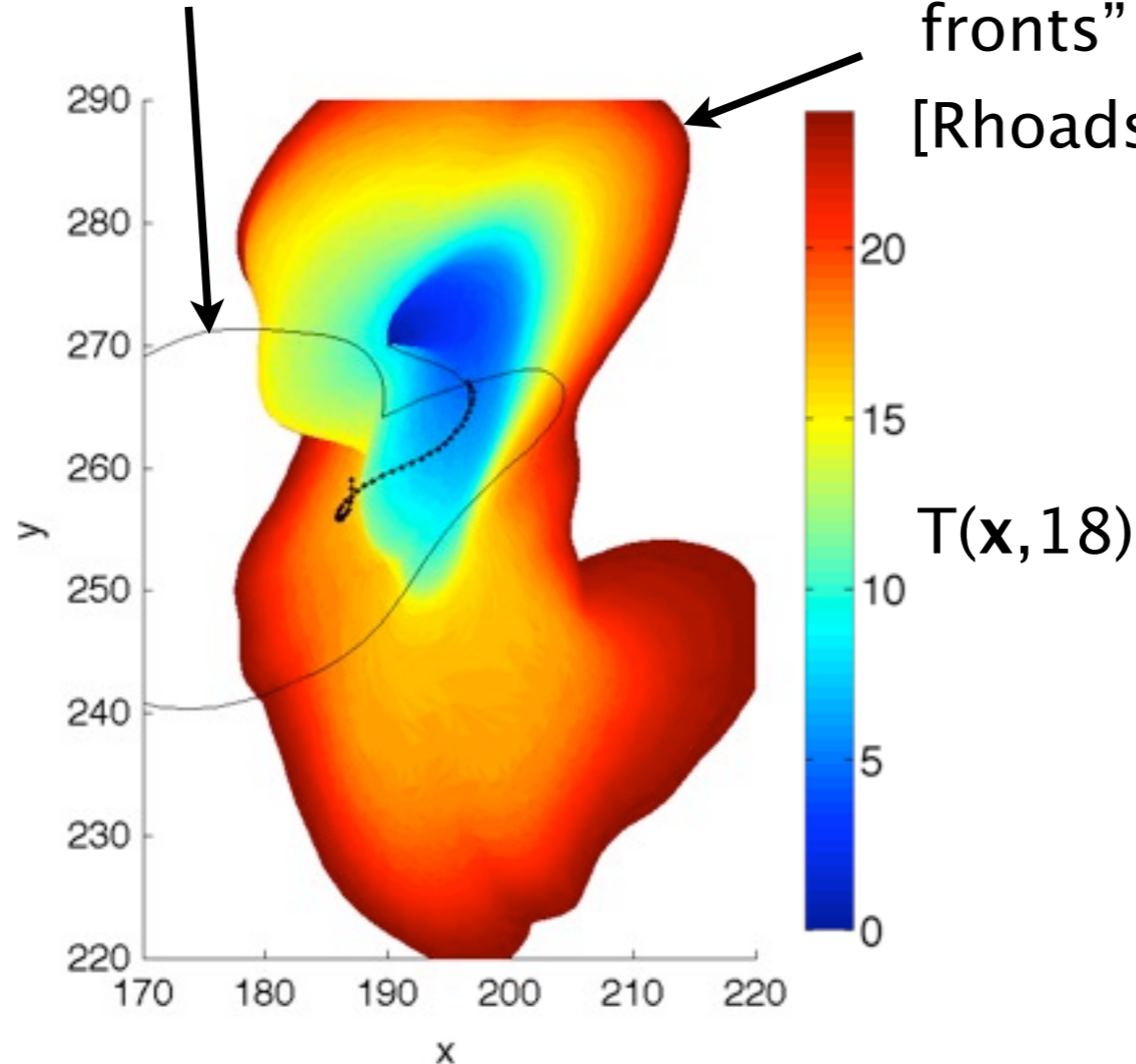


Another example (time-invariant gyre flow). Growth effectively linear instead of exponential.

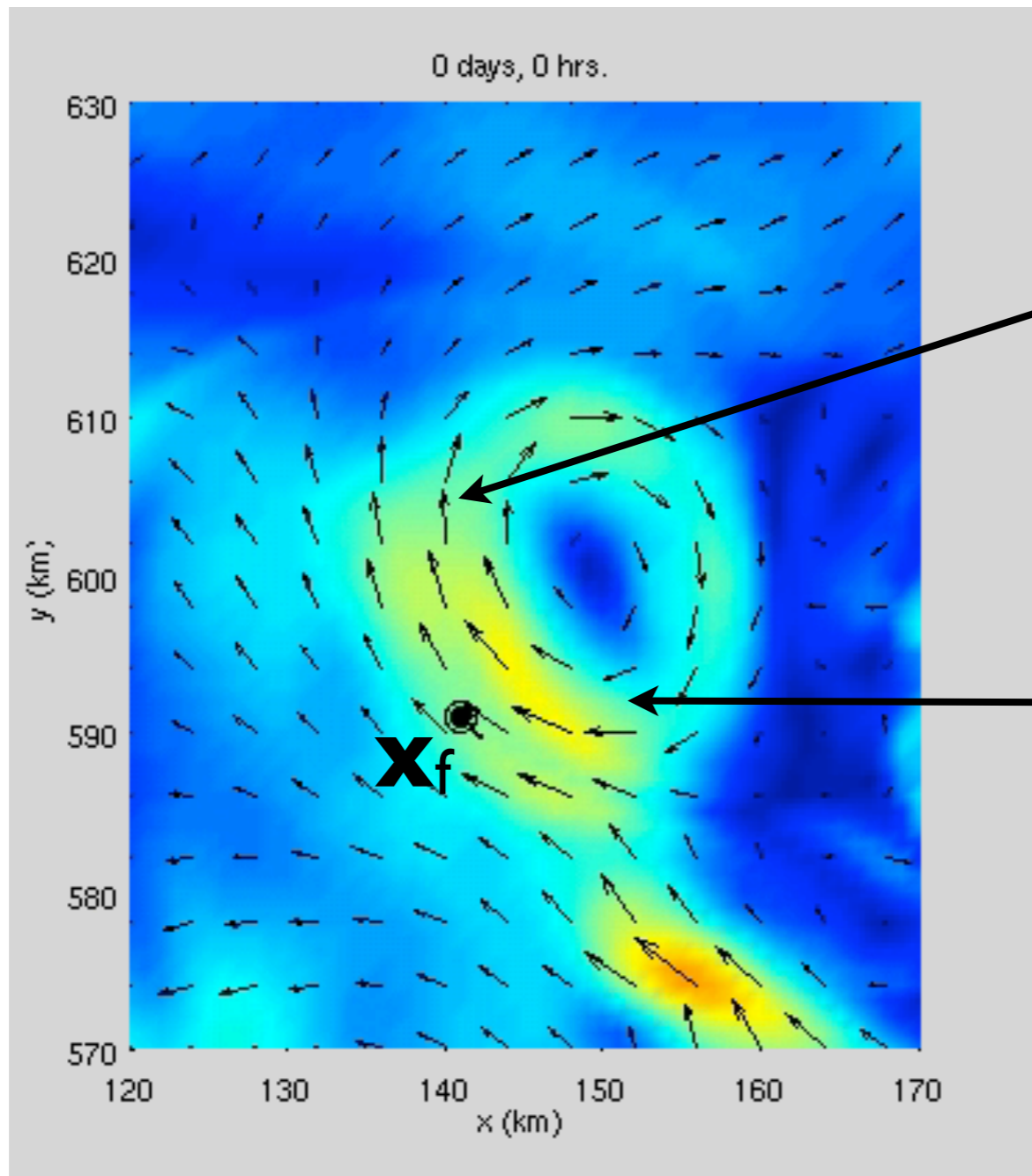
Forward method yields same trajectory as backward method.. but much more efficiently

“reachability front”
at time $t = 18$ h
[Rhoads, et al (2013)]

continuum of
“controllability
fronts” ($T_{\max} = 24$ h)
[Rhoads, et al (2010)]



Application: “approximate station keeping”



Naive strategy
fights currents.

Min time
strategy
“dodges”
currents (but
still never rests)

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Minimum energy problem

fixed t_f

no hard constraint on $\mathbf{x}(t_f)$

$$\min_{\mathbf{u}} \left\{ \overset{\text{end cost}}{\downarrow} h(\mathbf{x}(t_f)) + \overset{\text{weight on energy}}{\downarrow} \int_{t_0}^{t_f} W |\mathbf{u}|^2 dt \right\}$$

HJB: $\frac{\partial V}{\partial t} + \min_{\mathbf{u}} \{ (\mathbf{v} + \mathbf{u}) \cdot \nabla V + W |\mathbf{u}|^2 \} = 0$

$$\mathbf{u} = -\frac{\nabla V}{2W} \quad \left(\text{if } \frac{|\nabla V|}{2W} \leq s; \text{ otherwise } \mathbf{u} = -s \frac{\nabla V}{|\nabla V|} \right)$$

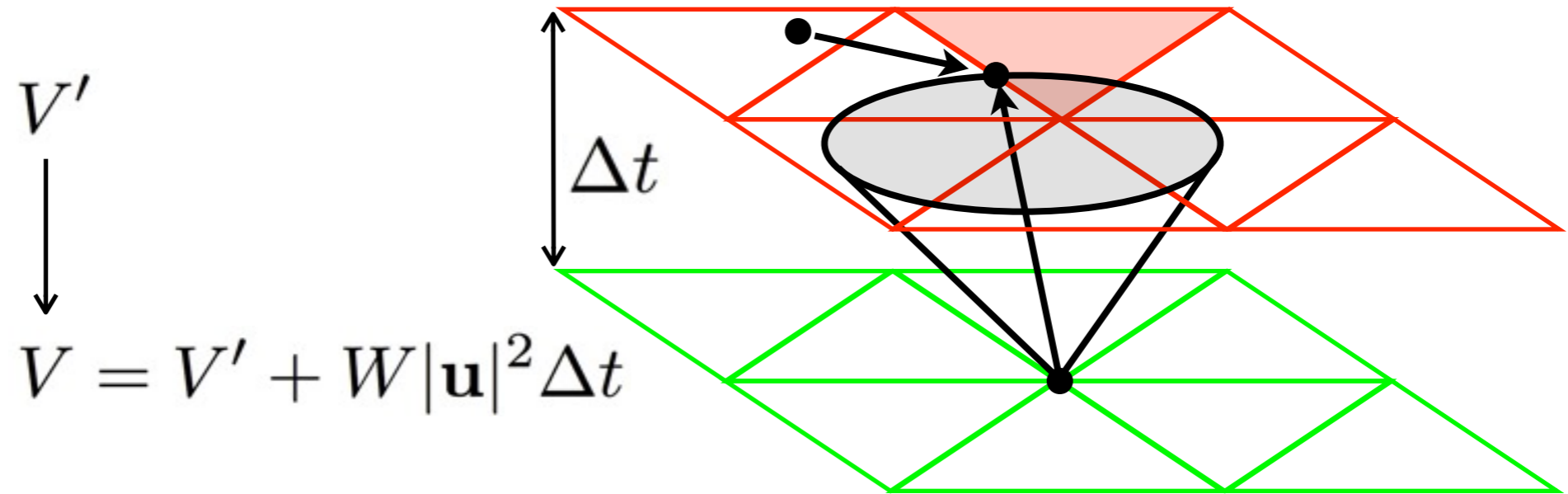
Boundary condition:

$$V(\mathbf{x}, t_f) = h(\mathbf{x})$$

Backward time-stepping

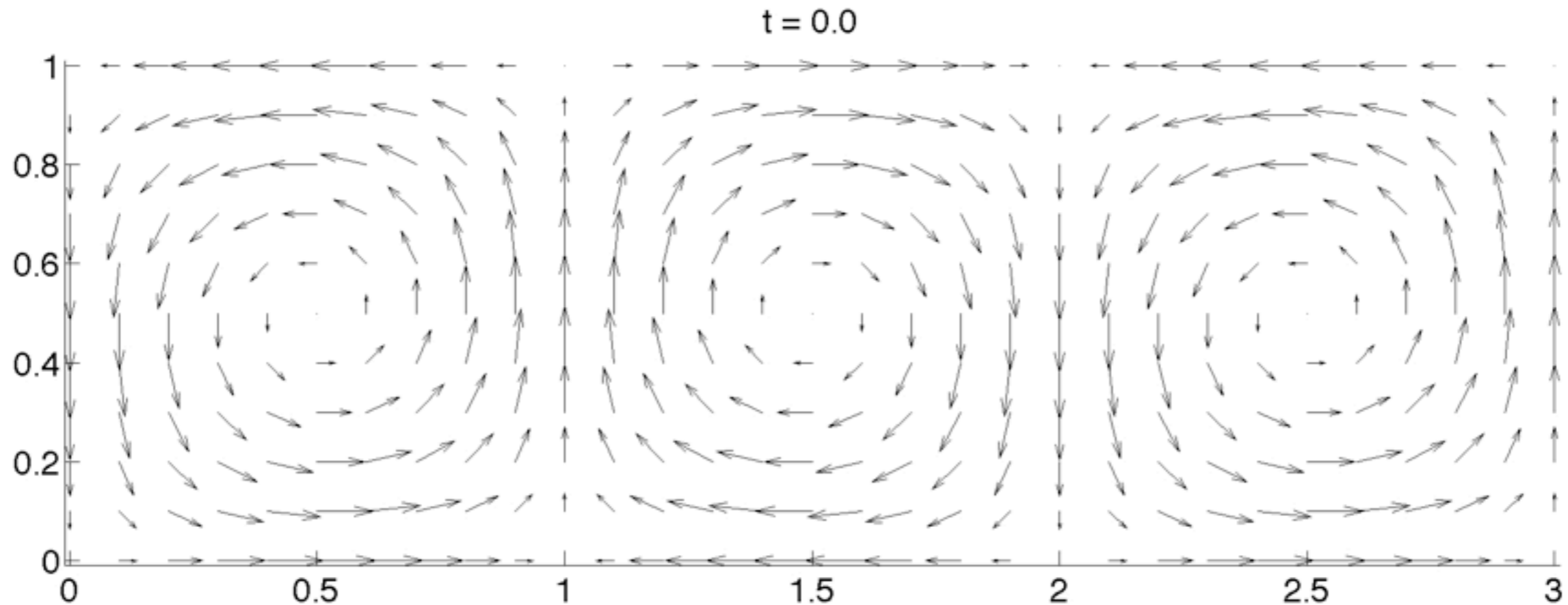
Semi-Lagrangian method

(first order.. exact pointwise minimization)

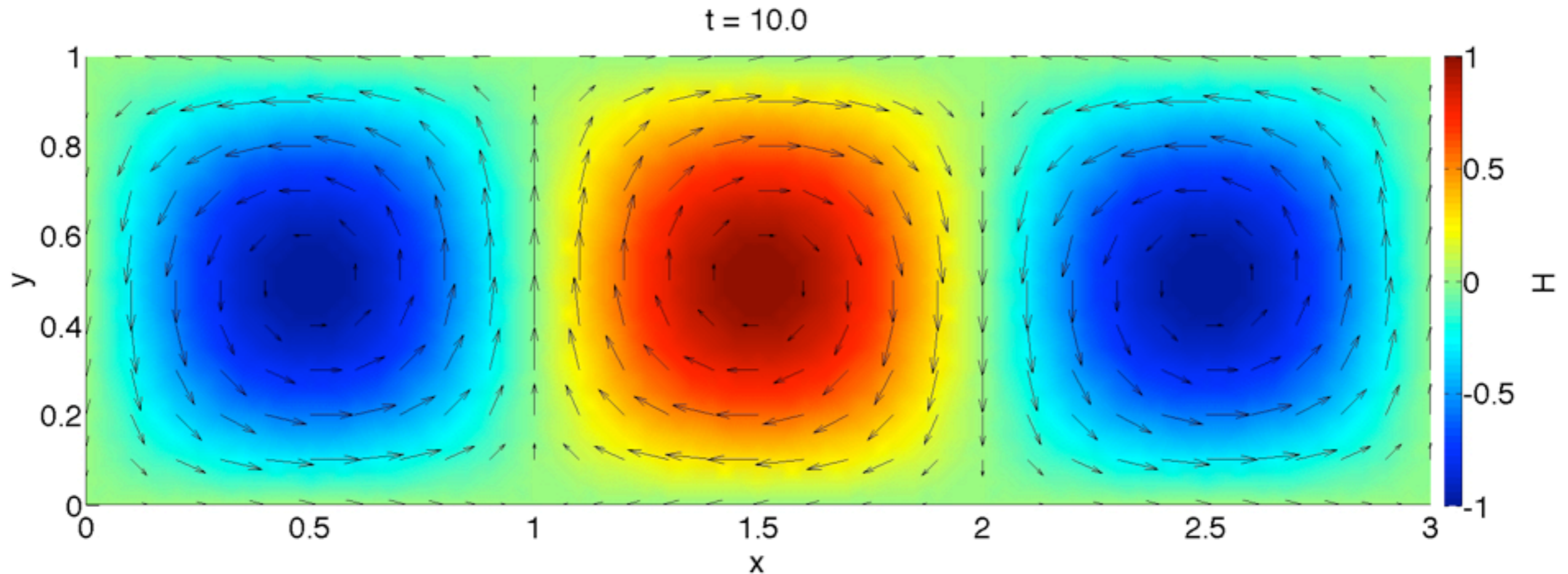


- for each time slice
 - for each grid point
 - for each reachable triangle
 - define V' by linear interpolation;
 - minimize V ;
 - update overall minimum;

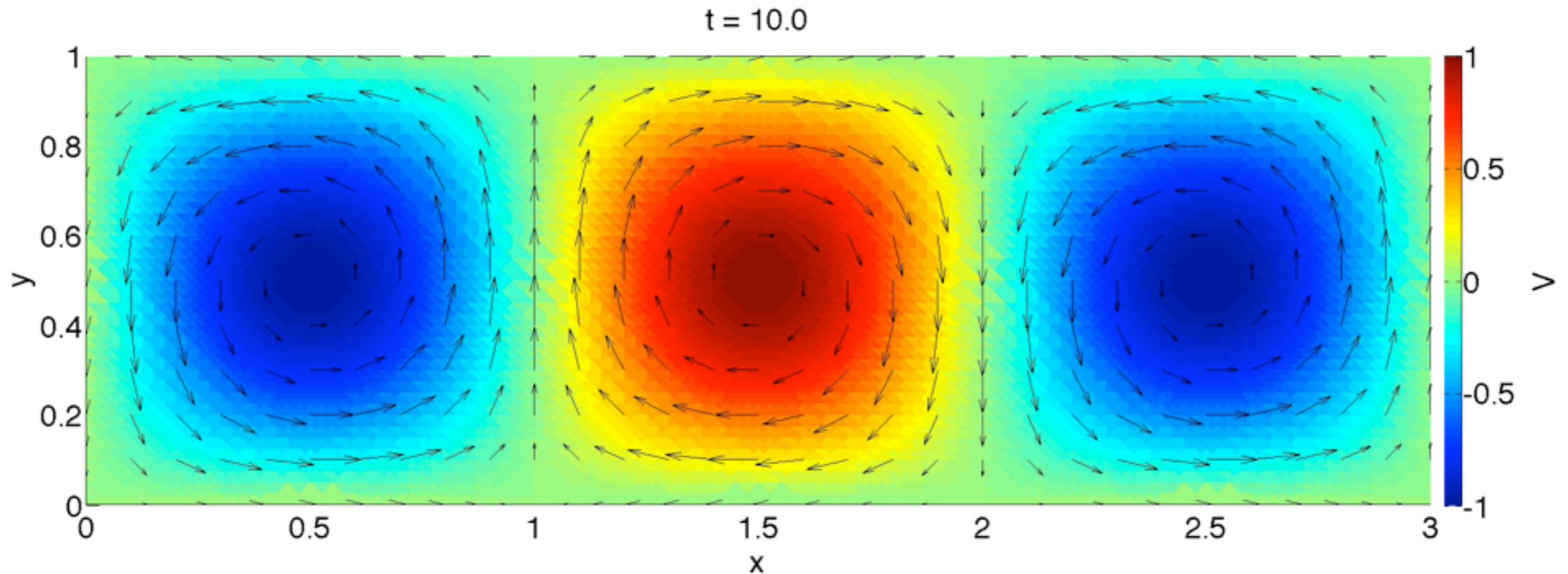
Ex: $\mathbf{v}(\mathbf{x},t)$ = time-varying 3-gyre flow



Effect over backwards time of $\mathbf{v}(\mathbf{x},t)$ on $h(\mathbf{x})$ (a double basin)

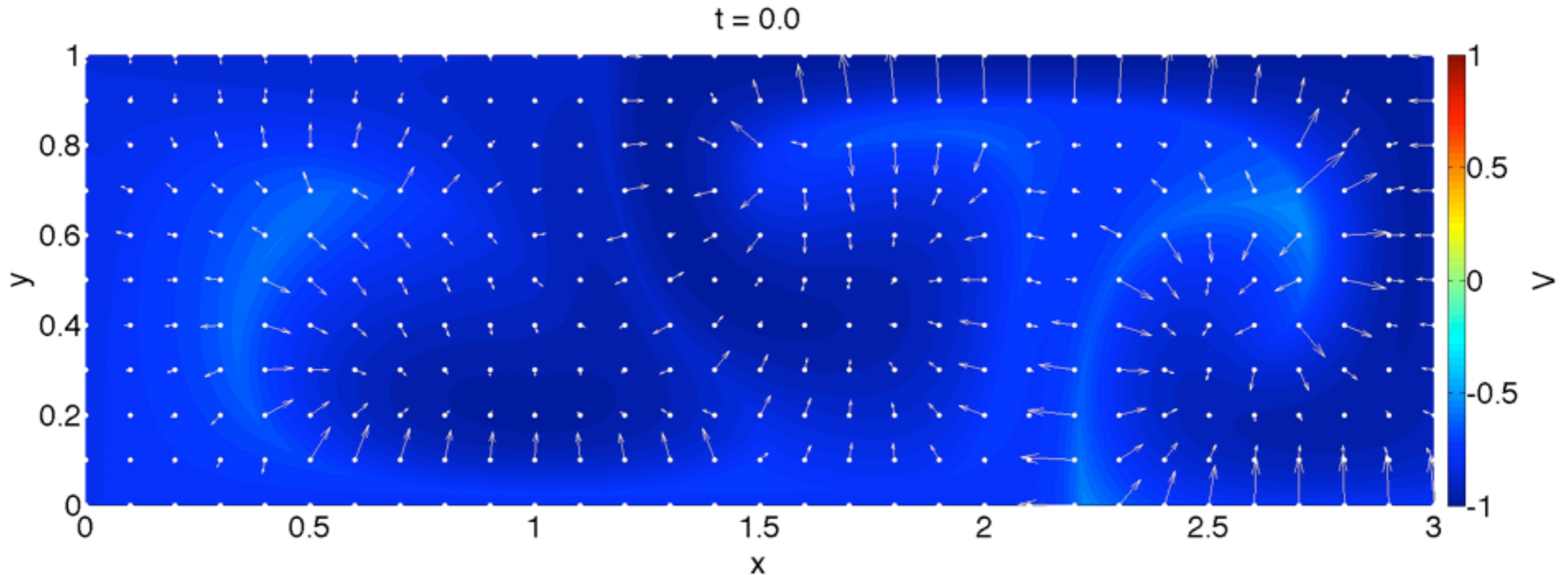


= “*pulled back end cost*” function $H(\mathbf{x},t)$.

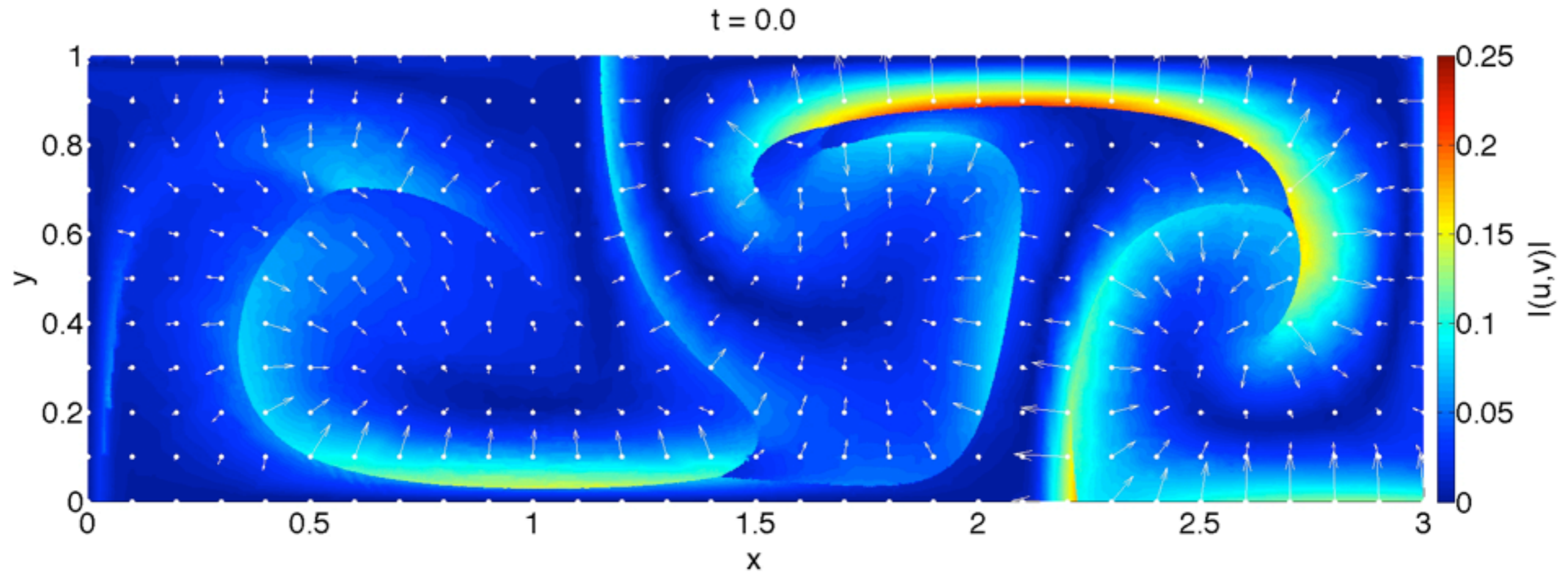
Solution $V(\mathbf{x},t)$ (for $W = 10, s = 1, t_f = 10, \Delta t = 0.1$)

= effect over backwards time of $\mathbf{v}(\mathbf{x},t) + \underline{\mathbf{u}(\mathbf{x},t)}$
 on $V(\mathbf{x},t_f) = h(\mathbf{x})$

Simulation forward in time of $\mathbf{u}(\mathbf{x},t)$ yields closed-loop $\mathbf{u}(t)$ (white arrows) and $\mathbf{x}(t)$ (white dots)

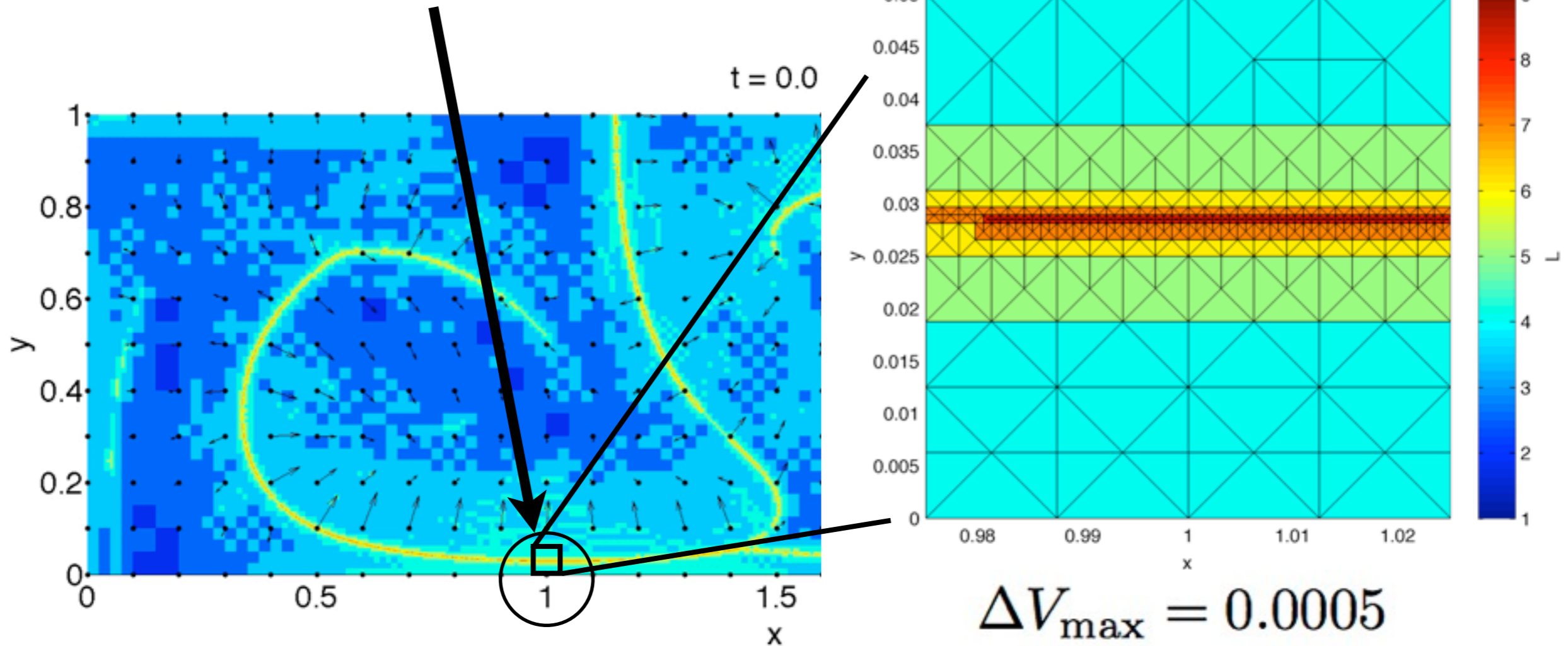


Shocks = cusps in $V(\mathbf{x},t)$...



... or discontinuities in $\mathbf{u}(\mathbf{x},t)$...

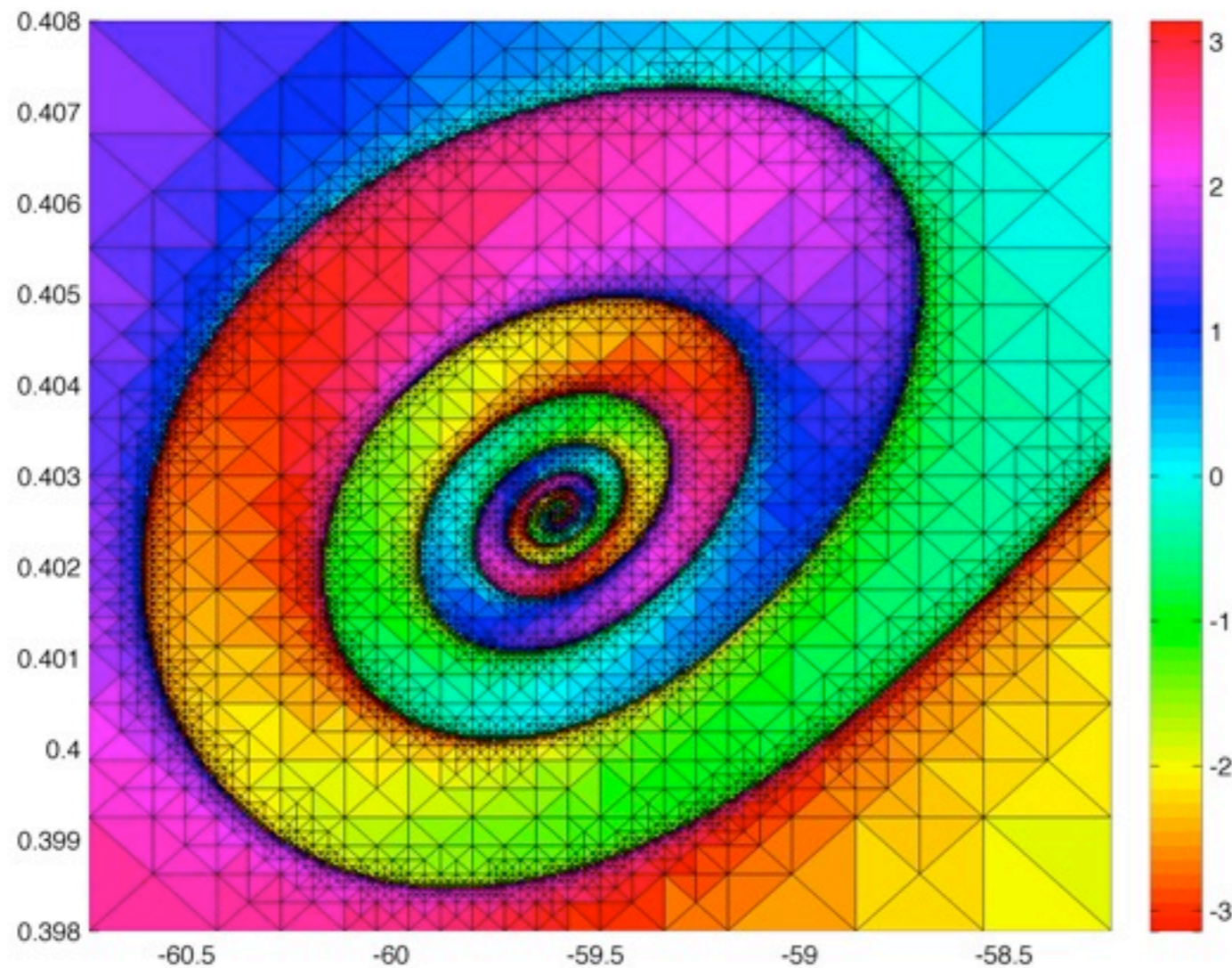
Radius = $s \Delta t = (1.0)(0.1) = 0.1$
 ... many triangles



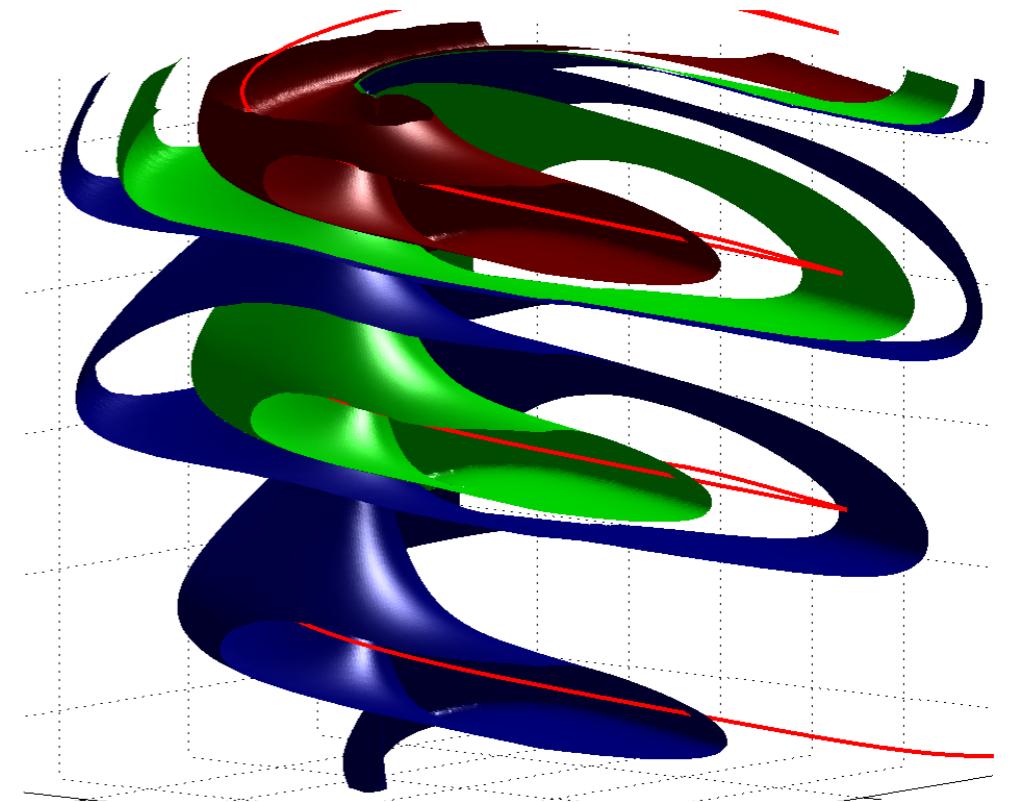
... or very sharp ridges in grid resolution level L

Another application: neuron phase dynamics

After refining to max level of 17, the number of vertices is 8983.



Phase function near unstable fixed point of 2D Hodgkin-Huxley neuron model, via **quadtree (nd-tree)**



3 Isochrons (level sets of phase function) near limit cycle (red) of Hindmarsh – Rose 3D bursting neuron model, via **octree (nd-tree)** adaptive mesh, **Delaunay tetrahedralization**, and custom **marching tetrahedra** isosurface function

Adaptive grid captures shocks very well but computational complexity issues remain.

- n_t time slices
- $\sim n_x$ grid points (per time slice)
- $\sim (s/n_t)^2 n_x$ reachable triangles (per grid point)
- Suggests $O(s^2 n_x^2 / n_t)$ overall complexity, but:
 - Grid points and triangles are concentrated in a very small area.
 - Memory complexity is $O(n_x n_t)$.

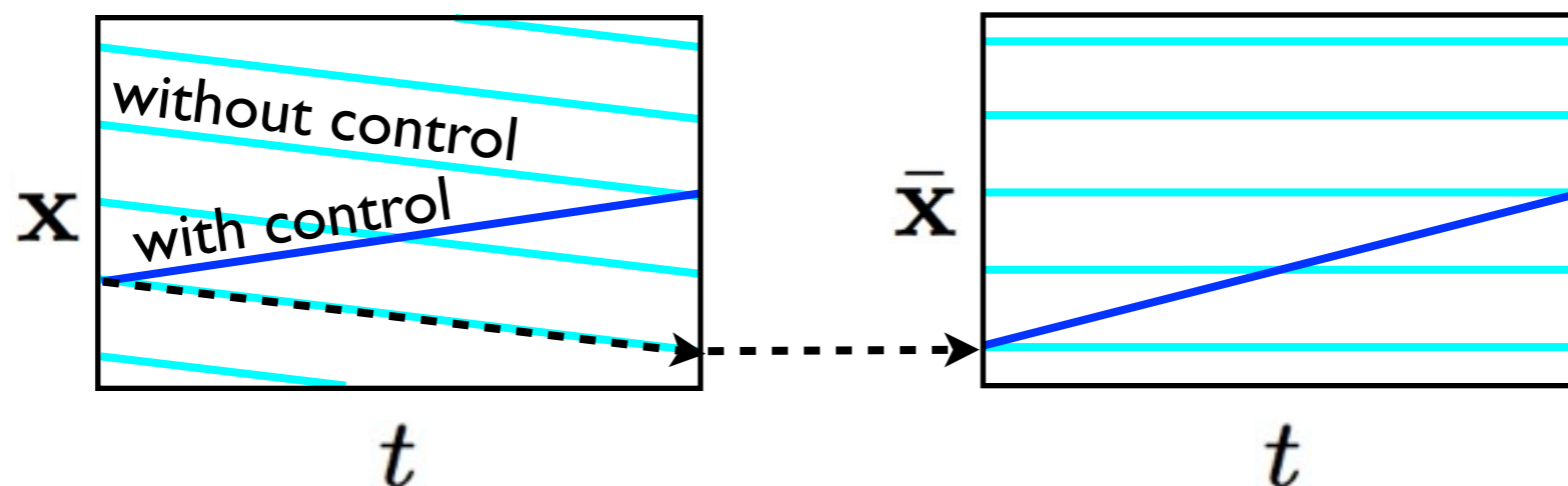
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Fixed final time flow map $F_t^{t_f}$ yields alternate state coordinates where: (a) “flow” is zero but (b) control is multiplied by time-varying matrix

$$\dot{\mathbf{x}} = \mathbf{v} + \mathbf{u} \quad \rightarrow \quad \bar{\mathbf{x}} := F_t^{t_f}(\mathbf{x}) \quad \rightarrow \quad \dot{\bar{\mathbf{x}}} = J\mathbf{u}$$

where $J(\bar{\mathbf{x}}, t) := \nabla F_t^{t_f}(F_{t_f}^t(\bar{\mathbf{x}})) = \nabla F_t^{t_f}(\mathbf{x})$ is the flow map Jacobian.

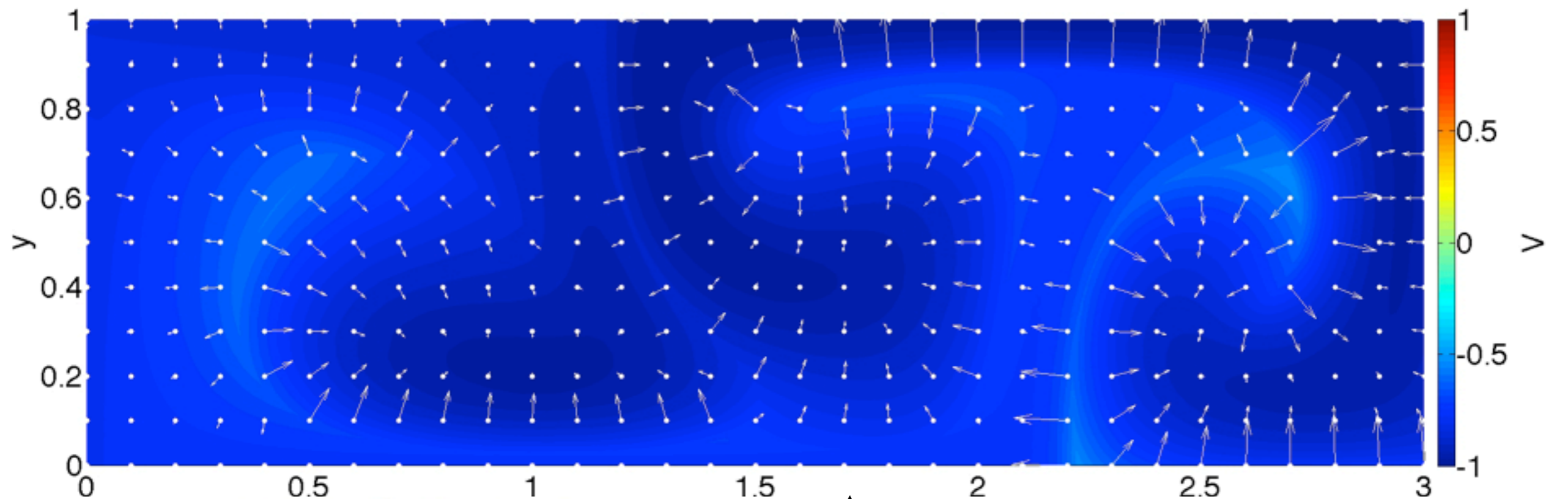


Very simple example (in 1D, with constant $v < 0$, and thus $J = \text{identity}$):

$$V(\mathbf{x}, t)$$

$t = 0.0$

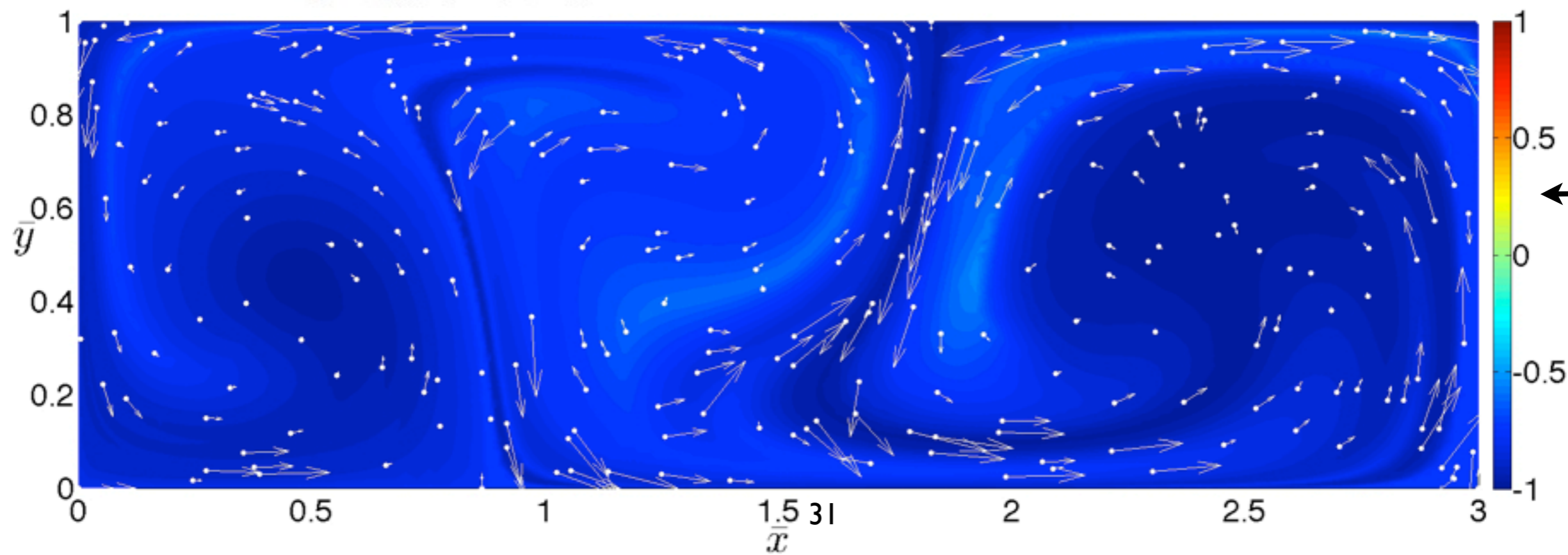
Potential benefit: $V(F_{10}^t(\bar{\mathbf{x}}), t)$ decreases monotonically.



$$V(F_{10}^t(\bar{\mathbf{x}}), t)$$

$t = 0.0$

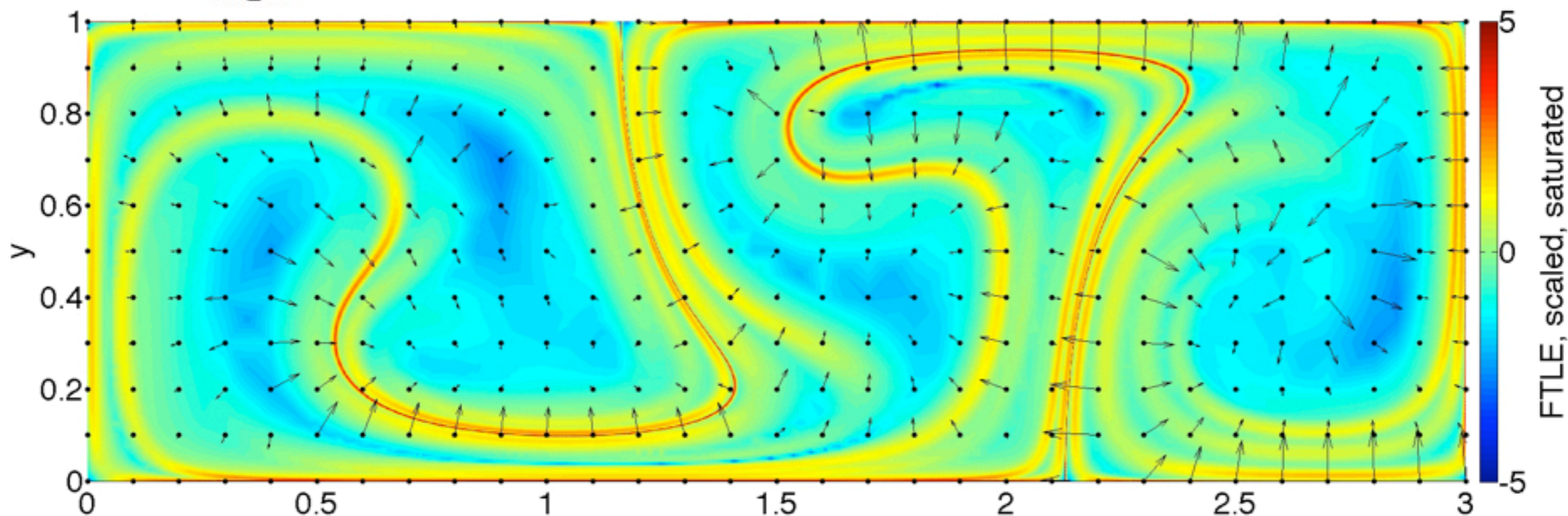
↕ Koopman operator



$$\max_{\mathbf{u} \in S^1} \left| \nabla F_t^{10}(\mathbf{x}) \mathbf{u} \right|$$

$t = 0.0$

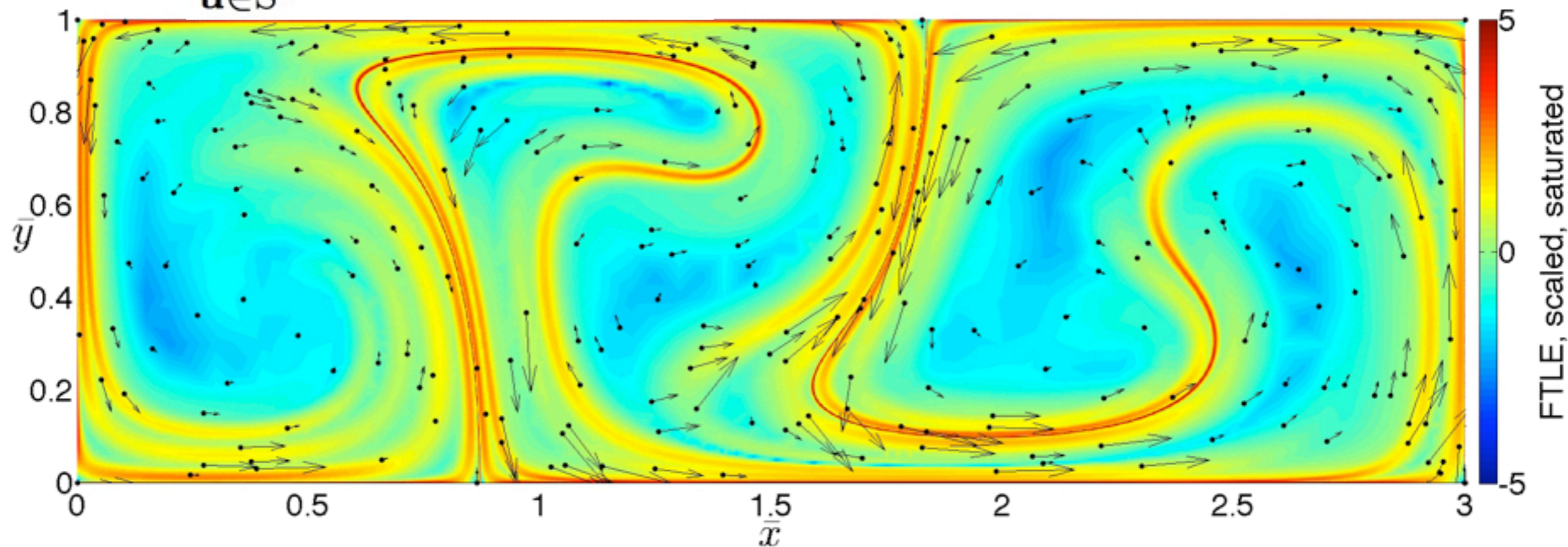
i.e. finite time Lyapunov exponents
[Shadden, Lekien, Marsden (2005)]



$$\max_{\mathbf{u} \in S^1} \left| \nabla F_t^{10}(F_{10}^t(\bar{\mathbf{x}})) \mathbf{u} \right|$$

x

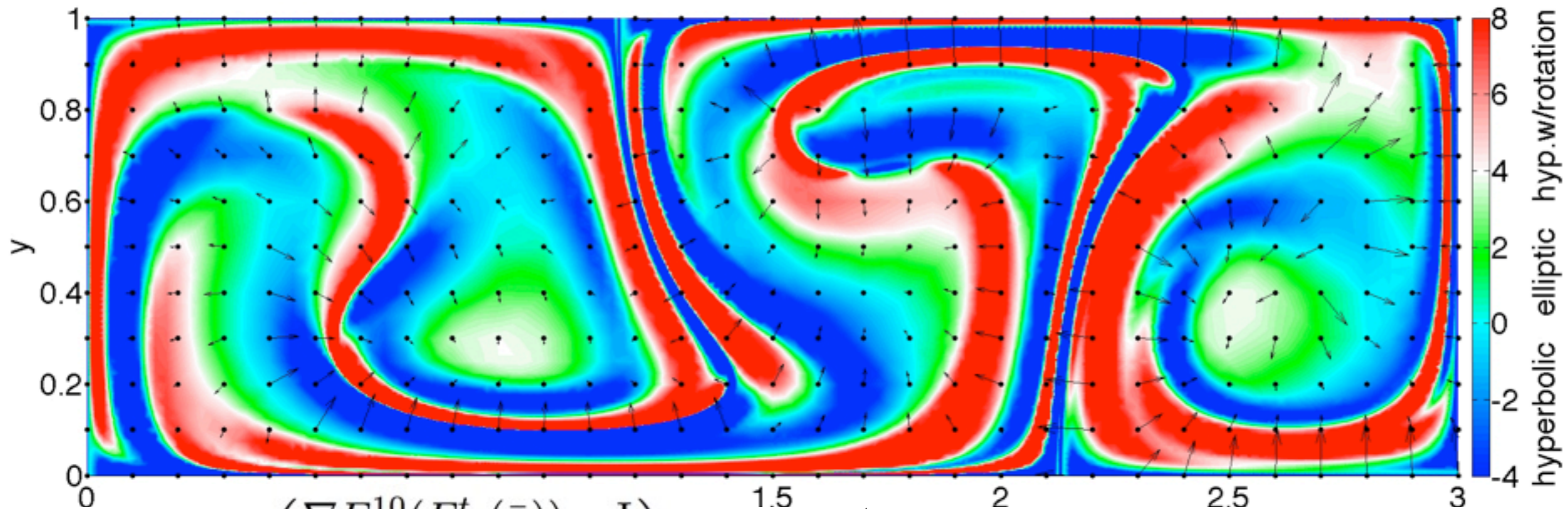
↕ Koopman operator



i.e. mesohyperbolicity
[Mezic, Loire, et al (2010)]

$$\det \left(\frac{\nabla F_t^{10}(\mathbf{x}) - \mathbf{I}}{10 - t} \right)$$

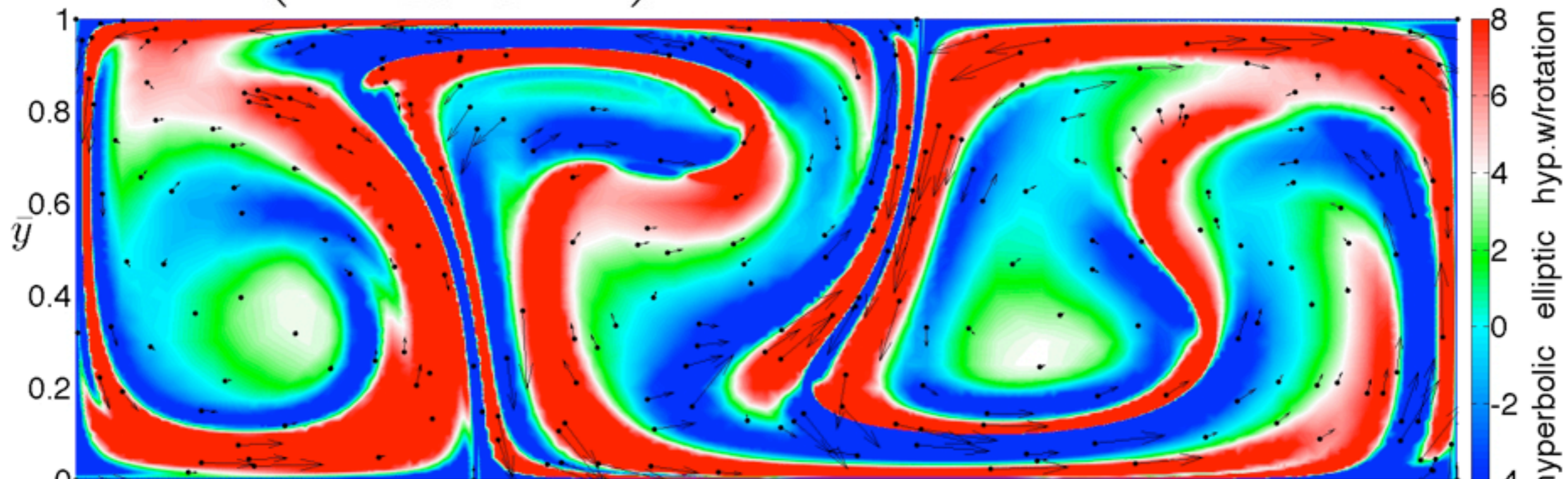
t = 0.0



$$\det \left(\frac{\nabla F_t^{10}(F_{10}^t(\bar{\mathbf{x}})) - \mathbf{I}}{10 - t} \right)$$

t = 0.0

↕ Koopman operator



Why not incorporate the control objective?

Pulled back end cost function $H(\mathbf{x}, t) := h(\bar{\mathbf{x}})$
yields “local Lagrangian control” (LLC)

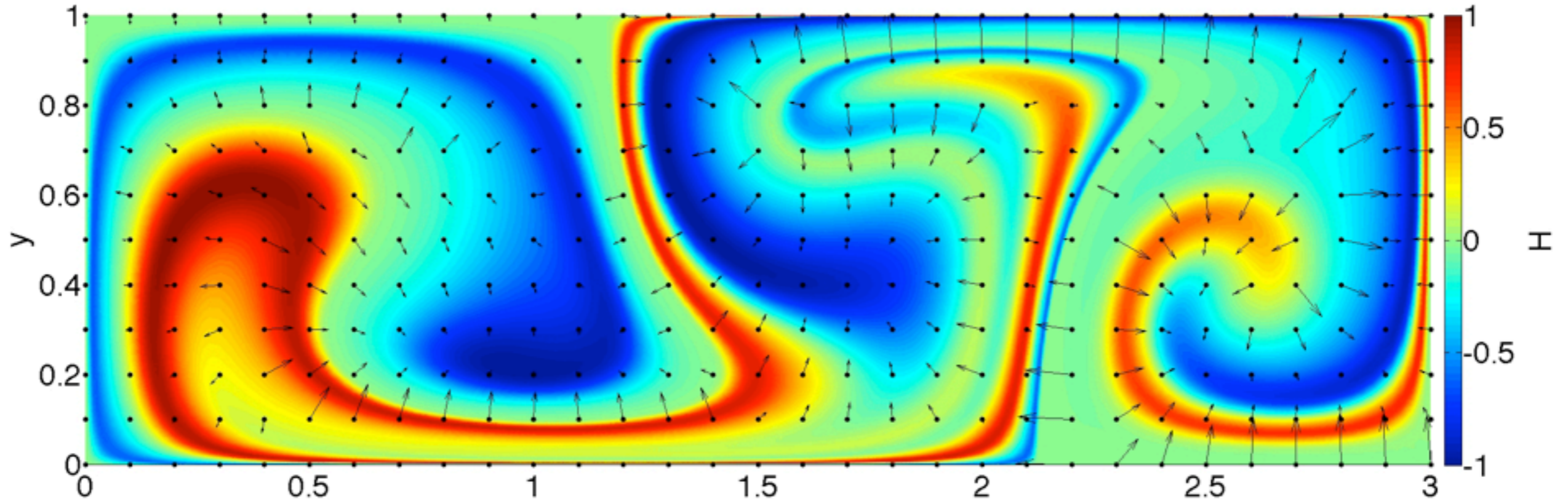
- **Good:** $\mathbf{u} = -\frac{\nabla H}{2W} \left(\text{if } \frac{|\nabla H|}{2W} \leq s; \text{ otherwise } \mathbf{u} = -s \frac{\nabla H}{|\nabla H|} \right)$
- **Better:** $\mathbf{u} = -\frac{\nabla H}{2\bar{W}} \left(\text{if } \frac{|\nabla H|}{2\bar{W}} \leq s; \text{ otherwise } \mathbf{u} = -s \frac{\nabla H}{|\nabla H|} \right),$

where $\bar{W} = \bar{W}(t) := W + t_f - t.$

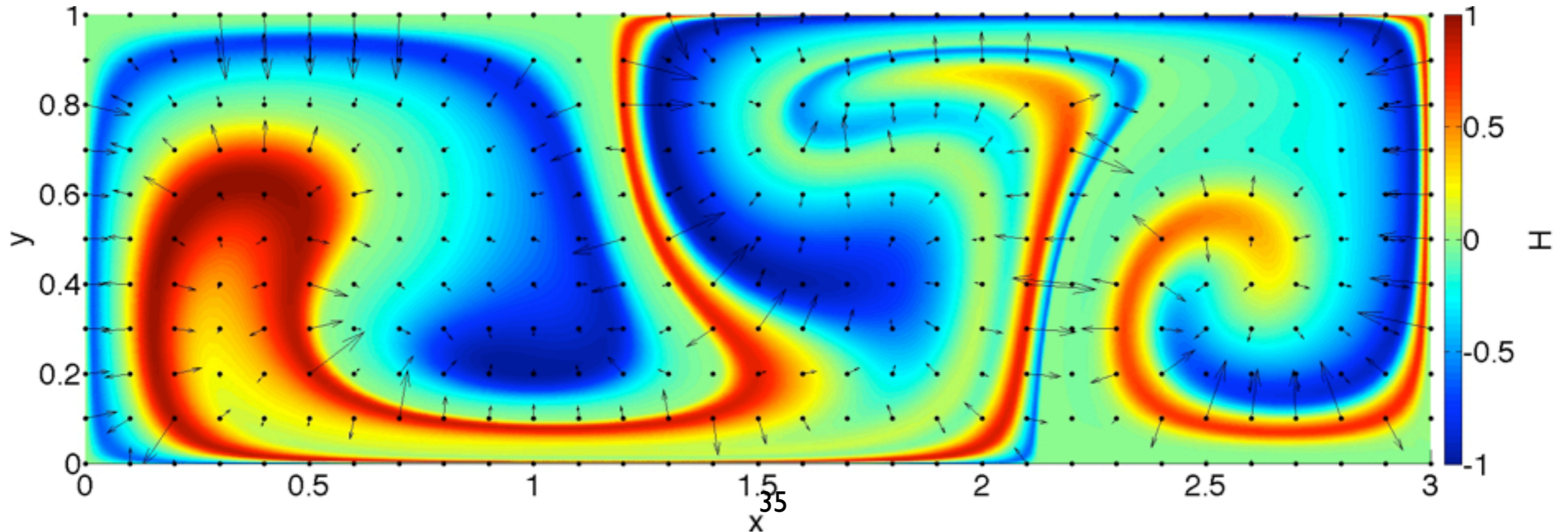
For control based on FTLE see [Inanc, Shadden, Marsden (2005)], [Senatore, Ross (2008)]

Optimal (crosses red ridges in H)

$t = 0.0$

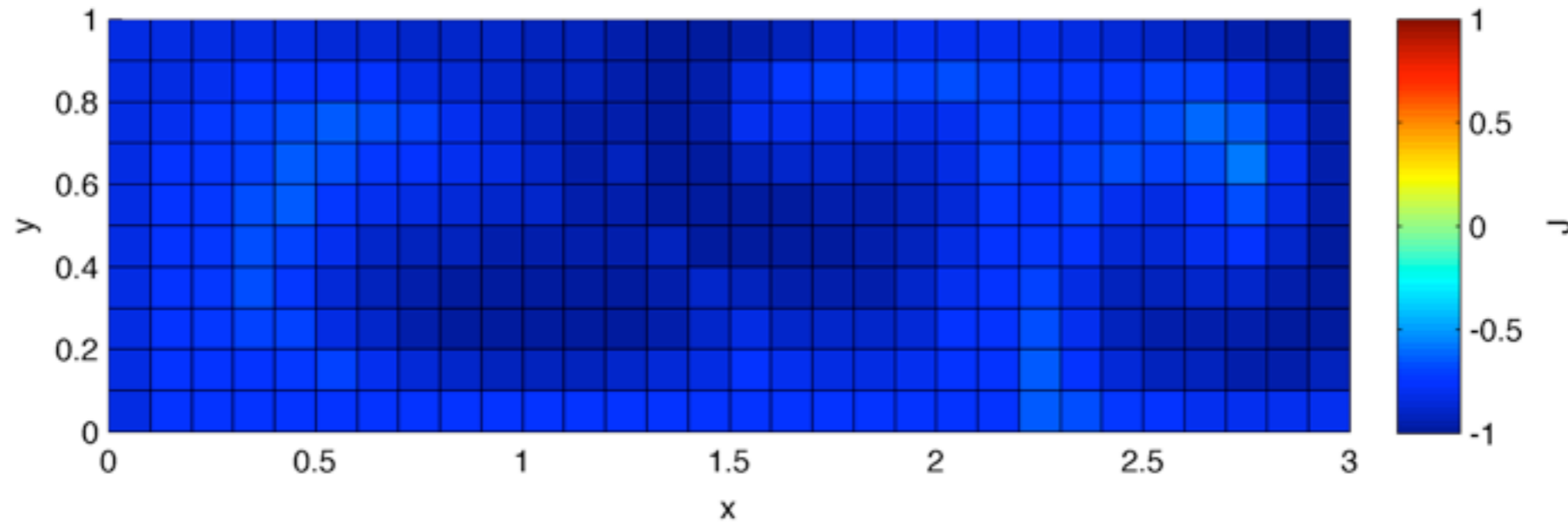


LLC (descends H monotonically)

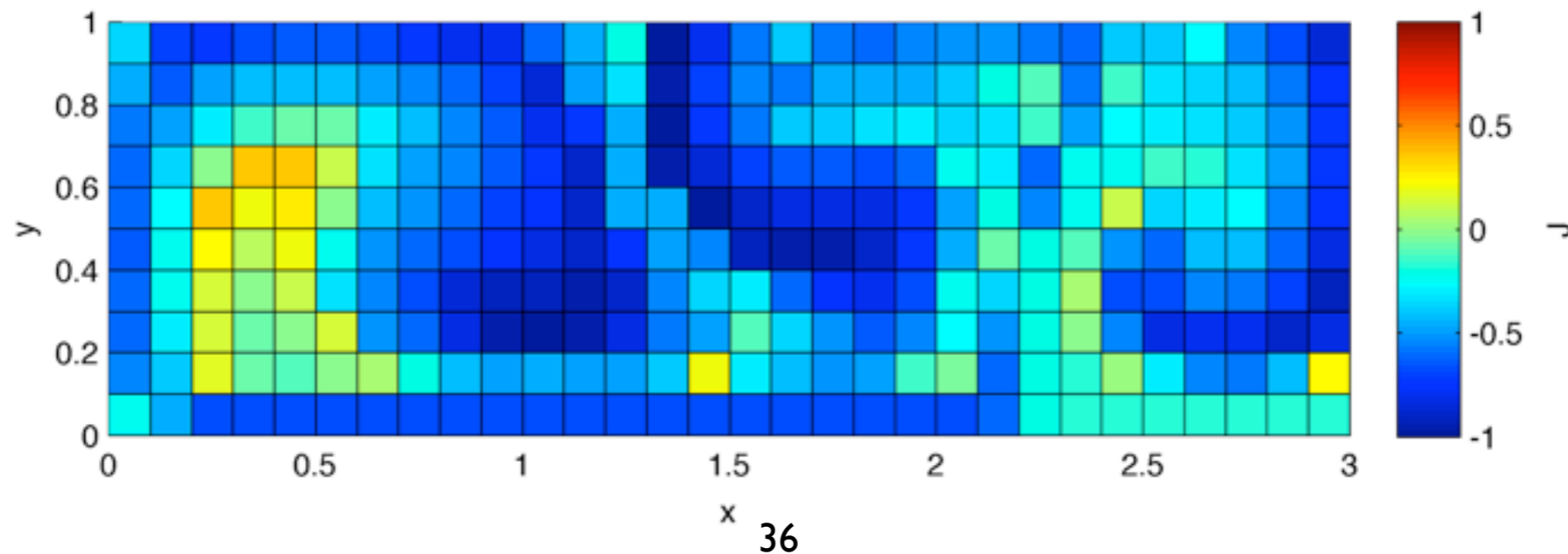


How suboptimal is LLC?

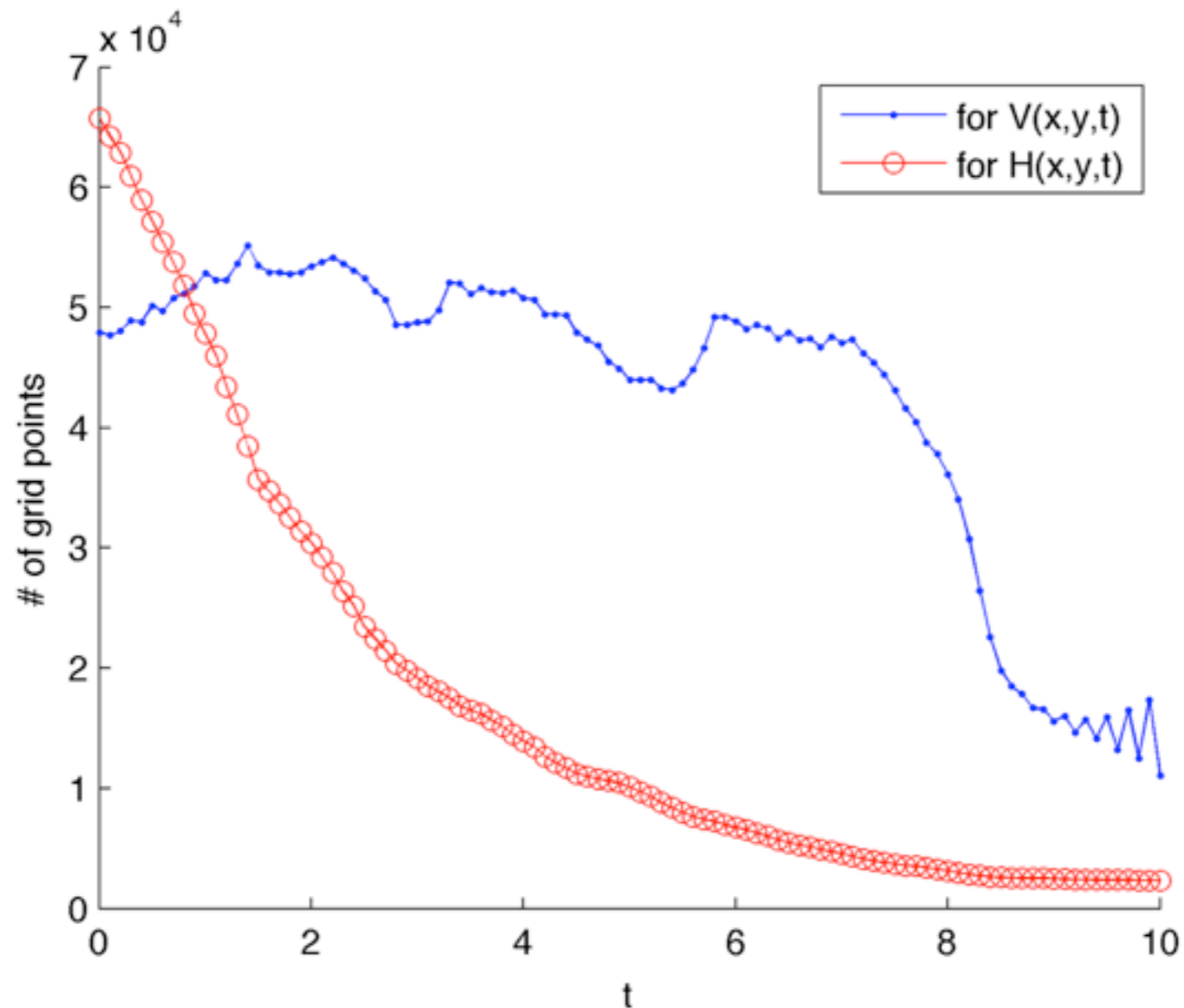
Optimal trajectory costs



LLC trajectory costs



Present *global* method for LLC does not demonstrate the advantage of its being defined *locally*.



Problem, Method	Minimum time, Forward Lagrangian	Minimum energy, Bwd. semi-Lagrangian	Minimum energy, Using flow map
Related Work	[Lolla et al '12], [Nishida et al '07], [Holzhuter '04], [Osinga Hauser '06]	[Falcone Ferretti '02], [Kumar Vladimirsky '09], [Vladimirsky Zheng '13]	[Inanc Shadden Marsden '05], [Senatore Ross '08], [Garth et al '07] [Miron et al '12]
Contribution(s)	Captures not only shocks but discontinuities in time-varying case [Rhoads et al '13]. More efficient than backward Lagrangian method of [Rhoads et al '10].	Adaptive grid and exact pointwise minimization.	New perspective on fixed final time control and simple greedy algorithm in LLC. [Rhoads et al '13] Adaptive grid works very well for efficient flow map computation.
Details	~15 min, Matlab (vs ~3 hrs for backward method)	~1 day, C++	~30 min, C++
Issues	trimming	computational complexity, first order accuracy	“Zig-zagging” if LLC is computed locally with standard gradient discretizations.
Recommendations	Better incorporate into minimum energy w/ $W=0$ and more general boundary conditions.	Higher order discretization & iterative minimization. Lagrangian or Eulerian method.	(a) Solve HJB in new coordinates, (b) better local LLC computation, (c) combine adaptive grid w/ flow map composition.

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- Charlotte Becker
- Office of Naval Research

Thank you.

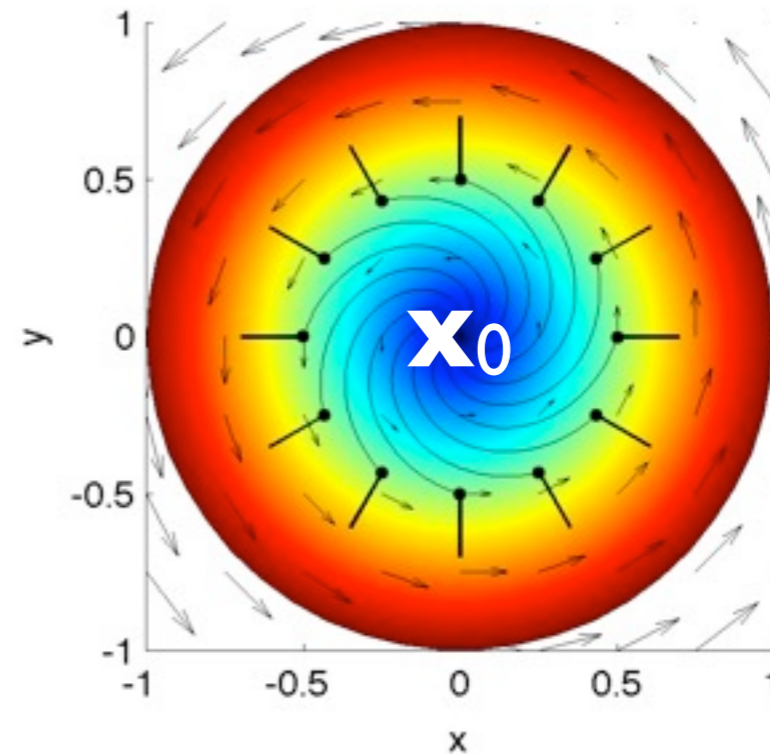
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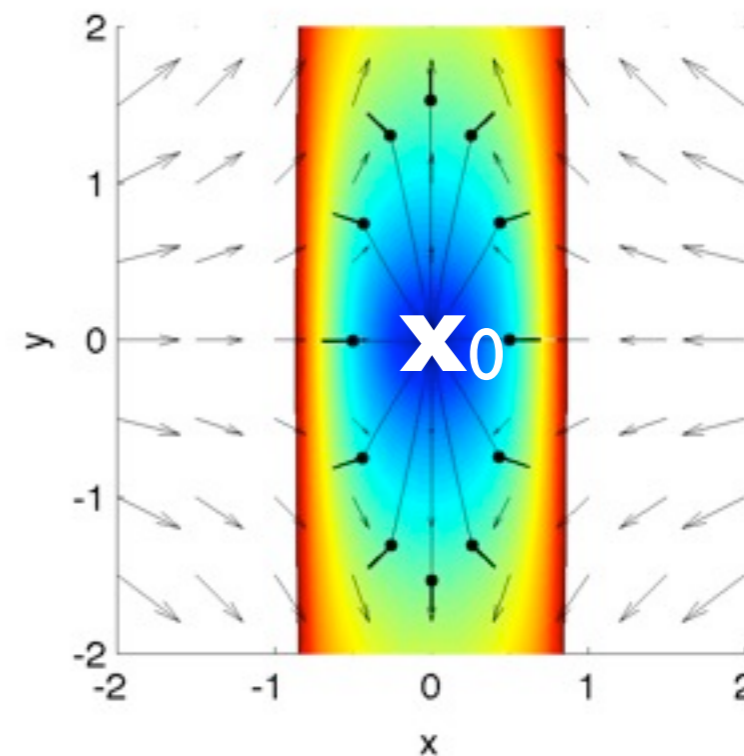
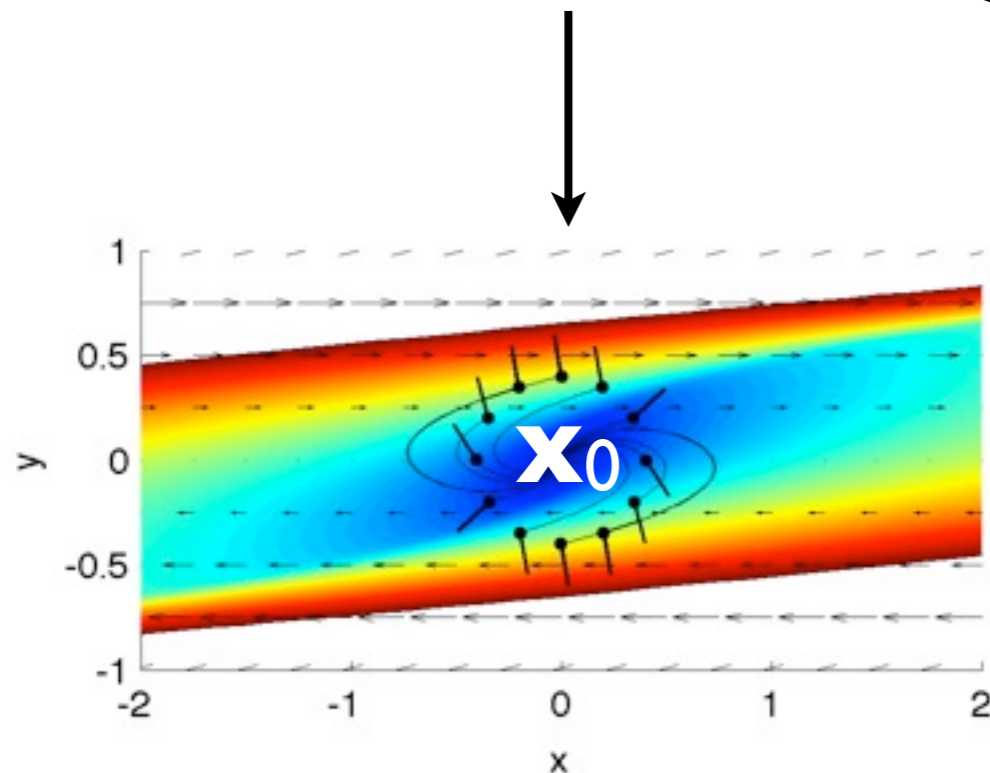
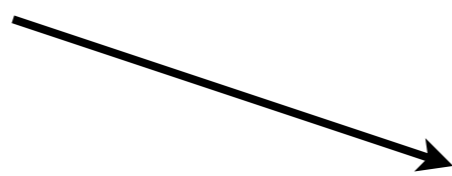
Supplemental Slides

Effect of simple LTI flows

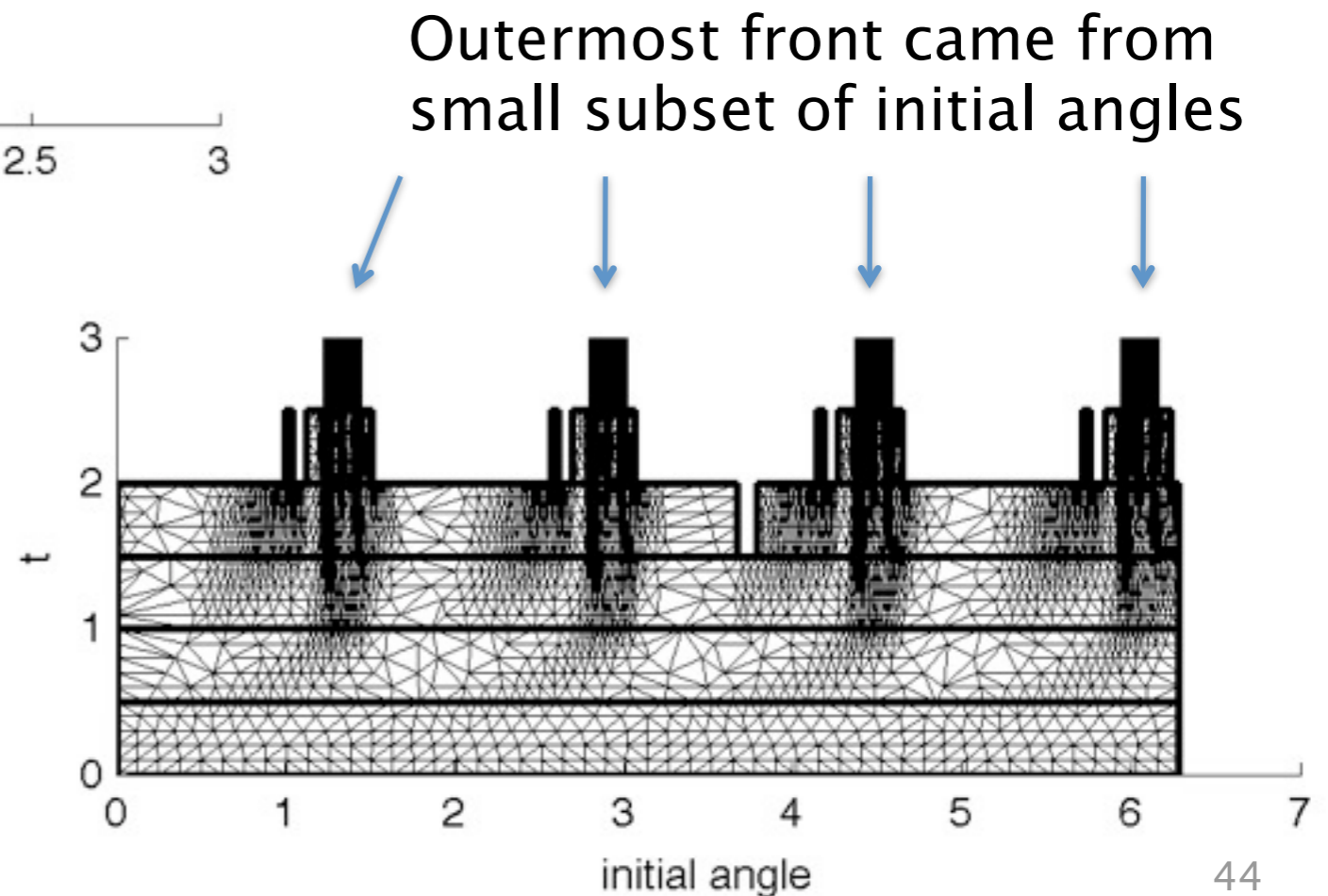
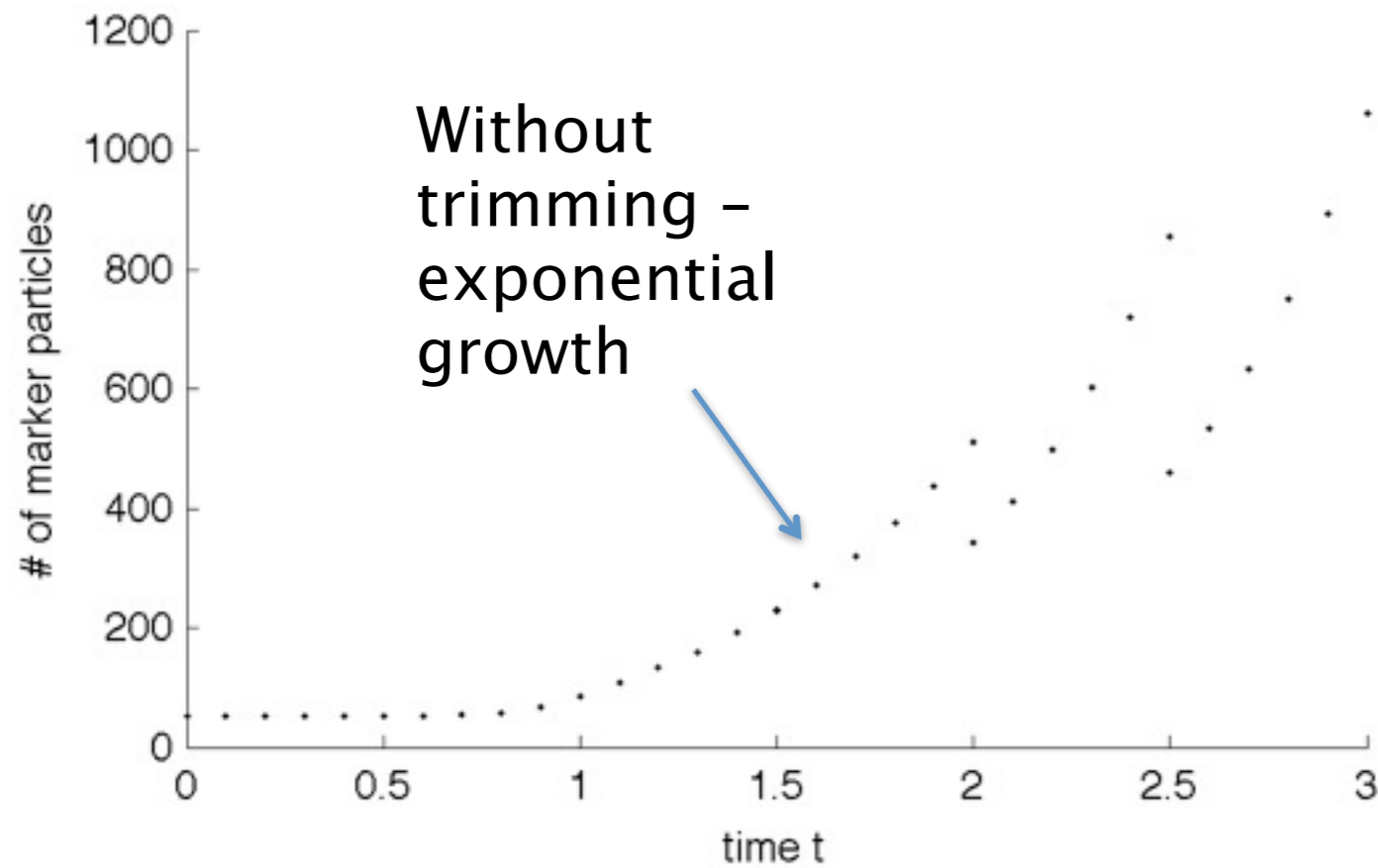
Elliptic:
swim outward.



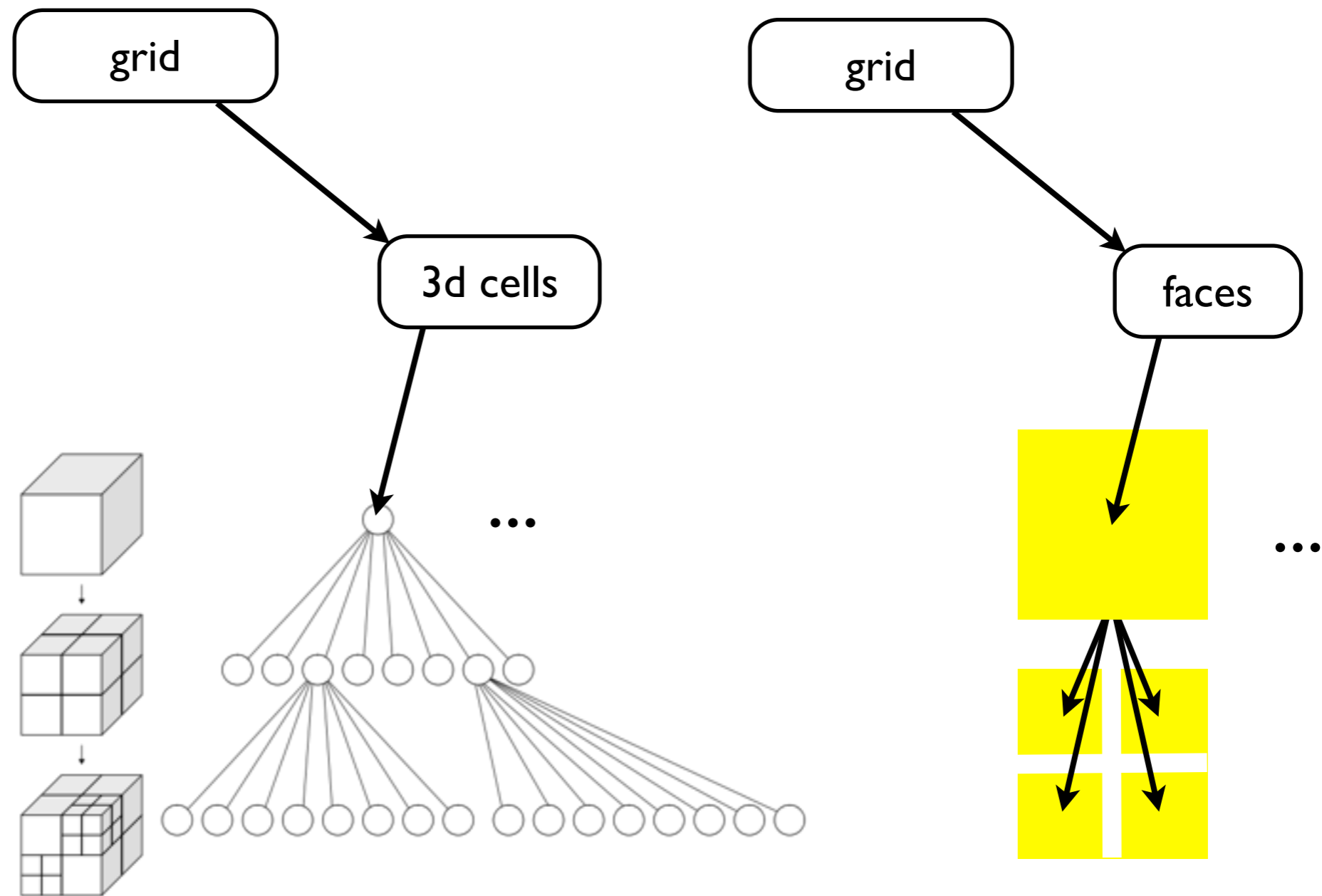
Hyperbolic:
use structure.



Many locally optimal trajectories trimmed away

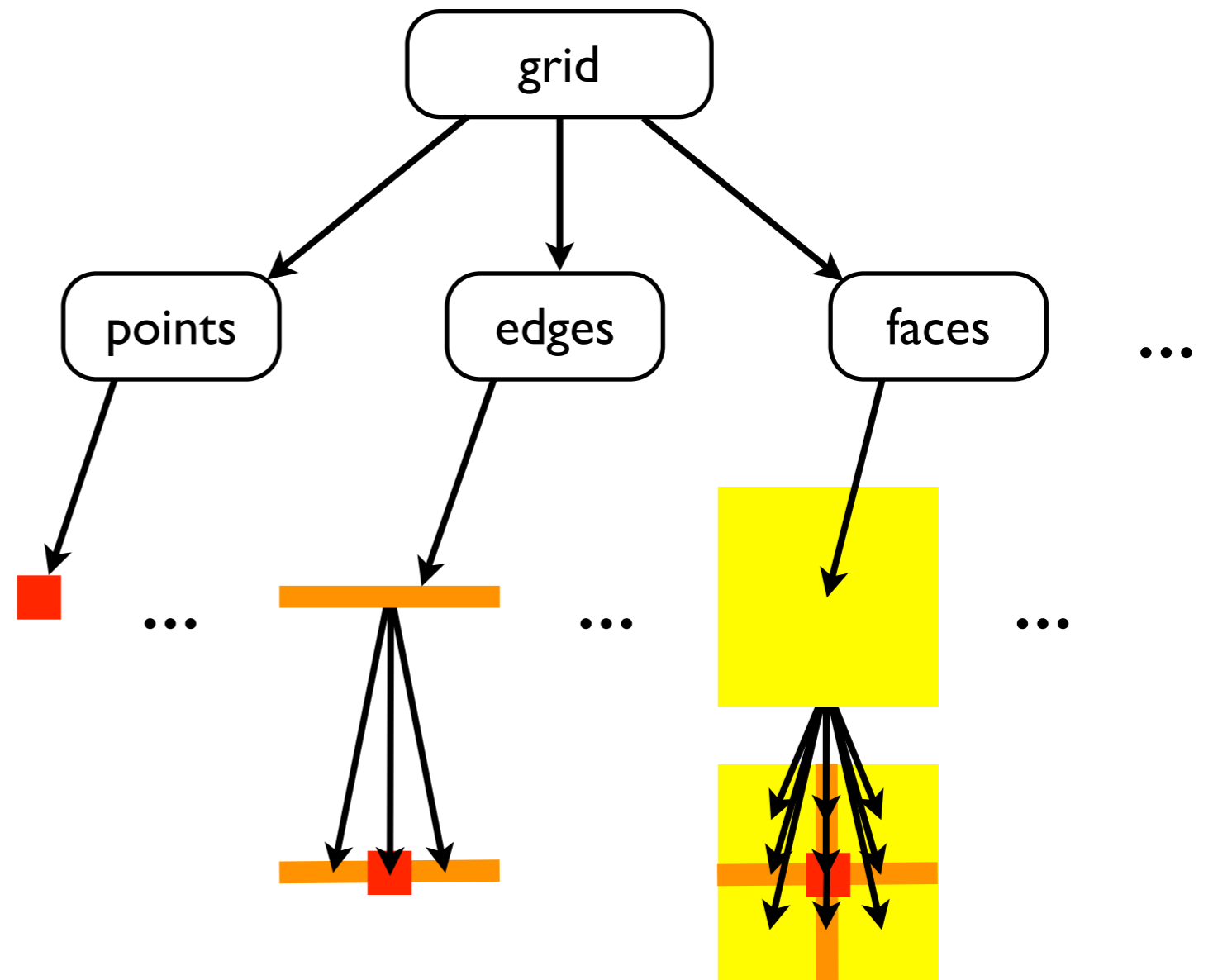


Adaptive grid structures: basic octree, quadtree



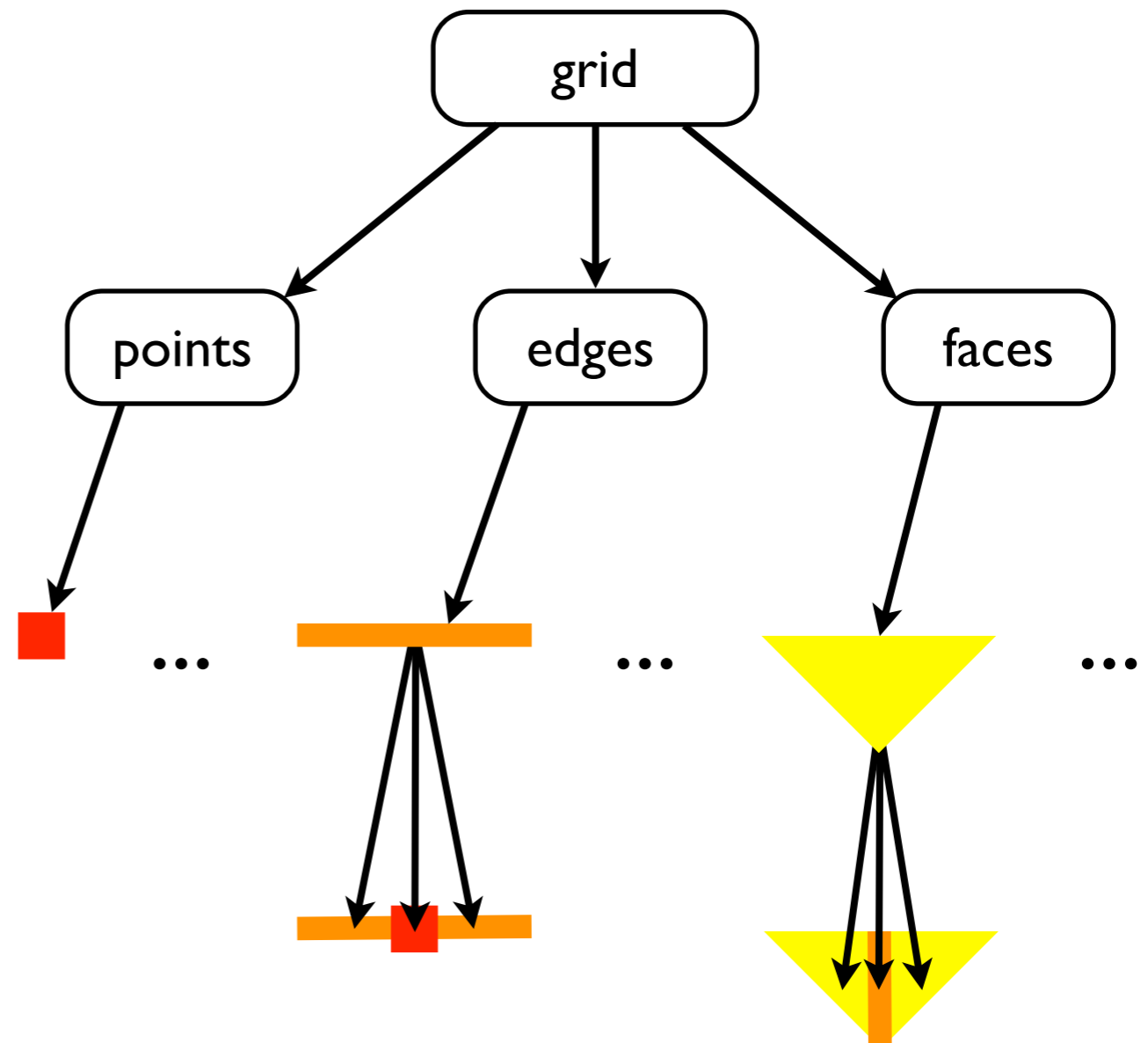
Adaptive grid structures: general “nd-tree”

- Grid is kept *graded*, via recursive refinement of neighbors.
- For visualization and computation of level sets: *Delaunay triangulation/ tetrahedralization*



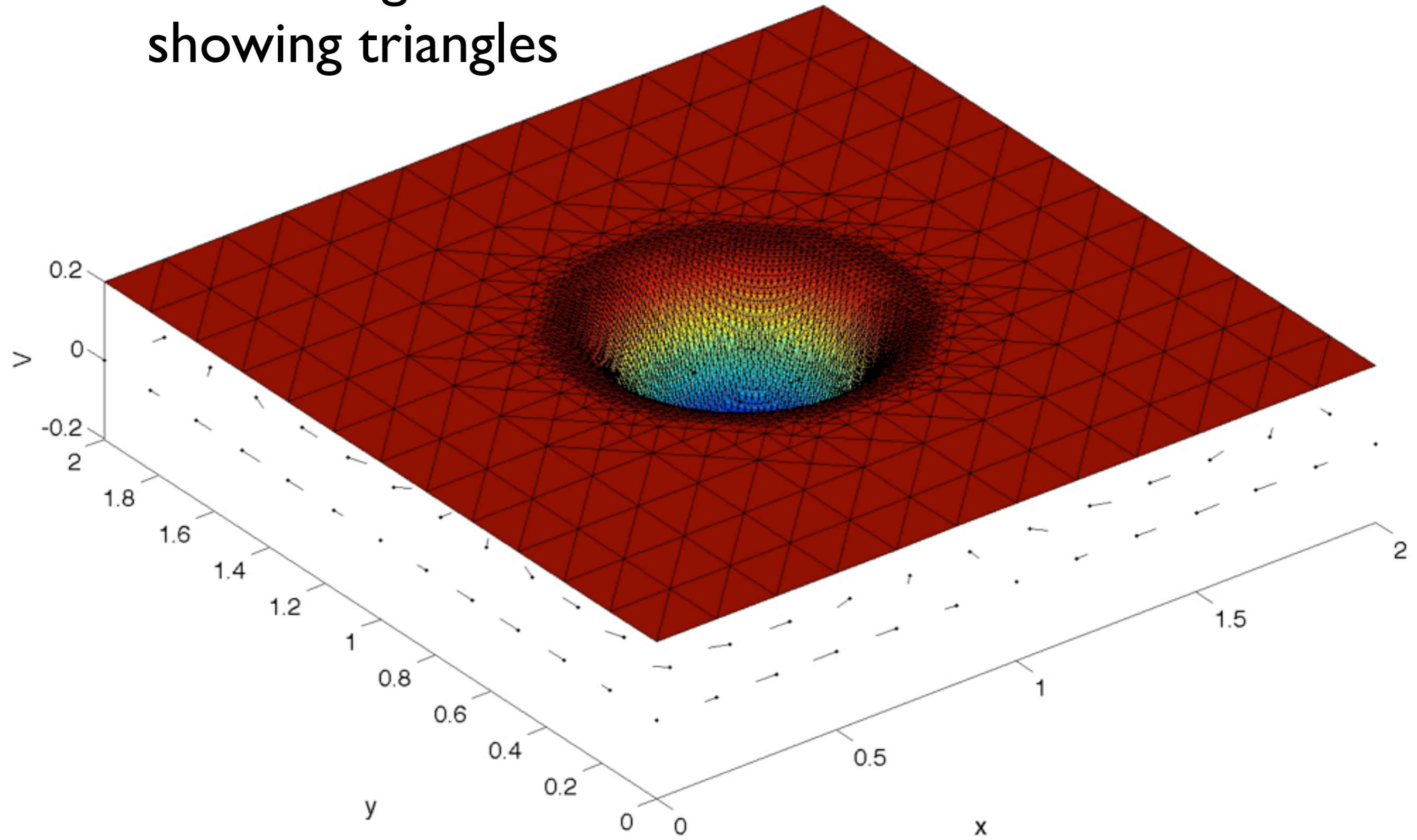
Adaptive grid structures: triangles

- Grid refinement initiated by edge refinement.
- Edge refinement based on error estimate.
- Grid kept *graded* by simply refining hypotenuse first.
- Fast binary triangle search



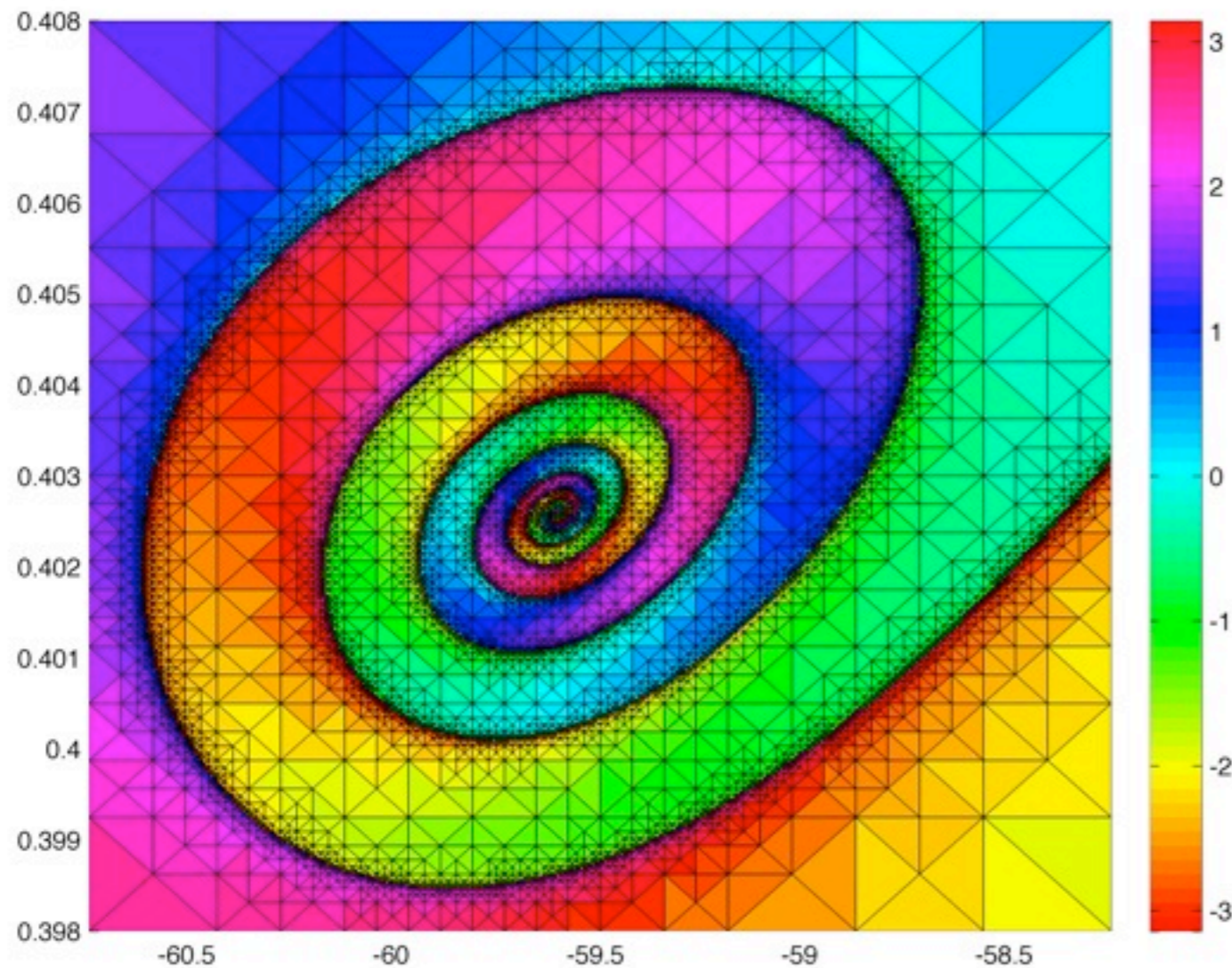
Same thing in 3d,
showing triangles

t = 10.000

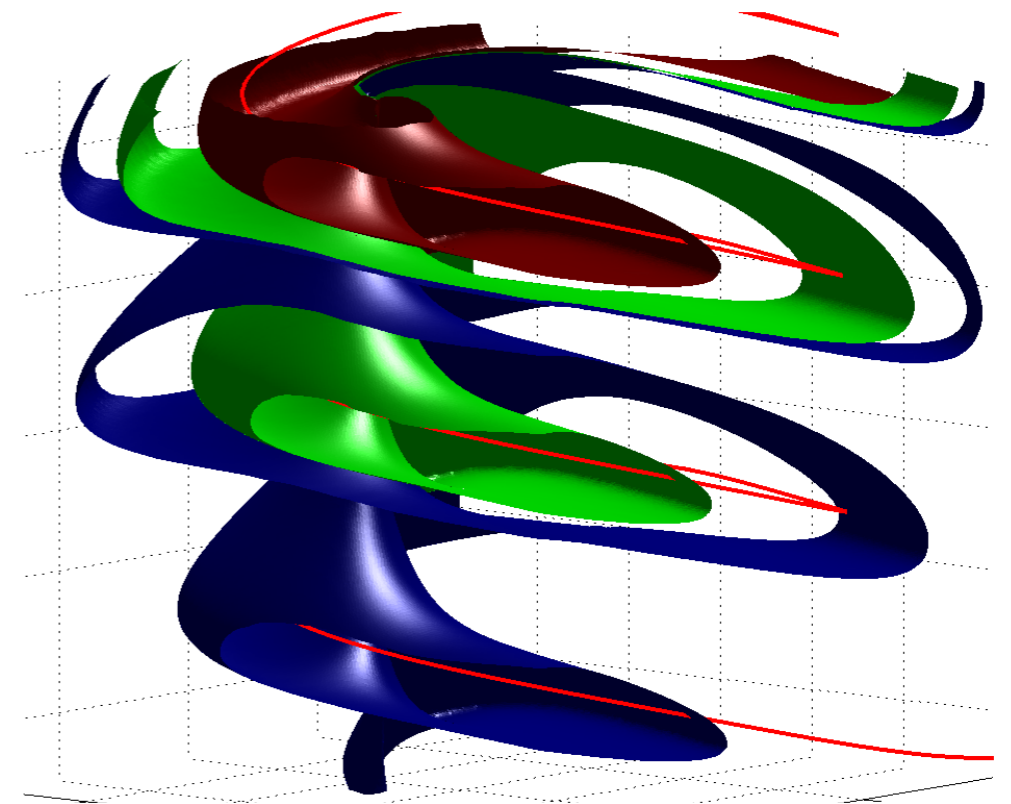


Another application: neuron phase dynamics

After refining to max level of 17, the number of vertices is 8983.

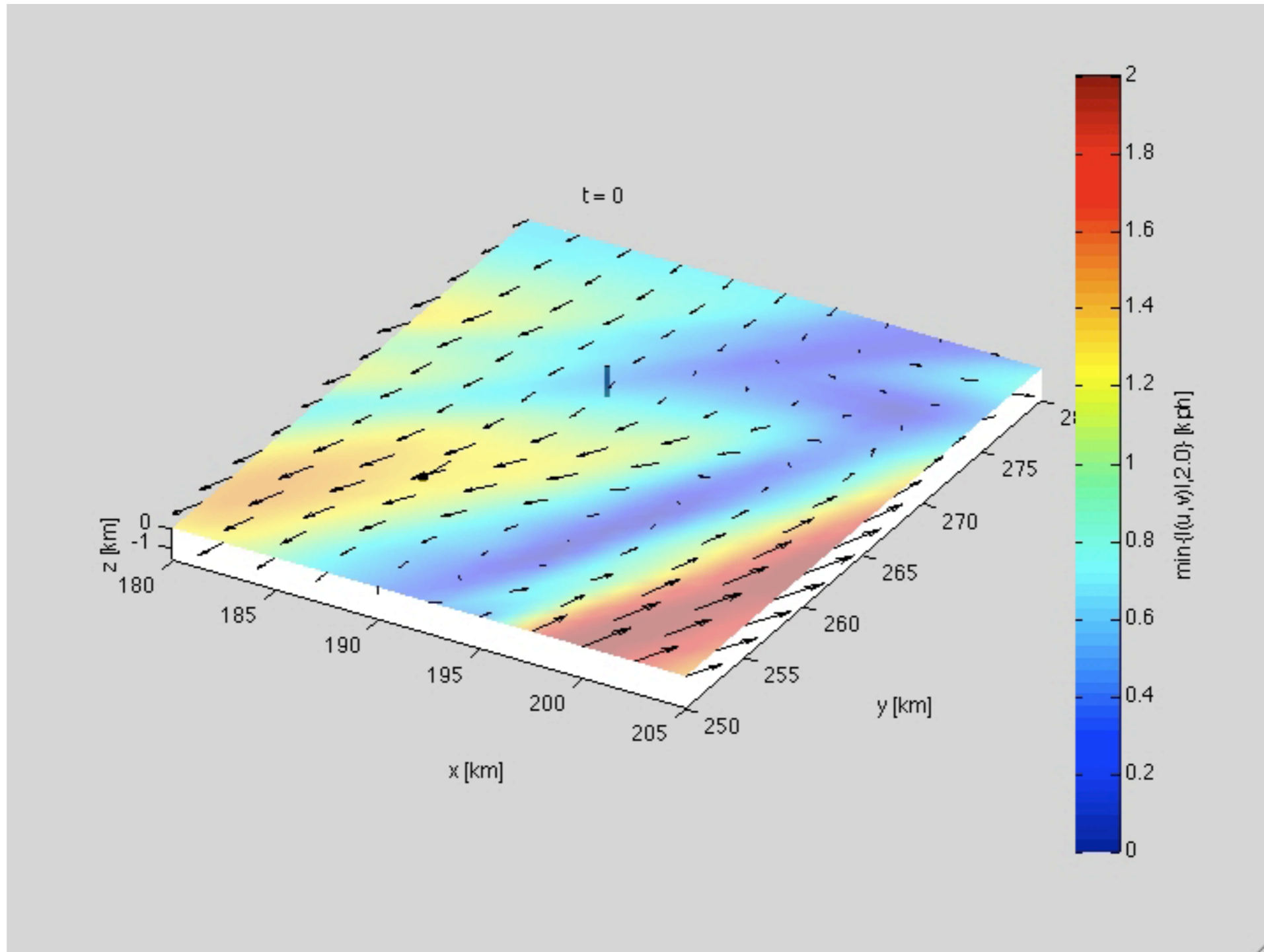


Phase function near unstable fixed point of 2D Hodgkin-Huxley neuron model, via **quadtree (nd-tree)**

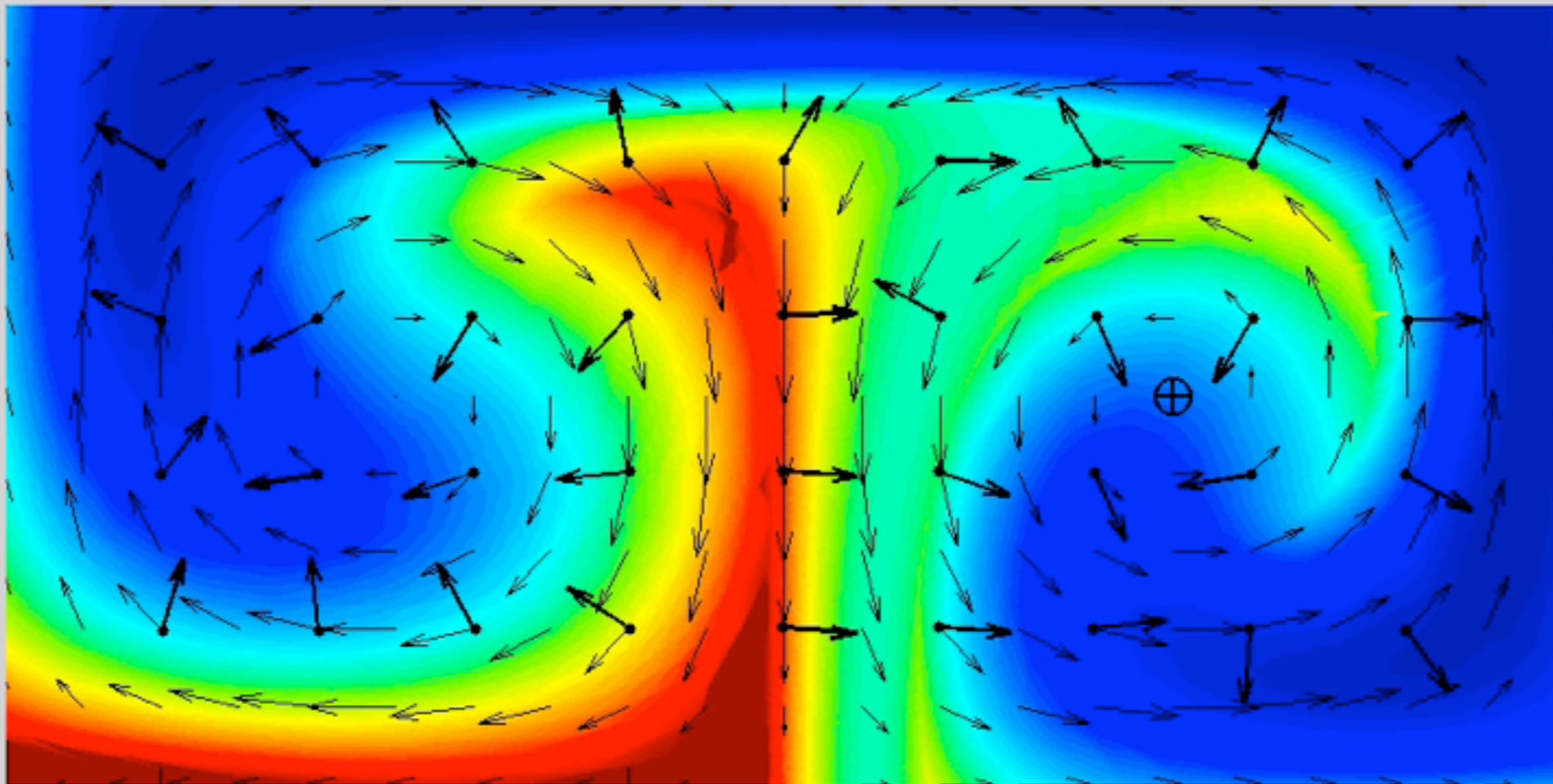


3 Isochrons (level sets of phase function) near limit cycle (red) of Hindmarsh - Rose 3D bursting neuron model, via **octree (nd-tree)** adaptive mesh, **Delaunay tetrahedralization**, and custom **marching tetrahedra** isosurface function

3d, time-varying flow

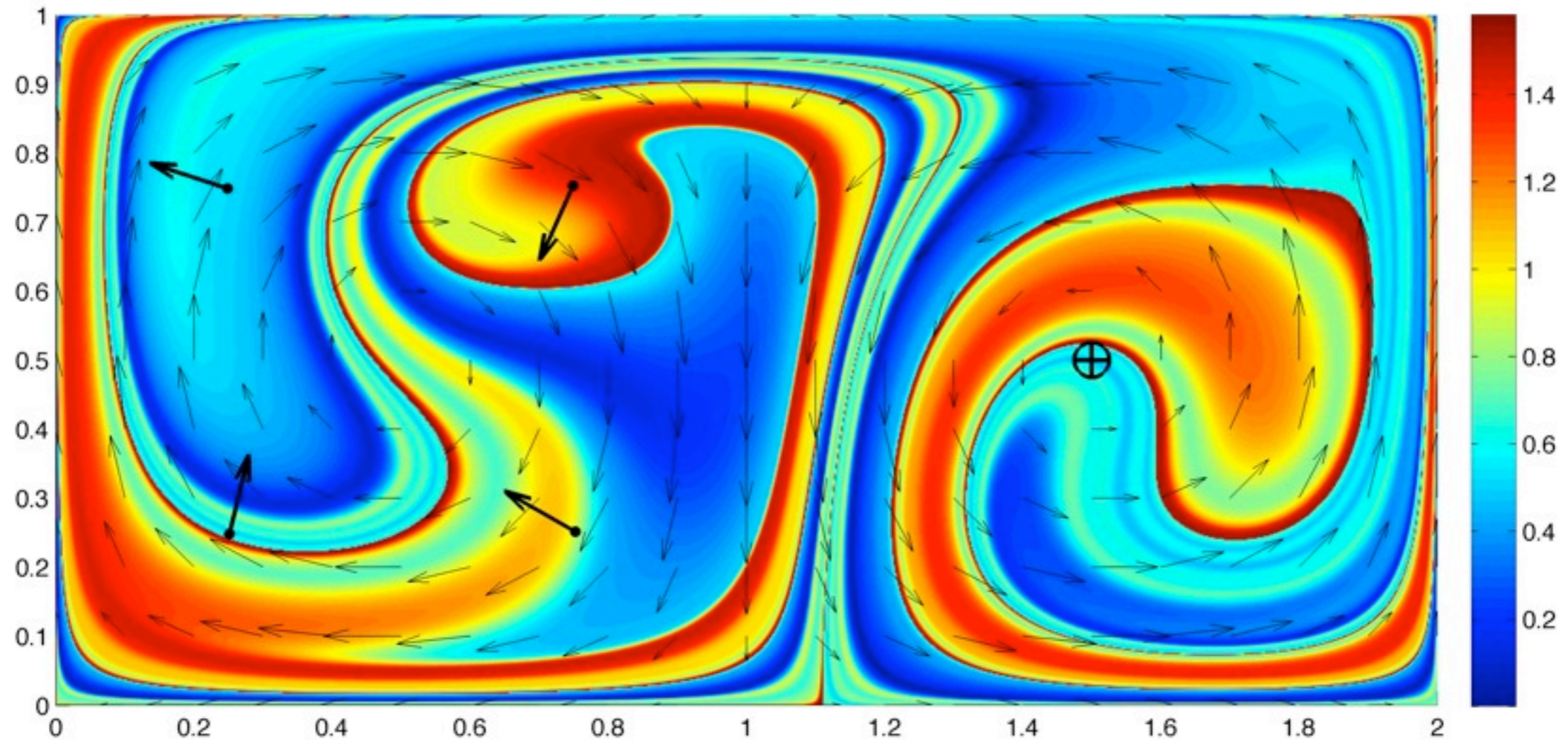


Problem 3 - Minimum energy: time-varying double gyre



$W = 1.5$, $h(\mathbf{x}) := 0.5|\mathbf{x} - \mathbf{x}_f|^2$, $V_{\max} = 0.05$
(max speed that results is about 0.1)

Longer times ($T = 20$): even steeper gradients



... challenging robust feedback problem?

