Flexible Self-Healing Gradients

Jacob Beal BBN Technologies ACM SAC, March 2009

"Gradient": Local Calculation of Shortest-Distance Estimates

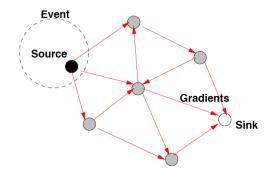
Common SA/SO building block

- Pattern Formation
 - Nagpal, Coore, Butera
- Distributed Robotics
 - Stoy, Werfel, McLurkin
- Networking
 - DV routing, Directed Diffusion



Nagpal, 2001



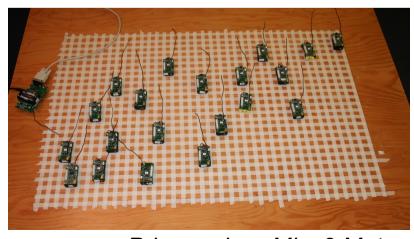


Intanagonwiwat, et al. 2002

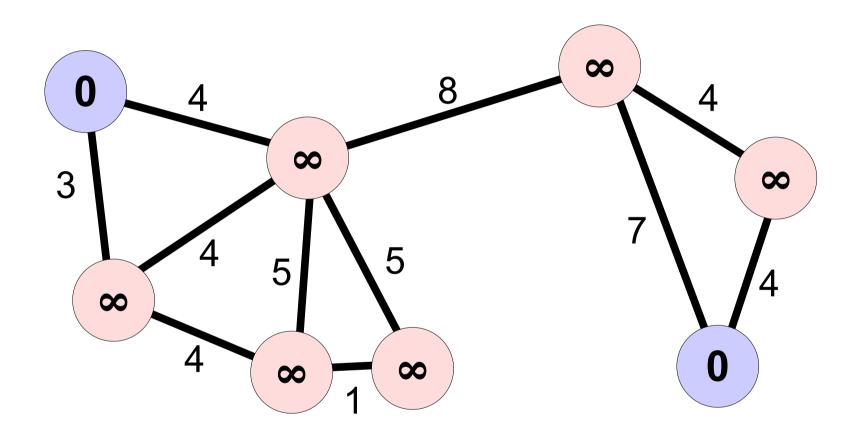
Need to adapt to changes

Previous Self-Healing Gradients

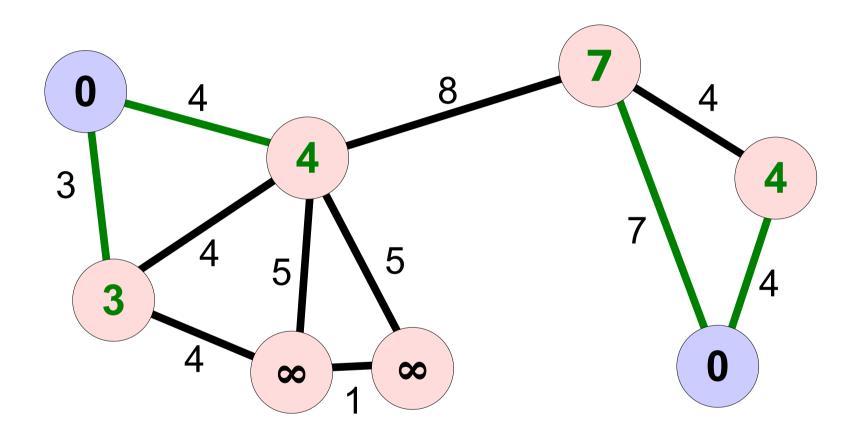
- "Invalidate and Rebuild"
 - GRAB: single source, rebuild on high error
 - TTDD: static subgraph, rebuild on lost msg.
- "Incremental Repair"
 - Hopcount: Clement & Nagpal, Butera
 - CRF-Gradient



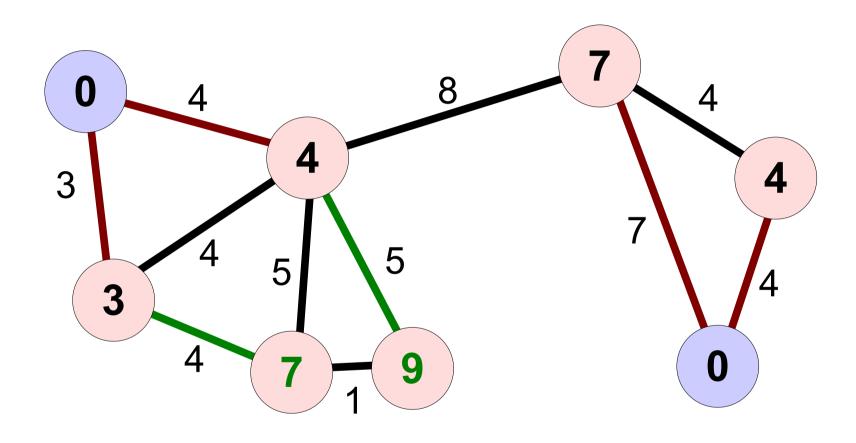
Prior work w. Mica2 Motes



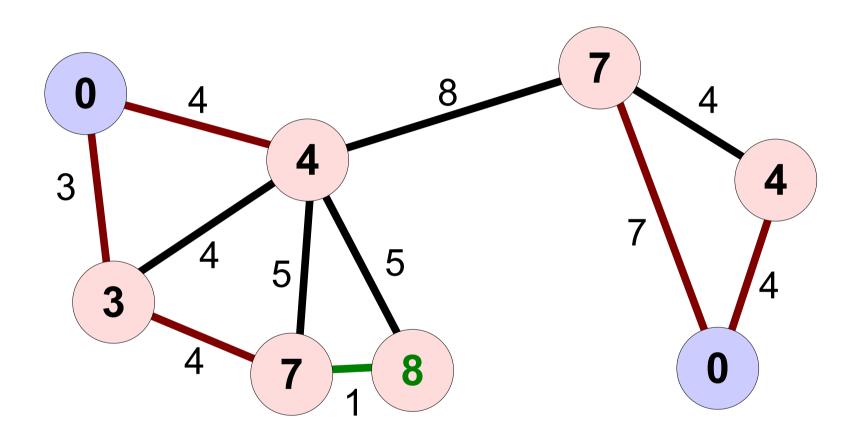
$$g_{x} = \begin{cases} 0 & \text{if } x \in S \\ \min\{g_{y} + d(x, y) \mid y \in N_{x}\} & \text{if } x \notin S \end{cases}$$



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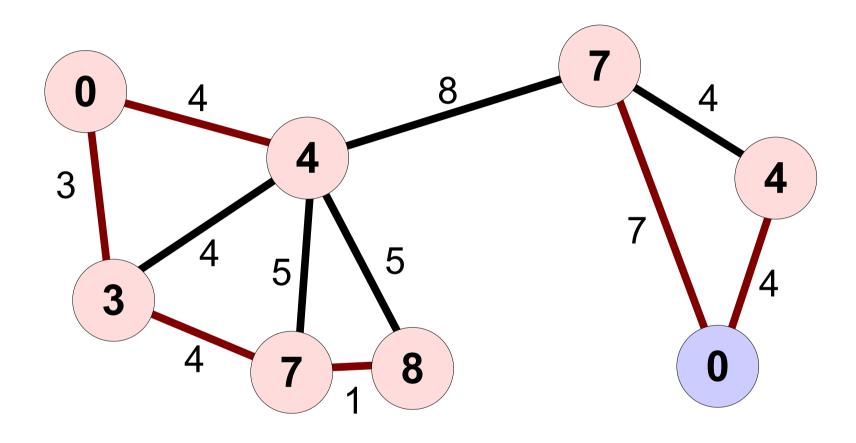


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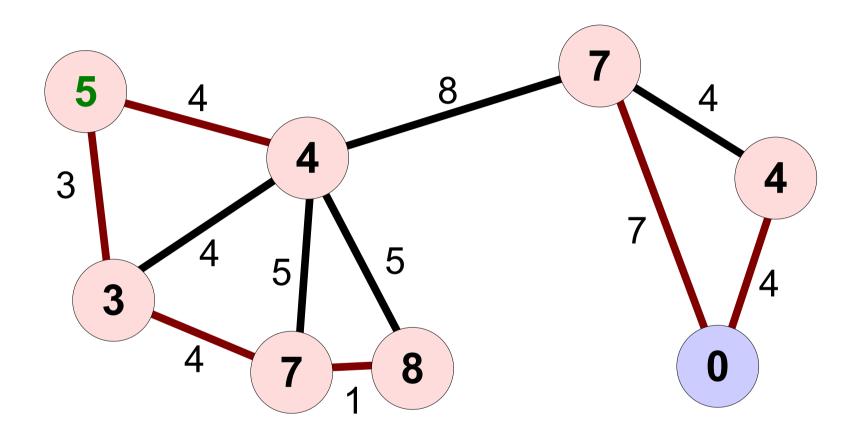
CRF Rising Values



- zero at source
- rise at v_o with relaxed constraint
- otherwise snap to constraint

$$v_0 = 5$$

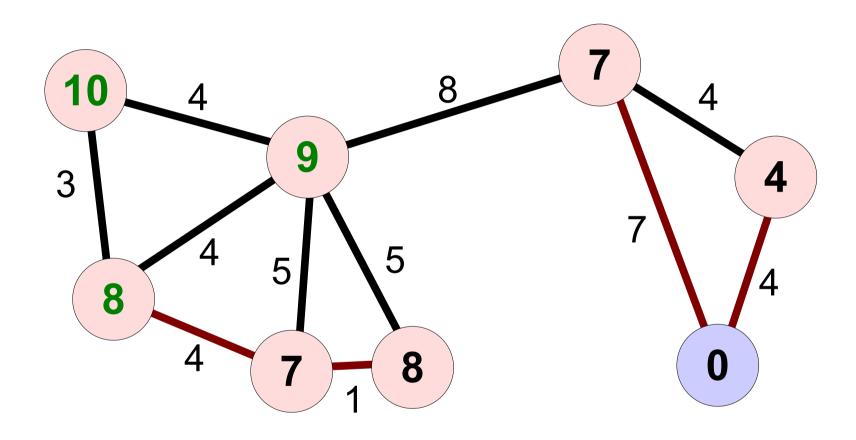
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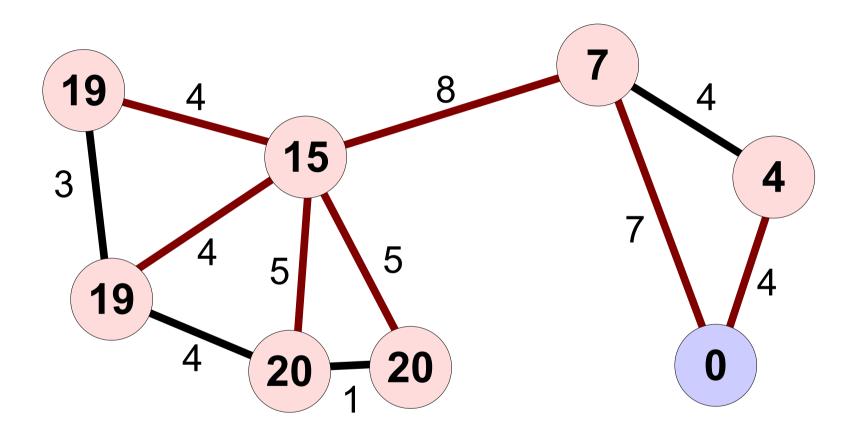
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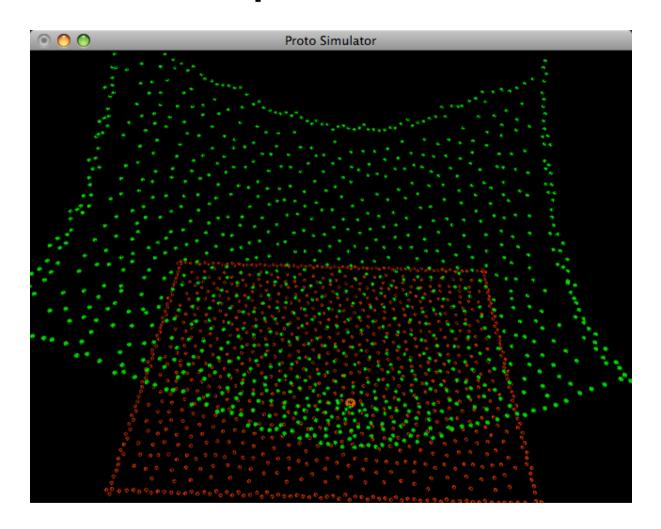
New Gradient Values



- zero at source
- rise at v_o with relaxed constraint
- otherwise snap to constraint

$$v_0 = 5$$

Perfection is expensive and "twitchy"

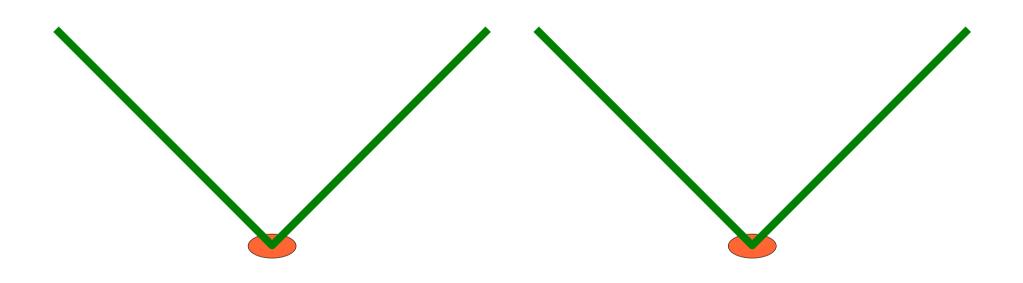


But most applications don't need perfection...

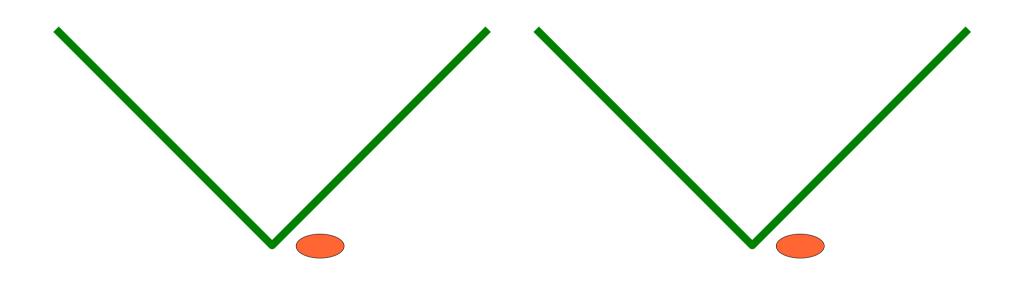
Making gradients tolerate error

- Hysteresis?
 - Past a threshold, unbounded communication
- Low-pass filtering?
 - Worse! Value change != msg cost

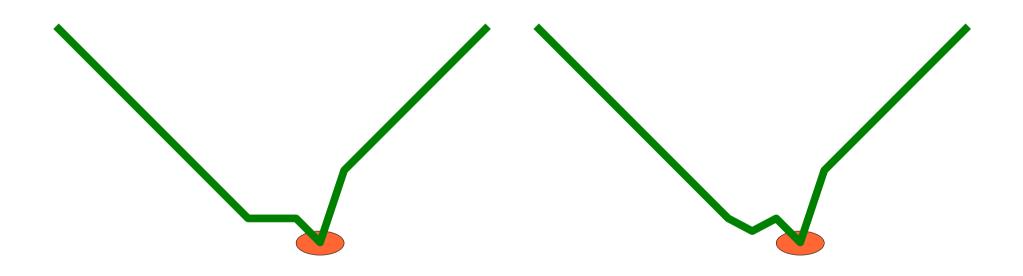
- "Elastic" connections!
 - Absorb error incrementally



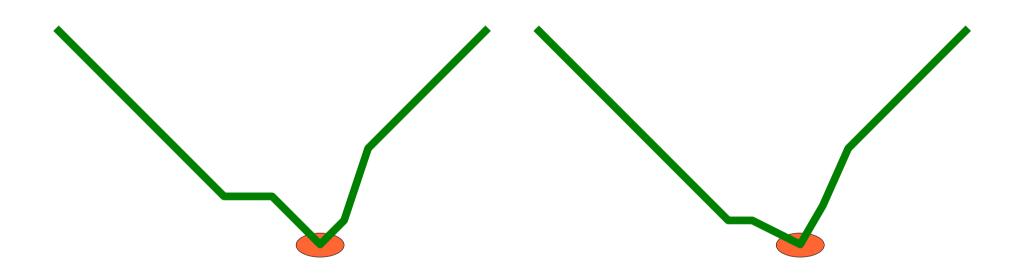
Attemped Perfection



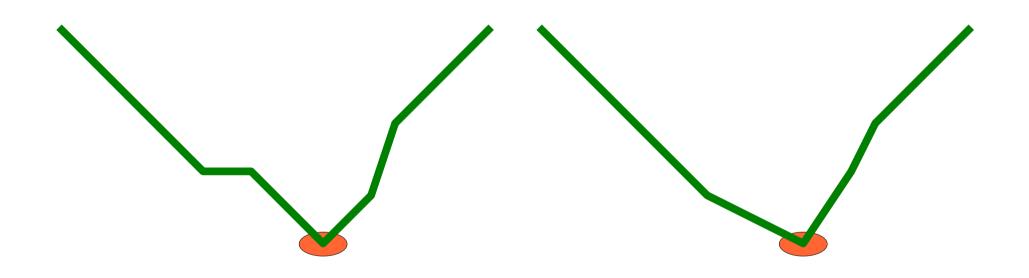
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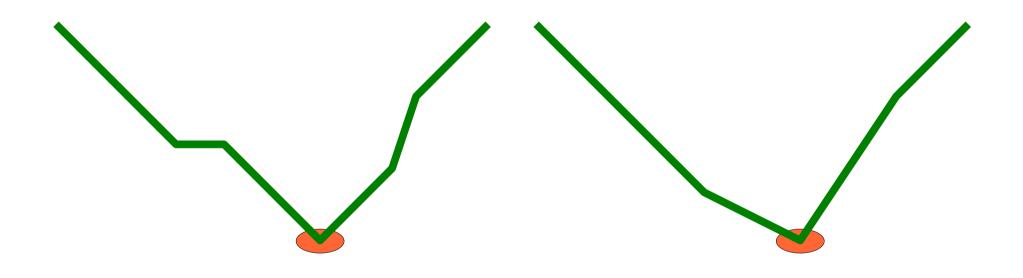
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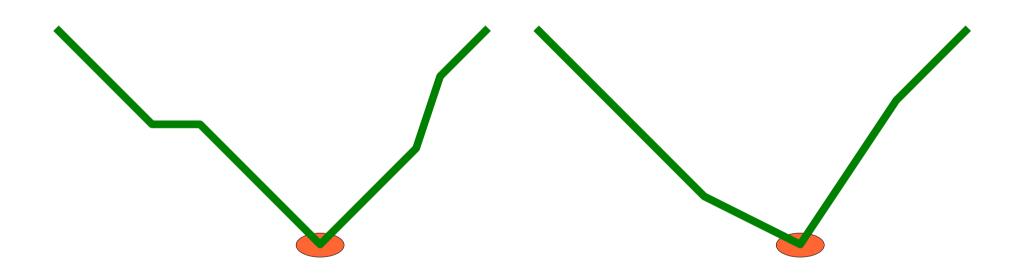
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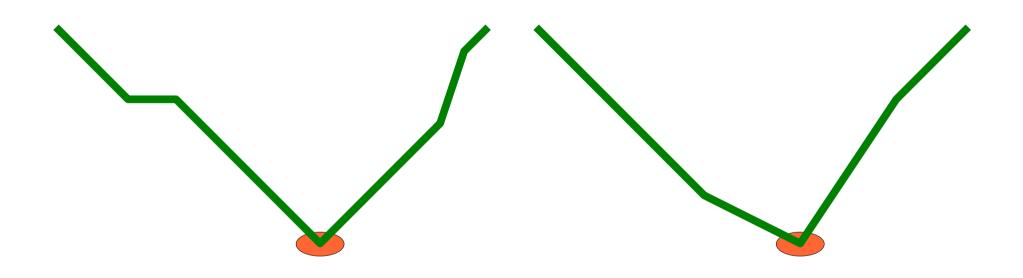
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Managing error through slope

Goal: ε-acceptable values

$$\bar{g}_x(t) \cdot (1 - \epsilon) \leq g_x(t) \leq \bar{g}_x(t) \cdot (1 + \epsilon)$$

Add local constraint via slope:

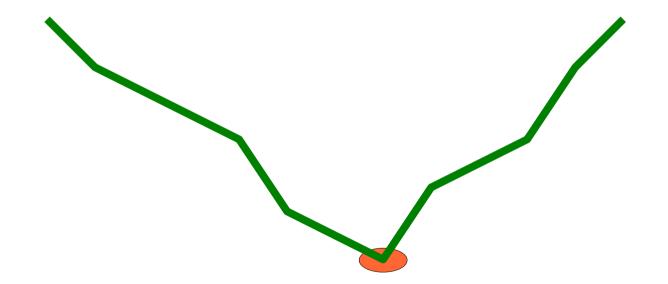
$$s_{x}(t) = max \left\{ \frac{g_{x}(t - \Delta_{t}) - g_{y}(t_{x,y})}{d(x, y, t_{x,y})} | y \in N_{x}(t) \right\}$$

→ "flexible" gradients

(allow small distortion for rising value problem)

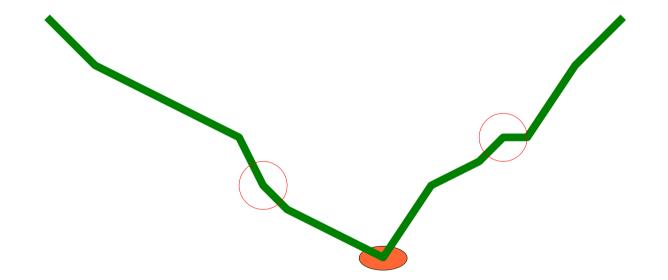
Getting the kinks out

- Flexed regions cannot absorb error
- Want eventual correctness



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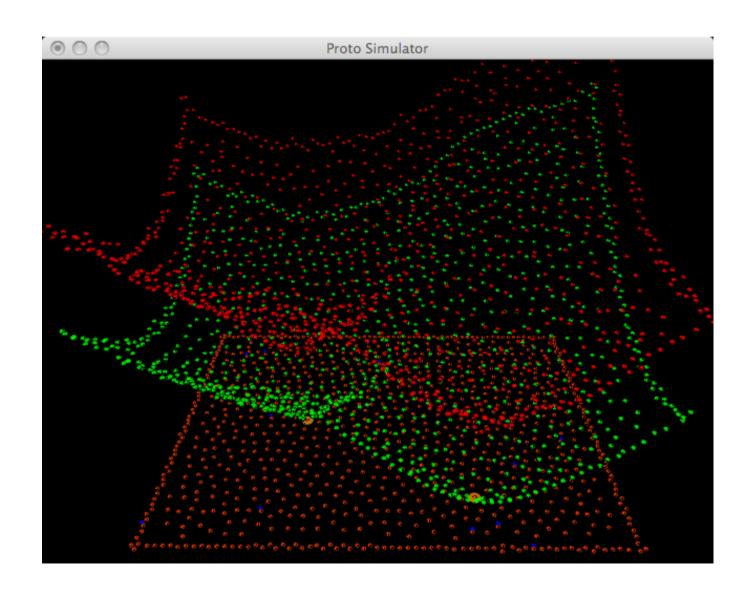


Solution: occasional ε =0 steps

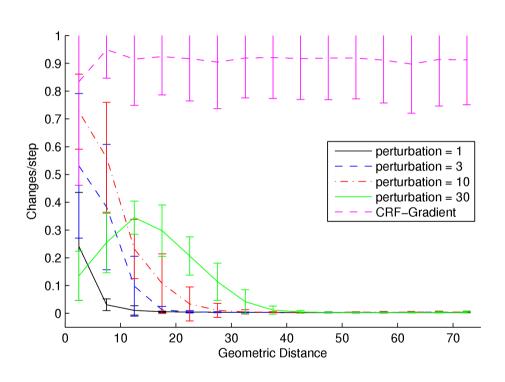
Flex-Gradient Algorithm (simplified)

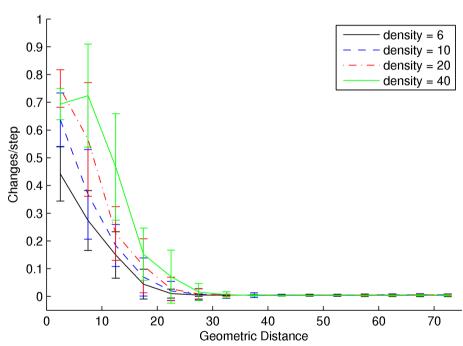
- Sources take $g_x(t)=0$
- Else measure maximum slope and minimum distance through neighbors (w. r/δ distortion):
 - If value is more than 2x lowest value through neighbor, snap to slope=1
 - Else if slope is not ε-acceptable, make ε-acceptable
 - Once every $g_x(t)$ updates, use $\epsilon=0$

Flex-Gradient vs. CRF-Gradient

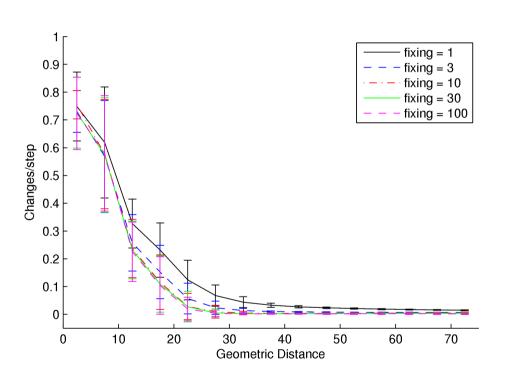


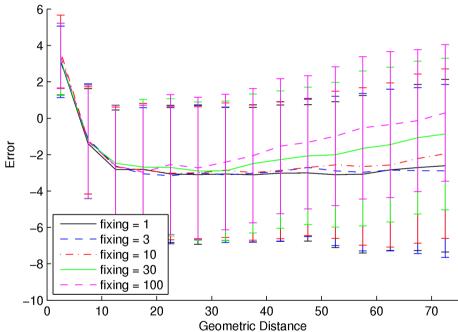
Perturbations affect limited range



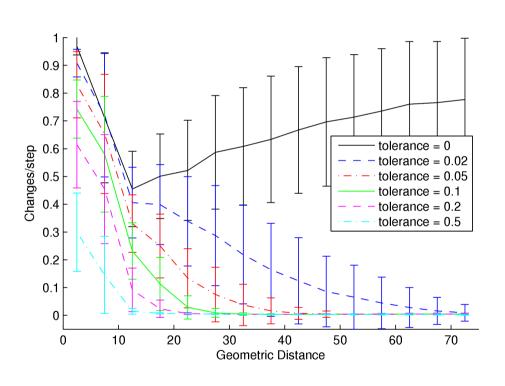


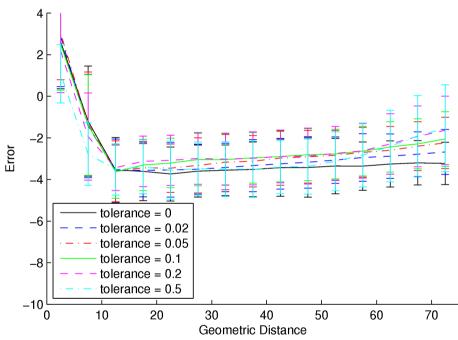
Even infrequent repair helps





A little tolerance goes a long way





Contributions

- Tolerating small errors can reduce communication cost by orders of magnitude
- Flex-Gradient algorithm heals slope changes
 - Oscillation affects bounded radius
 - Long-term changes are propagated everywhere