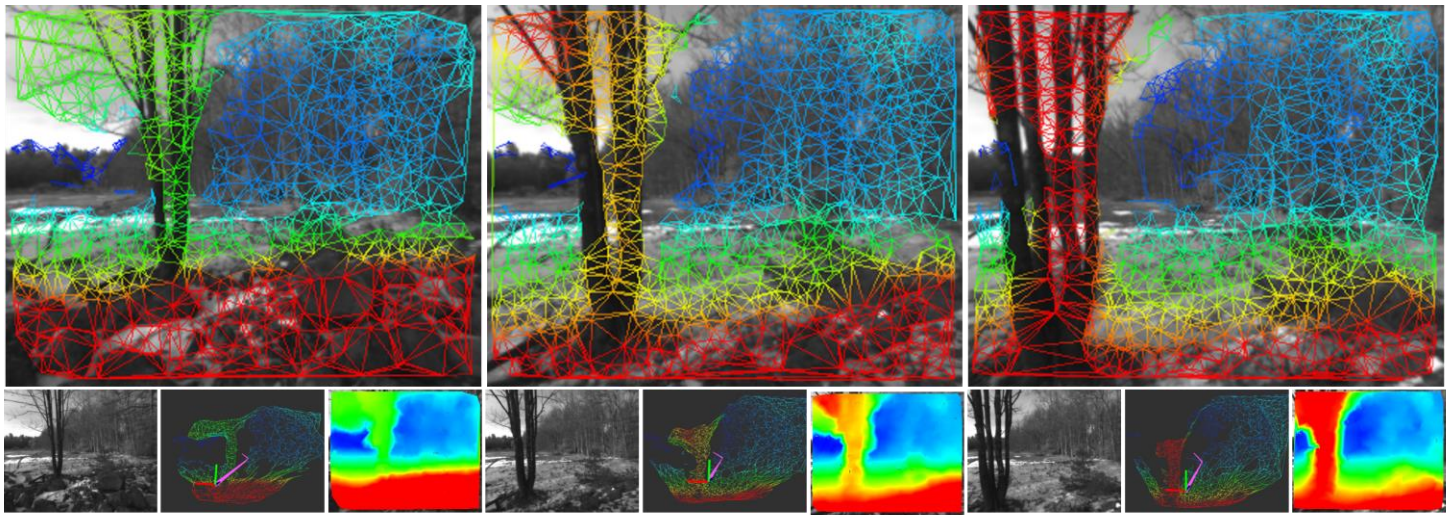
FLaME: Fast Lightweight Mesh Estimation using Variational Smoothing on Delaunay Graphs



W. Nicholas Greene

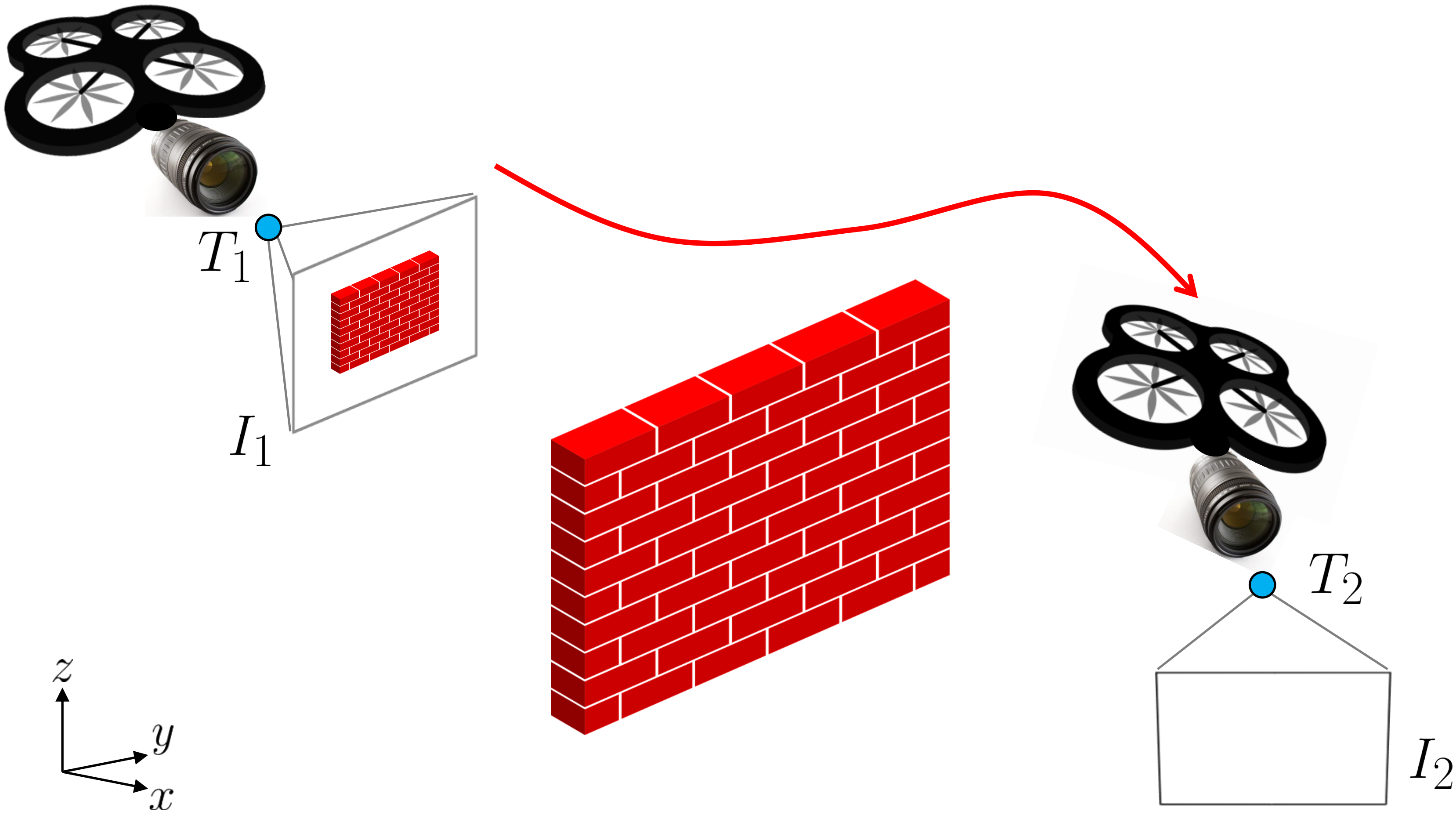
Robust Robotics Group, MIT CSAIL

LPM Workshop IROS 2017

September 28, 2017

with Nicholas Roy

We want Autonomous Vision-Based Navigation



https://commons.wikimedia.org/wiki/File%3AQuadcopter_Drone.png
https://commons.wikimedia.org/wiki/File%3ACanon_90-300mm_camera_lens.jpg

But Dense Monocular SLAM is Expensive

Sparse Methods

Mono-Slam (Davison, ICCV 2007)
PTAM (Klein and Murray, ISMAR 2007)
SVO (Forster et al., ICRA 2014)

Efficiency

Density

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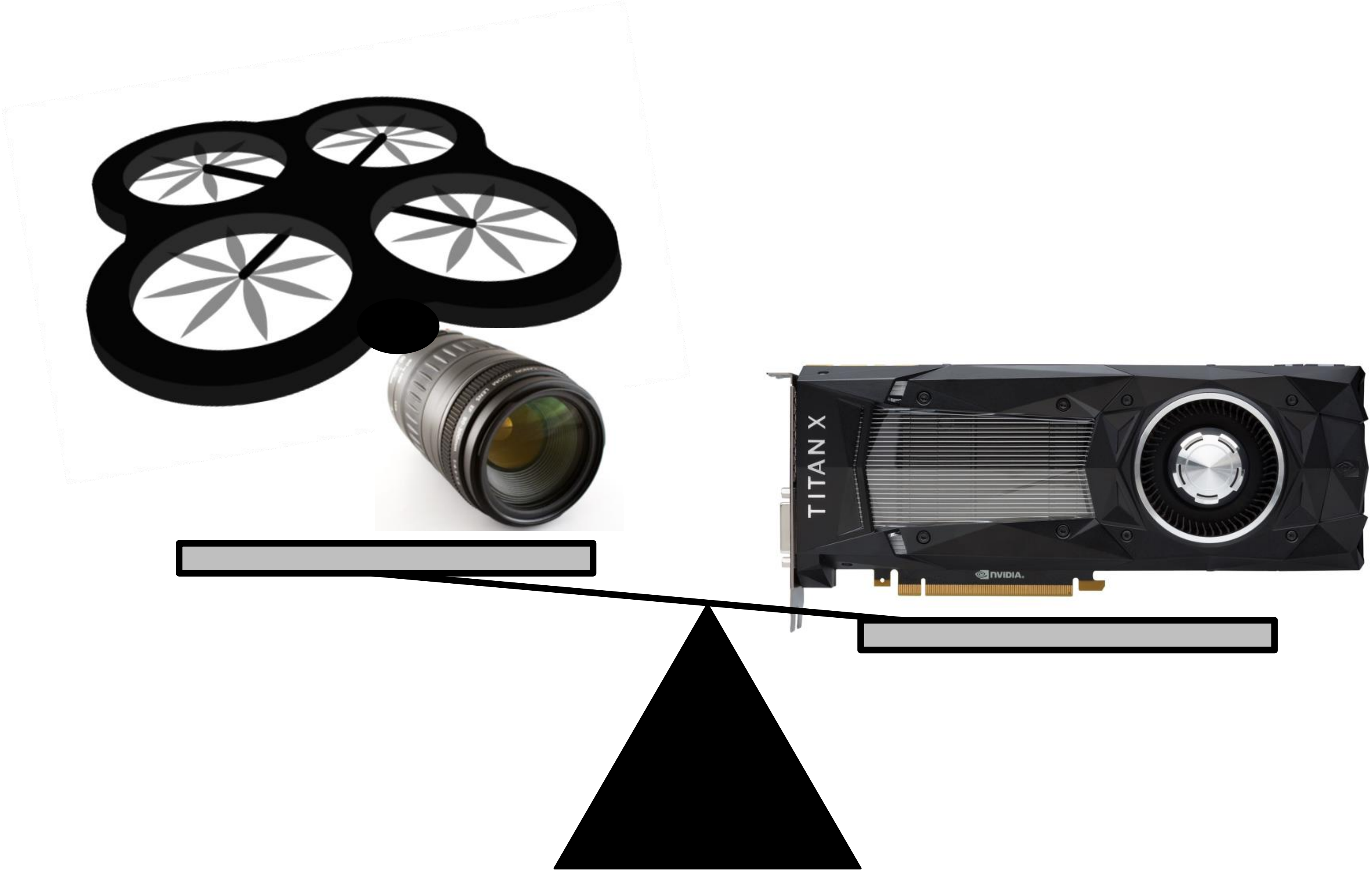

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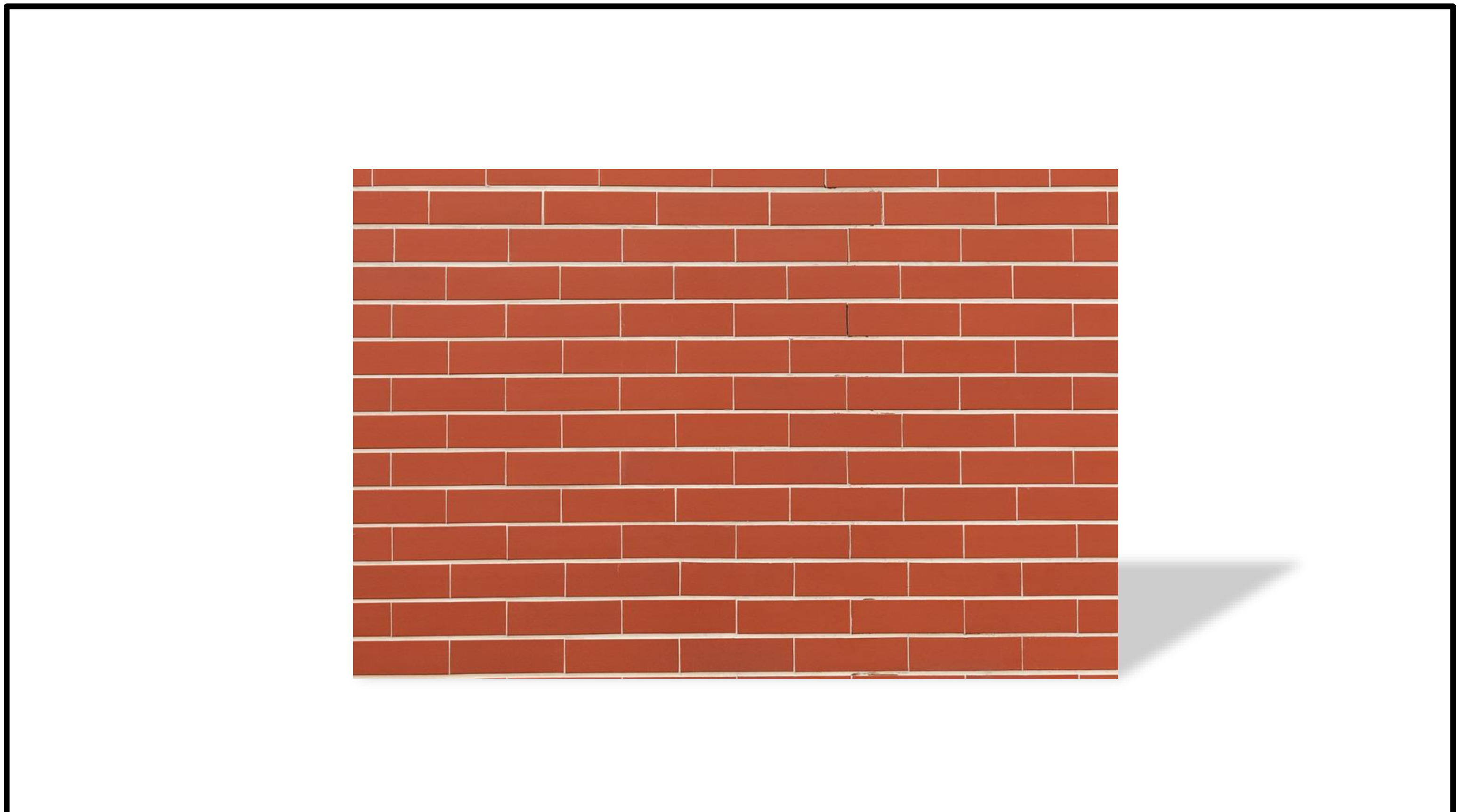
?

Efficiency

Density

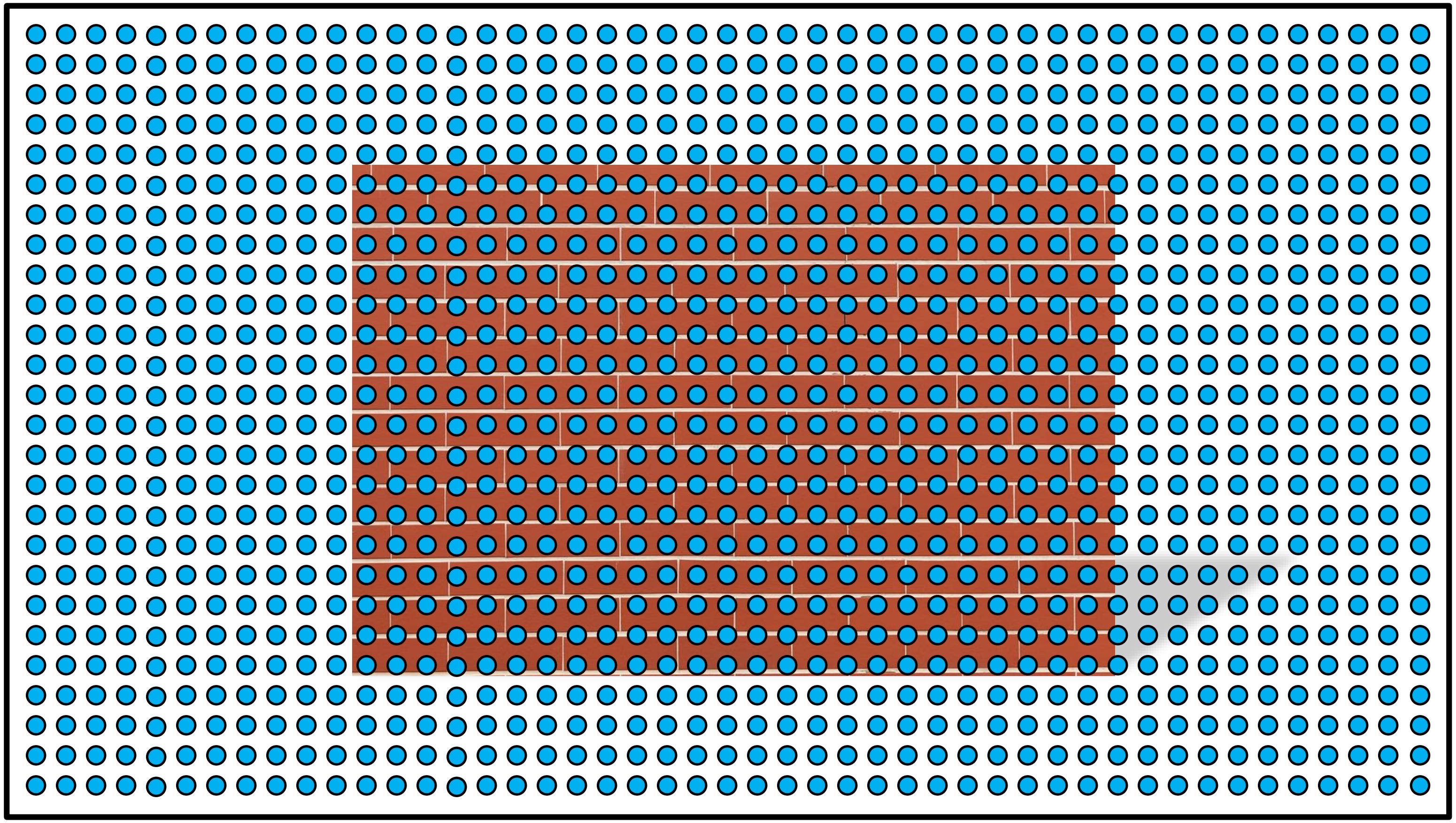
Can we more efficiently estimate dense geometry?

What Would a Dense Method Do?



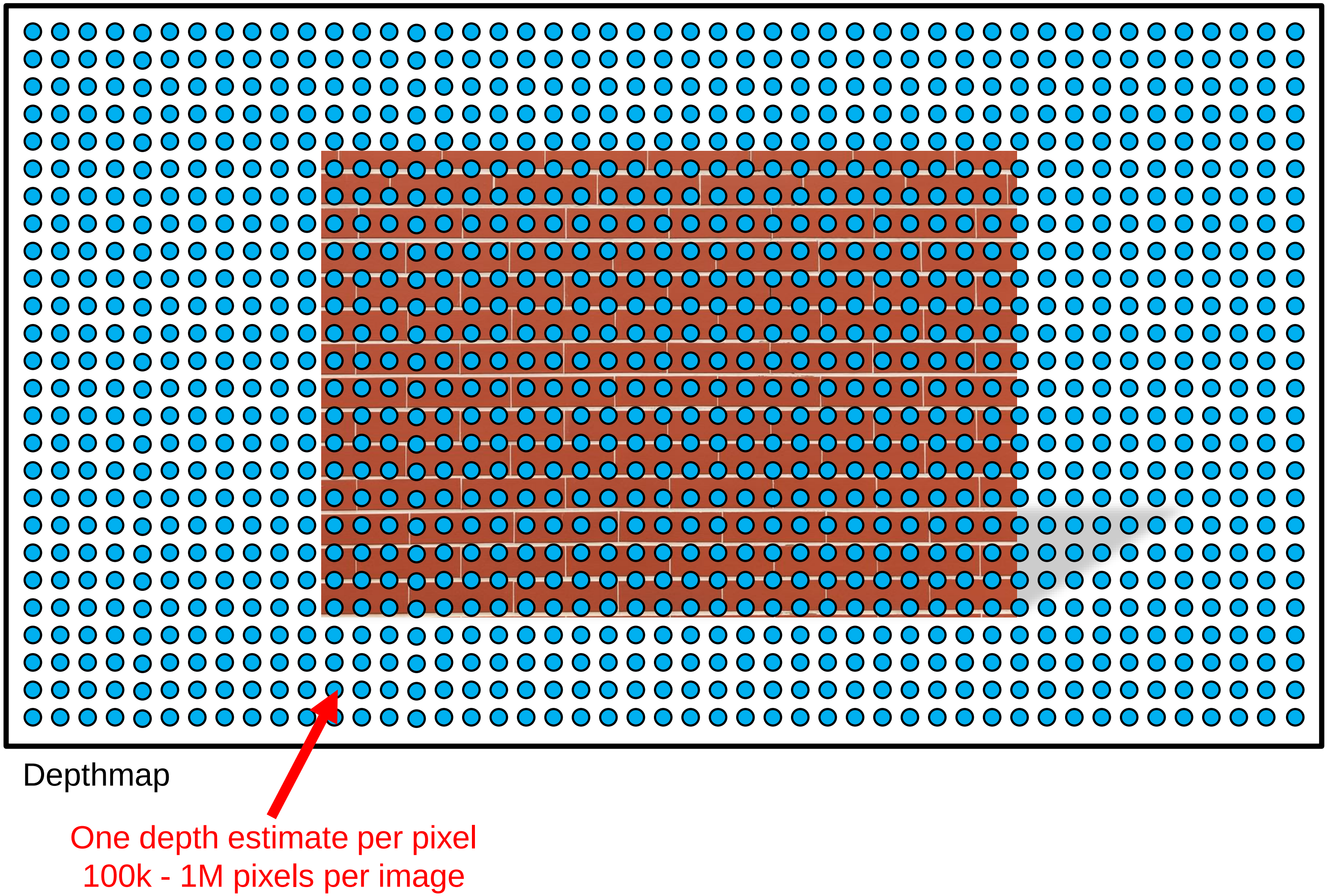
Image

Estimate Depth for Every Pixel

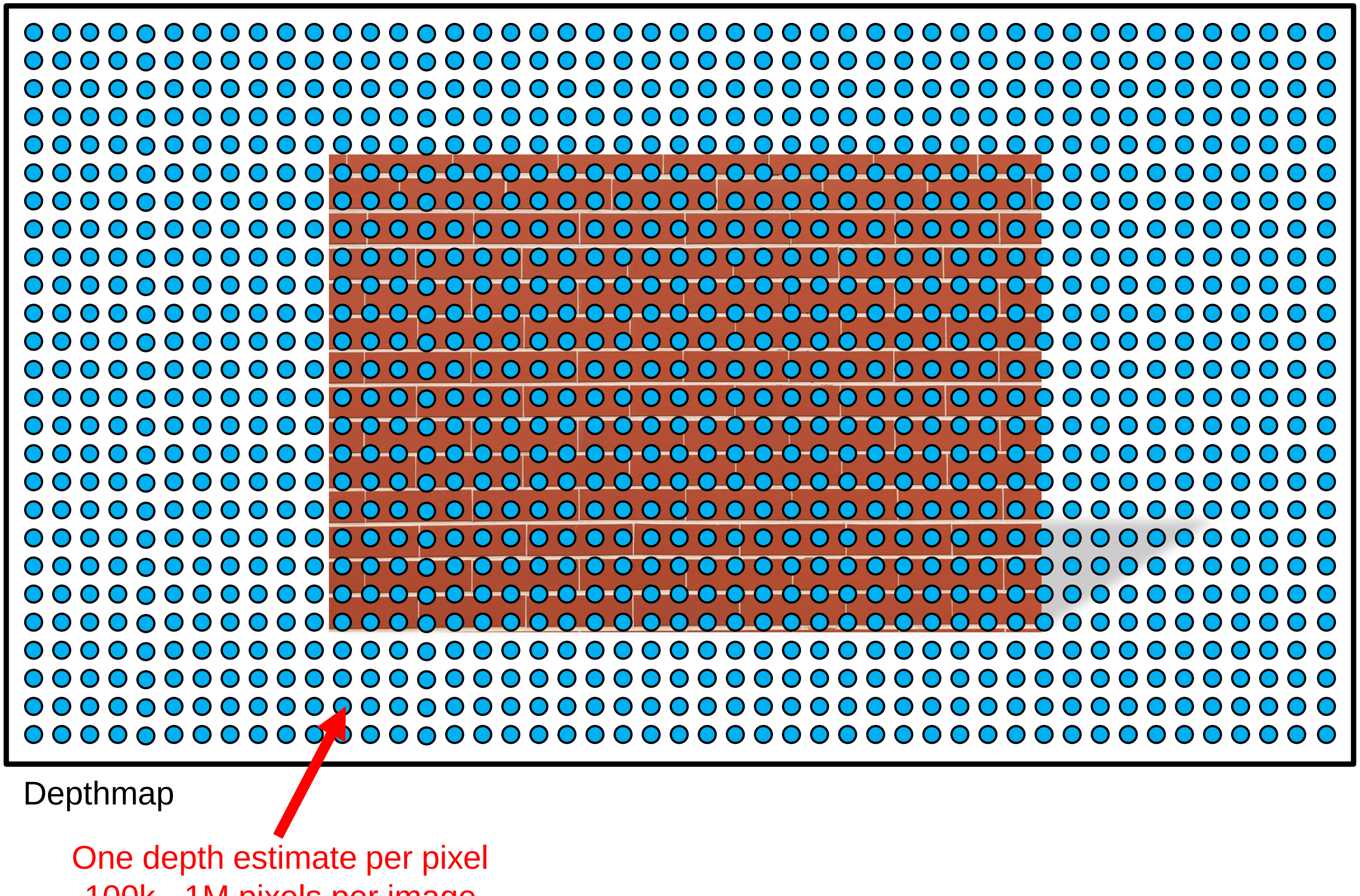


Depthmap

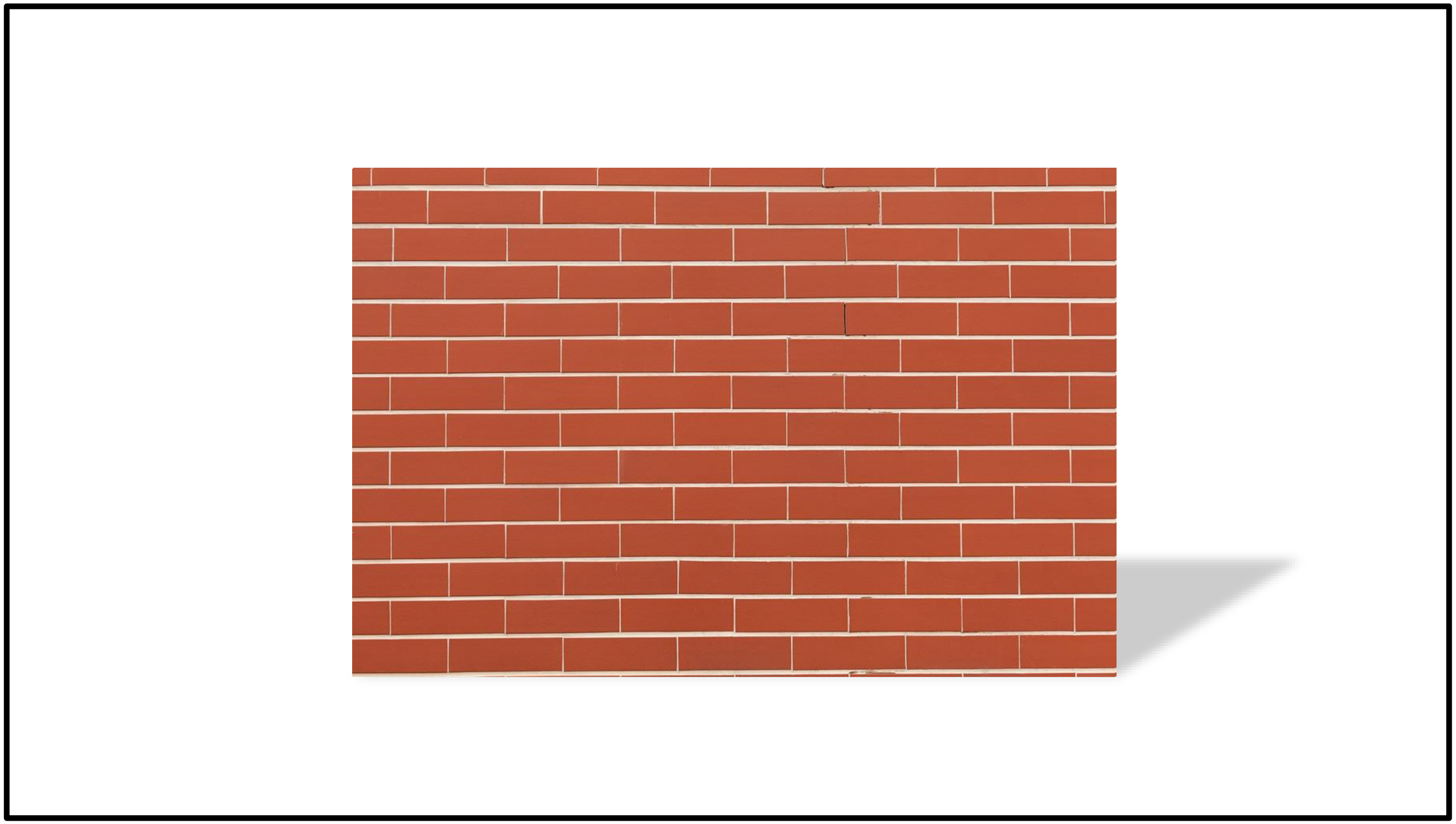
Dense Methods Oversample Geometry



Dense Methods Make Regularization Hard(er)



Meshes Encode Geometry with Fewer Depths



Depthmap

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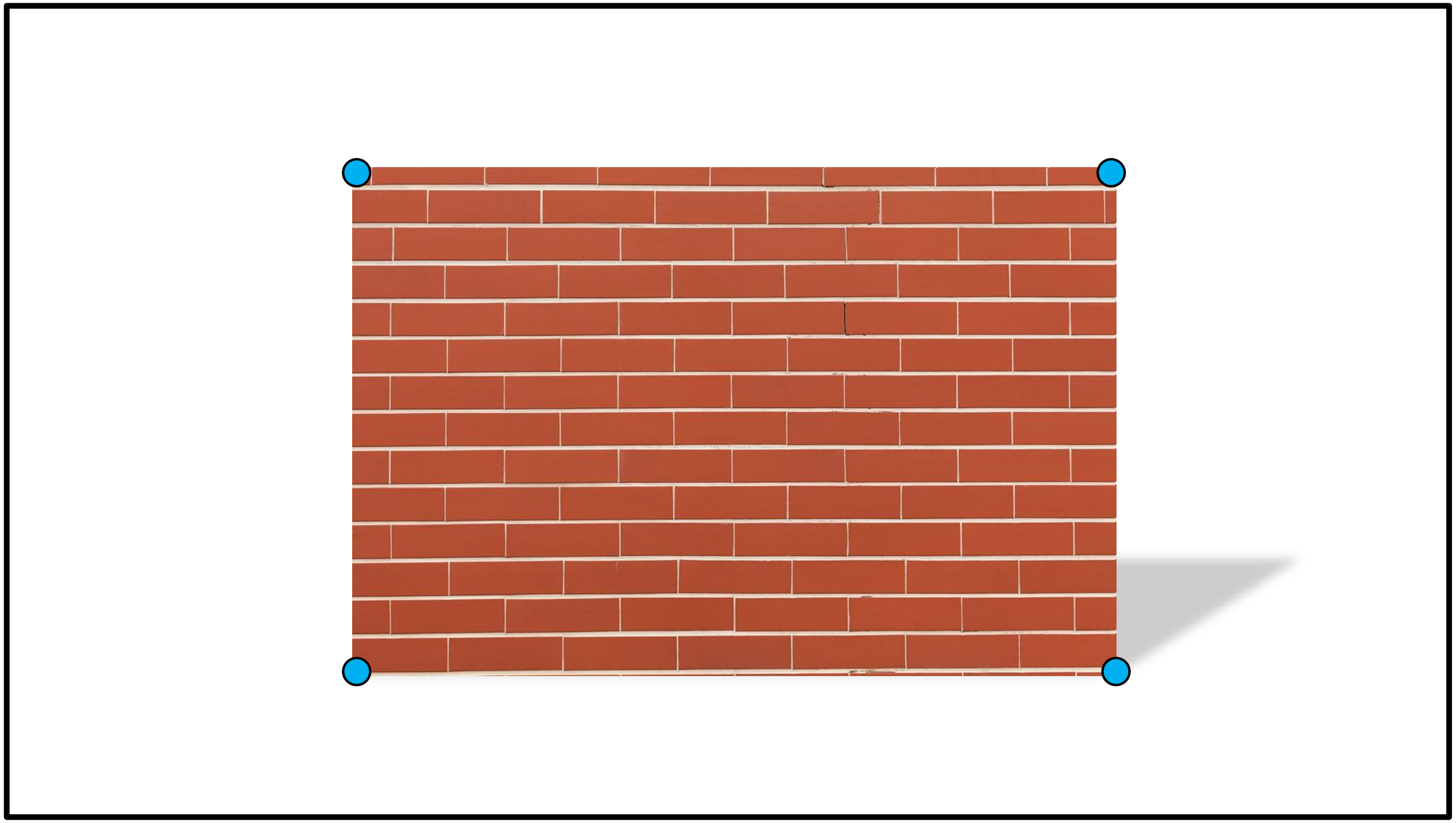

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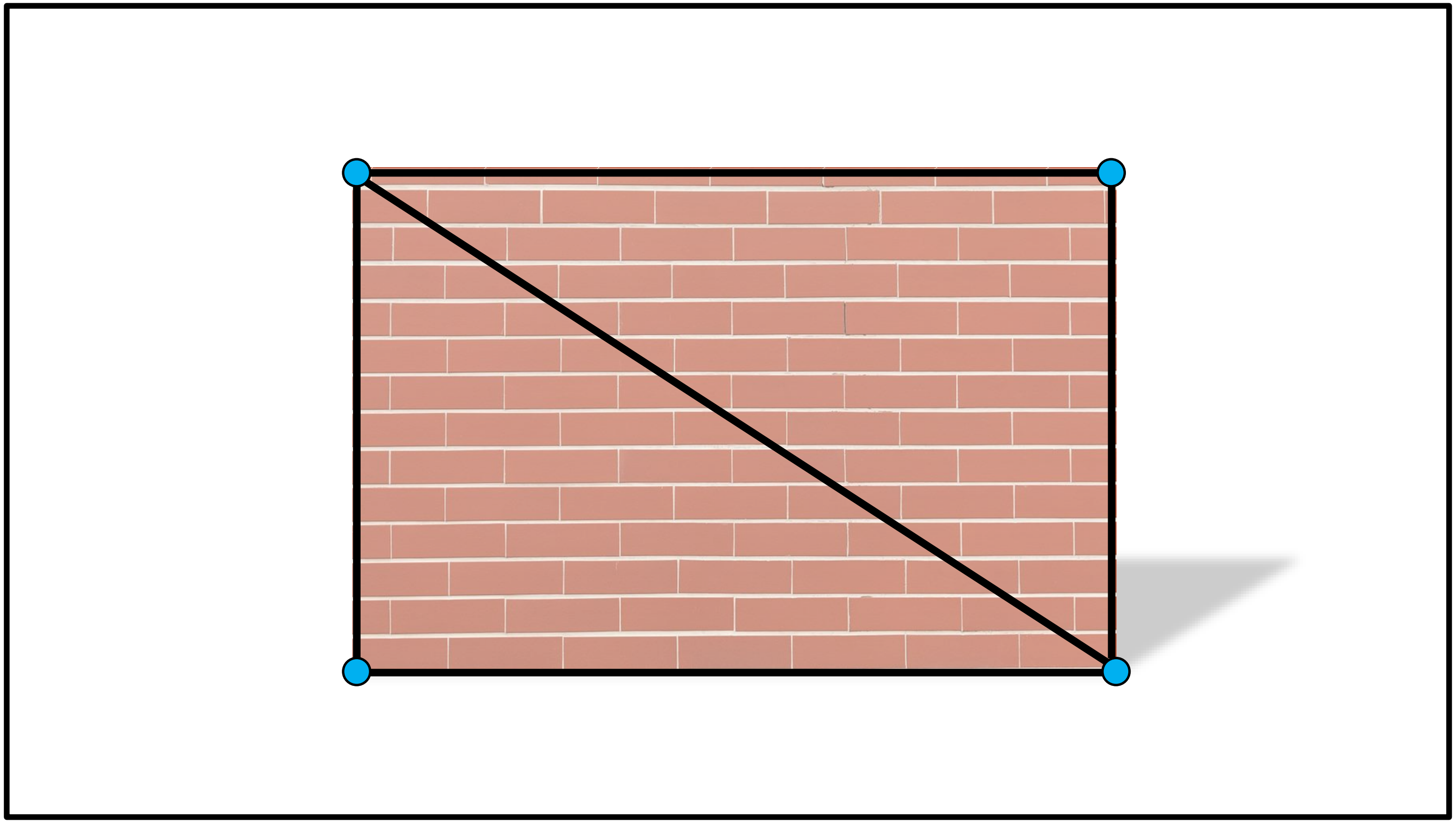

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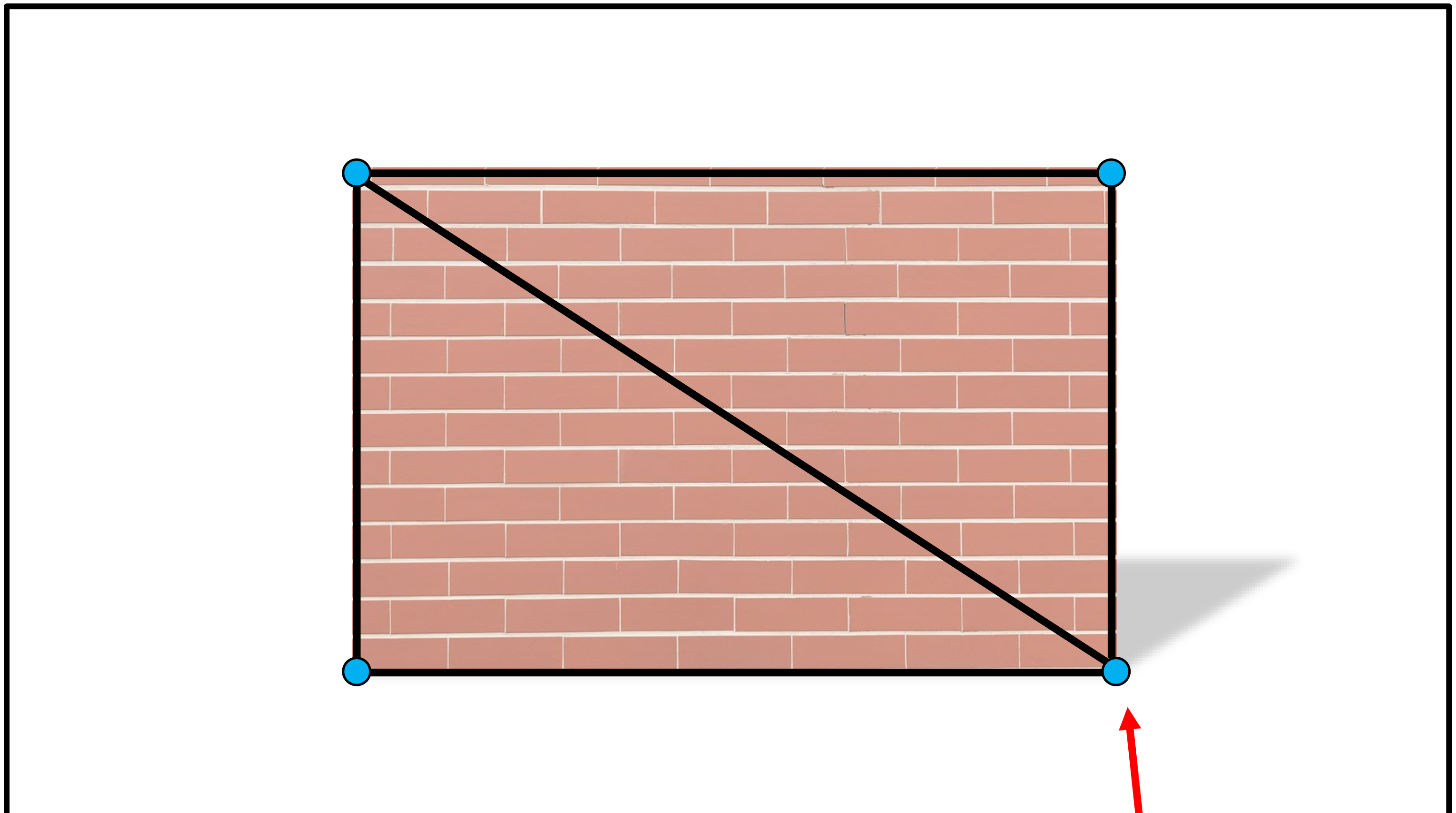
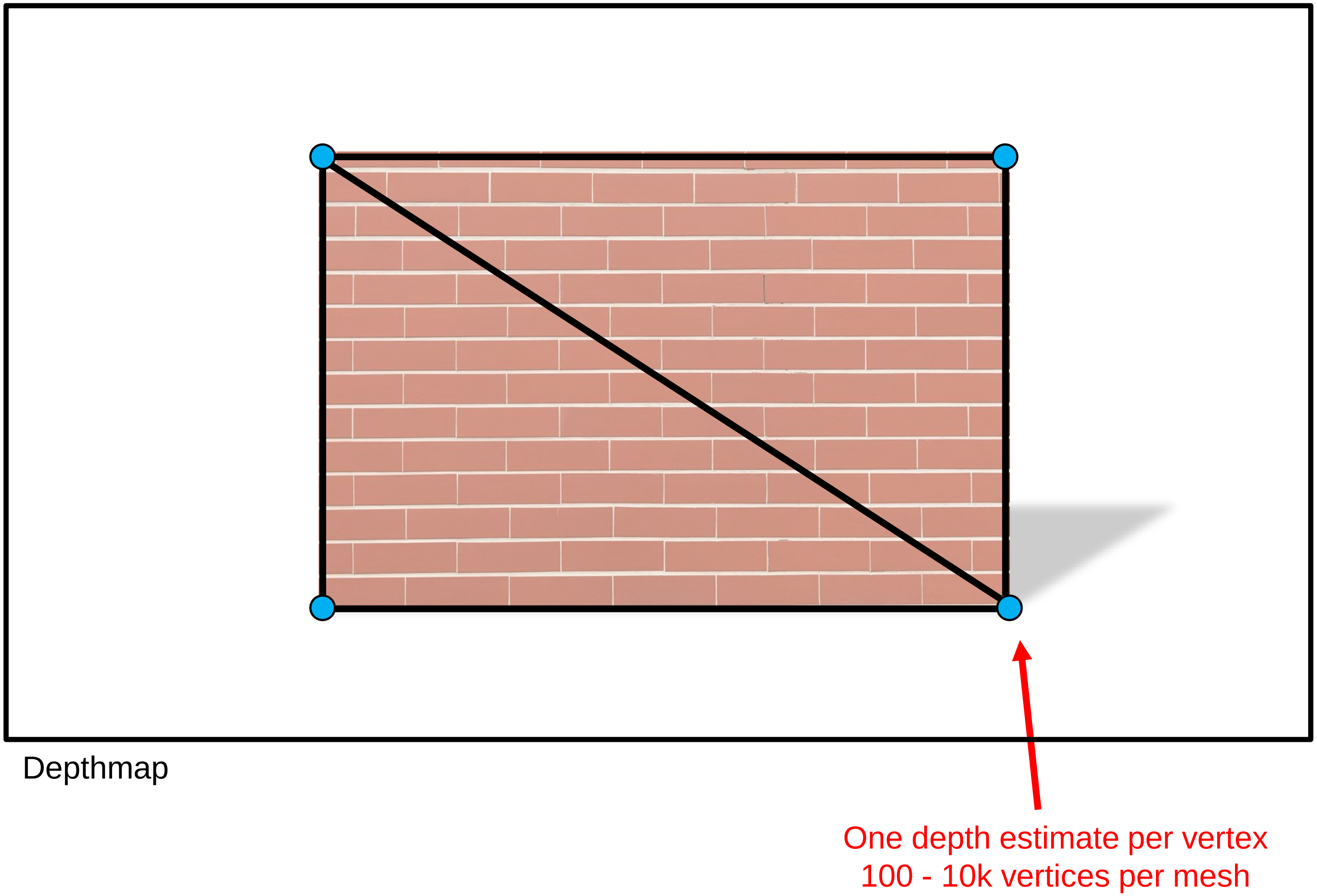


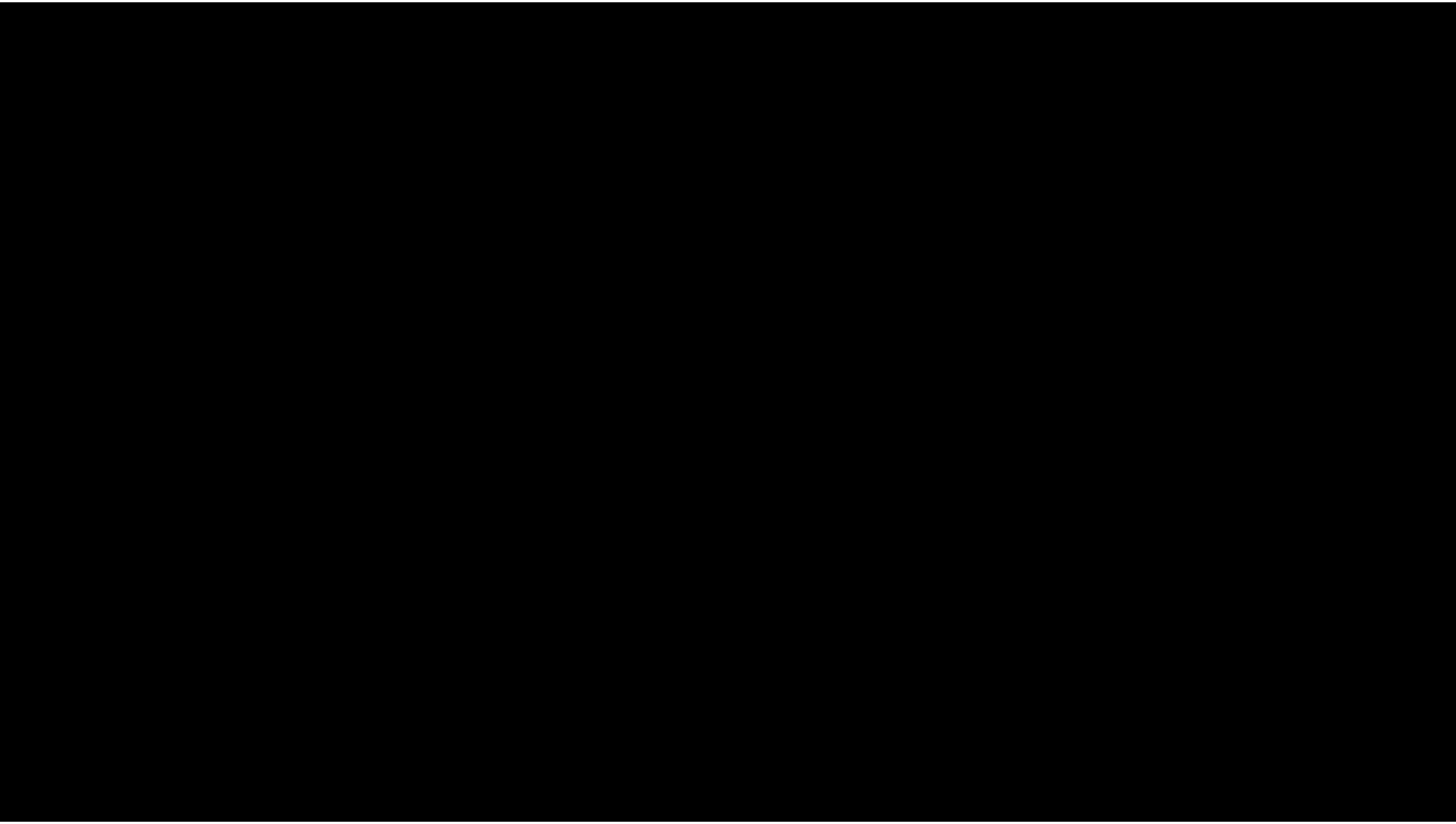
Depthmap

One depth estimate per vertex
100 - 10k vertices per mesh

Meshes Make Regularization Easy(er)



FLaME: Fast Lightweight Mesh Estimation



Fast (< 5 ms/frame) ***Lightweight*** (< 1 Intel i7 CPU core) ***Runs Onboard MAV***

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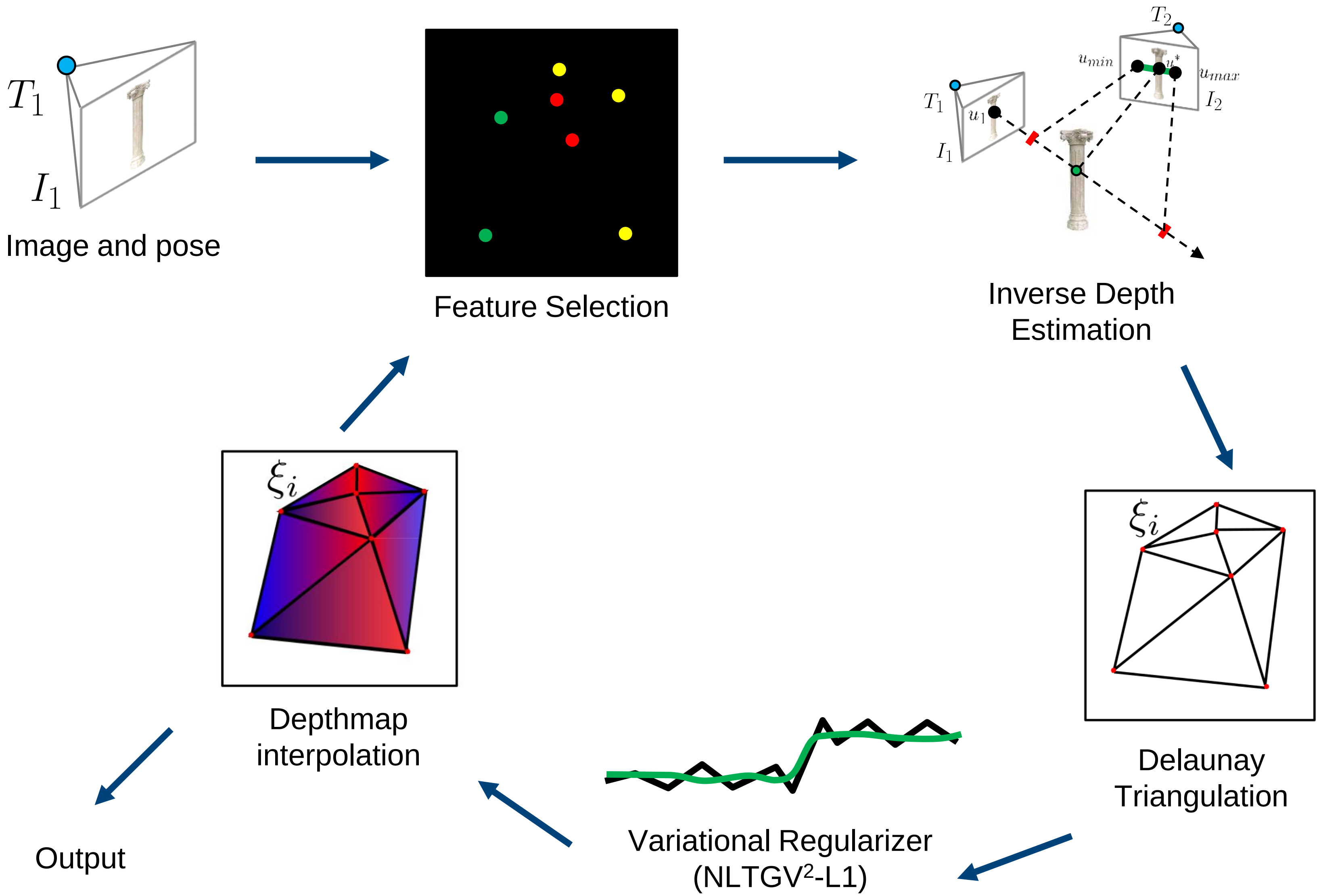

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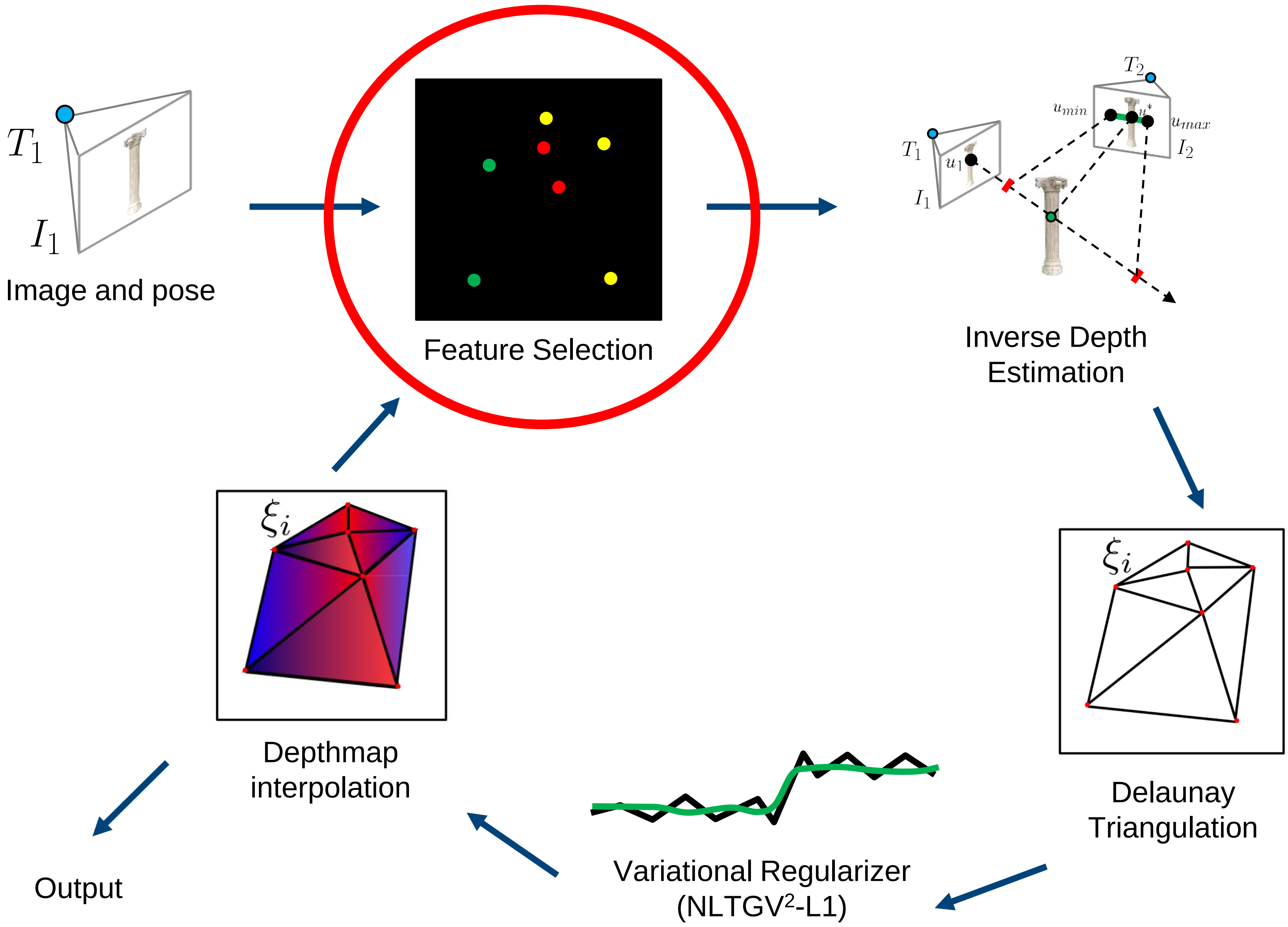
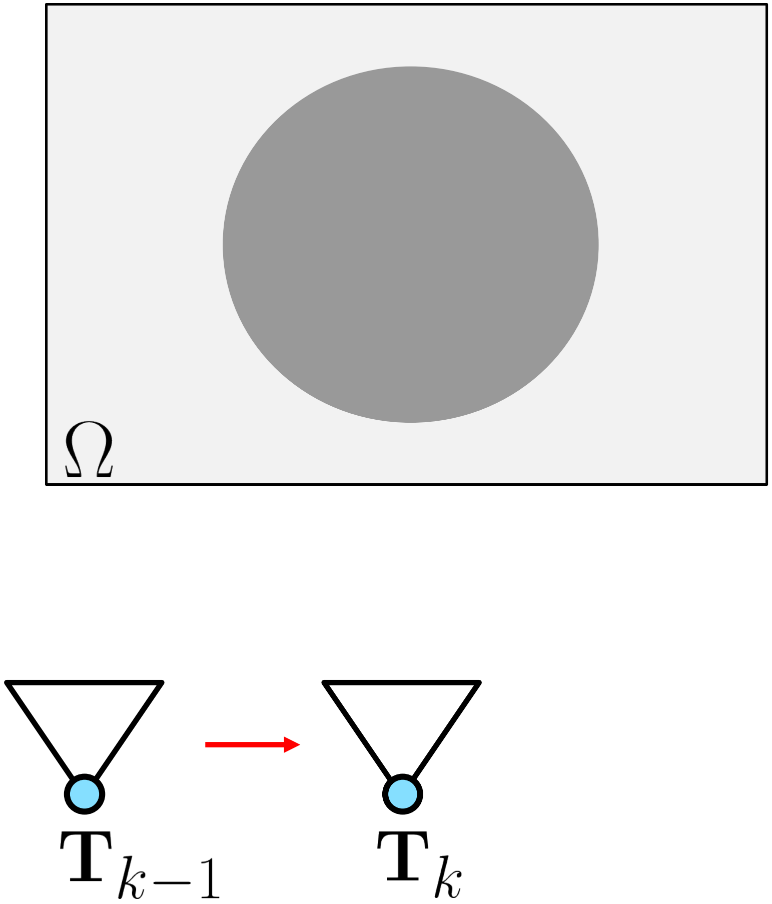


Select Easily Trackable Features

- At each frame we sample ***trackable*** pixels or ***features*** over the image
- These ***features*** will serve as ***potential vertices*** to add to the mesh



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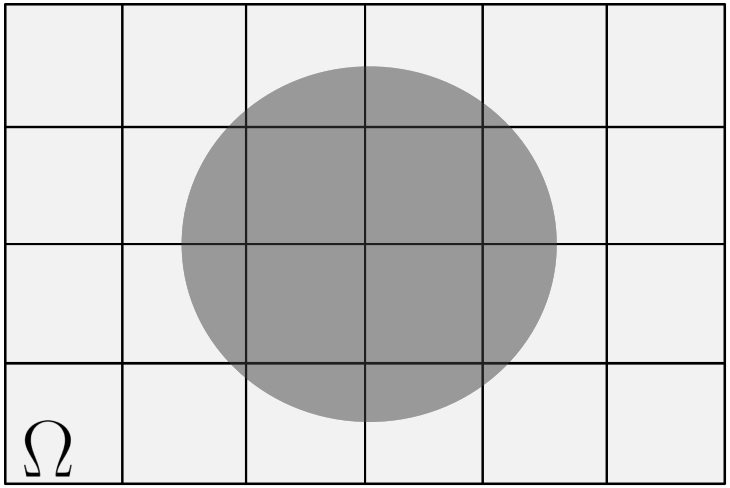

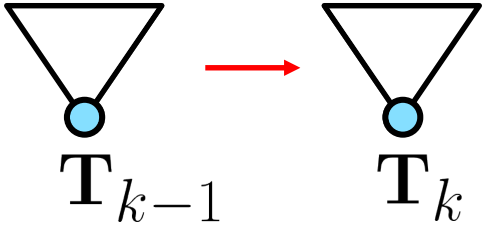

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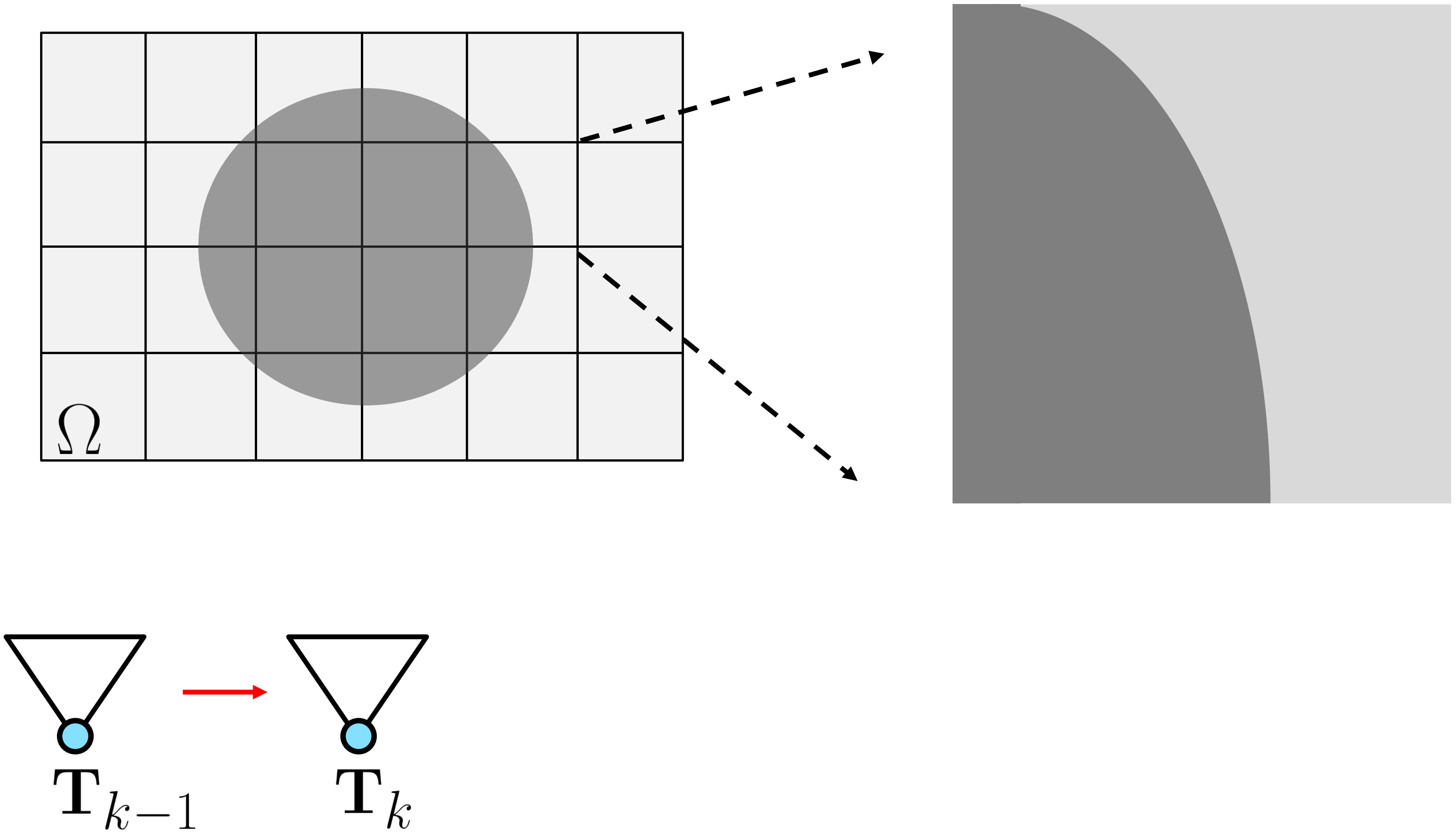

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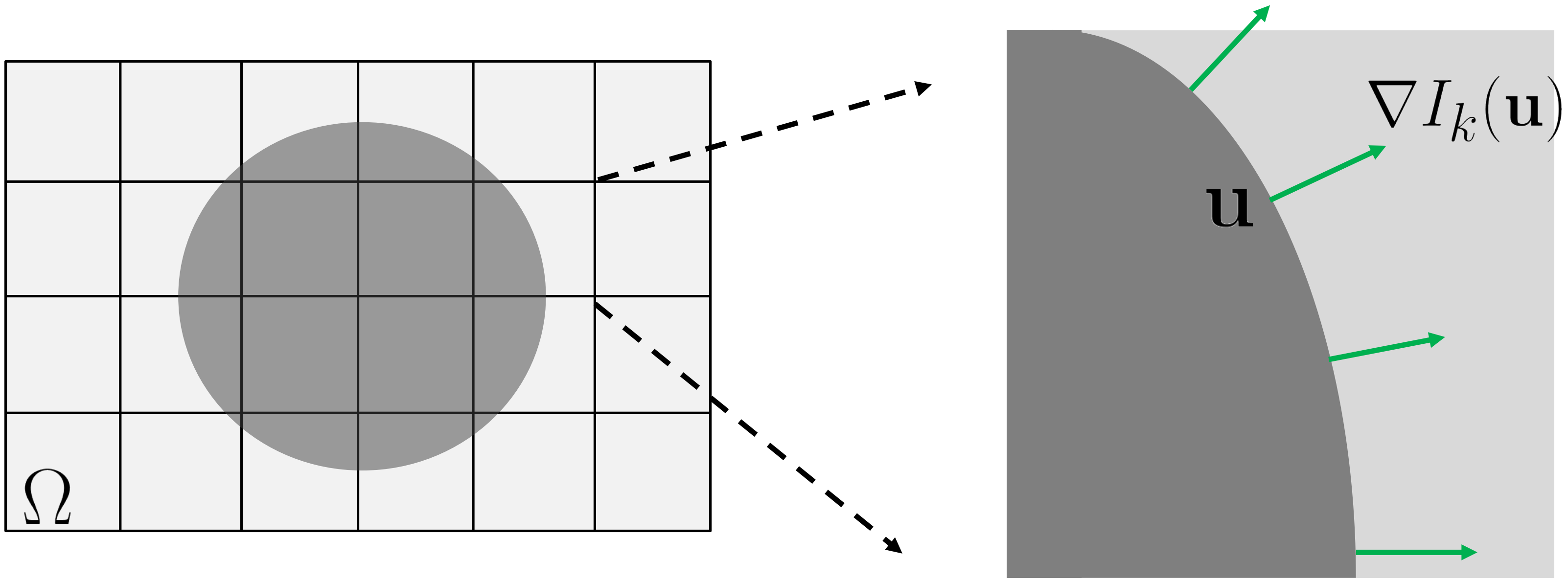

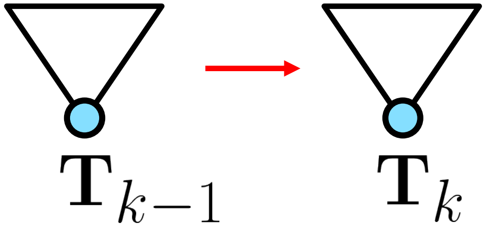

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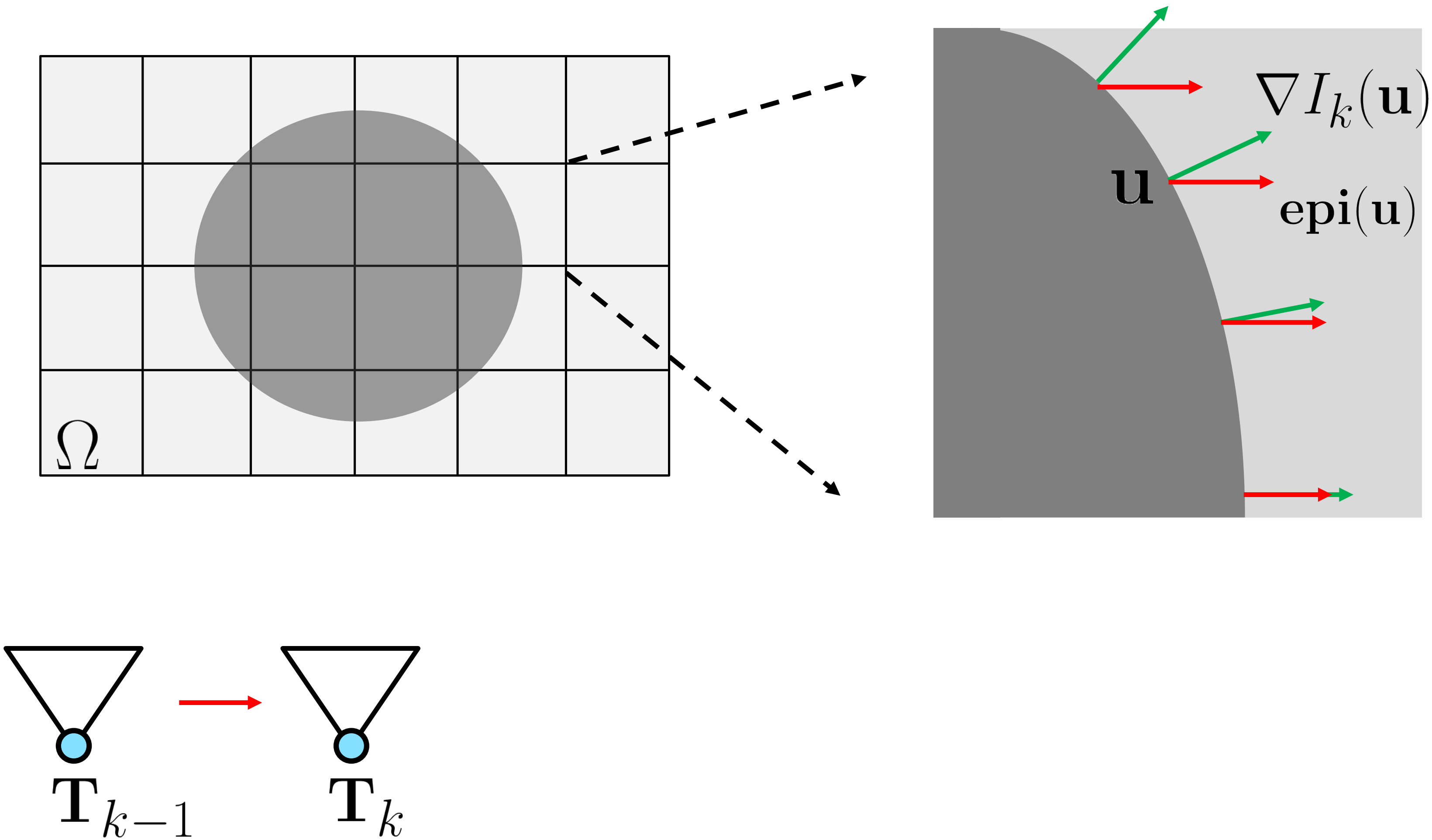

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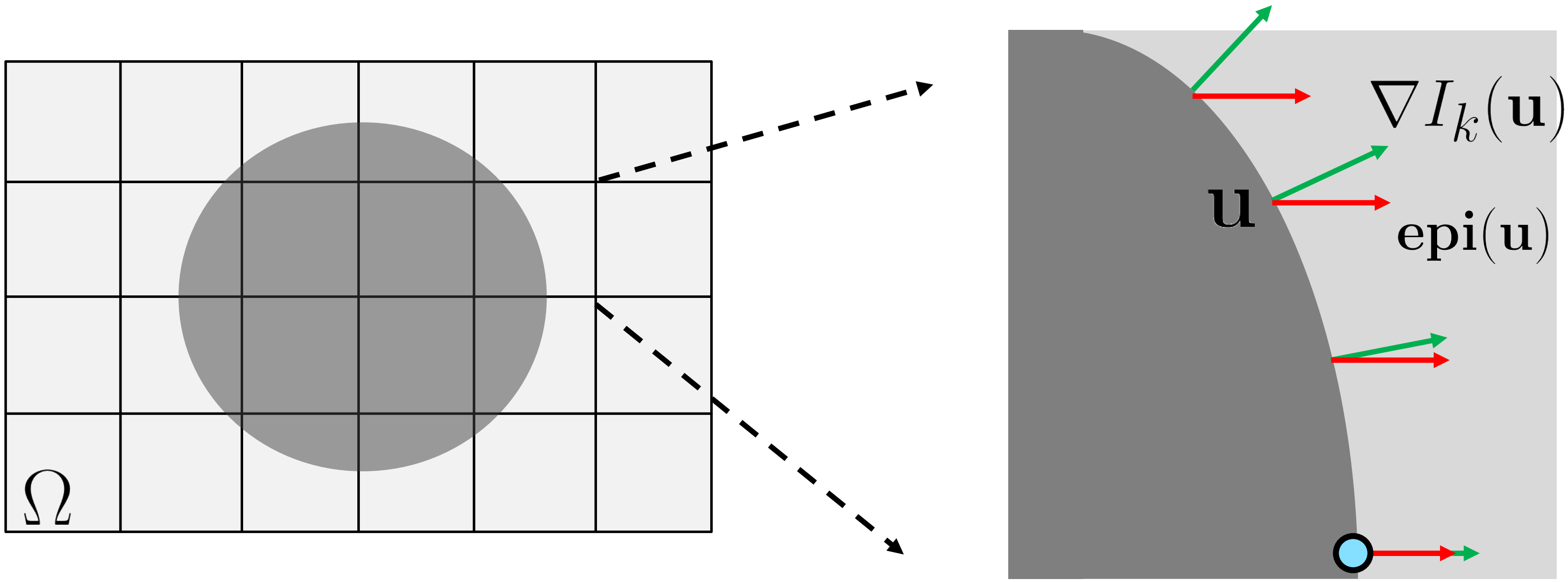

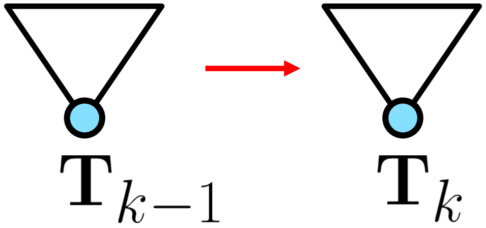

Select pixel in each grid cell with maximum score:

$$s(\mathbf{u}) = |\nabla I_k(\mathbf{u}) \cdot \mathbf{epi}(\mathbf{u})|$$

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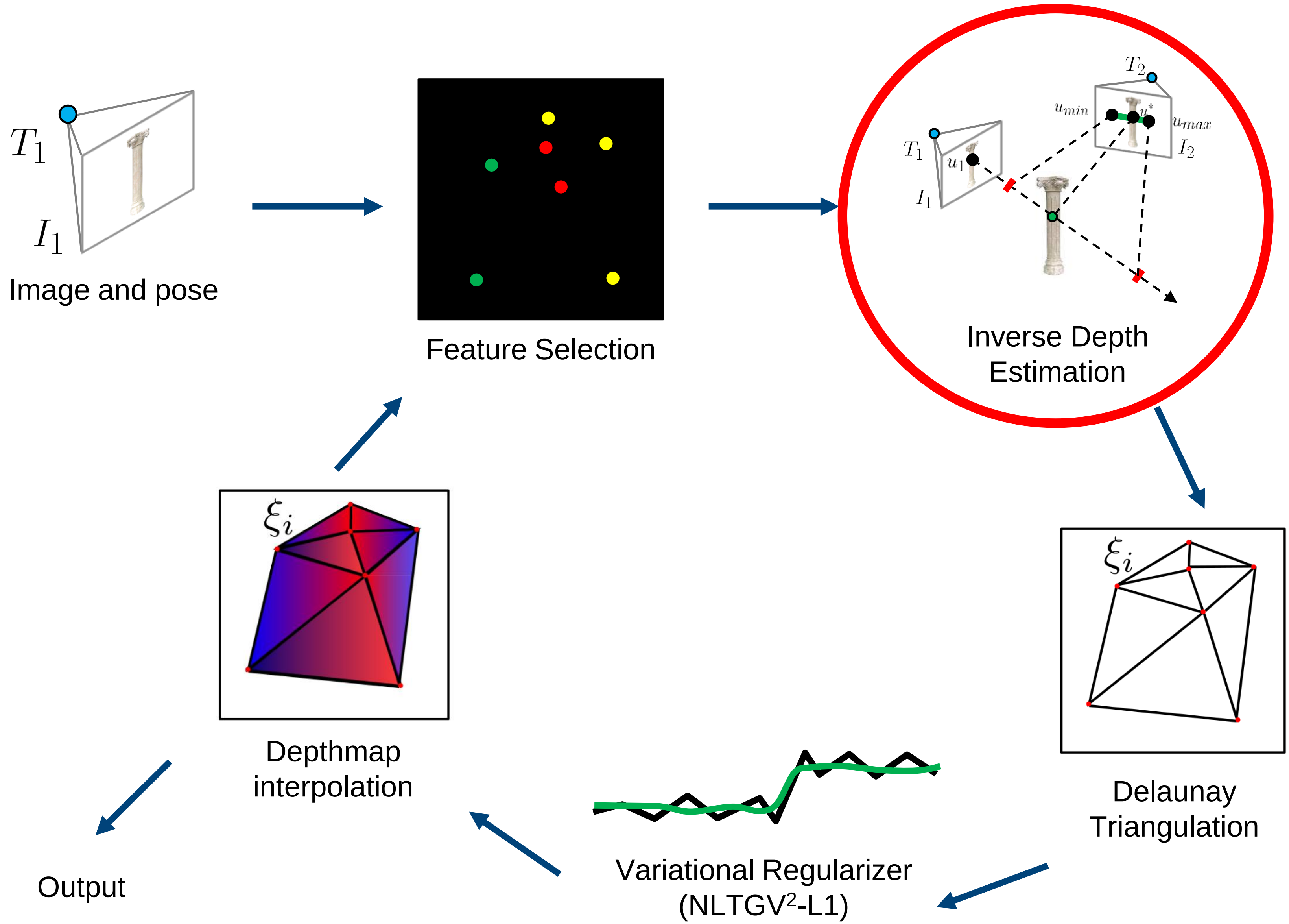
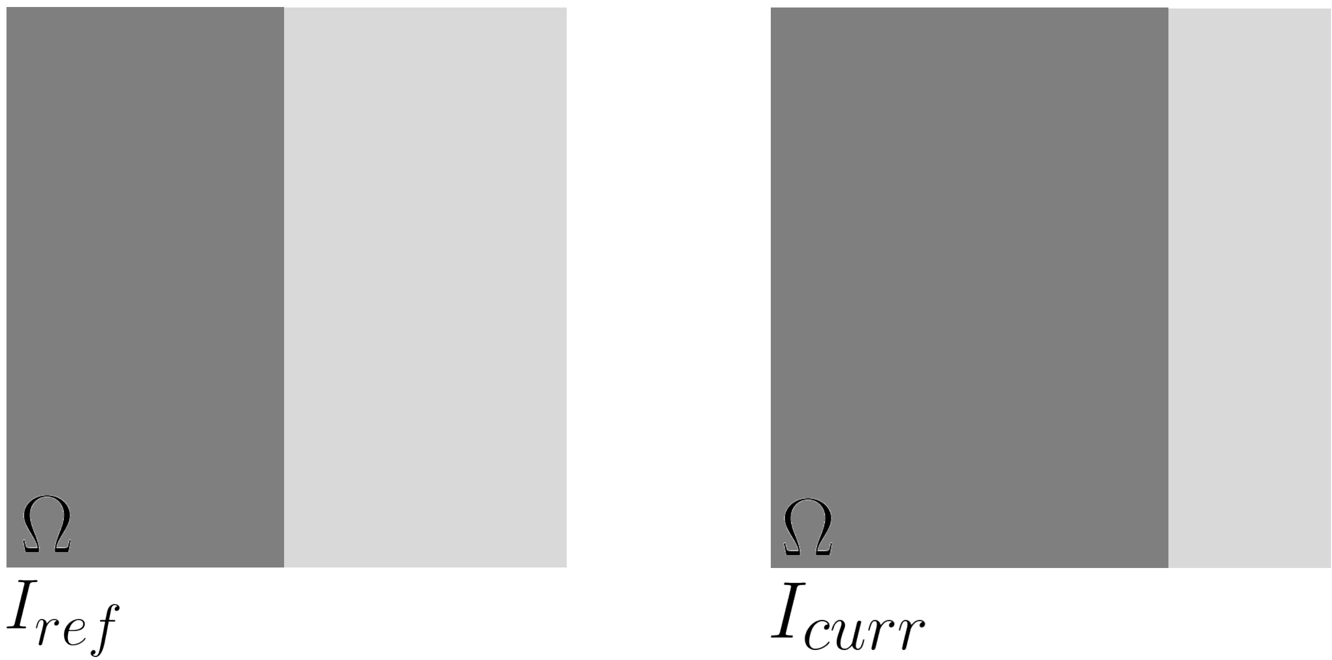


Estimate Inverse Depths for Features

- We ***track*** features across new images using ***direct epipolar stereo comparisons***



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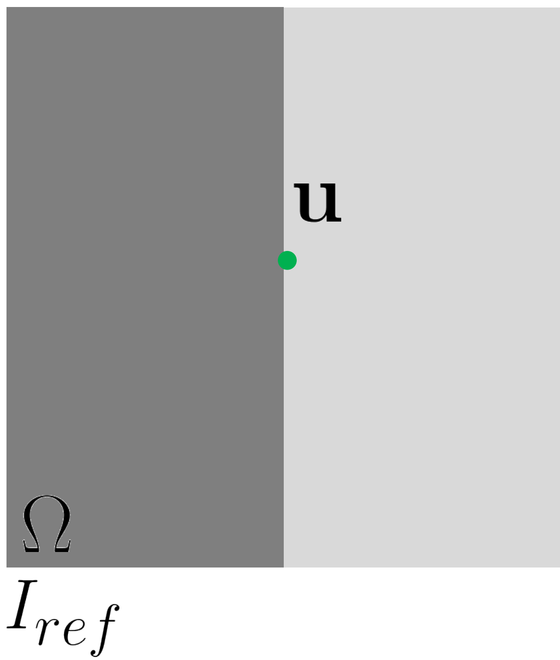

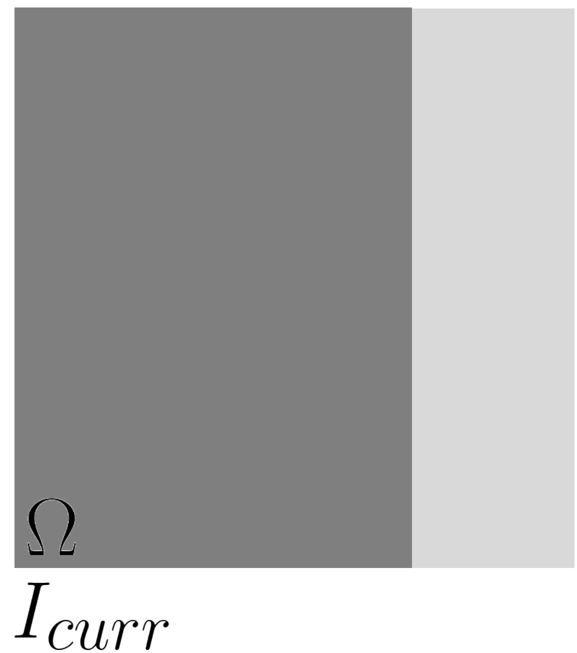

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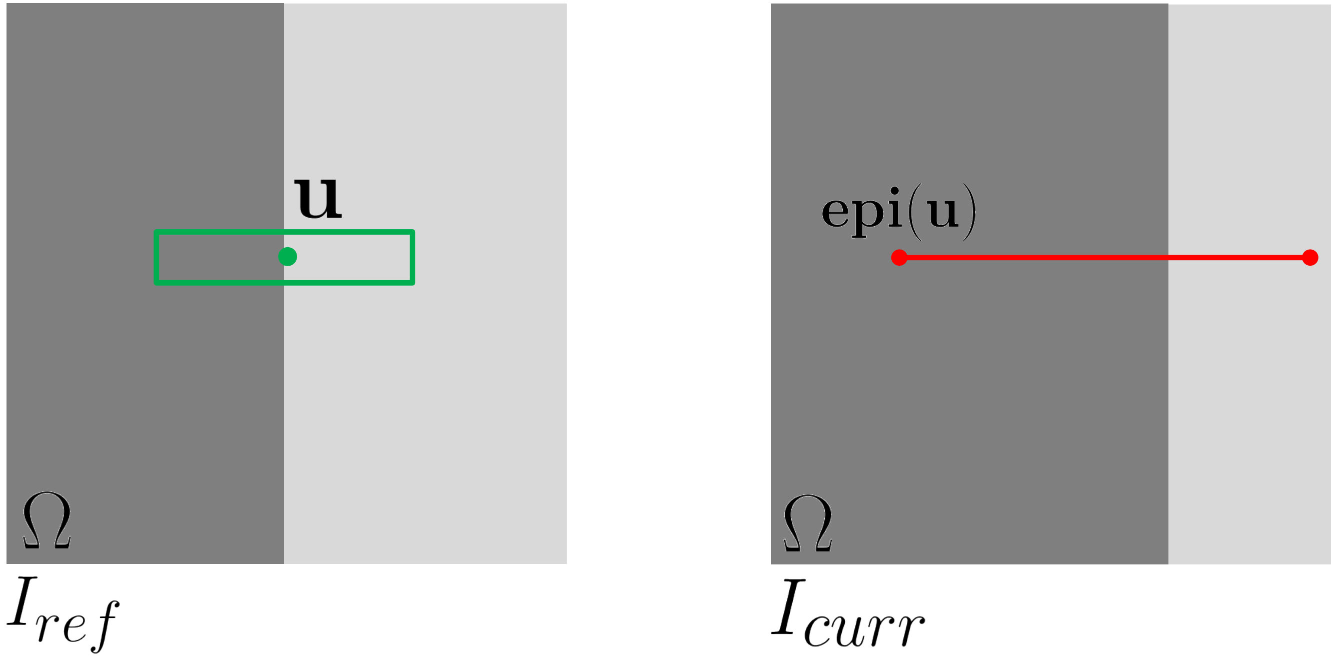

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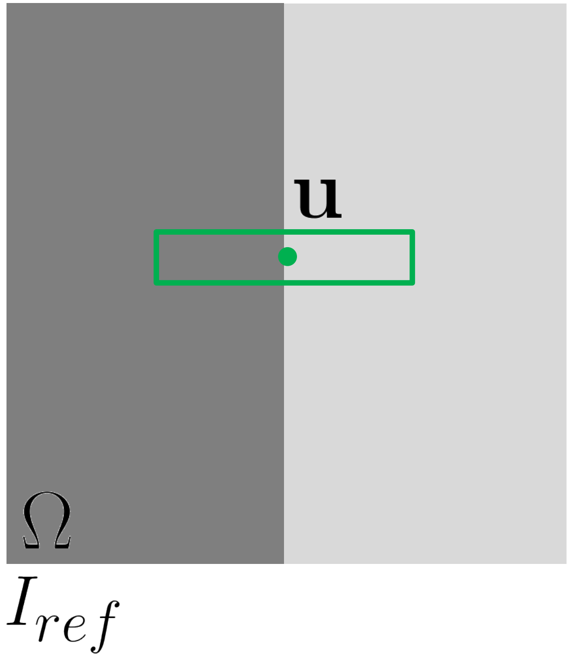

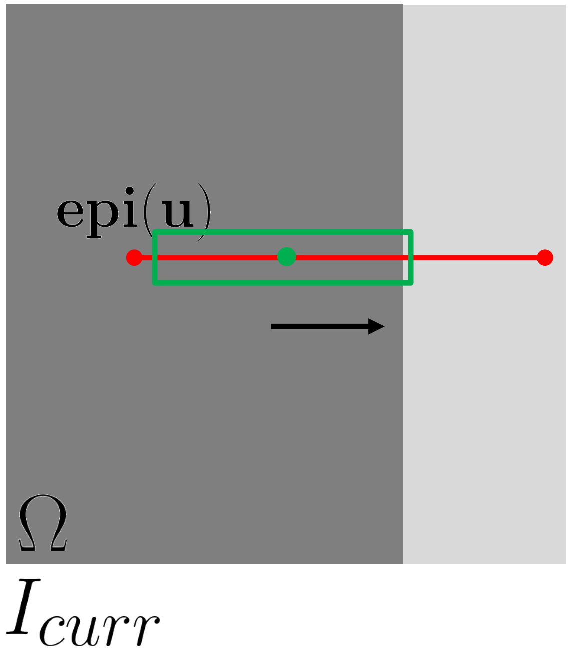

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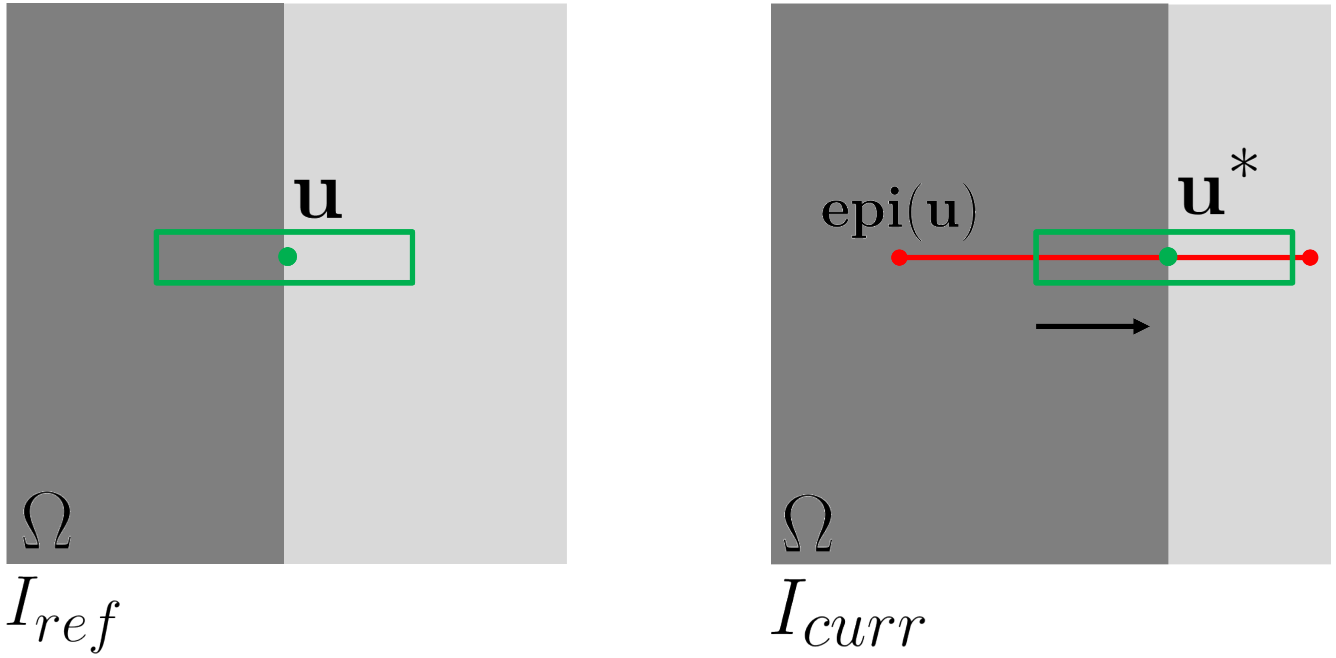

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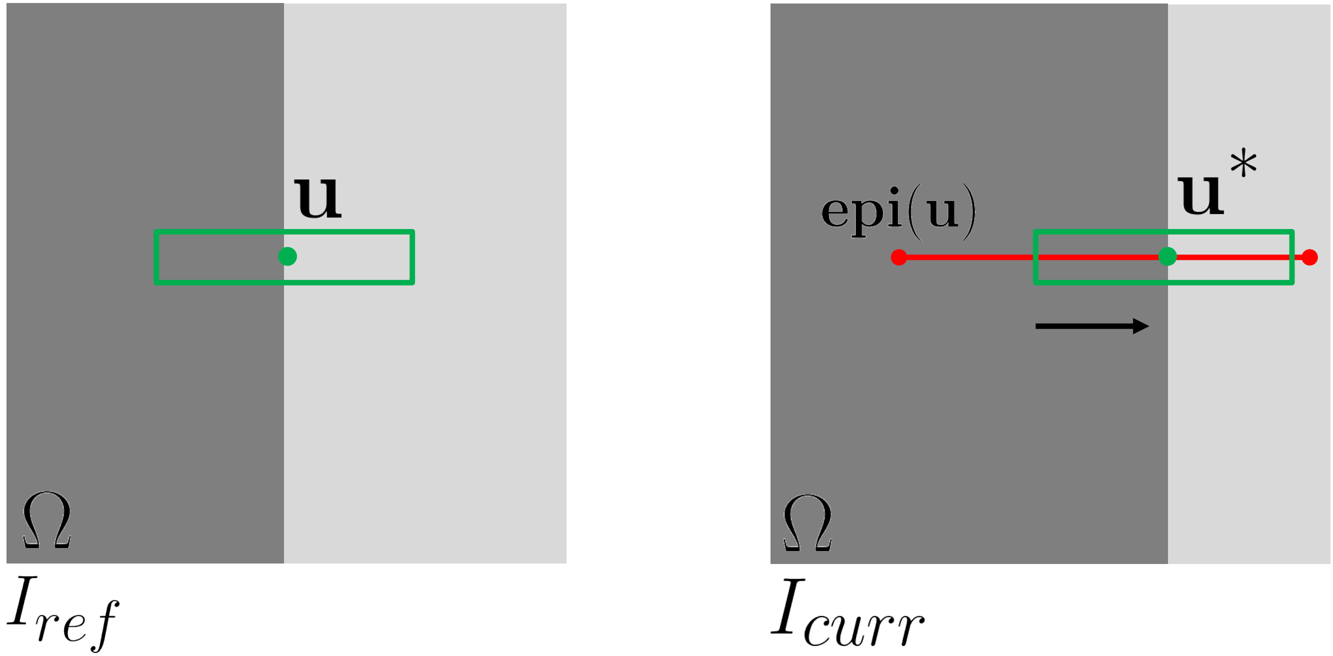

- Each successful match generates an inverse depth ***measurement*** (ξ_z, σ_z^2)

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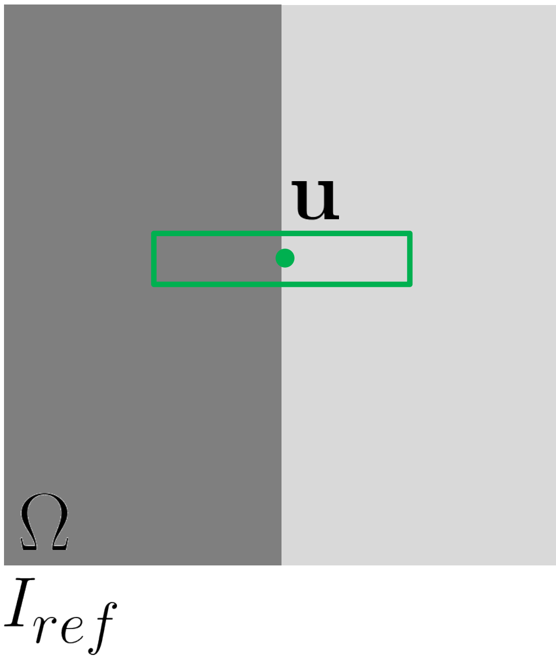

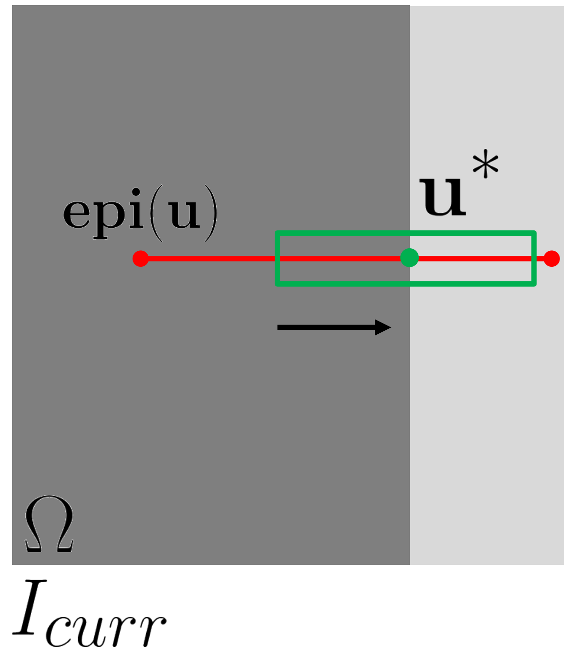

- Each successful match generates an inverse depth ***measurement*** (ξ_z, σ_z^2)
- Measurements are ***fused*** over time using Bayesian update

$$\xi_f \leftarrow \frac{\xi_f \sigma_z^2 + \xi_z \sigma_f^2}{\sigma_f^2 + \sigma_z^2}, \quad \sigma_f^2 \leftarrow \frac{\sigma_f^2 \sigma_z^2}{\sigma_f^2 + \sigma_x^2}$$

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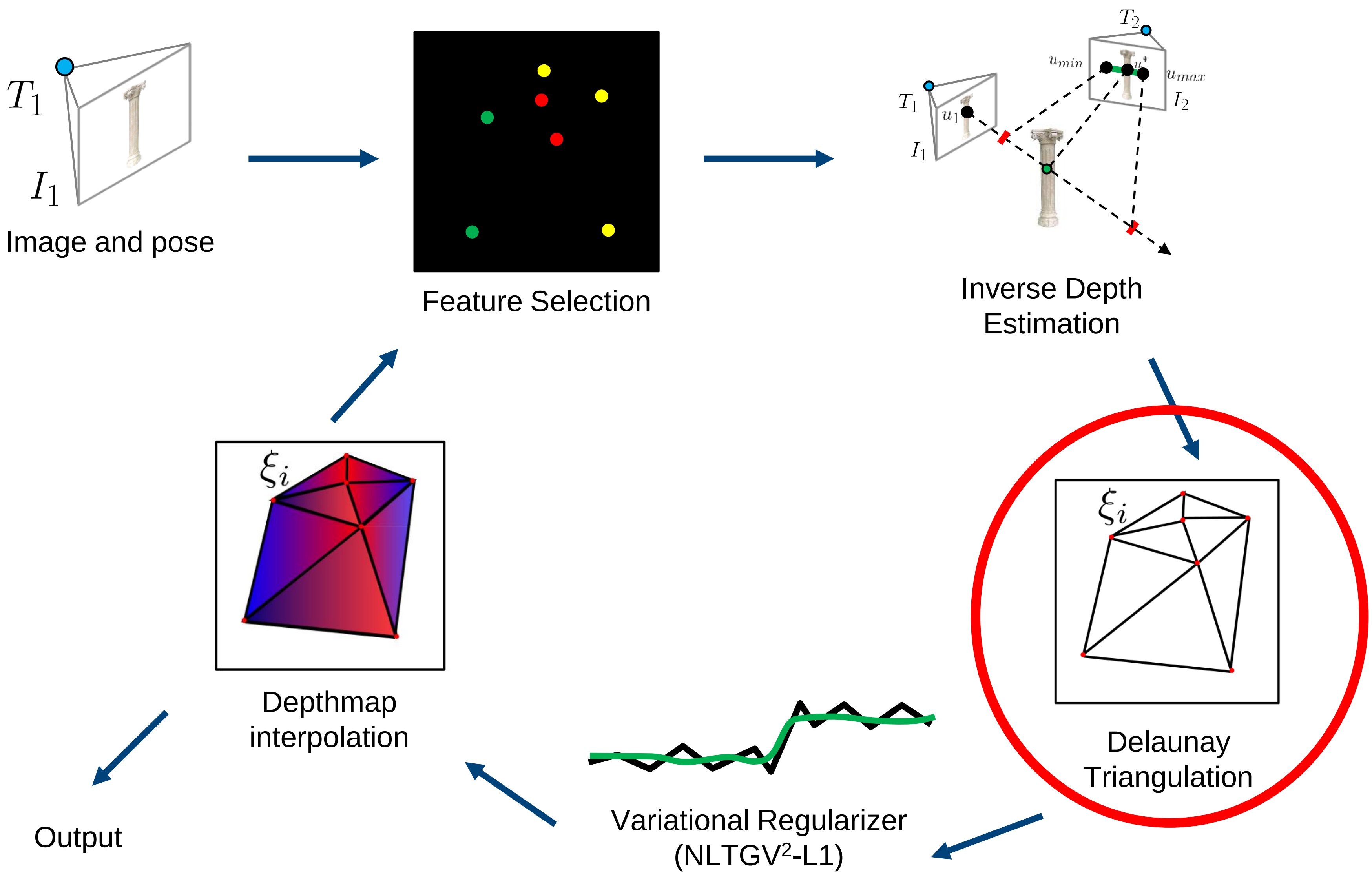
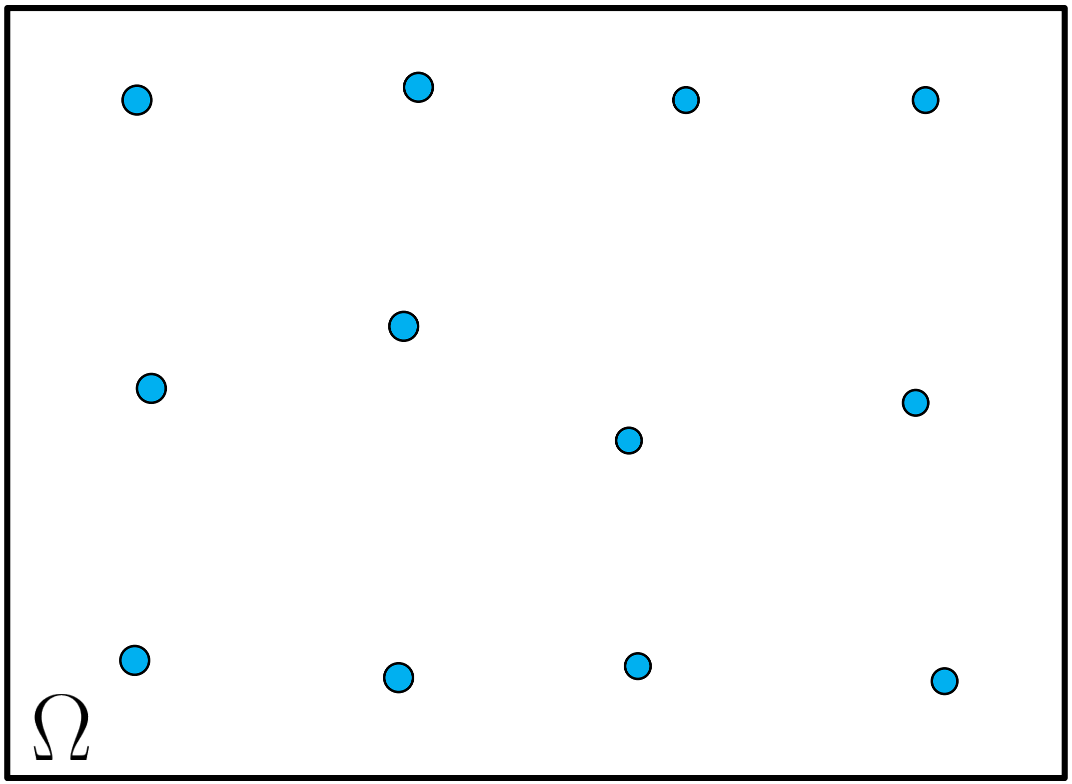


Triangulate Features into Mesh

- Once a features inverse depth variance drops below threshold, we insert it into the mesh using ***Delaunay triangulations***



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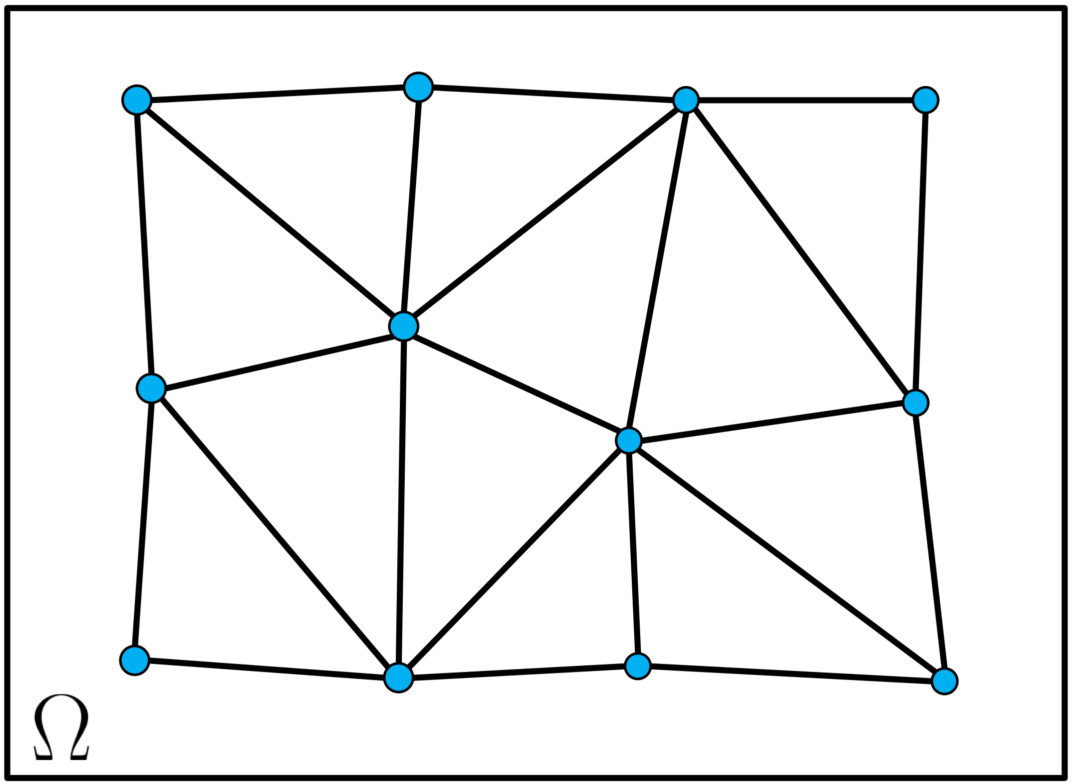

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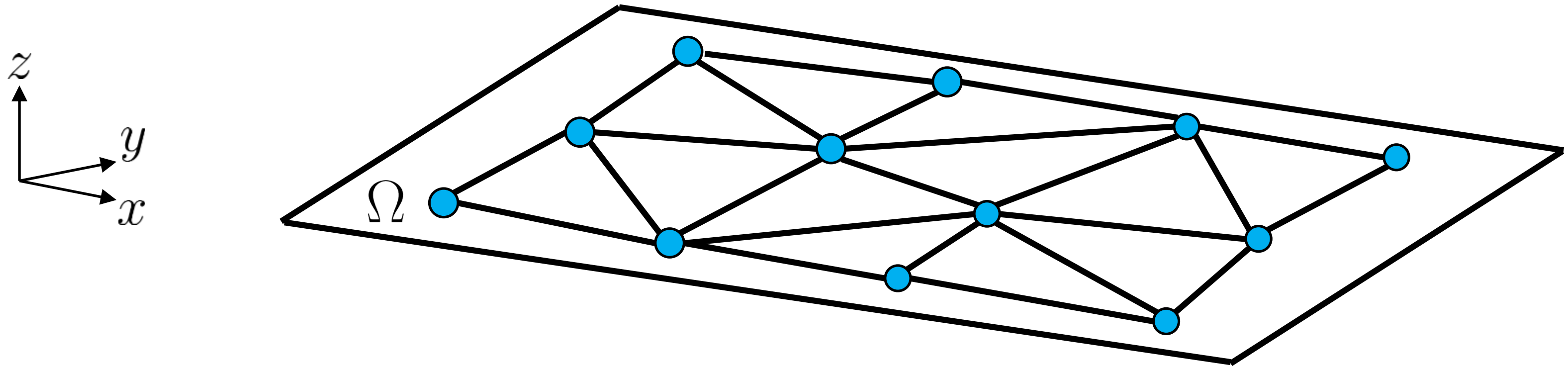

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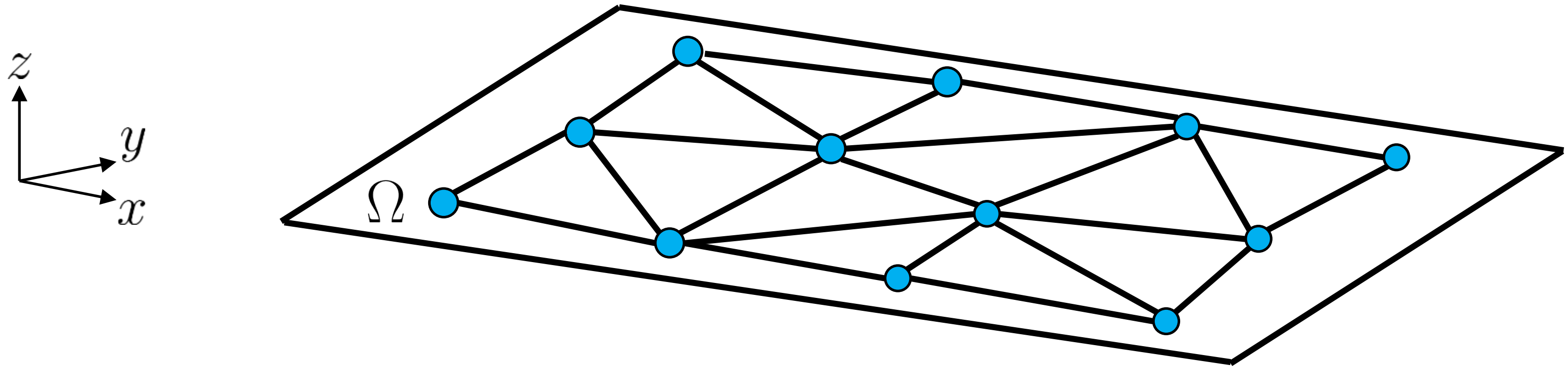
- Once a features inverse depth variance drops below threshold, we insert it into the mesh using ***Delaunay triangulations***
- We can project 2D mesh into 3D using the inverse depth for each vertex



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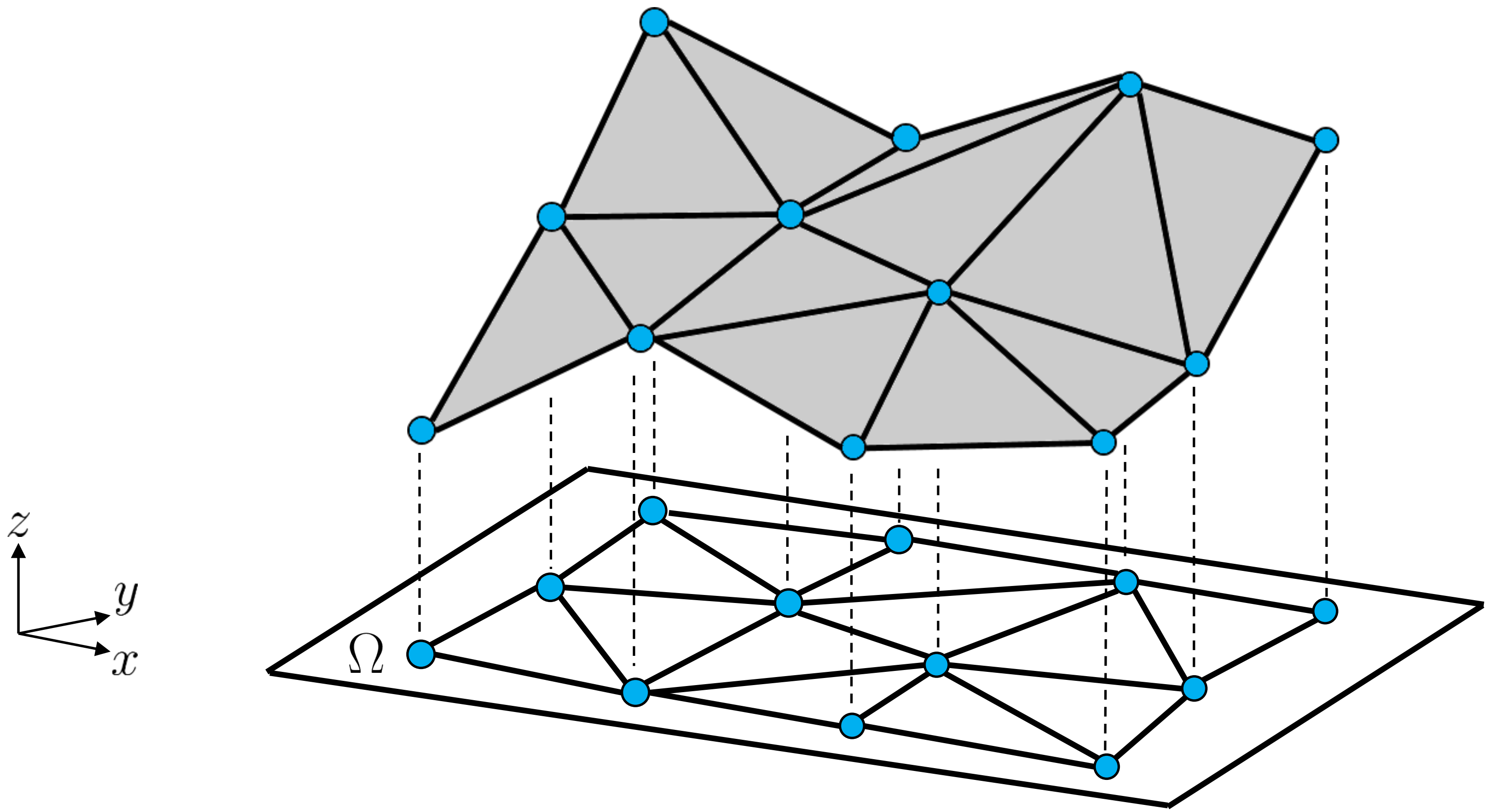

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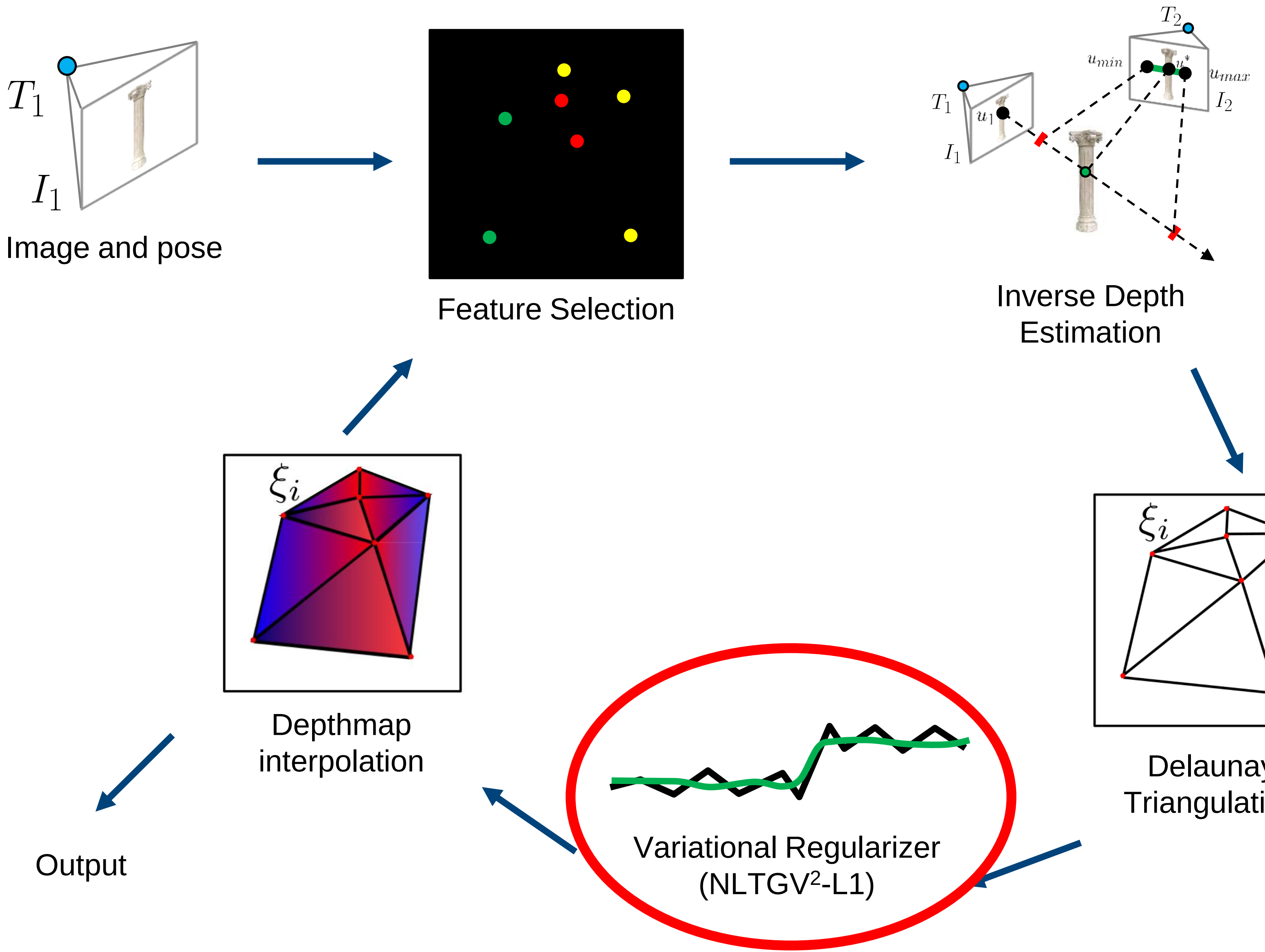
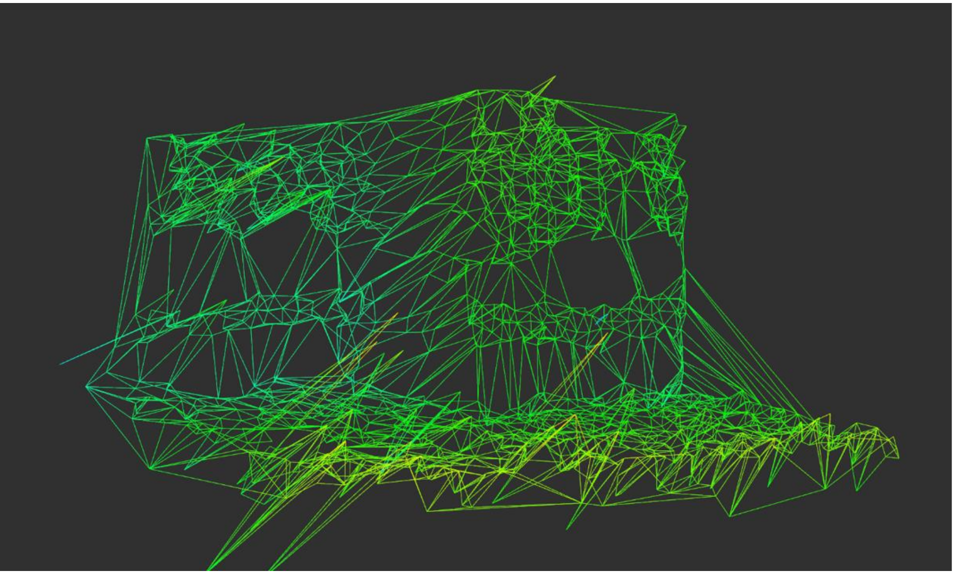


Smooth Mesh Using Variational Regularization

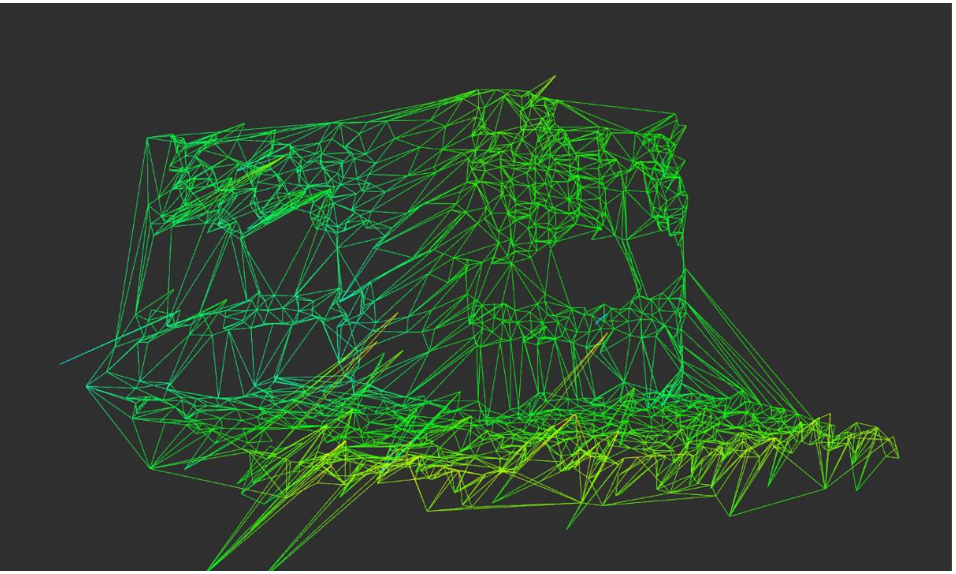
- Mesh inverse depths are noisy and prone to outliers
- Need to spatially regularize/smooth inverse depths



Raw

Smooth Mesh Using Variational Regularization

- Mesh inverse depths are noisy and prone to outliers
- Need to spatially regularize/smooth inverse depths
- Will exploit graph structure to make optimization fast and incremental



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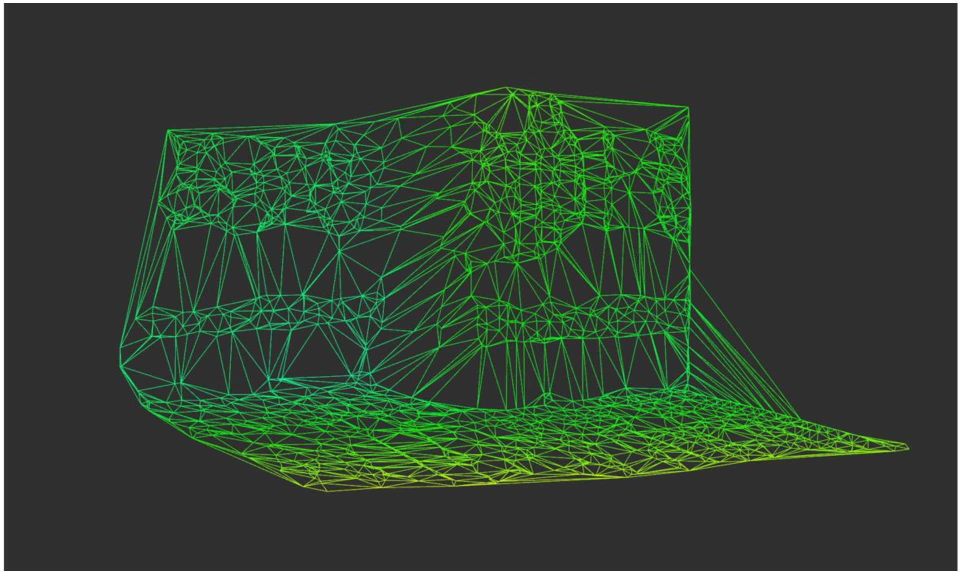
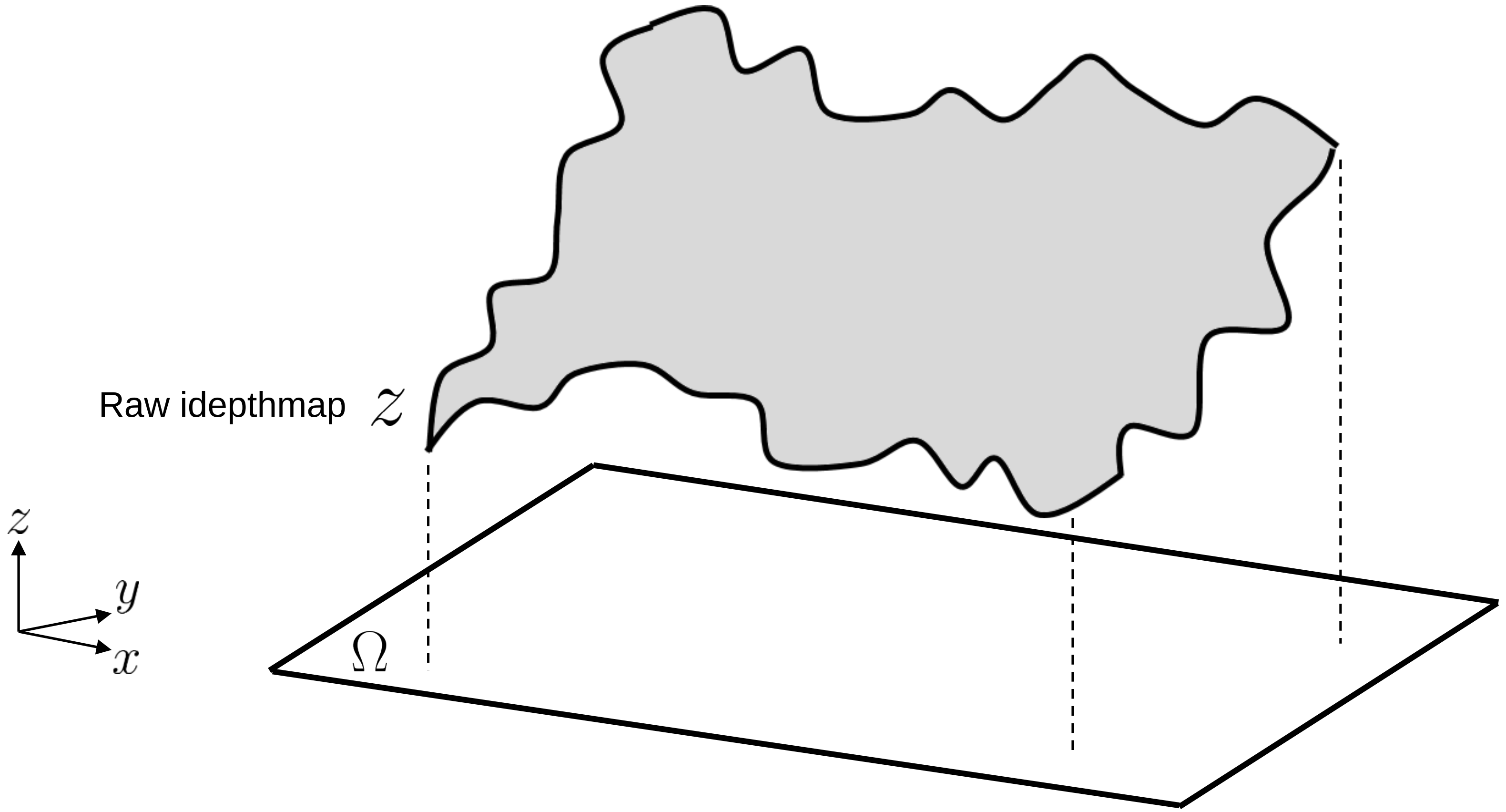


Smoothed

Define Variational Cost over Inverse Depthmap



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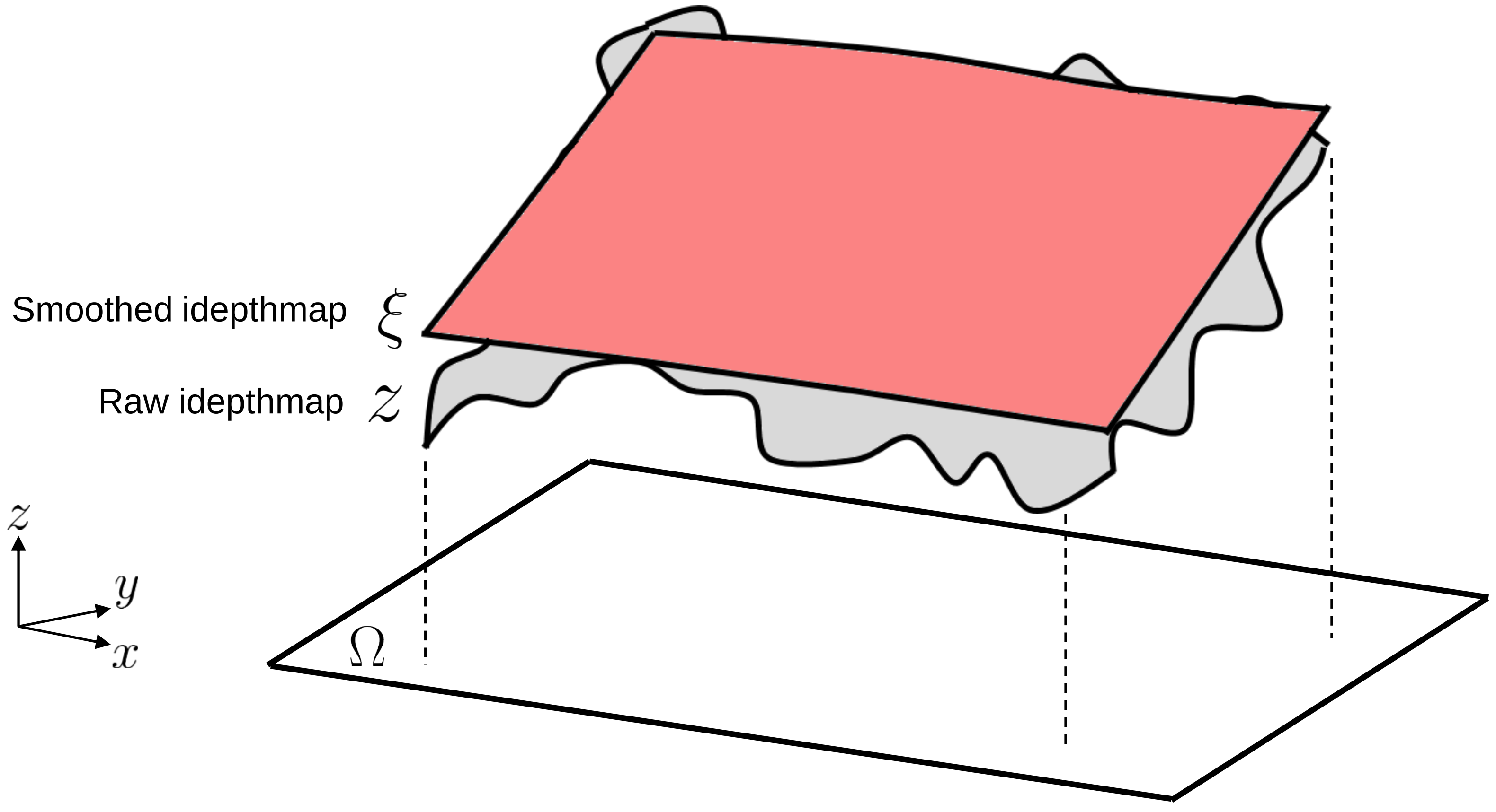
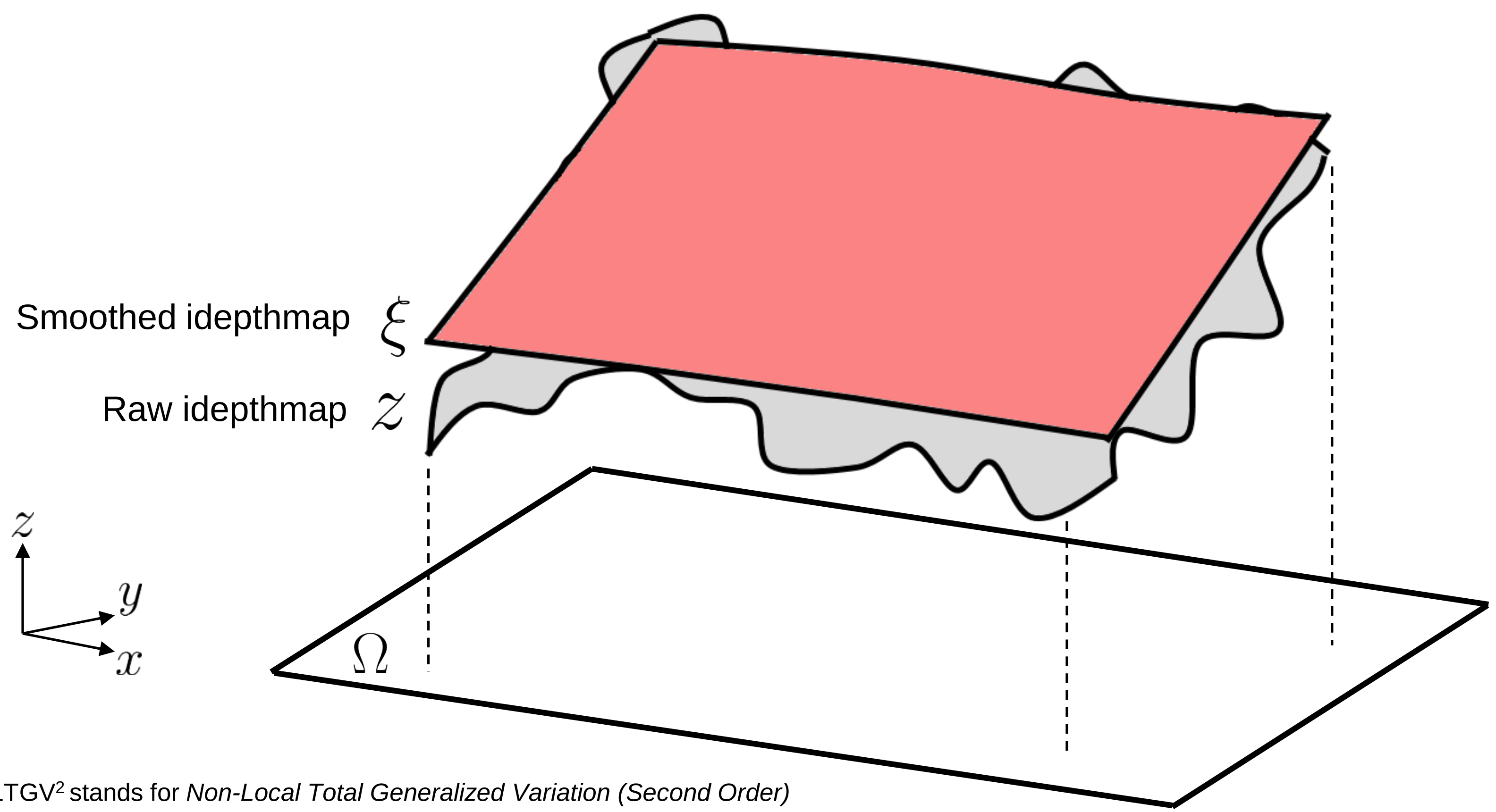


Define Variational Cost over Inverse Depthmap

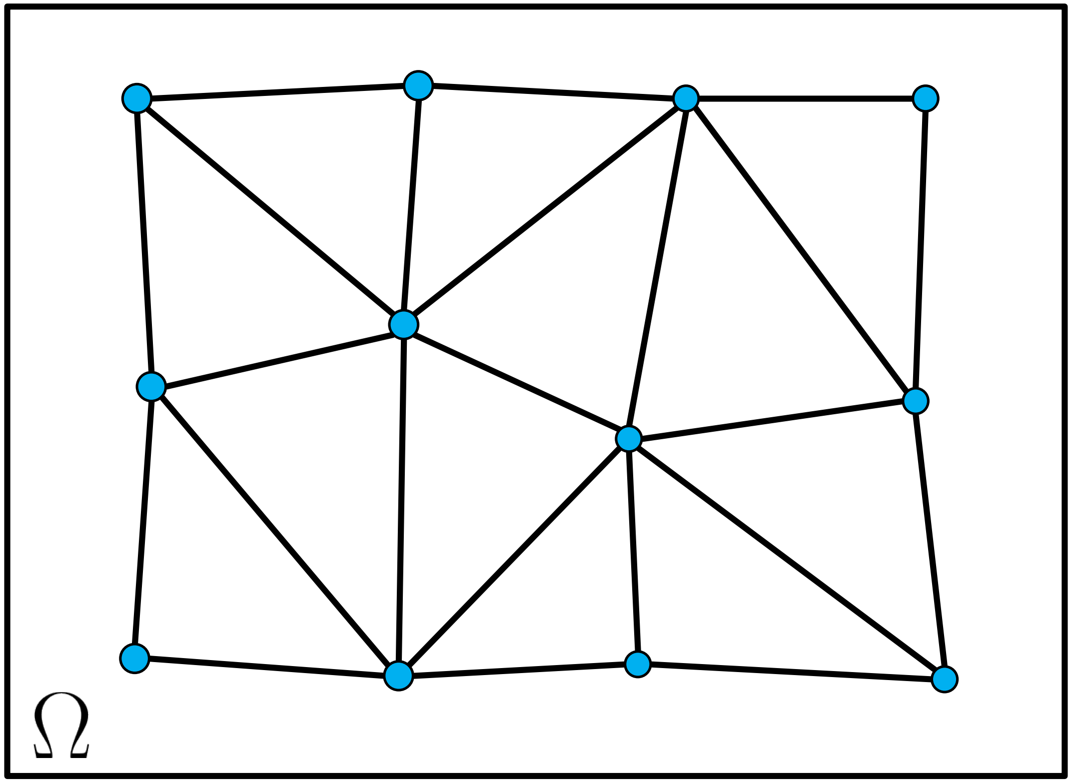
$$E(\xi) = \mathrm{NLTGV}^2(\xi) + \lambda \int_\Omega |\xi(\mathbf{u}) - z(\mathbf{u})| \; d\mathbf{u}$$



NLTGV[2] stands for *Non-Local Total Generalized Variation (Second Order)*
Ranftl et al. 2014, Pinies et al. 2015

Approximate Cost over Mesh

- Reinterpret mesh as graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$



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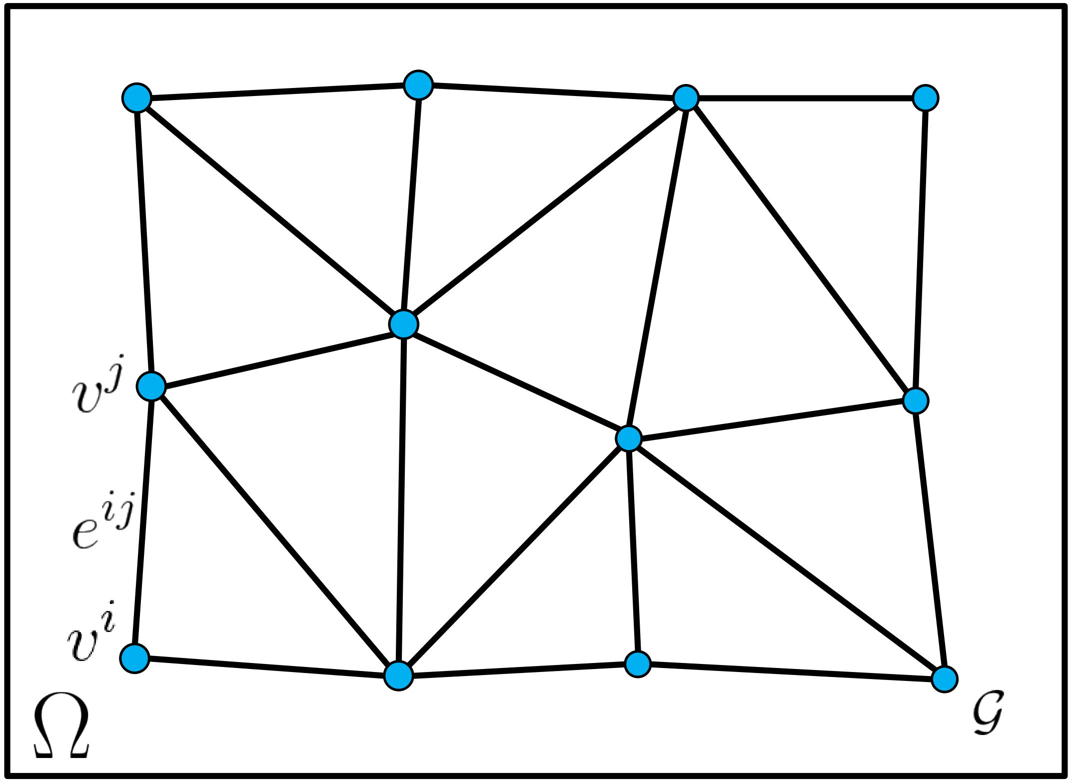

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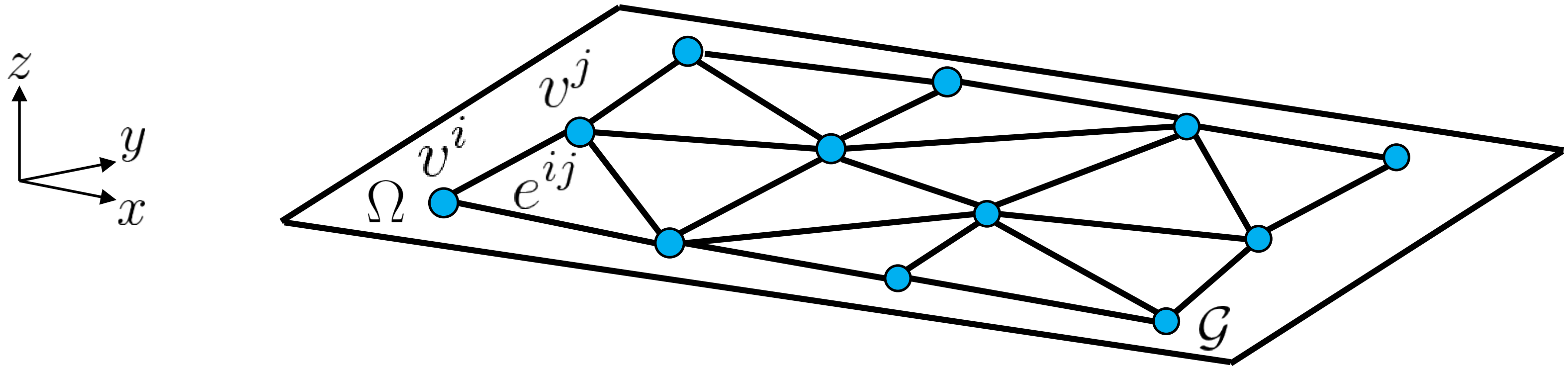

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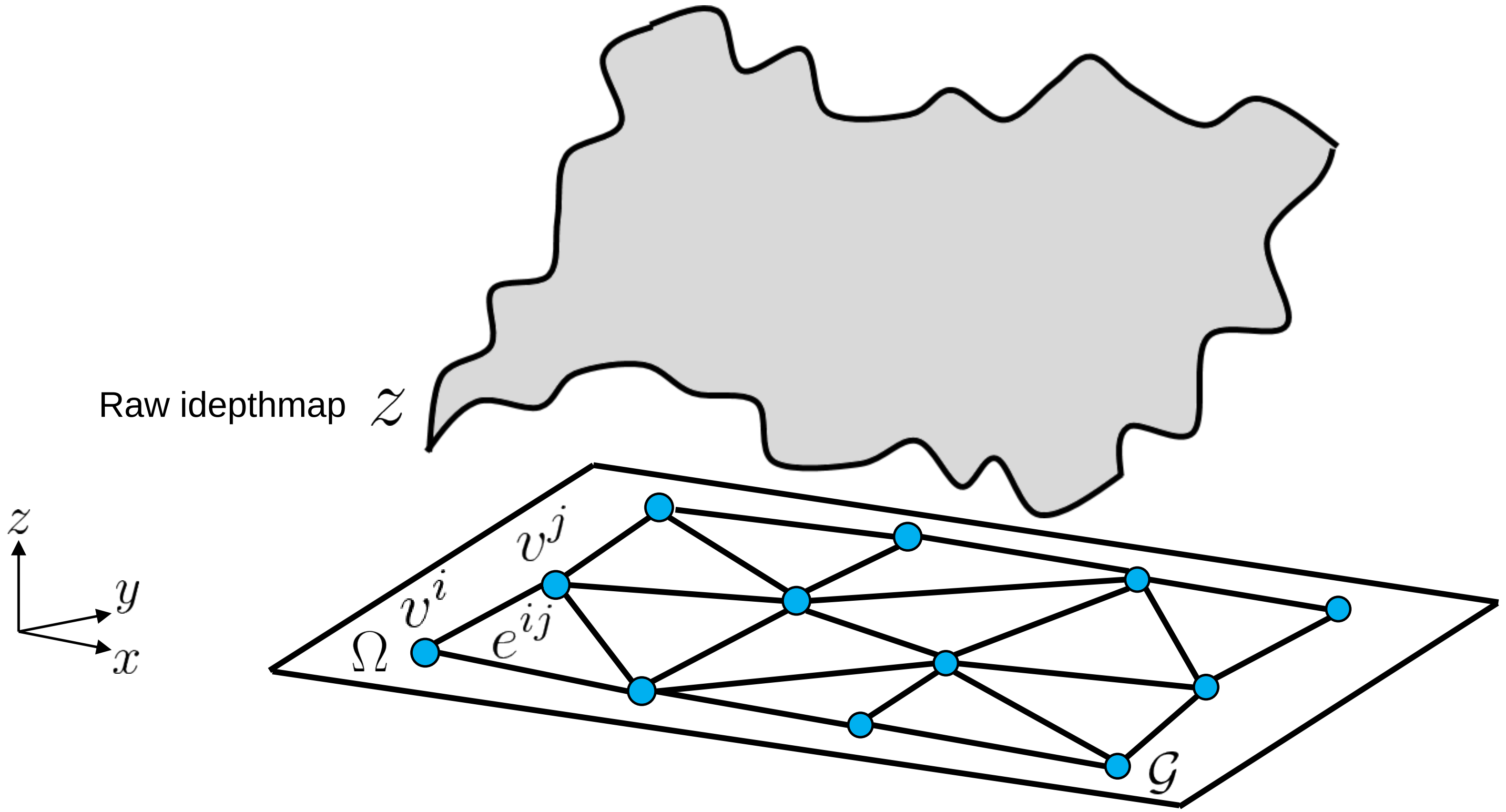

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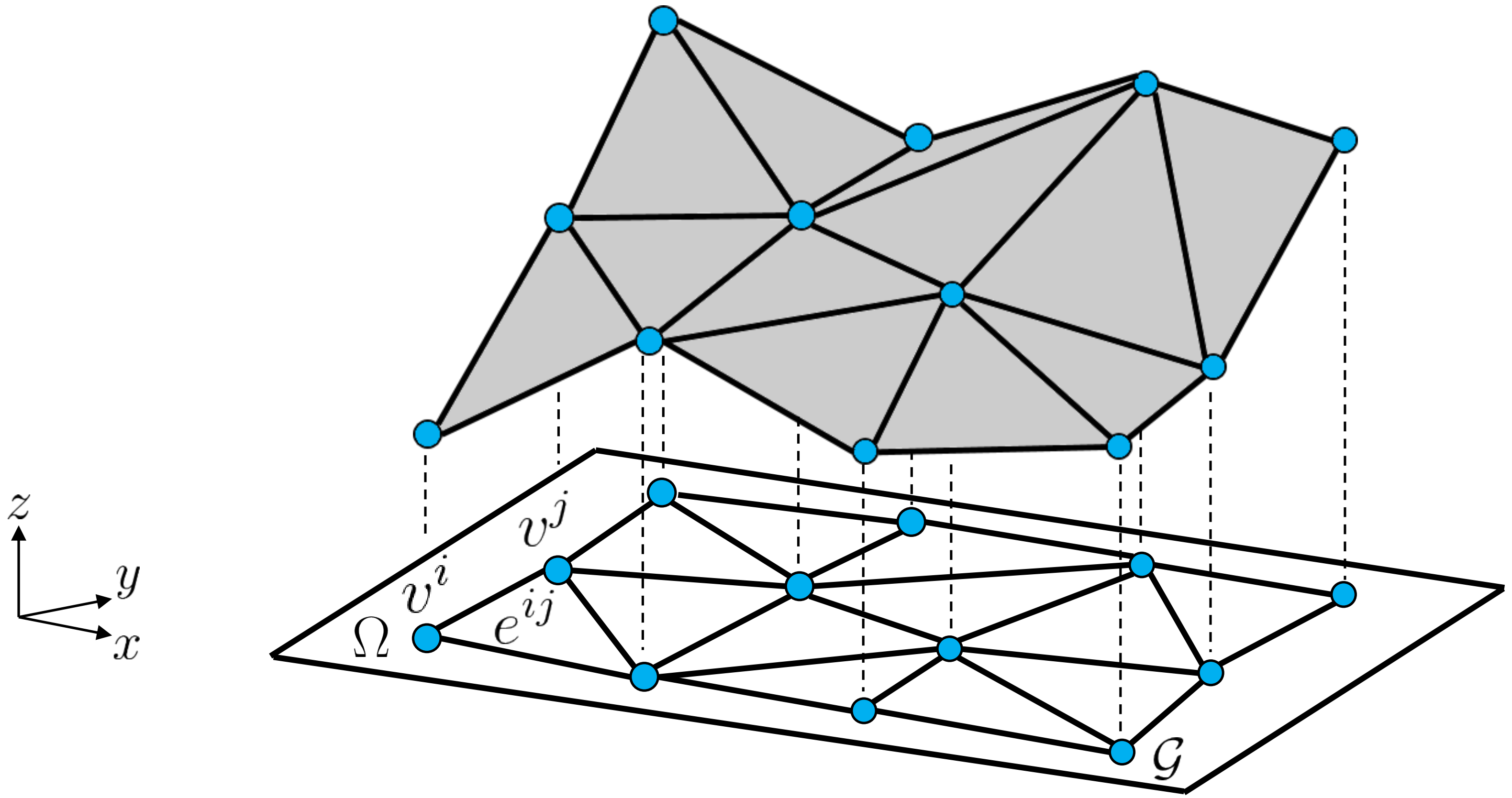
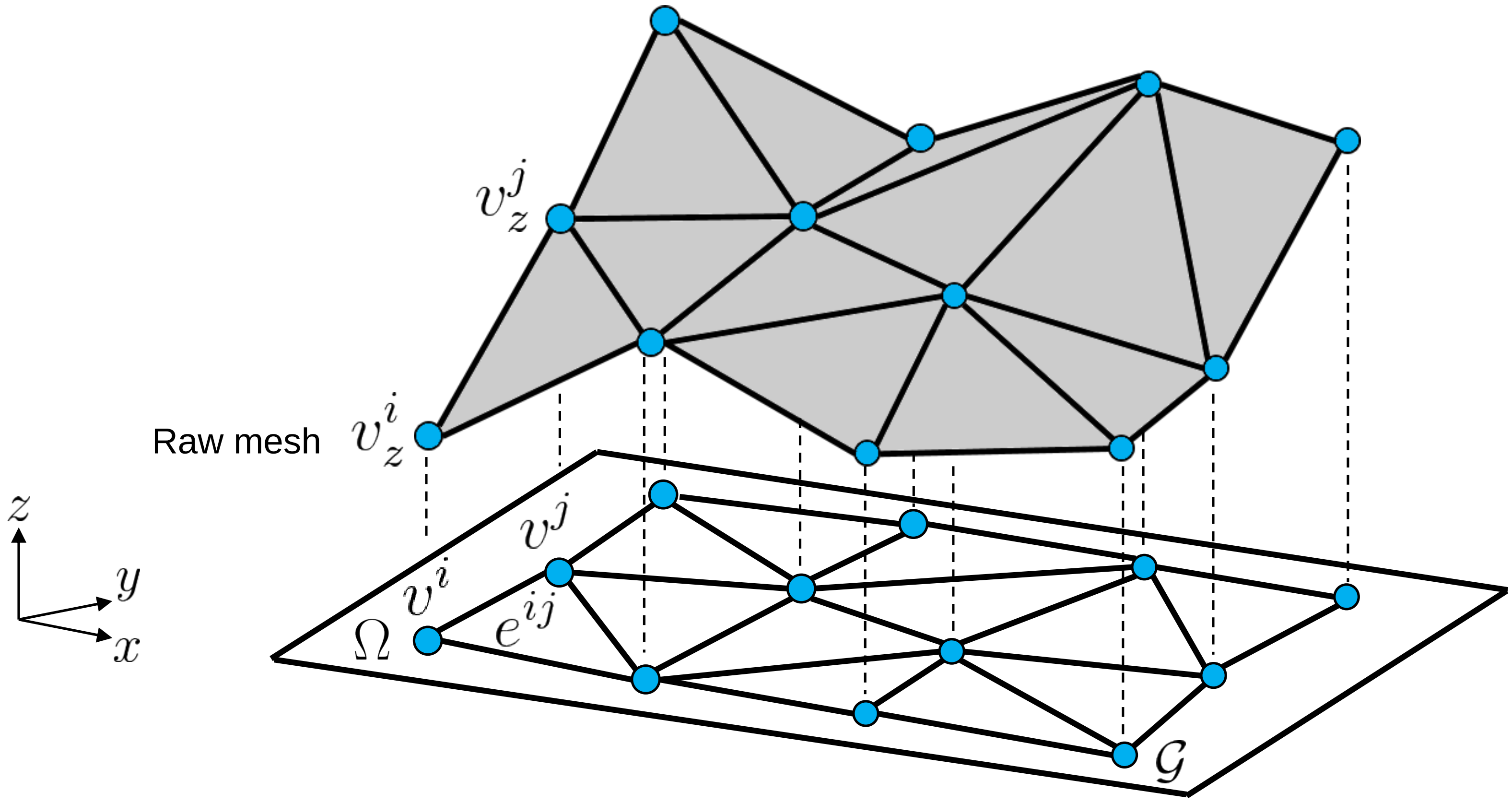


Approximate Cost over Mesh



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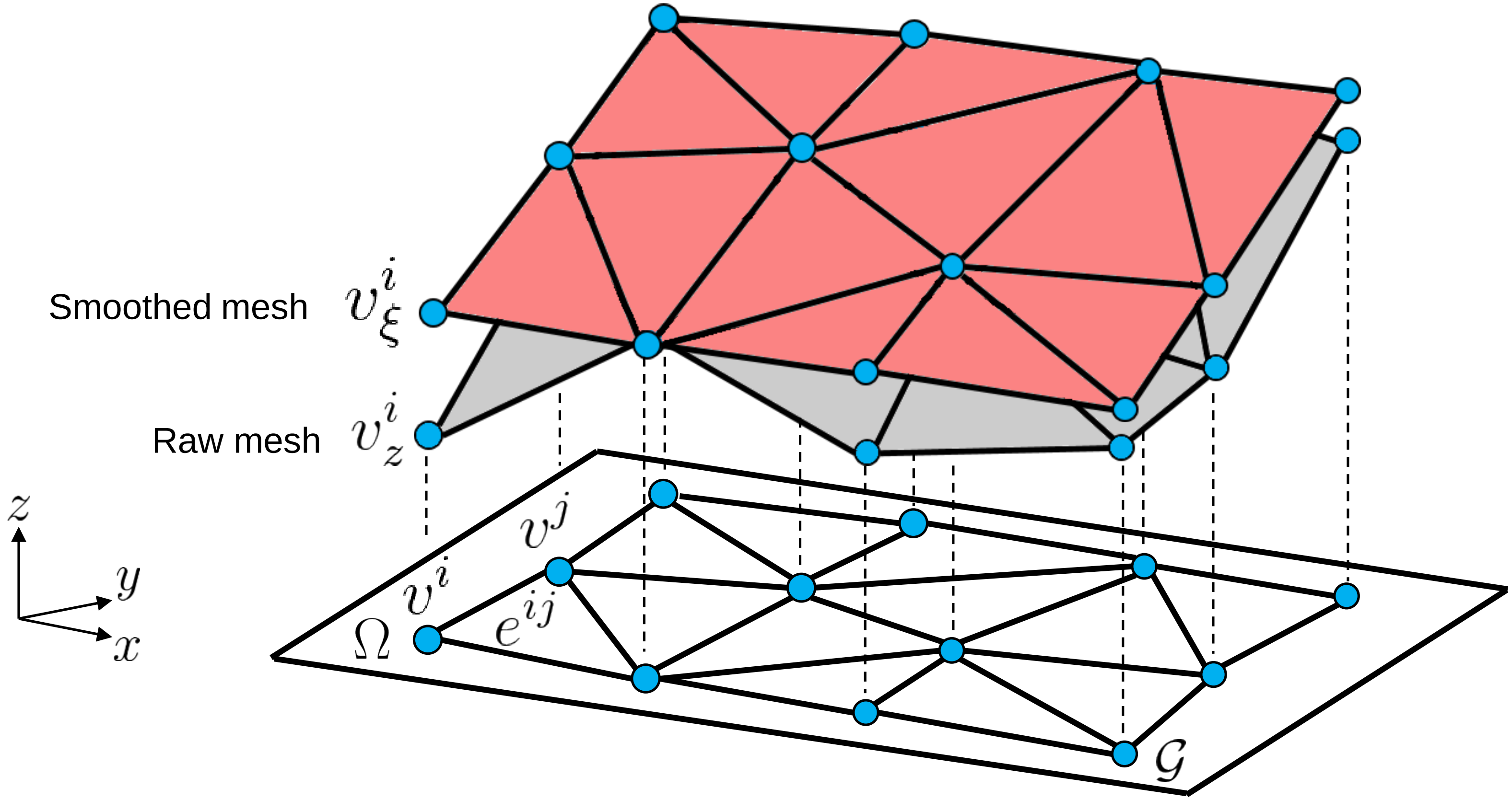

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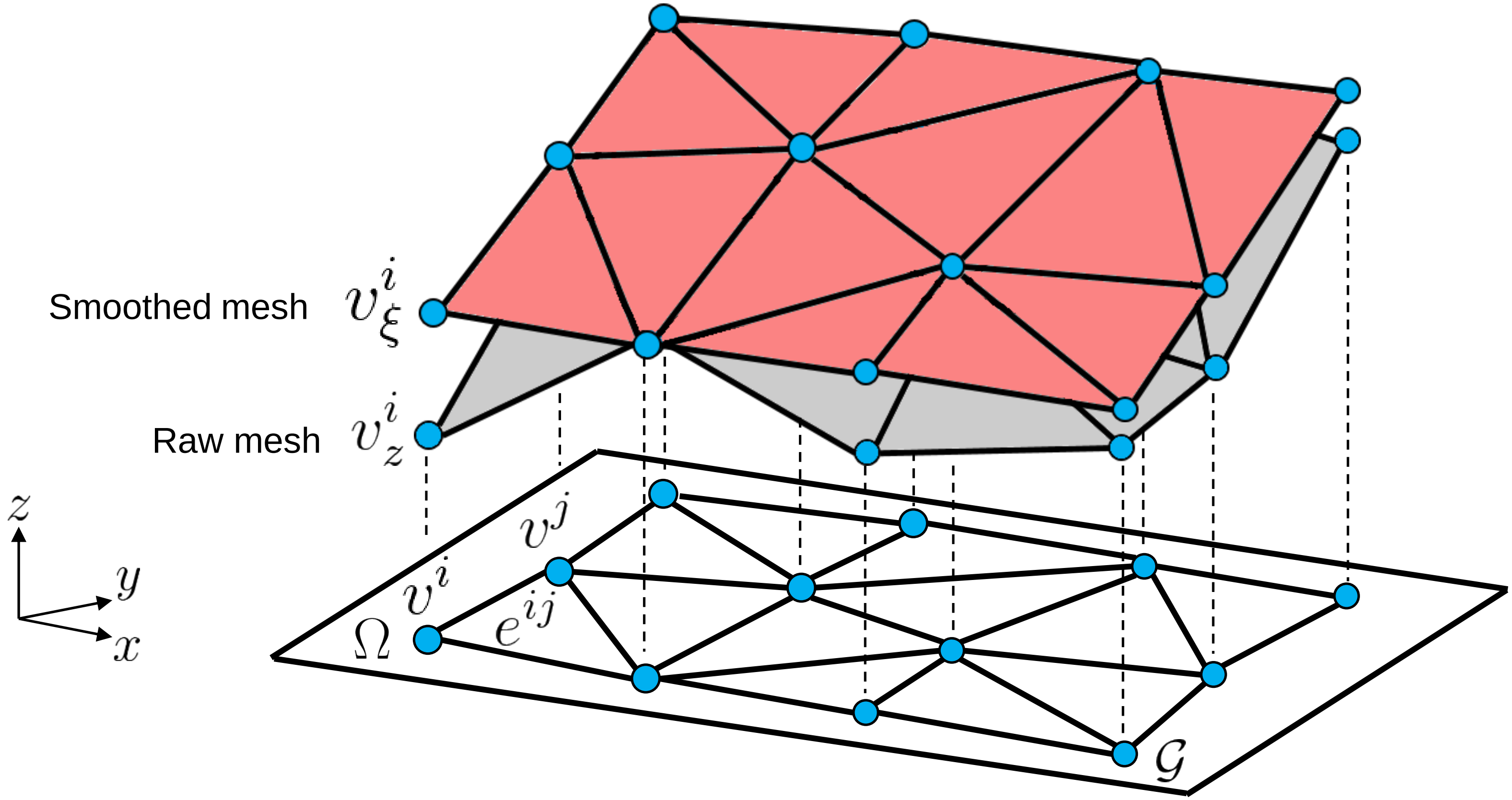
$$E(\xi) = \mathrm{NLTGV}^2(\xi) + \lambda \int_\Omega |\xi(\mathbf{u}) - z(\mathbf{u})| \, d\mathbf{u}$$



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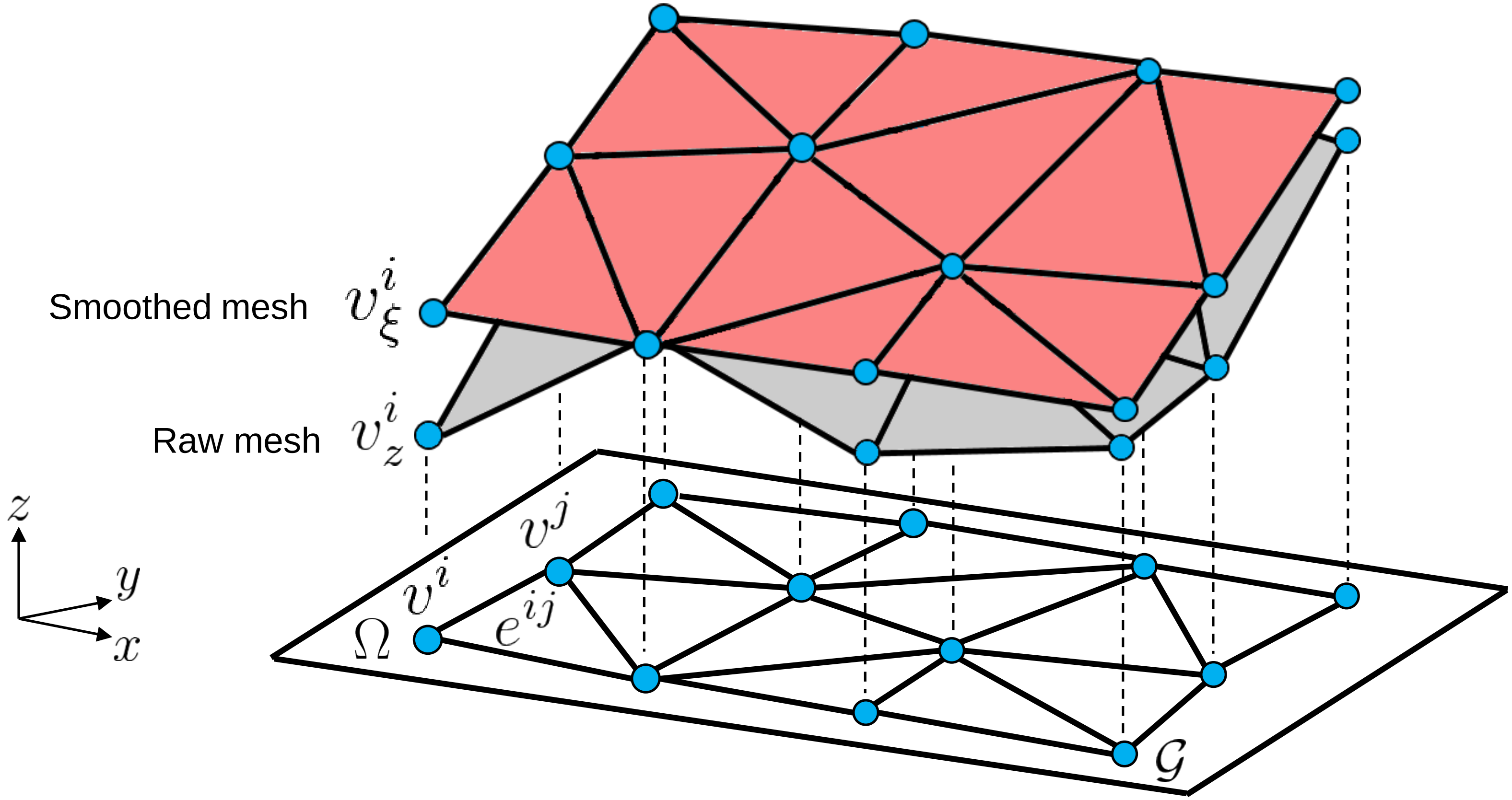
Math…



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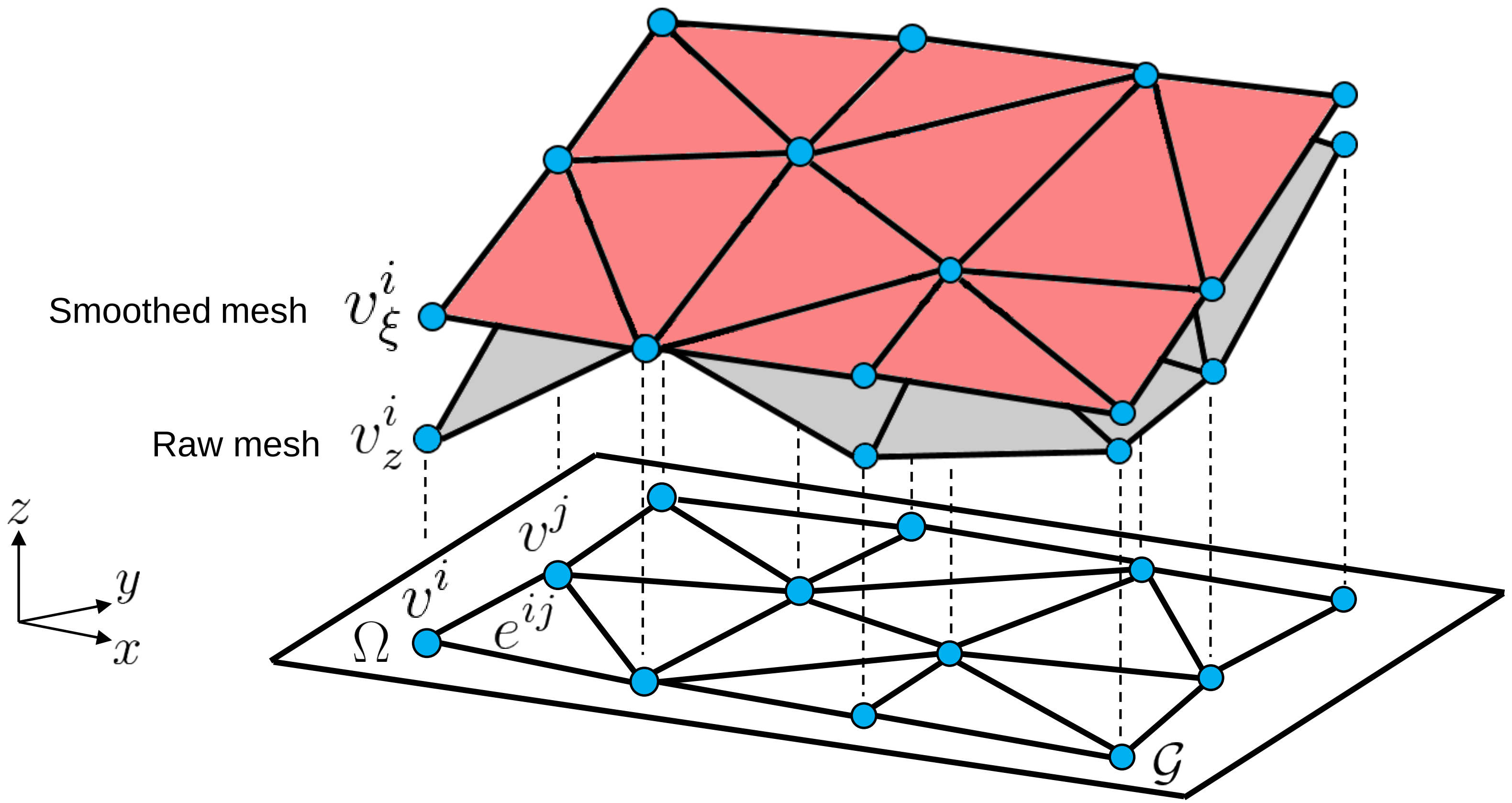
Math…

$$E(\mathcal{G}) = \sum_{e \in \mathcal{E}} ||\mathbf{D}_e(v^i, v^j)||_1 + \lambda \sum_{v \in \mathcal{V}} |v_\xi - v_z|$$



Optimize using Primal-Dual on Graph

$$\min E(\mathcal{G})$$

Optimize using Primal-Dual on Graph

$$\min E(\mathcal{G}) \xrightarrow{\text{Math...}}$$

Optimize using Primal-Dual on Graph

$$\min E(\mathcal{G})$$

$\xrightarrow{\text{Math...}}$

Algorithm 2 NLTGV$^2 - L_1$ Graph Optimization

// Choose $\sigma, \tau > 0, \theta \in [0,1]$.
while not converged **do**
  for each $e \in \mathcal{E}_k$ **do**
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Math…

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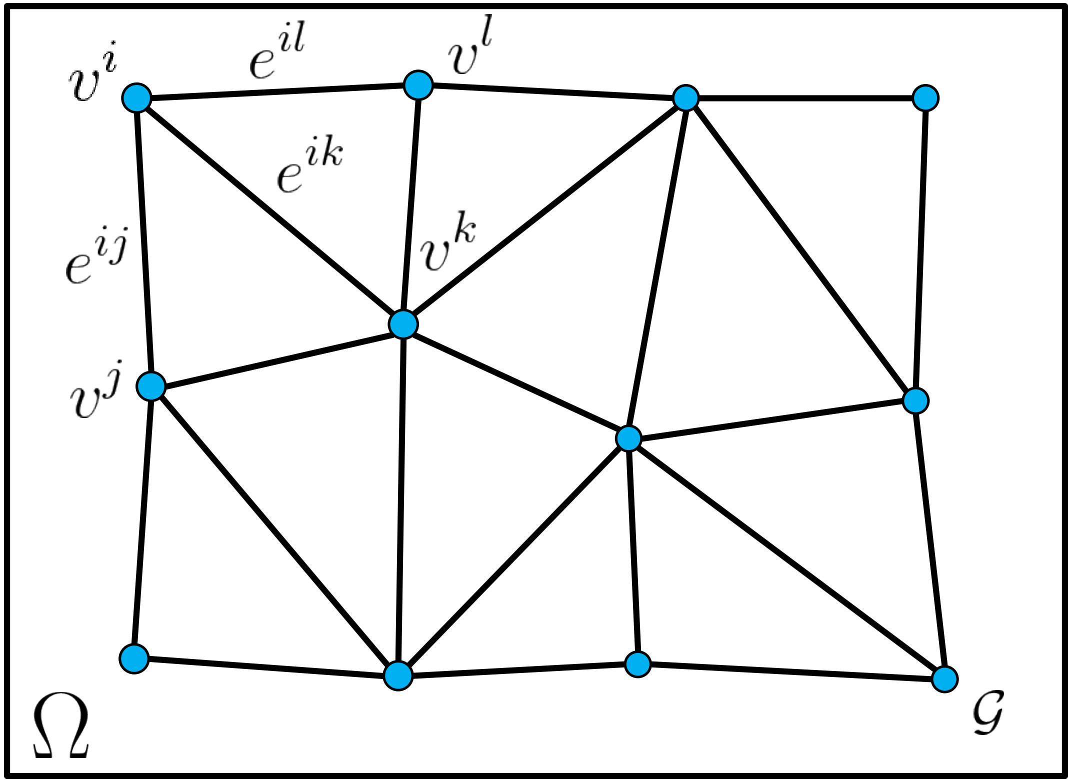

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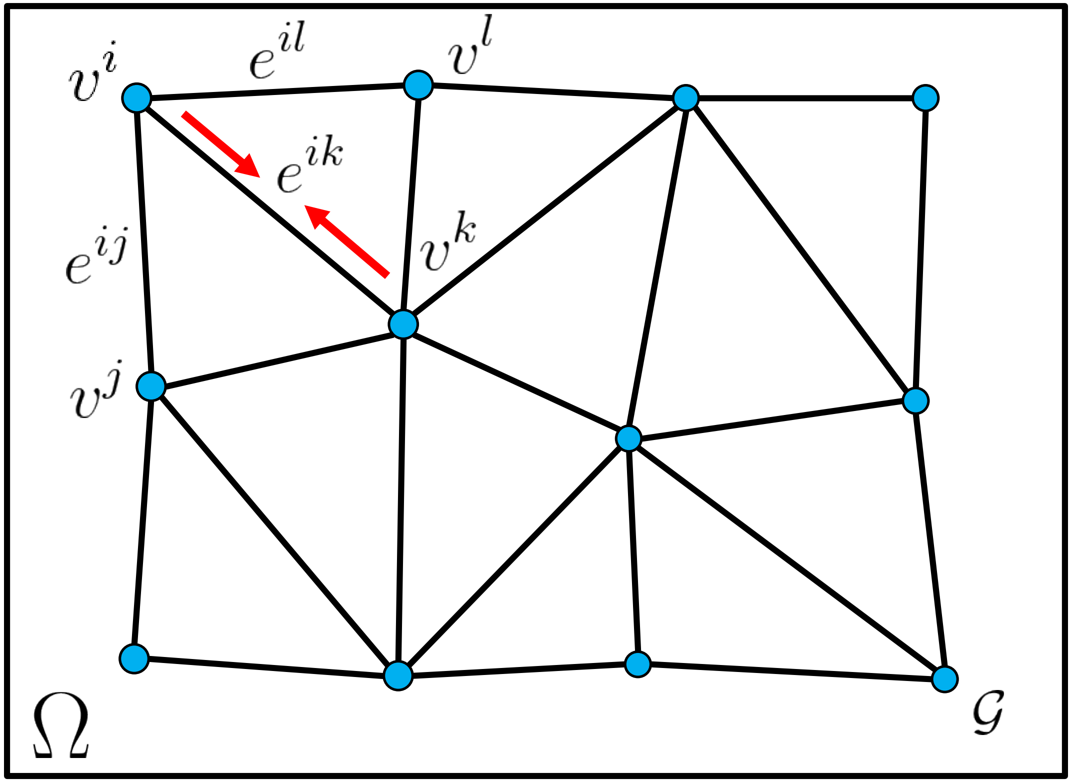

Edges update using vertices

Optimize using Primal-Dual on Graph

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Math…

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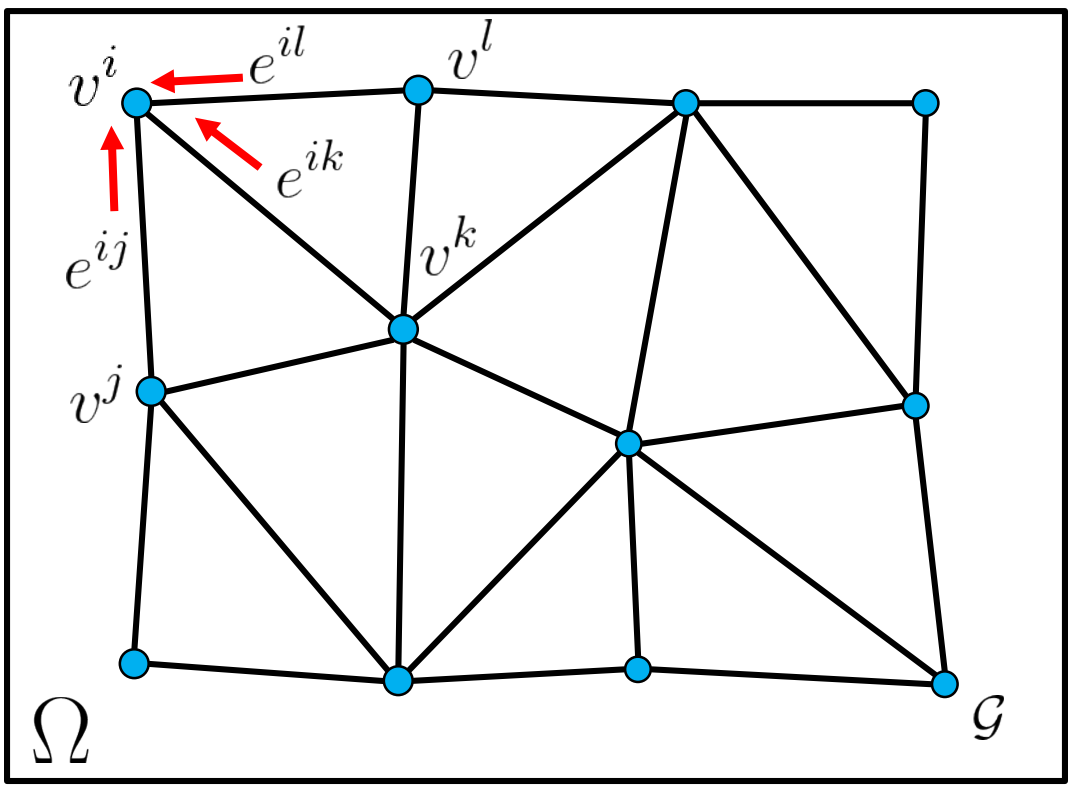

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Math…

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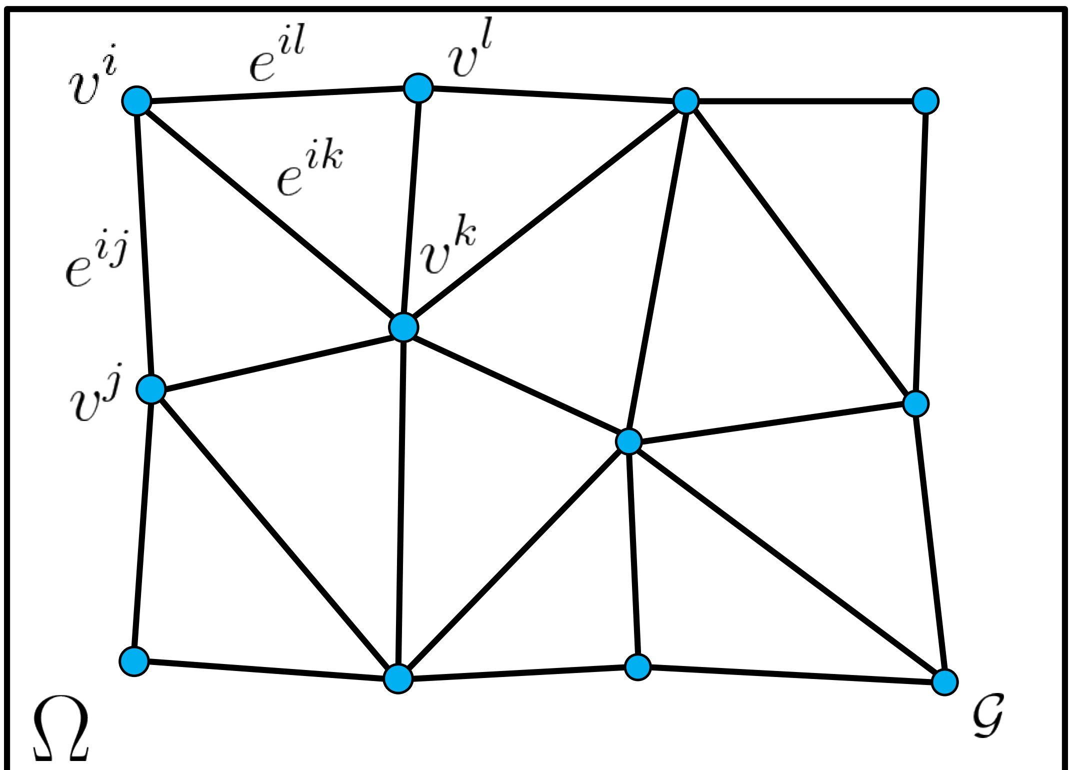

Optimization steps are fast even without GPU (<< frame rate)

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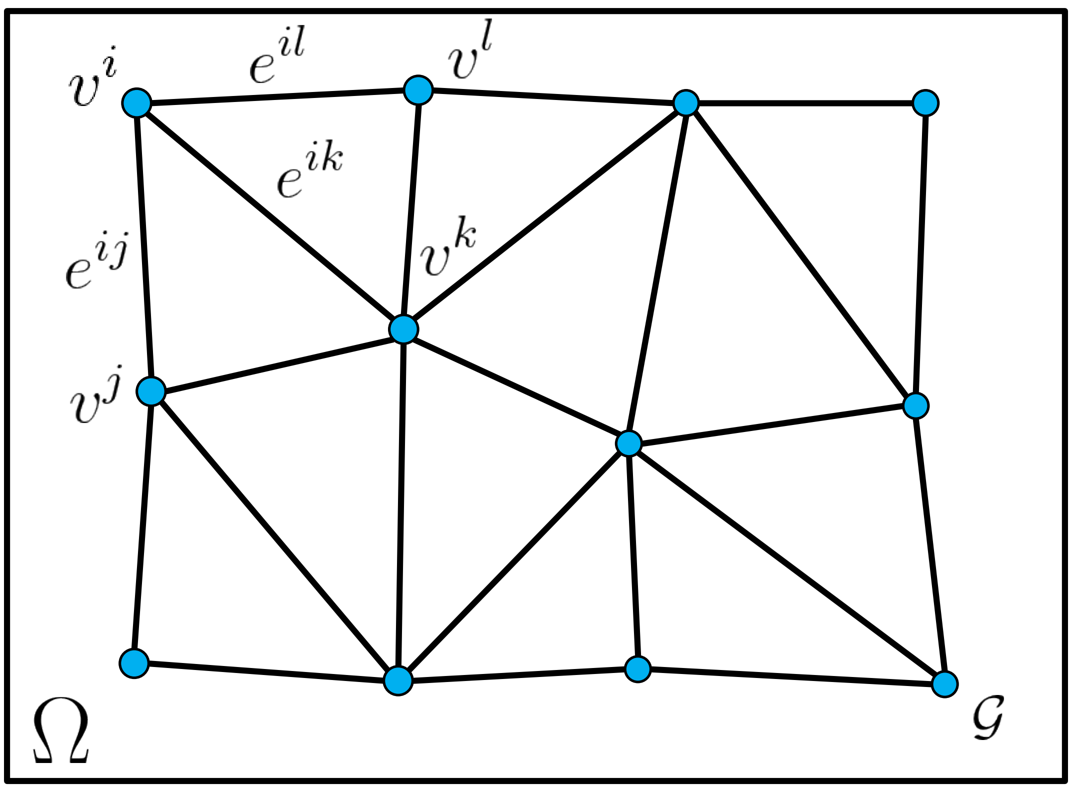

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Math…

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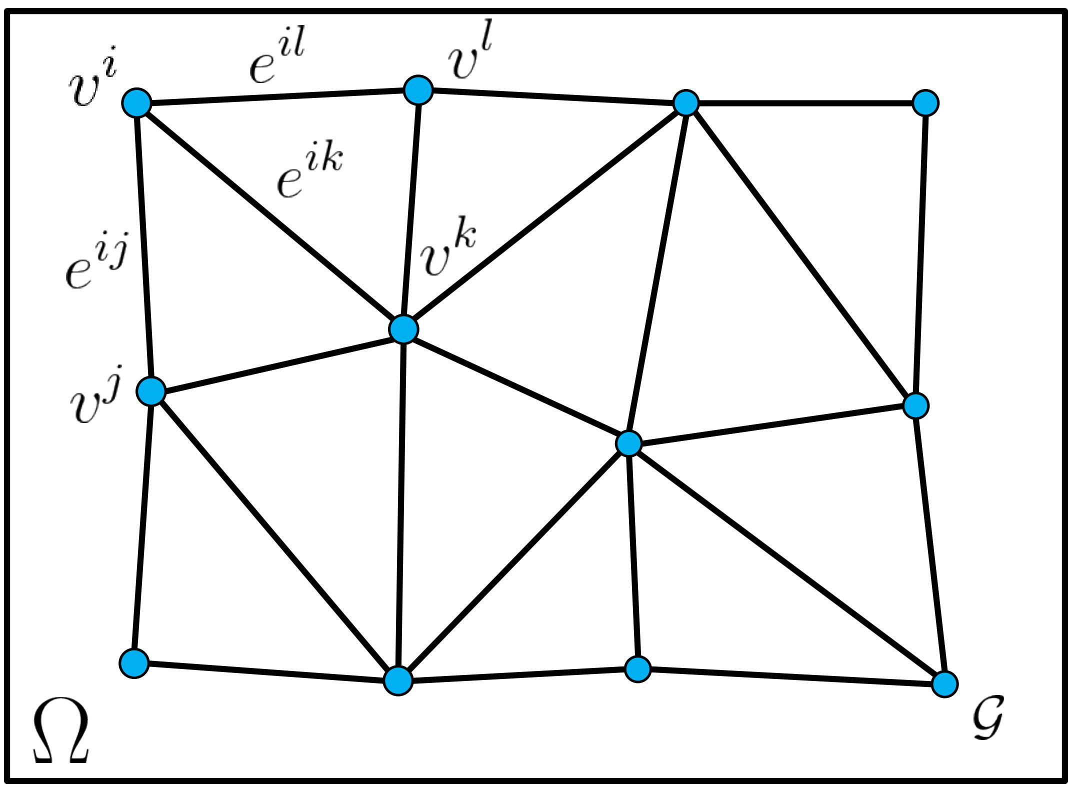

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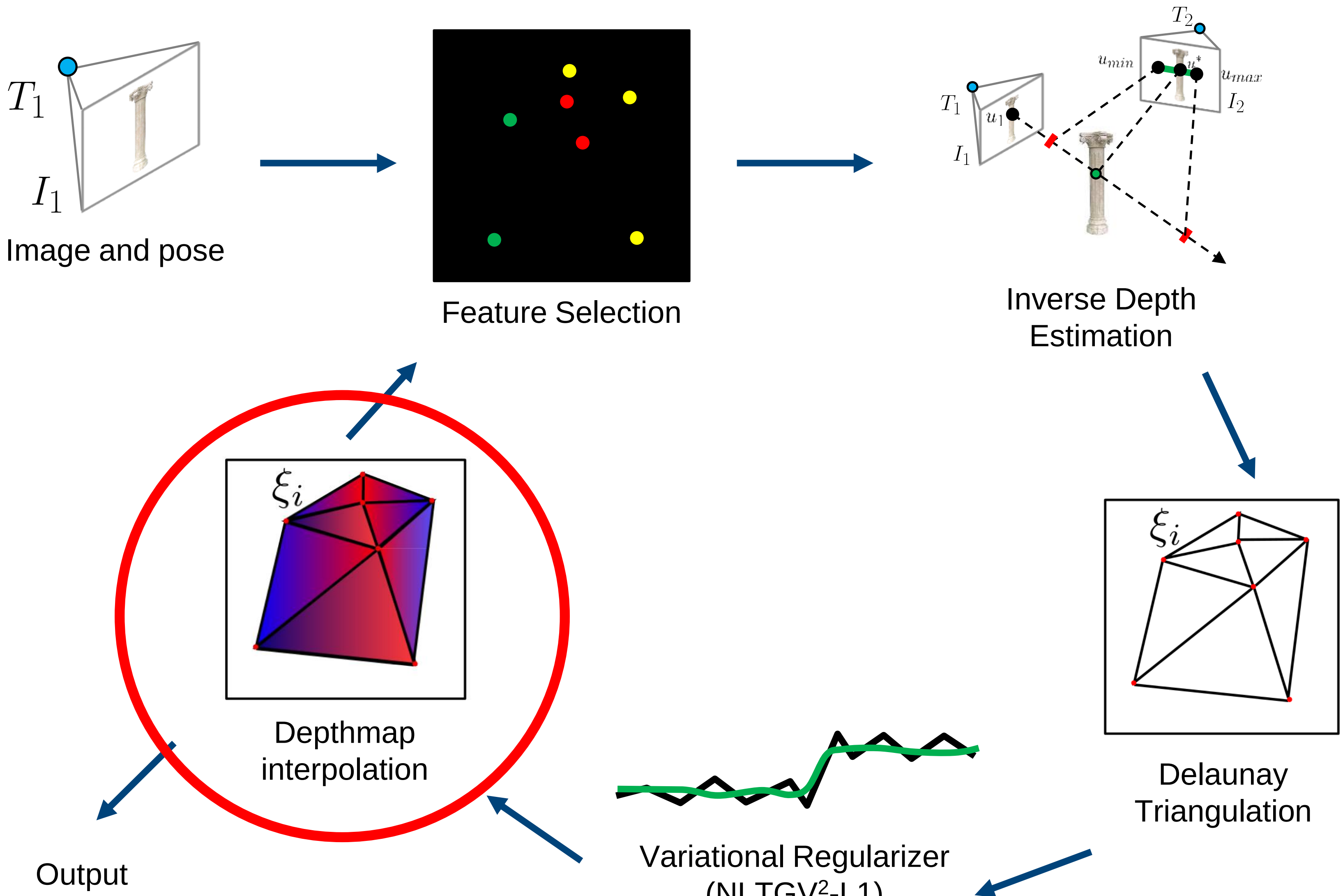
Mesh can be augmented without restarting optimization

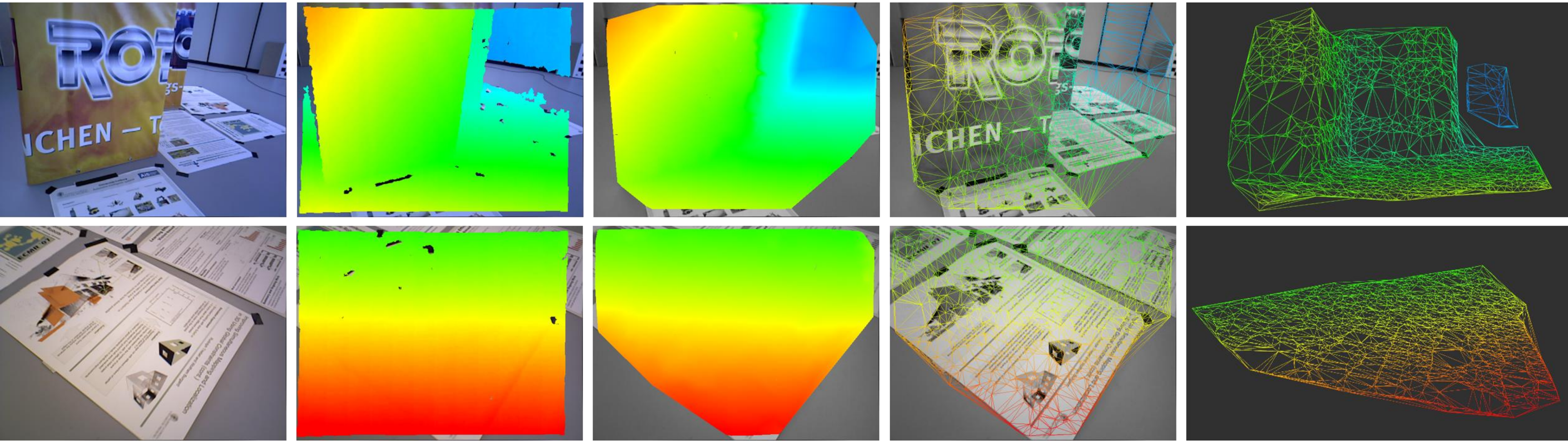
FLaME: Fast Lightweight Mesh Estimation



Benchmark Results

Compared FLaME to two existing CPU-only approaches:

- LSD-SLAM
- MLM



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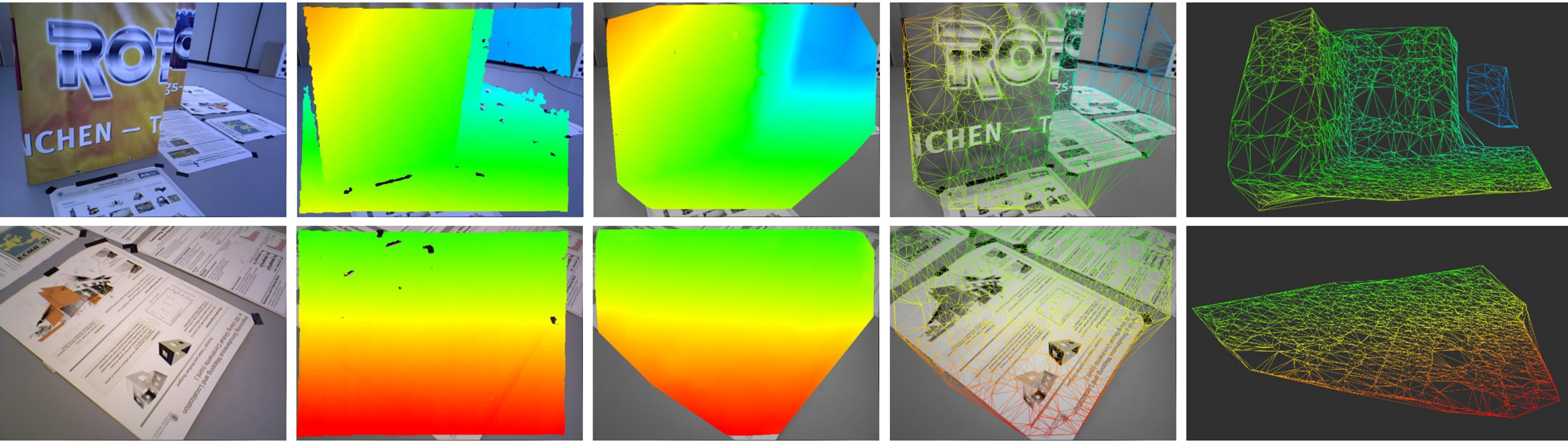
Evaluated on two benchmark datasets (ground truth poses):
- TUM RGBD SLAM (640x480 @ 30 Hz)
- EuRoC MAV (752x480 @ 20 Hz)



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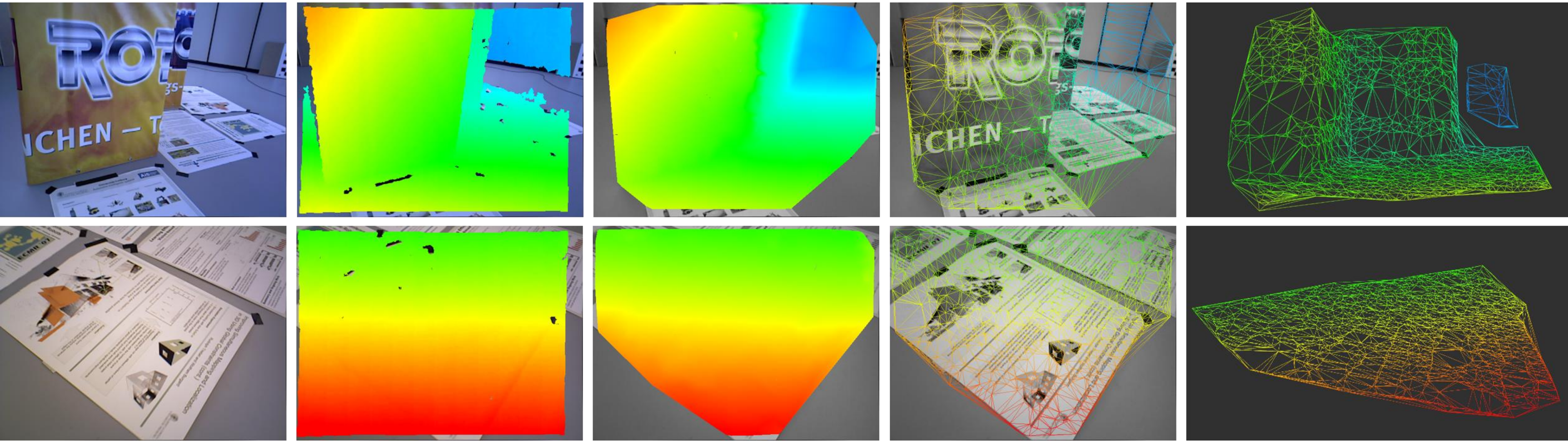
Desktop Intel i7 CPU only



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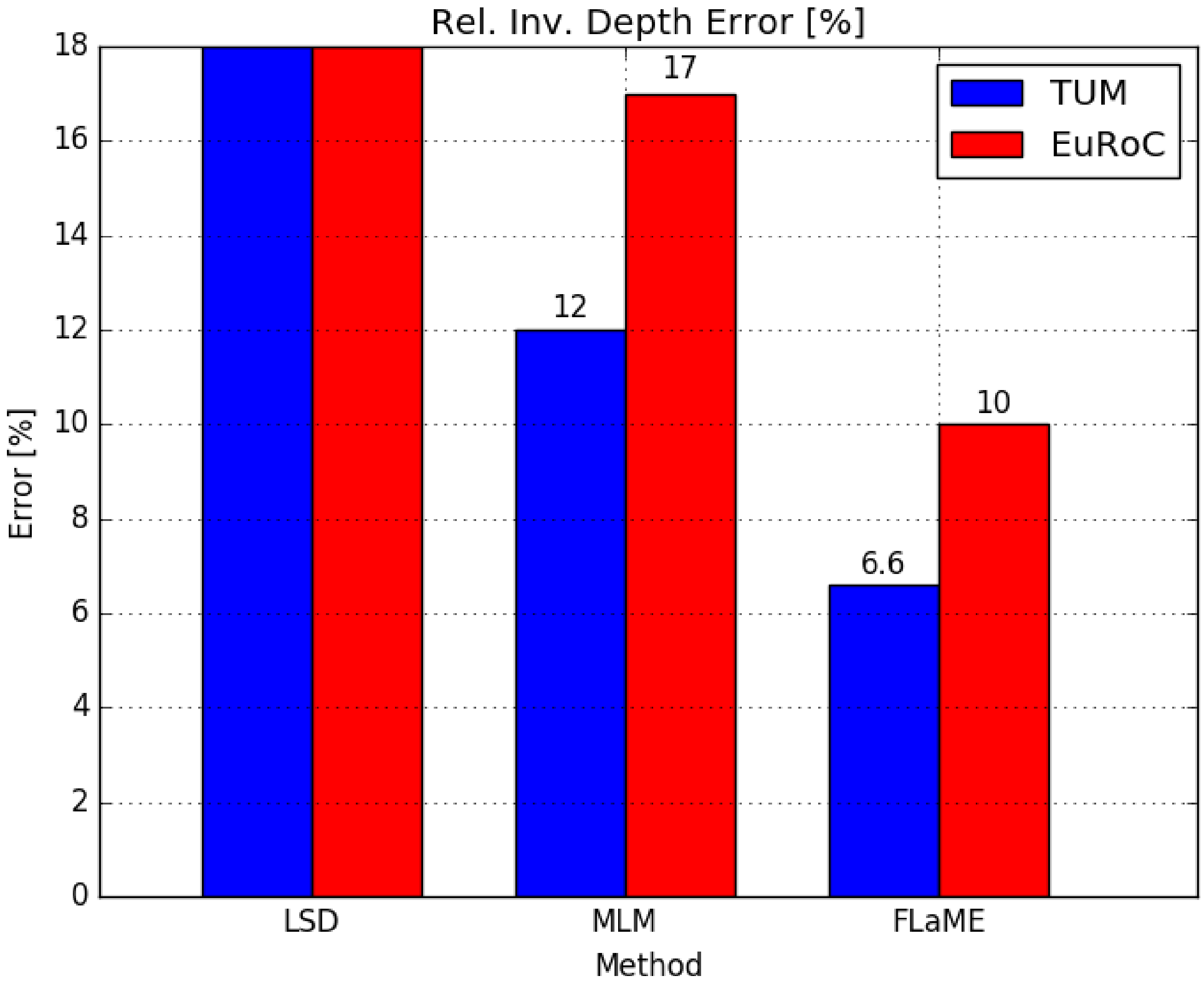
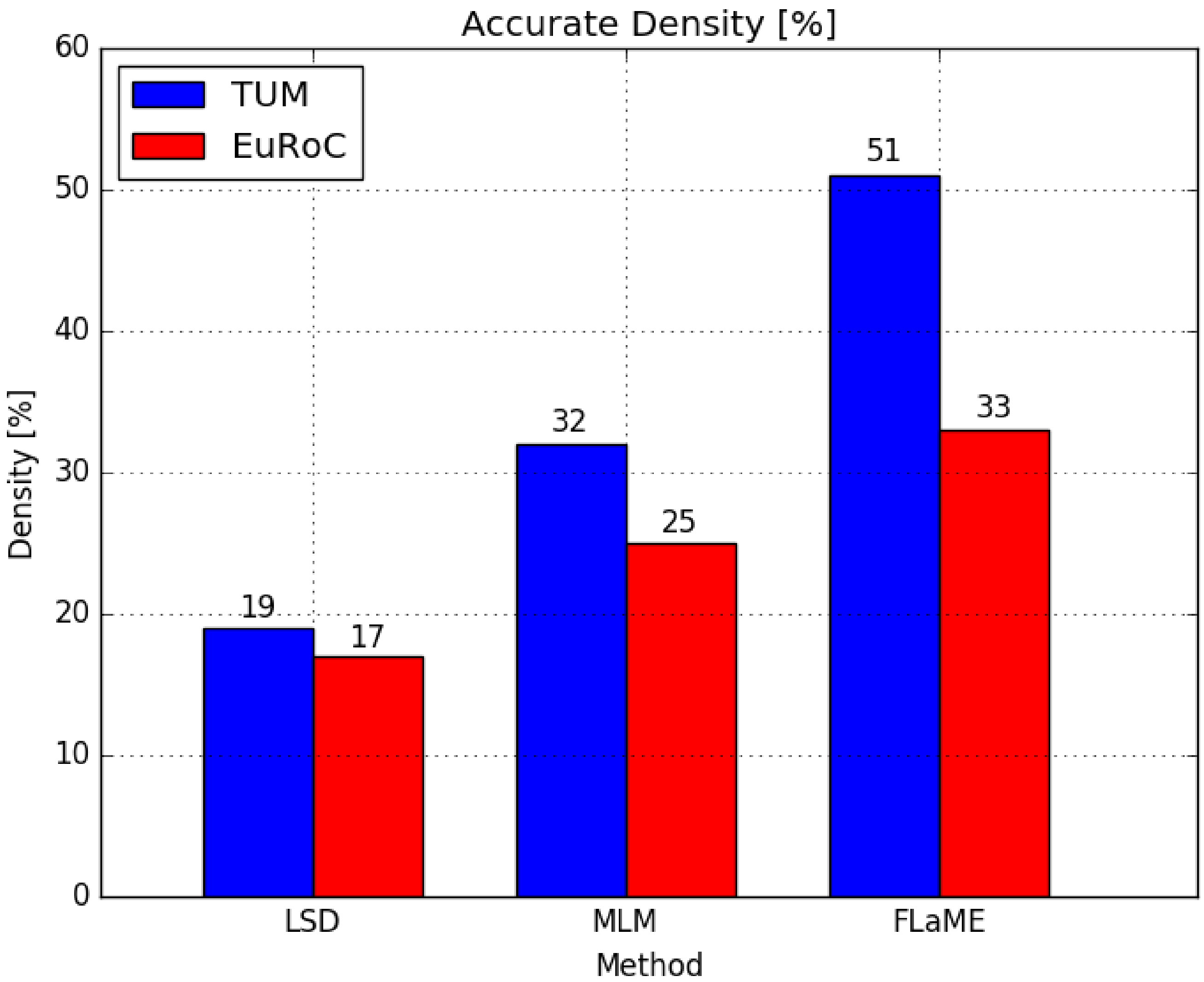


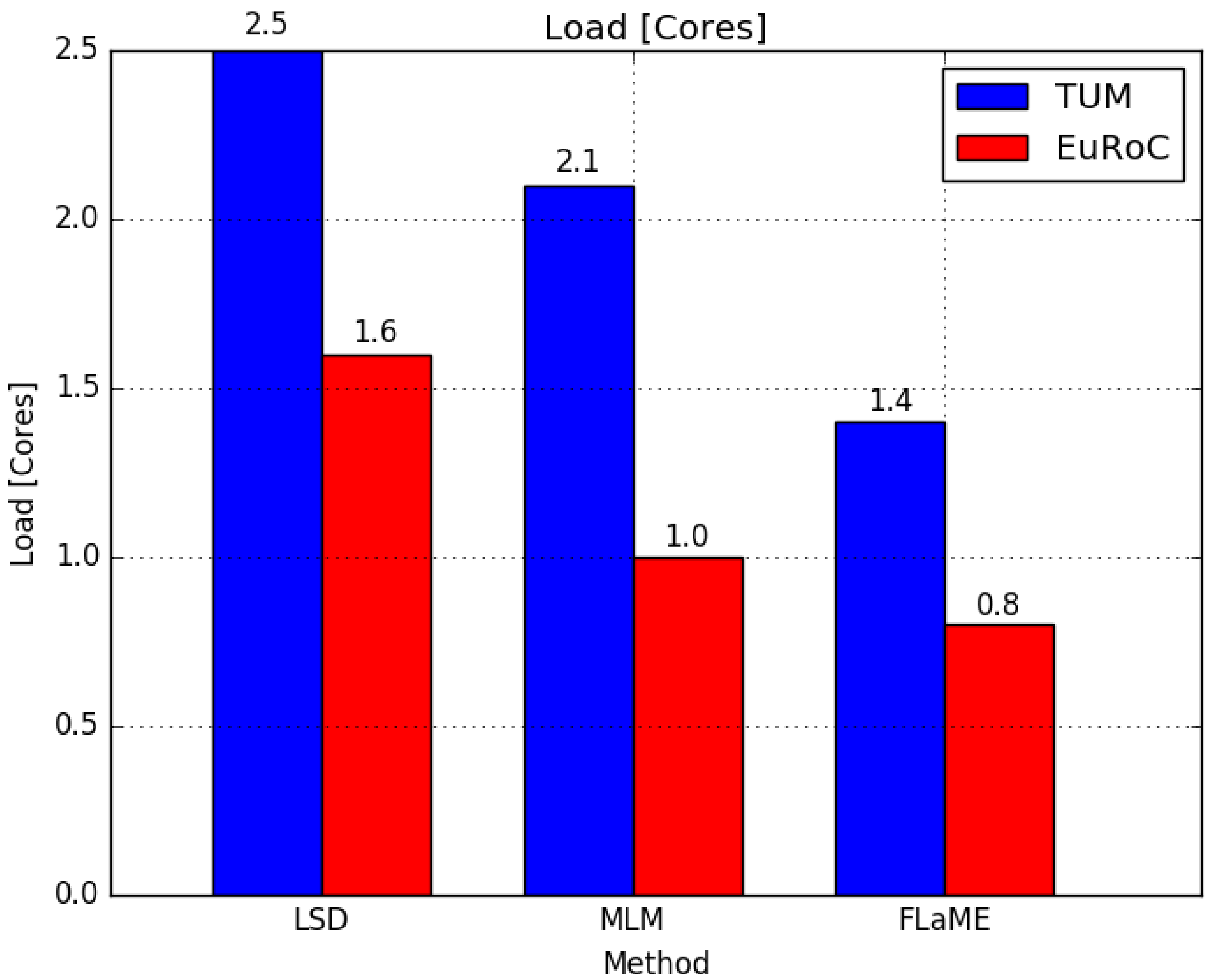
Lower Error

Benchmark Results



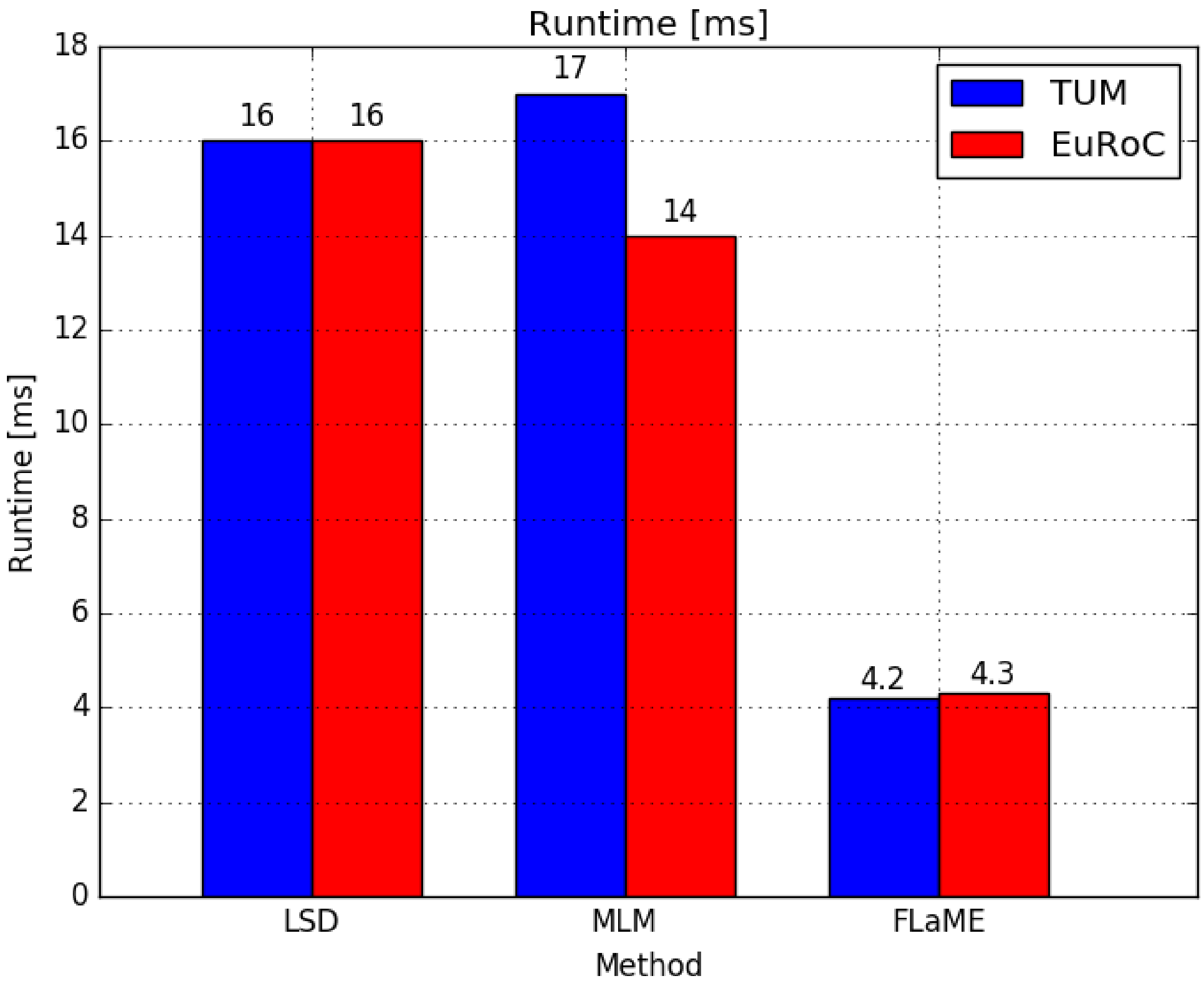
More Dense

Benchmark Results



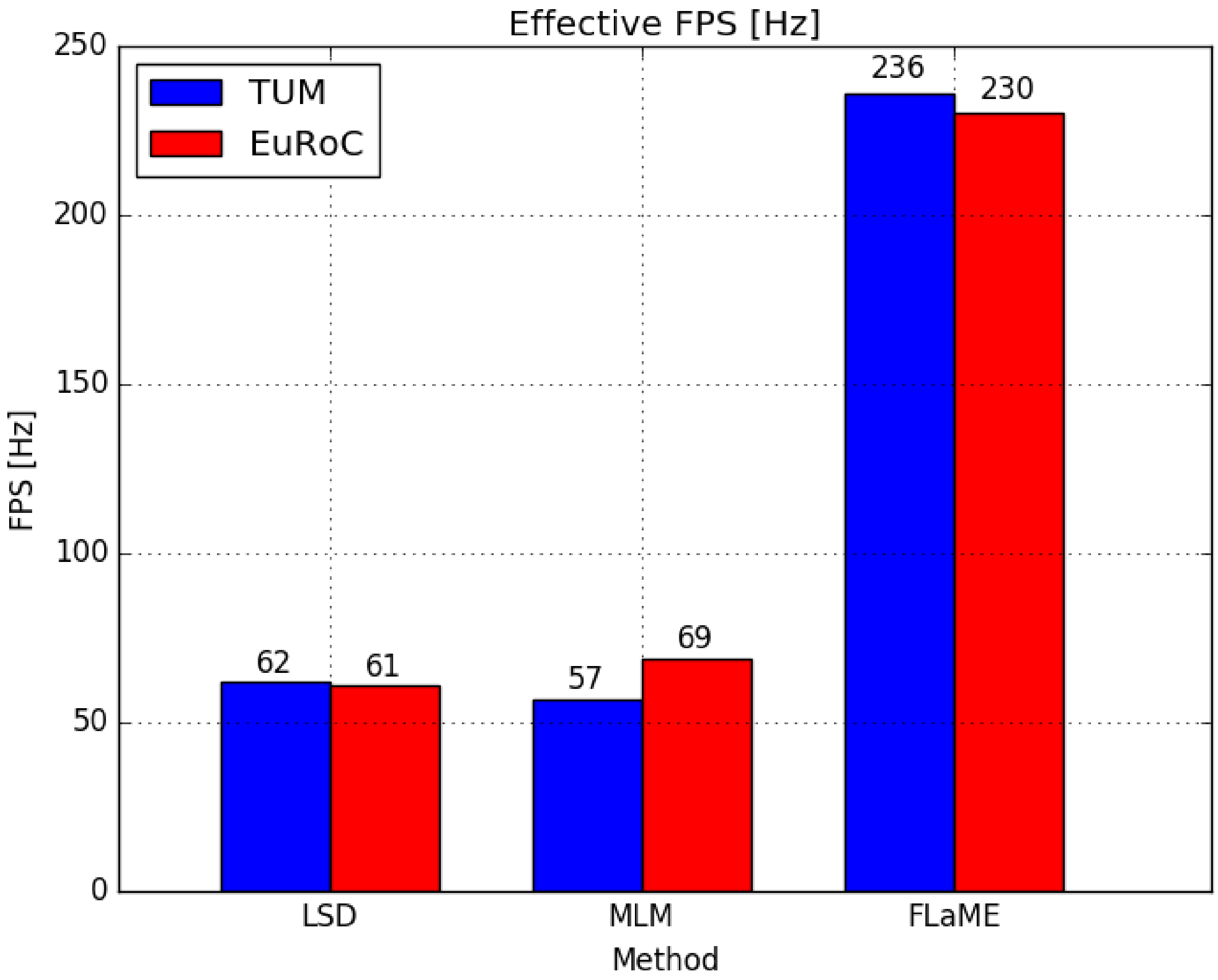
Less Load

Benchmark Results



Faster

Benchmark Results



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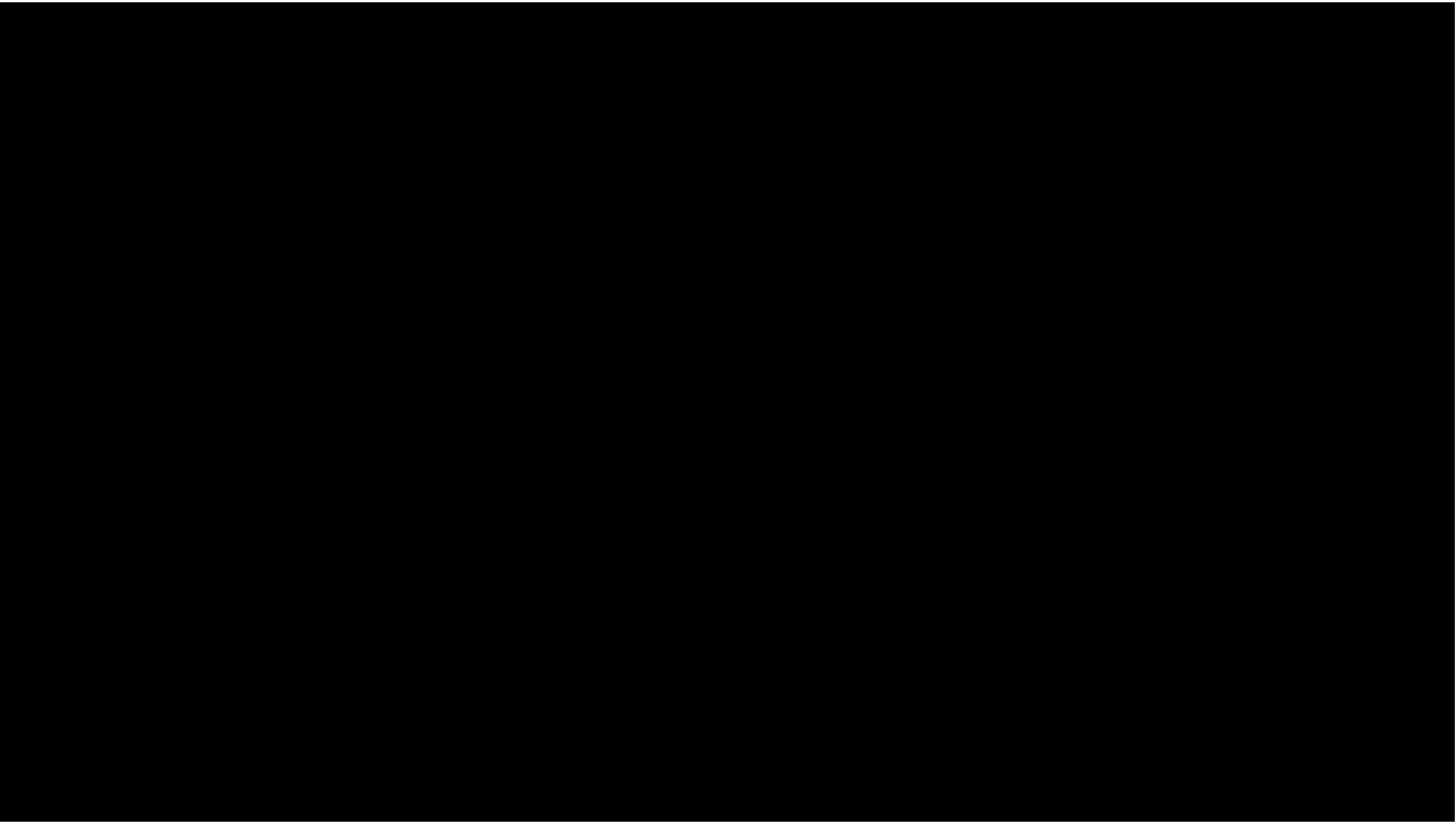
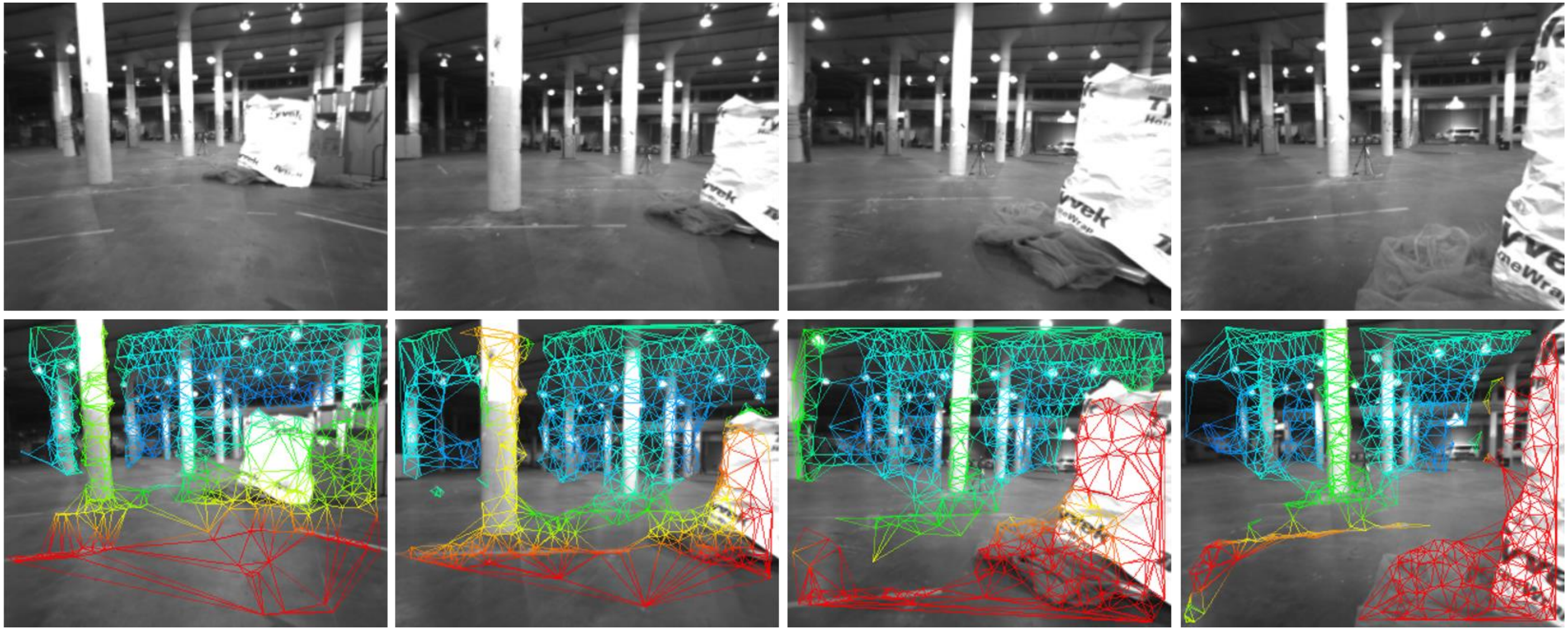
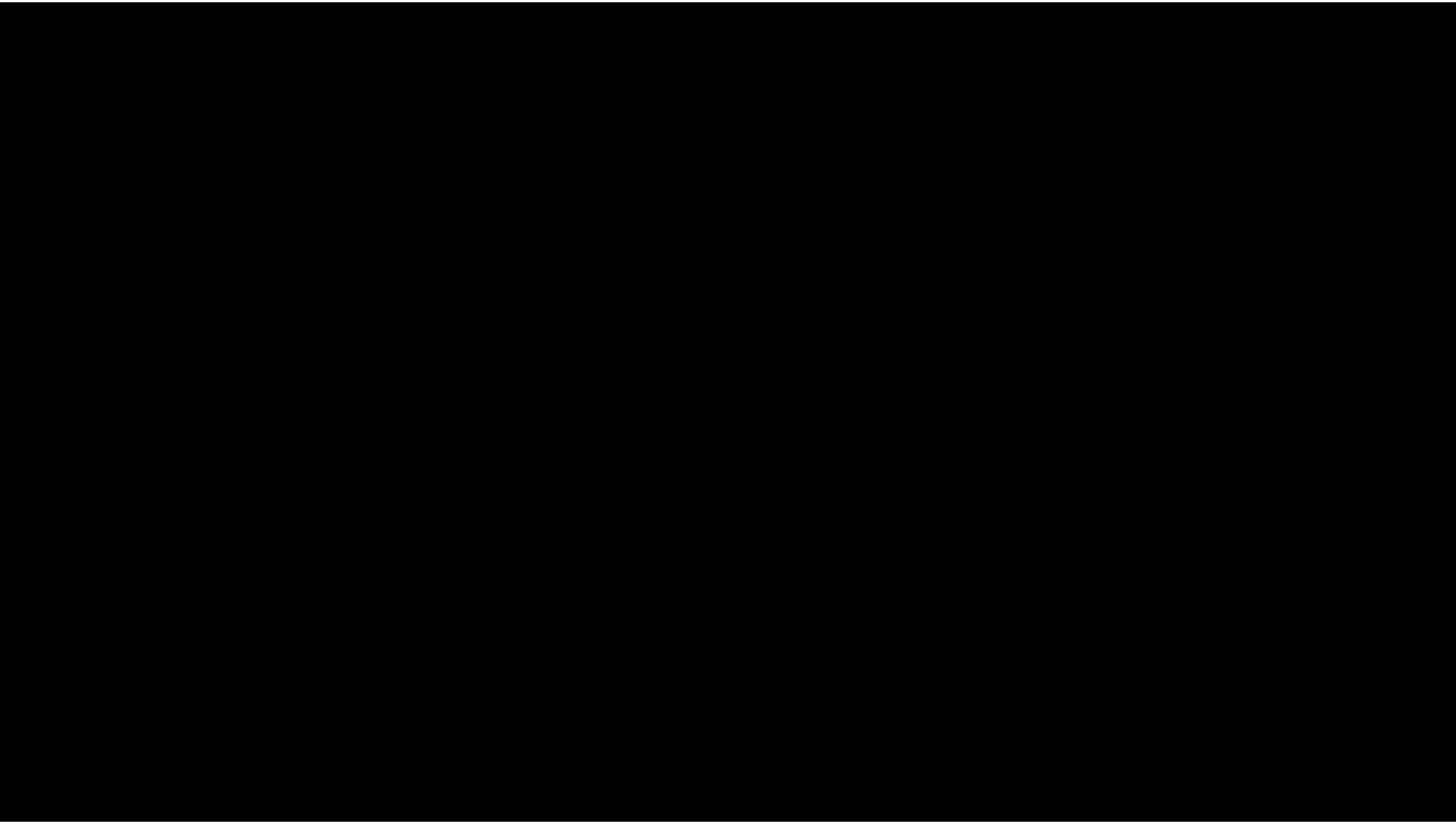


Flight Experiments



DJI F450 frame
Intel NUC flight computer
10 ms/frame runtime
1.5 core load
Indoor Flight at 2.5 m/s
Outdoor Flight at 3.5 m/s

Flight Experiments



FLaME Contributions

- Proposed a lightweight method for dense online monocular depth estimation

Paper

Code*

W. Nicholas Greene (wng@csail.mit.edu)

* Coming soon!

FLaME Contributions

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- Formulated the reconstruction problem as a non-local variational optimization over a Delaunay graph, which allows for a fast, efficient approach to depth estimation

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- Demonstrated real-world applicability with indoor and outdoor flight experiments running FLaME onboard, in-the-loop

Paper

Code*

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Acknowledgments

This material is based upon work supported by DARPA under Contract No. HR0011-15-C-0110 and by the NSF Graduate Research Fellowship under Grant No. 1122374. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors(s) and do not necessarily reflect the views of the National Science Foundation.

We also thank John Ware, John Carter, and the rest of the MIT-Draper FLA Team for continued development and testing support.

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