ROBOTICS & PERCEPTION GROUP

Universität Zürich[UZH]

Lecture 10
Multi-view Stereo
(3D Dense Reconstruction)

Davide Scaramuzza

REMODE: Probabilistic, Monocular Dense Reconstruction in Real Time, ICRA’14, by Pizzoli, Forster, Scaramuzza

[M. Pizzoli, C. Forster, D. Scaramuzza, REMODE: Probabilistic, Monocular Dense Reconstruction in Real Time, ICRA’14]

3D Reconstruction from Multiple views

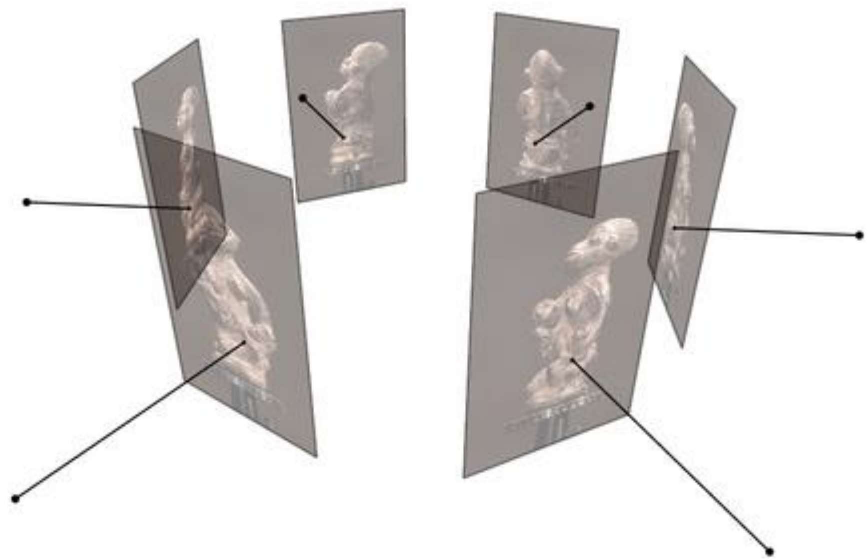
Assumption

- Cameras are calibrated
  - both **intrinsically**
    - $\boldsymbol{K}$ matrix for each camera is known
  - and **extrinsically**
    - relative positions $\boldsymbol{T}$ and orientations $\boldsymbol{R}$ between cameras are known (for instance, from SFM)

Multi-view stereo

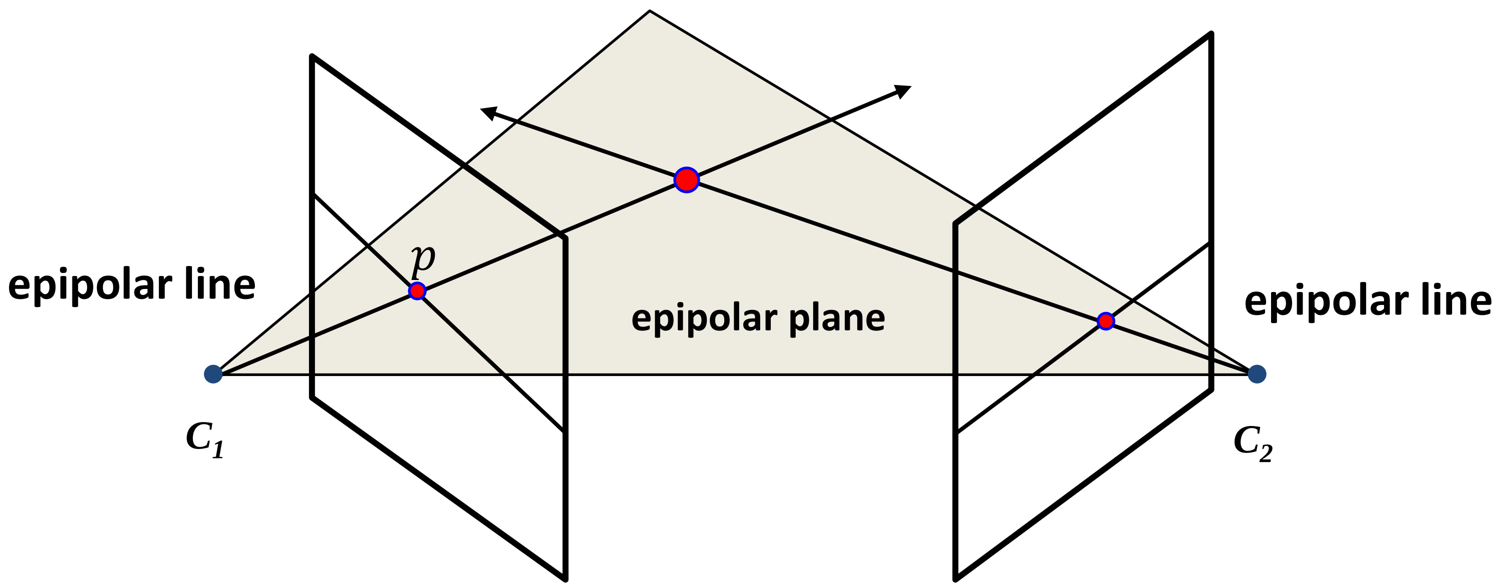
Input: calibrated images from several viewpoints

Output: 3D object model



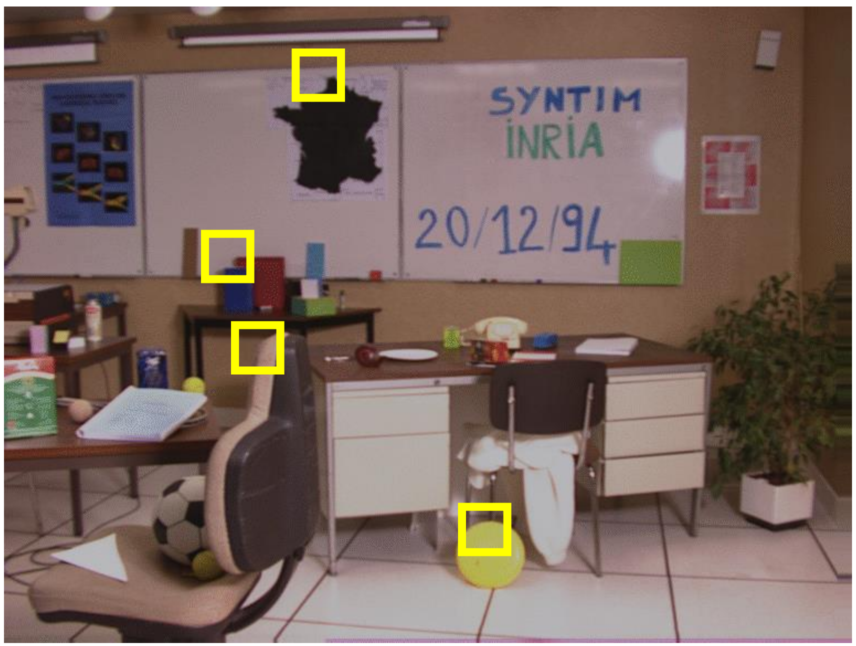
Review: The Epipolar Plane

The two camera centers and the feature p determine a plane called the "epipolar plane", which intersect each camera image plane into an epipolar line.

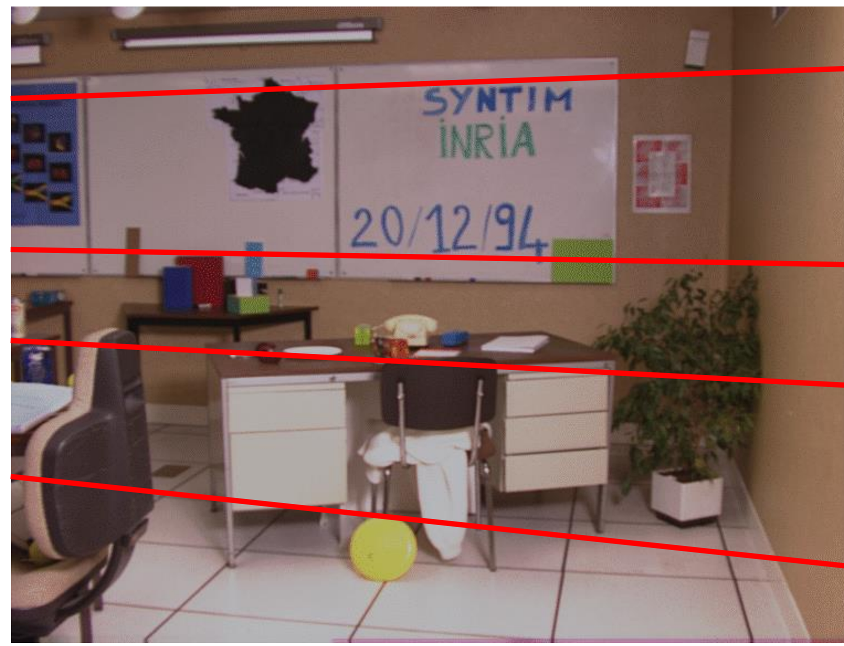


Review: Epipolar Lines for Correspondence Search

Thanks to the epipolar constraint, corresponding points only need to be searched along epipolar lines



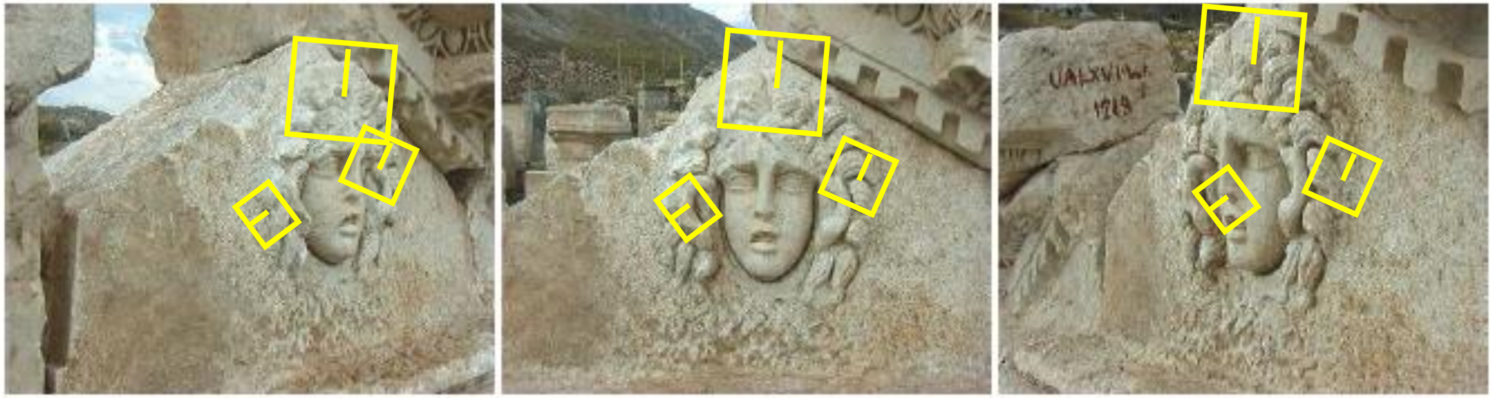
Left image

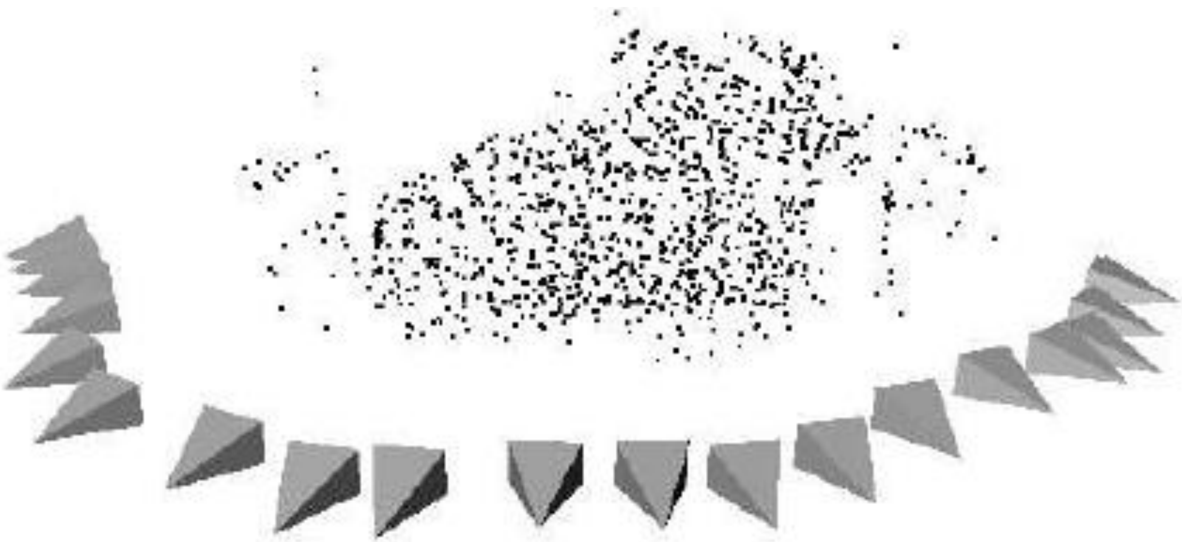


Right image

Sparse Reconstruction

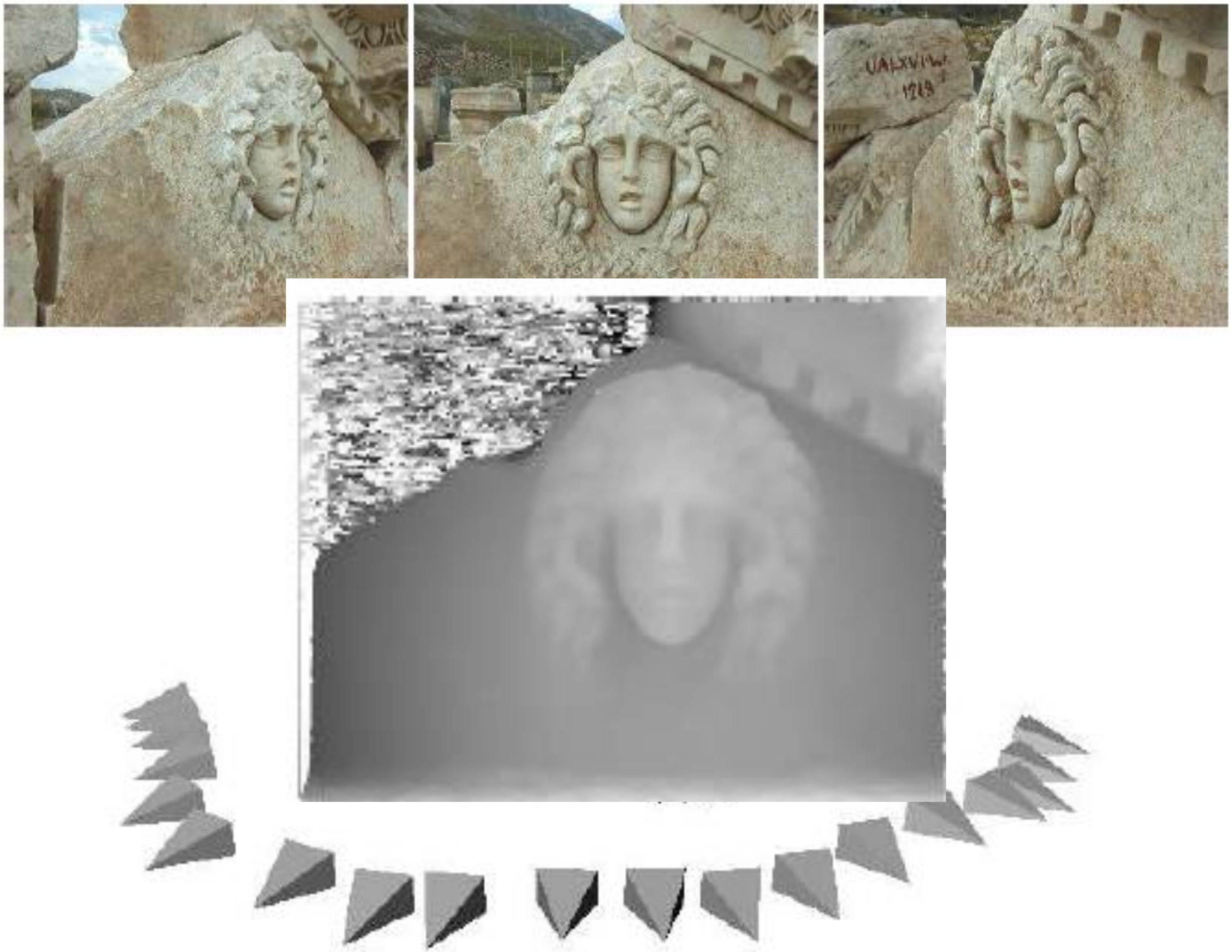
- Estimate the structure from a “sparse” set of features





Dense Reconstruction

- Estimate the structure from a "dense" region of pixels



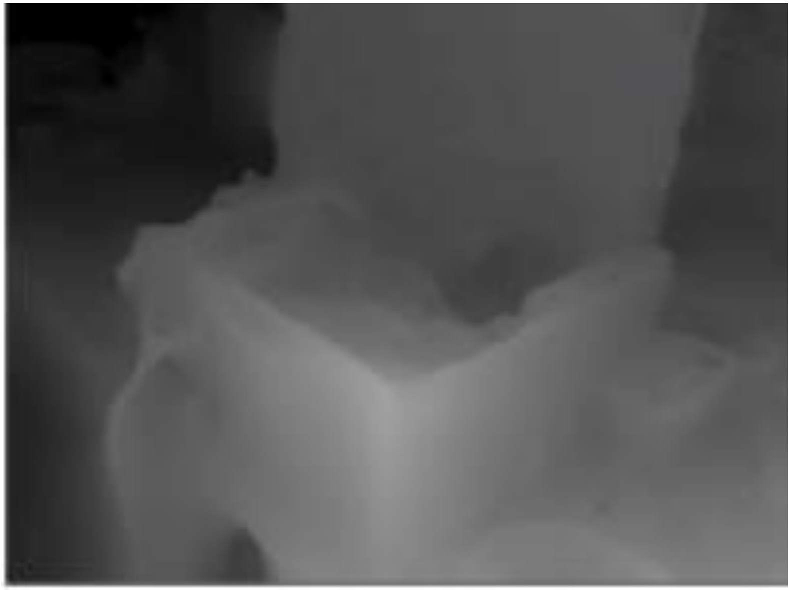
Dense reconstruction workflow

Step 1: Local methods

- Estimate depth for every pixel independently

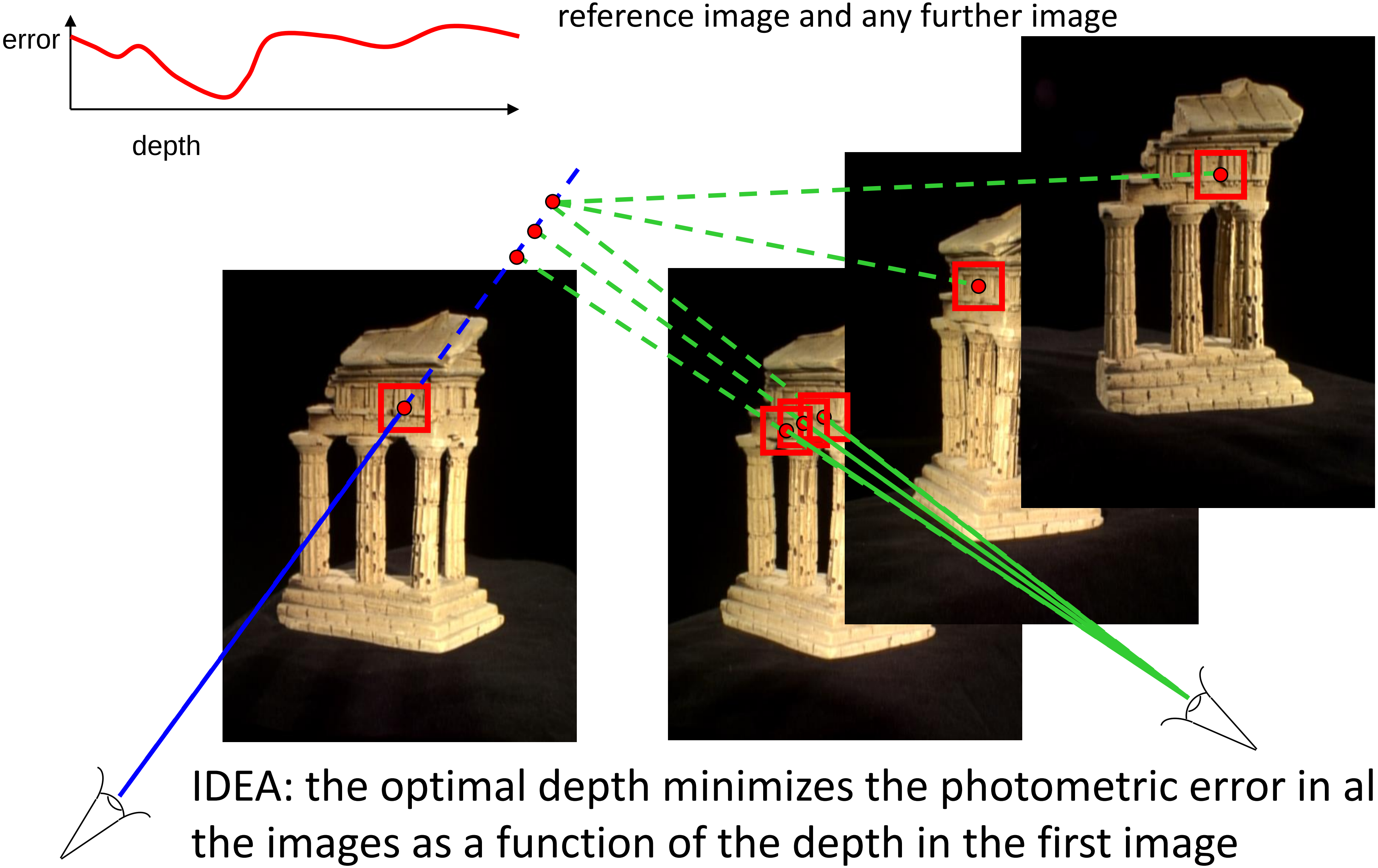
Step 2: Global methods

- Refine the depth surface as a whole by enforcing smoothness constraint



Photometric error (SSD or SAD)

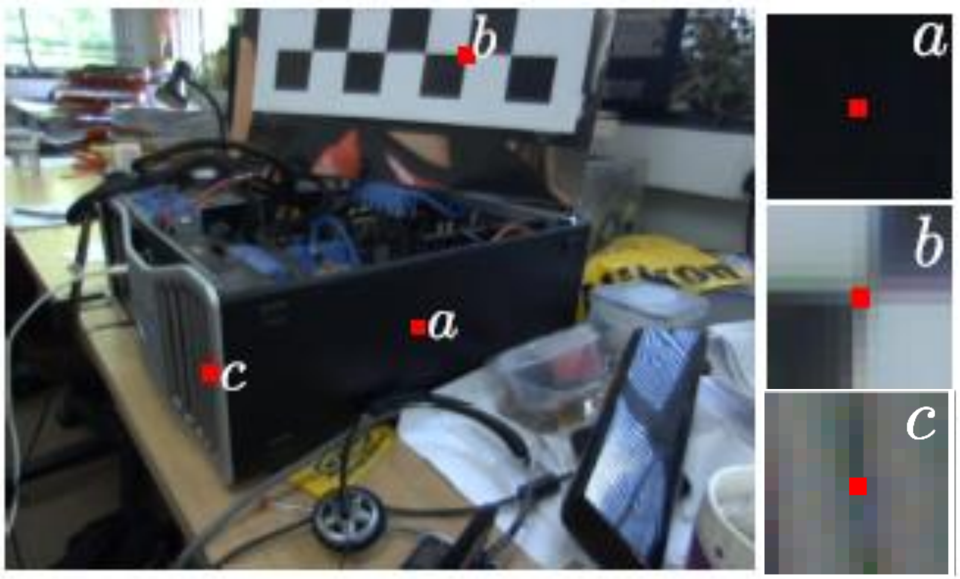
This error plot is derived for every combination of the reference image and any further image



IDEA: the optimal depth minimizes the photometric error in all the images as a function of the depth in the first image

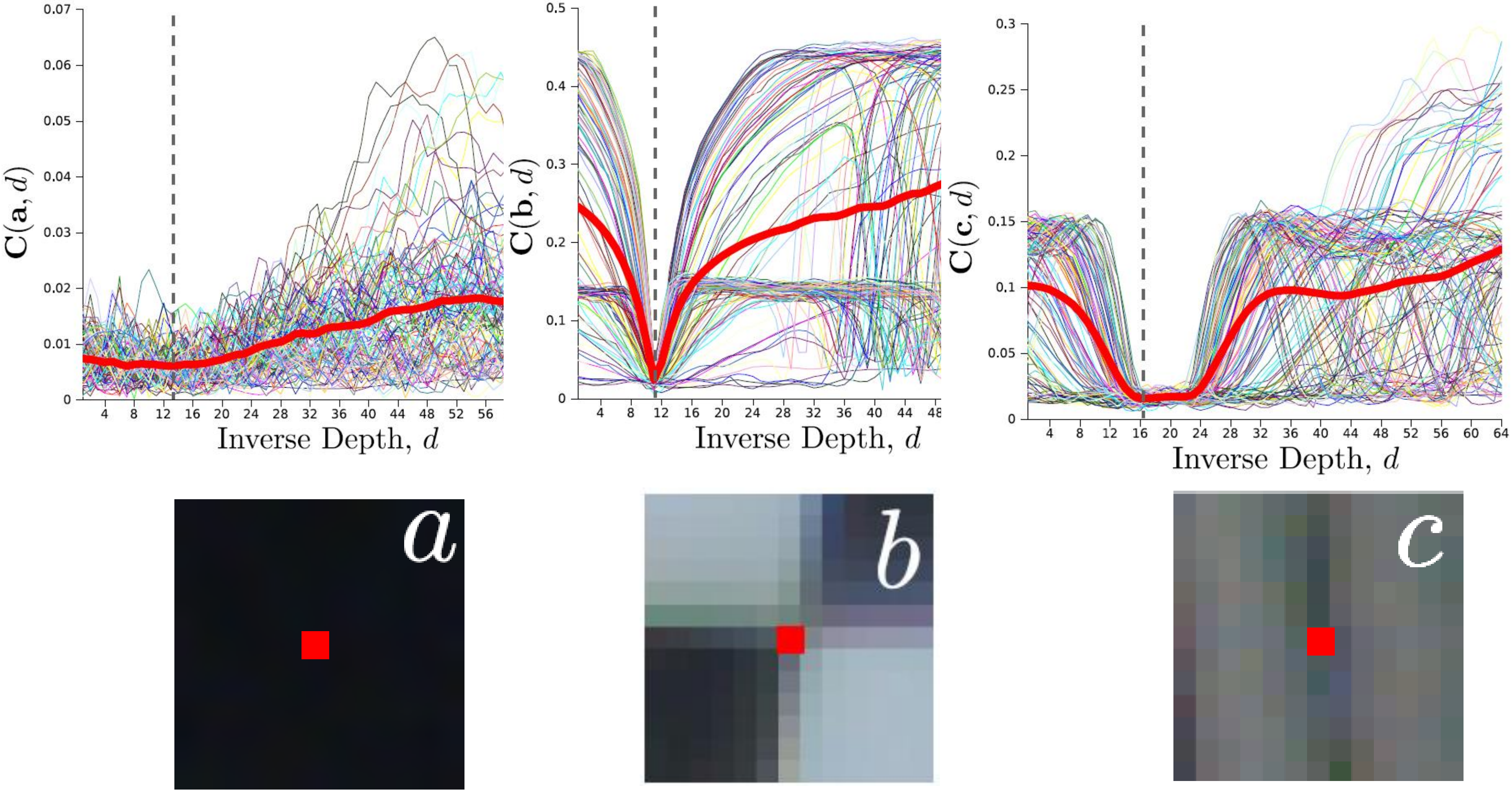
Aggregated photometric error

- Dense reconstruction requires establishing dense correspondences
- Correspondences are computed based on photometric error:
  - patch-based correlation (SAD, SSD, NCC)
  - Difference among pixel intensity values (patch 1x1 pixels)
  - What are the pros and cons of using small or large patches?
- Not all the pixels can be matched reliably
  - Viewpoint and illumination changes, occlusions
- Take advantage of many small baseline views where high quality matching is possible (why?)



[Newcombe et al. 2011]

Aggregated photometric error



- Photometric error for flat regions or edges parallel to the epipolar line show multiple minima (because of noise, lack of textures or repetitive textures)
- For distinctive pixels (as in ***b***) the aggregated photometric error has typically one clear minimum.

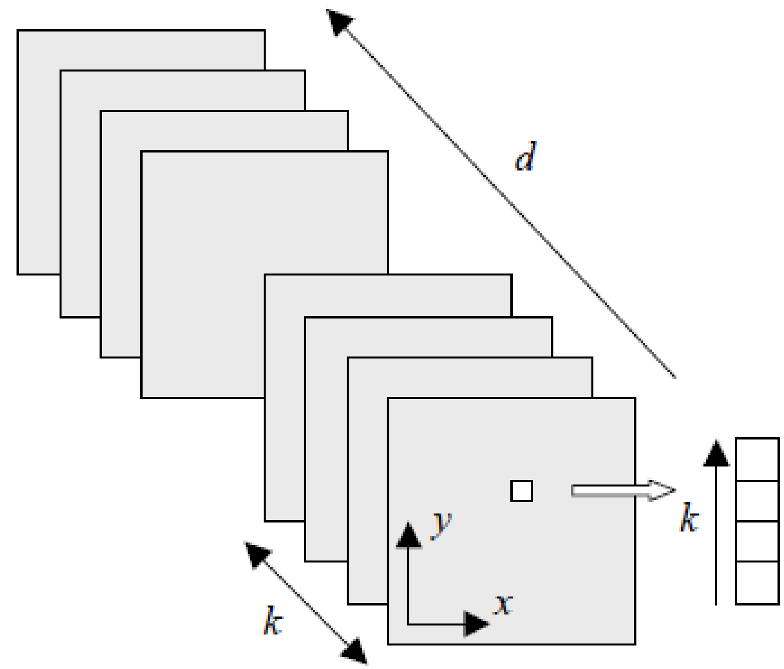
Disparity Space Image (DSI)

- For discrete depth hypotheses the aggregate photometric error with respect to the reference image can be stored in the Disparity Space Image (DSI)

$$C(u,v,d) = \sum_k \rho(\widetilde{I_k}(u',v',d) - I_r(u,v))$$

  $\widetilde{I_k}(u',v',d)$ is the pixel in the k-th image associated with the pixel (u',v') in the reference image I_r and depth hypothesis d

- $\rho(\cdot)$ is the photometric error (e.g., SSD, SAD)



[Szeliski and Golland 1999]

Disparity Space Image (DSI)

240 x 180 x 100 voxels

Solution

The solution to the depth estimation problem *is a* **function** $\boldsymbol{d}(\boldsymbol{u}, \boldsymbol{v})$ in the DSI that presents some **optimality properties**:

- **Minimum aggregated photometric cost** $arg \min_{d} C$

AND (optionally)

- **best piecewise smoothness** (global methods)

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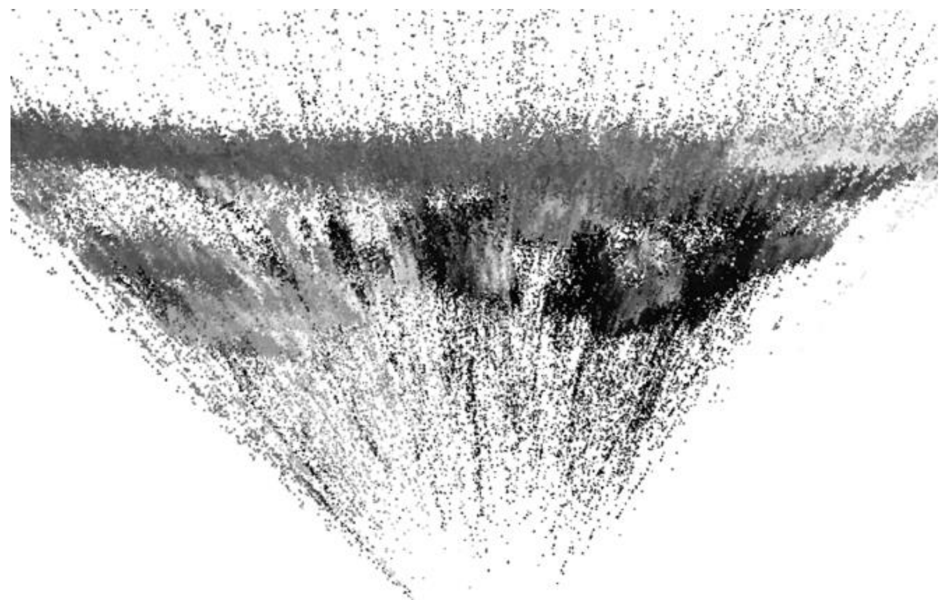

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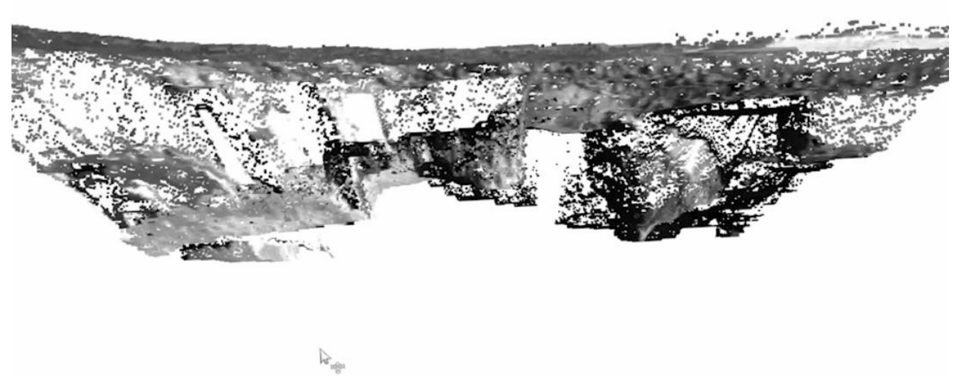


Solution

- **Global methods**
  - Formulated in terms of energy minimization
  - The objective is to find $d(u, v)$ that minimizes a global energy

$$E(d) = \underbrace{E_d(d)}_{\text{Data term}} + \underbrace{\lambda E_s(d)}_{\text{Regularization term}}$$

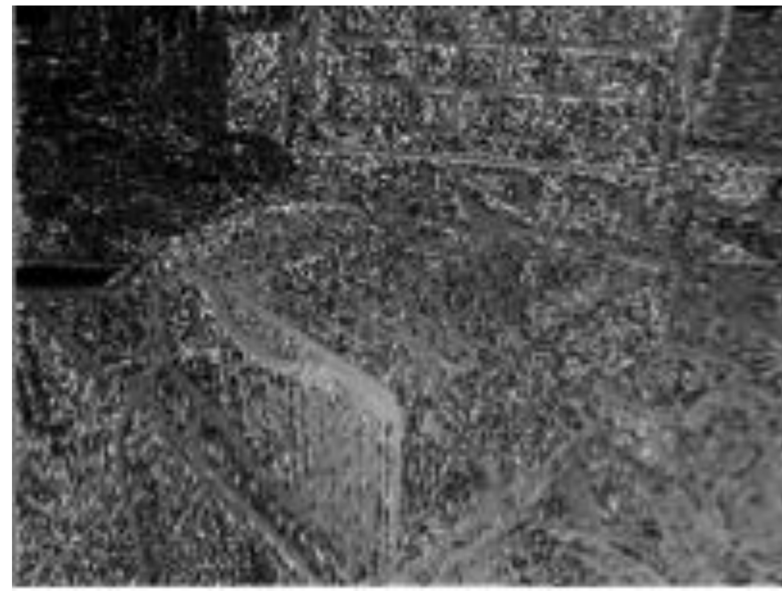
$$E_d(d) = \sum_{(u,v)} C(u, v, d(u, v))$$

$$E_s(d) = \sum_{(u,v)} \rho_d\big(d(u, v) - d(u + 1, v)\big) + \rho_d\big(d(u, v) - d(u, v + 1)\big)$$

  - ρ_d is a norm (e.g. L_2, L_1 or Huber norm)
  - λ controls the tradeoff data / regularization. What happens for large λ?

Regularized depth maps

- **The regularization term** $E_s(d)$
  - ***Smooths*** *non smooth surfaces* (results of noisy measurements) as well as discontinuities
  - ***Fills the holes***



Final depth image for different λ
[Newcombe et al. 2011]

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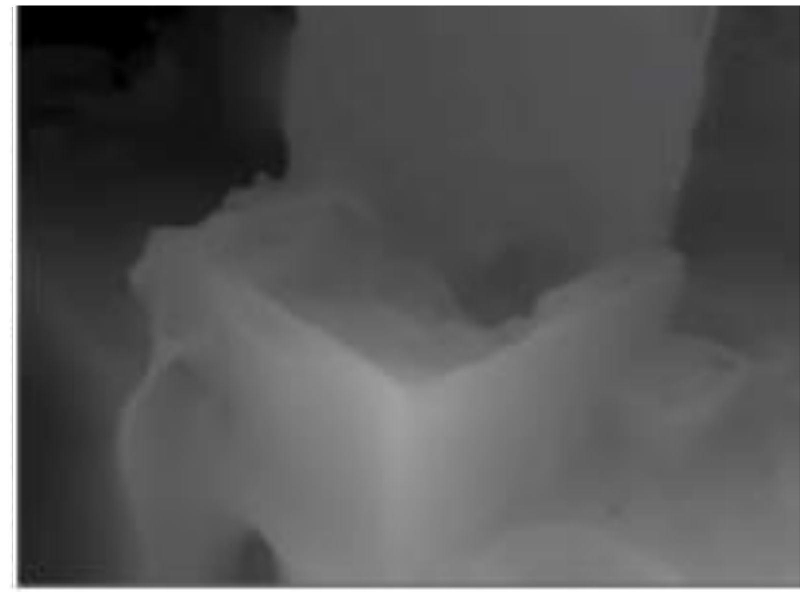


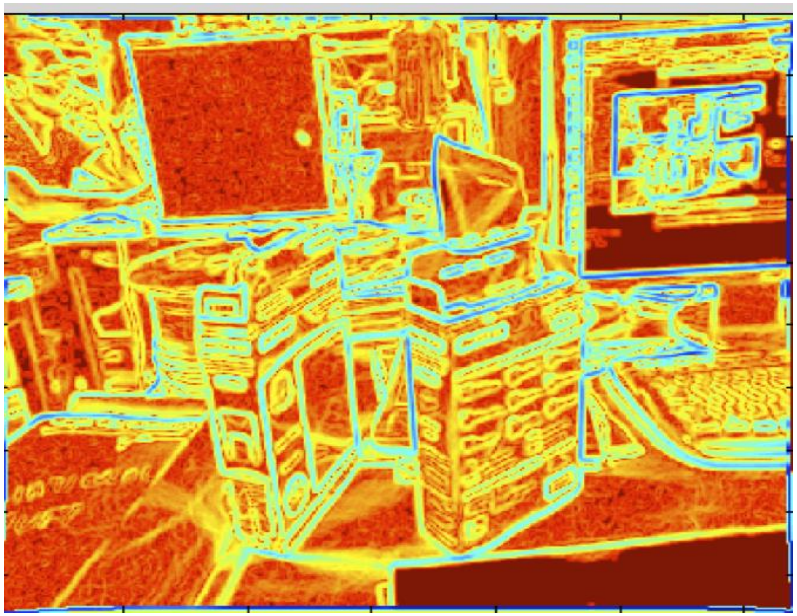
Final depth image for different λ
[Newcombe et al. 2011]

Regularized depth maps

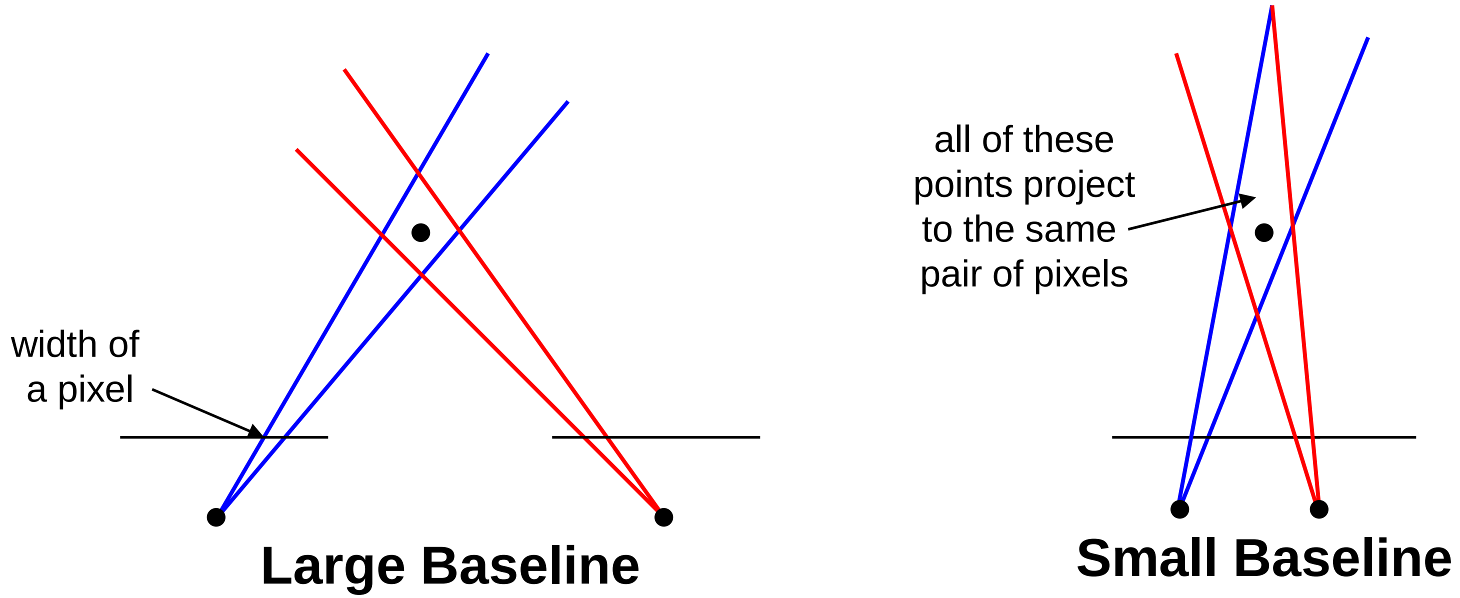
- Popular assumption: *discontinuities in intensity* **coincide** with *discontinuities in depth*
- ***Control smoothness penalties*** according to image gradient

$$\rho_d\big(d(u,v) - d(u+1,v)\big) \cdot \rho_I\,(\|I(u,v) - I(u+1,v)\|)$$

- ρ_I is some monotonically decreasing function of intensity differences: ***lowers*** *smoothness costs at* ***high intensity gradients***



Choosing the stereo baseline



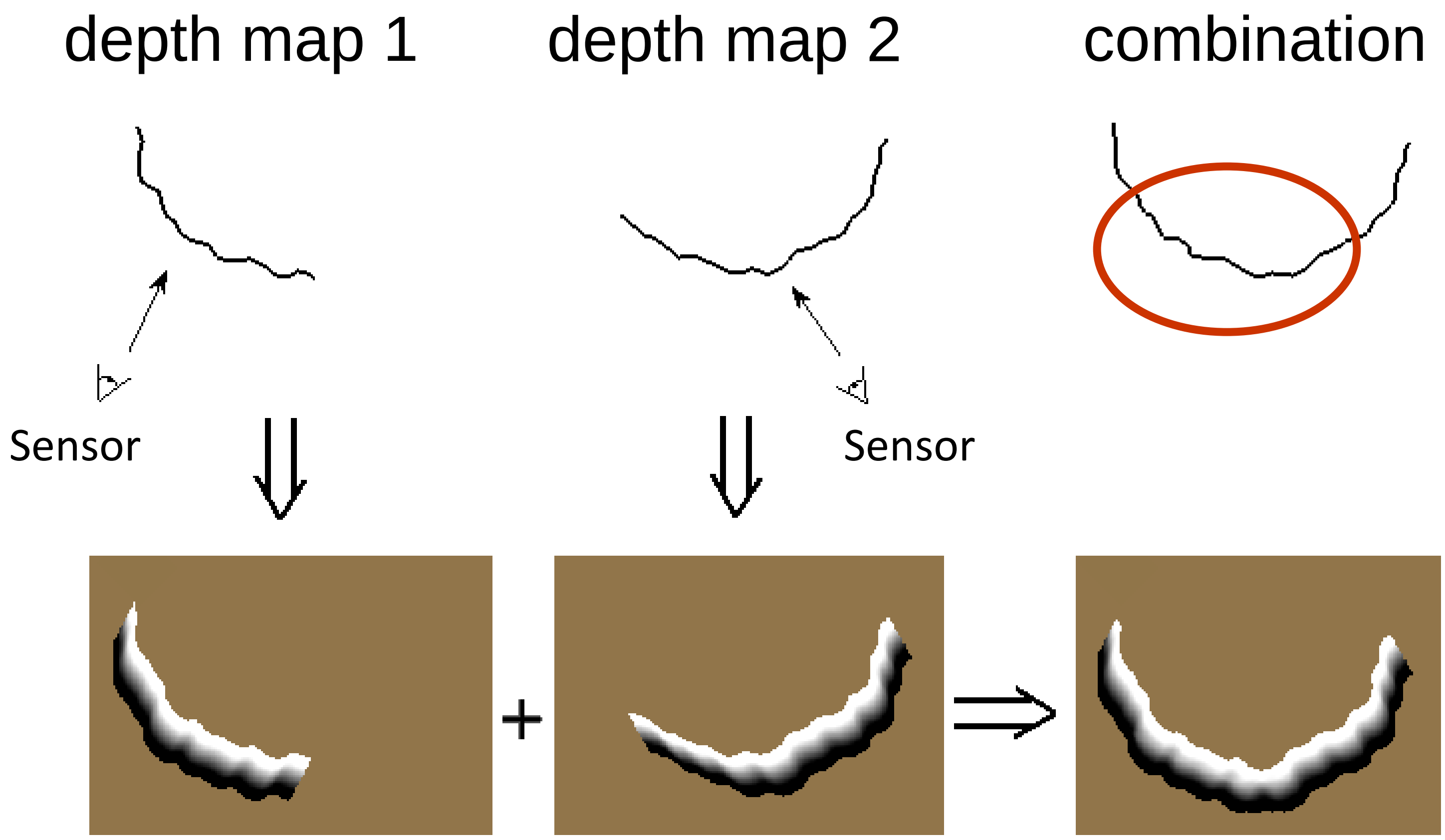
What's the optimal baseline ?

- Too small: ***large depth error***
- Too large: ***difficult search problem***

Solution

- Obtain depth map from small baselines
- When baseline becomes to large, create new reference frame (keyframe) and start new depth computation

Fusion of multiple depth maps



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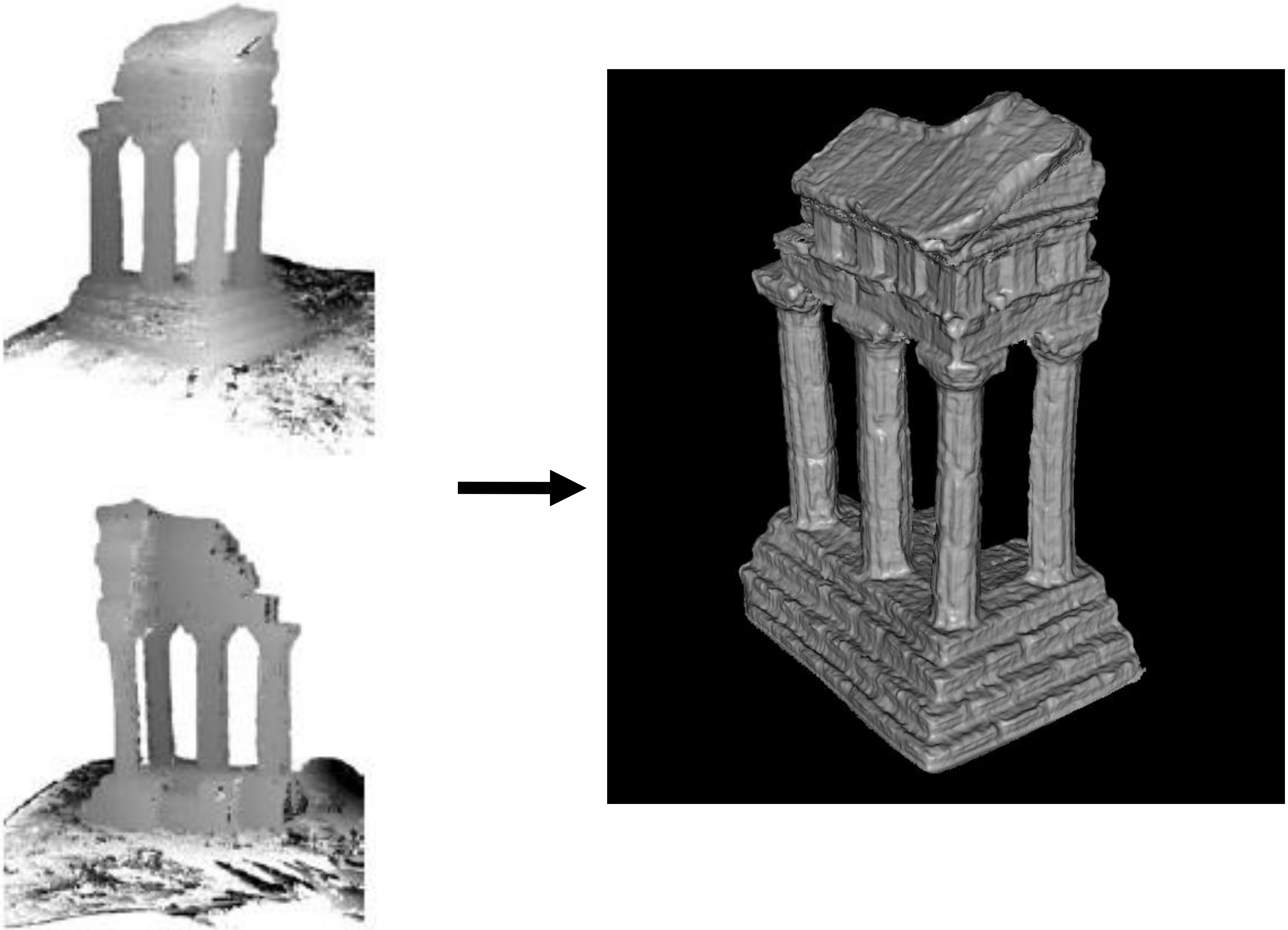


Depth map fusion

input image

317 images
(hemisphere)

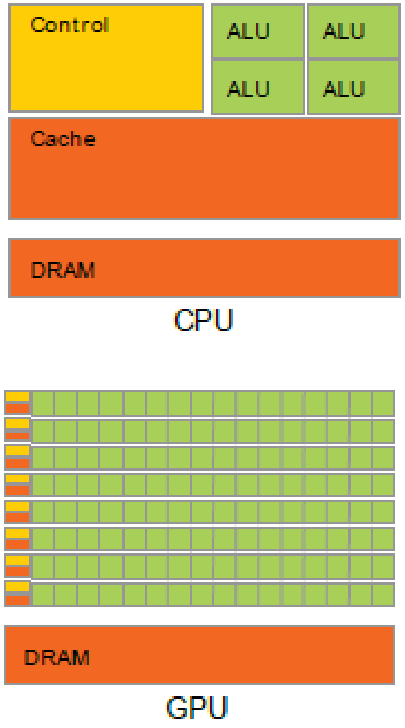
ground truth model

[Goesele, Curless, Seitz, 2006](#)

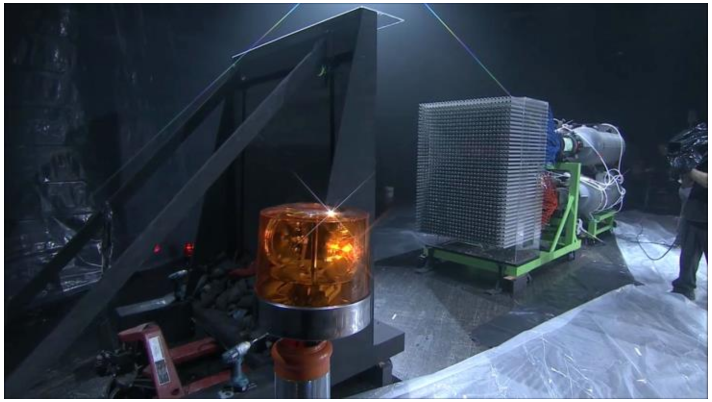
Michael Goesele

GPGPU

ALU: Arithmetic Logic Unit



- ***GPGPU = General Purpose computing on Graphics Processing Unit***
- Perform demanding calculations on the GPU instead of the CPU
- On the GPU: high processing power ***in parallel*** on thousands of cores
  - On a CPU a few cores optimized for sequential serial processing
- More transistors devoted to data processing
- More info: http://www.nvidia.com/object/what-is-gpu-computing.html#sthash.bW35IDmr.dpuf

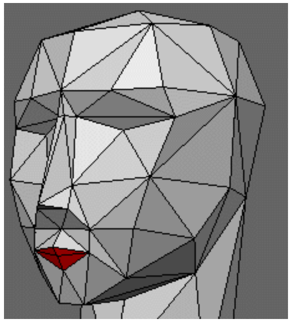


https://www.youtube.com/watch?v=-P28LKWTzrI

GPU Capabilities

- Fast pixel processing
  - Ray tracing, draw textures, shaded triangles faster than CPU
- Fast matrix / vector operations
  - Transform vertices
- Programmable
  - Shading, bump mapping
- Floating-point support
  - Accurate computations
- Deep Learning

Bump mapping



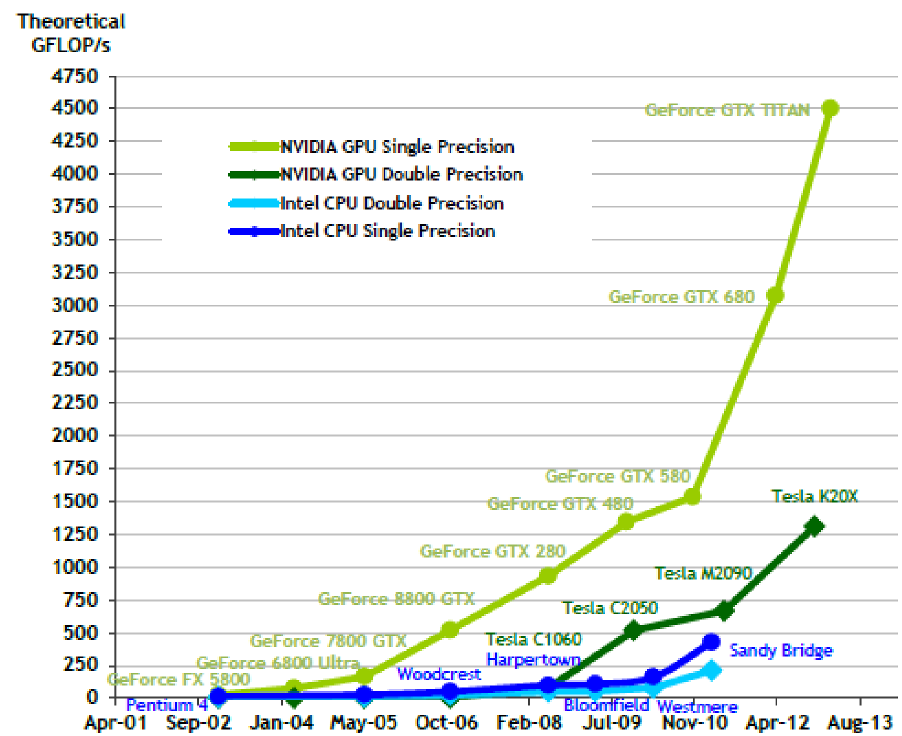
Shaded triangles

GPU for 3D DenseReconstruction

- **Image processing**
  - Filtering
  - Warping (e.g., epipolar rectification, homography)
  - Feature extraction (i.e., convolutions)
- **Multi-view geometry**
  - Search for dense correspondence
    - *Pixel-wise* operations (correlation)
    - Matrix and vector operations (epipolar geometry)
  - Photometric Cost Aggregation
- **Global optimization**
  - *Variational methods (i.e., regularization (smoothing))*
    - ***Parallel, in-place*** operations for gradient / divergence computation

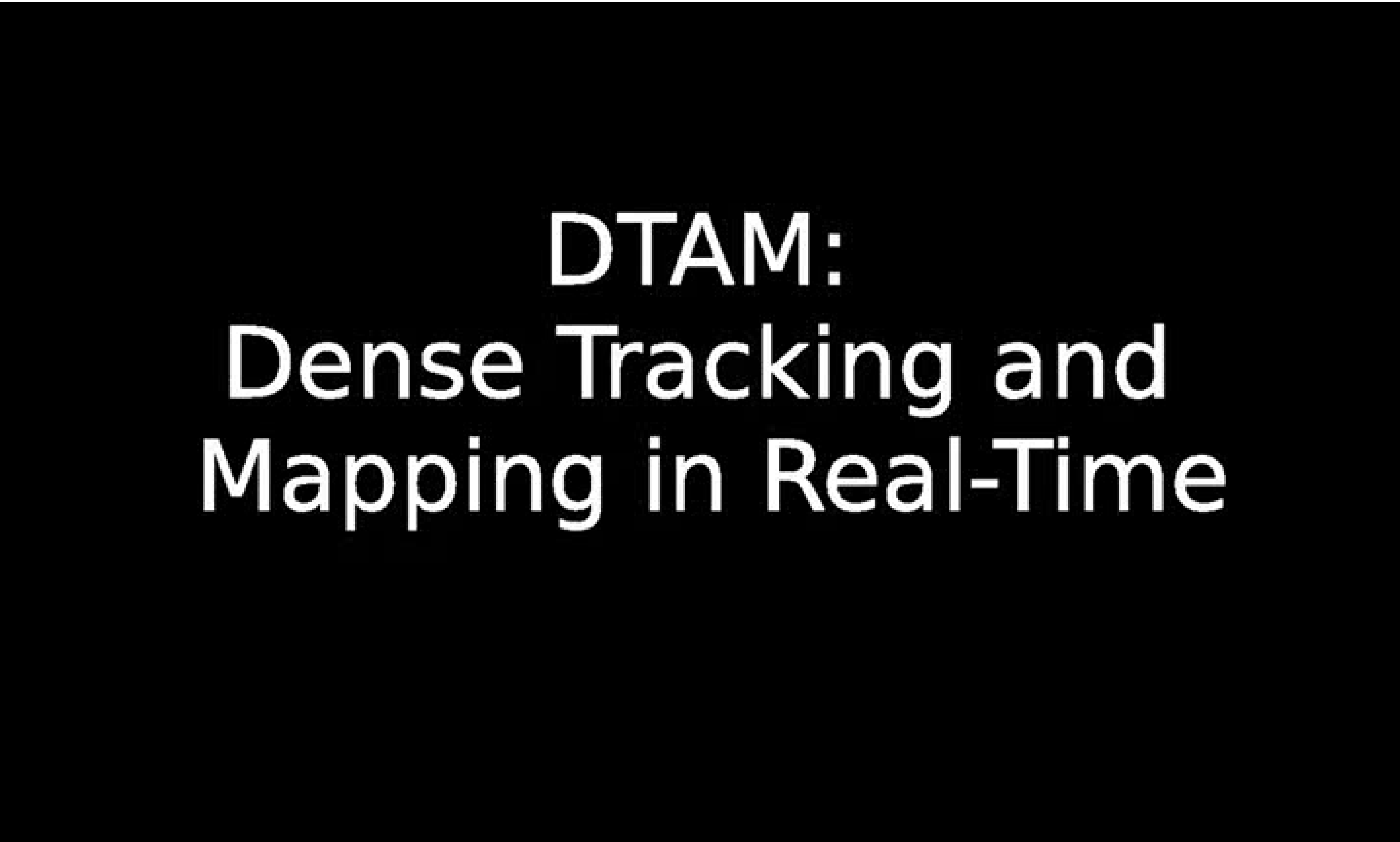
Why GPU

- GPUs run *thousands of lightweight threads **in parallel***
  - *Typically* on consumer hardware: 1024 threads per multiprocessor; 30 multiprocessor => **30k threads**.
  - Compared to CPU: 4 quad core support 32 threads (with HyperThreading).
- Well suited for **data-parallelism**
  - The same instructions executed on multiple data in parallel
  - High **arithmetic intensity**: *arithmetic operations / memory operations*



[Source: nvidia]

DTAM: Dense Tracking and Mapping in Real-Time, ICCV'11
by Newcombe, Lovegrove, Davison

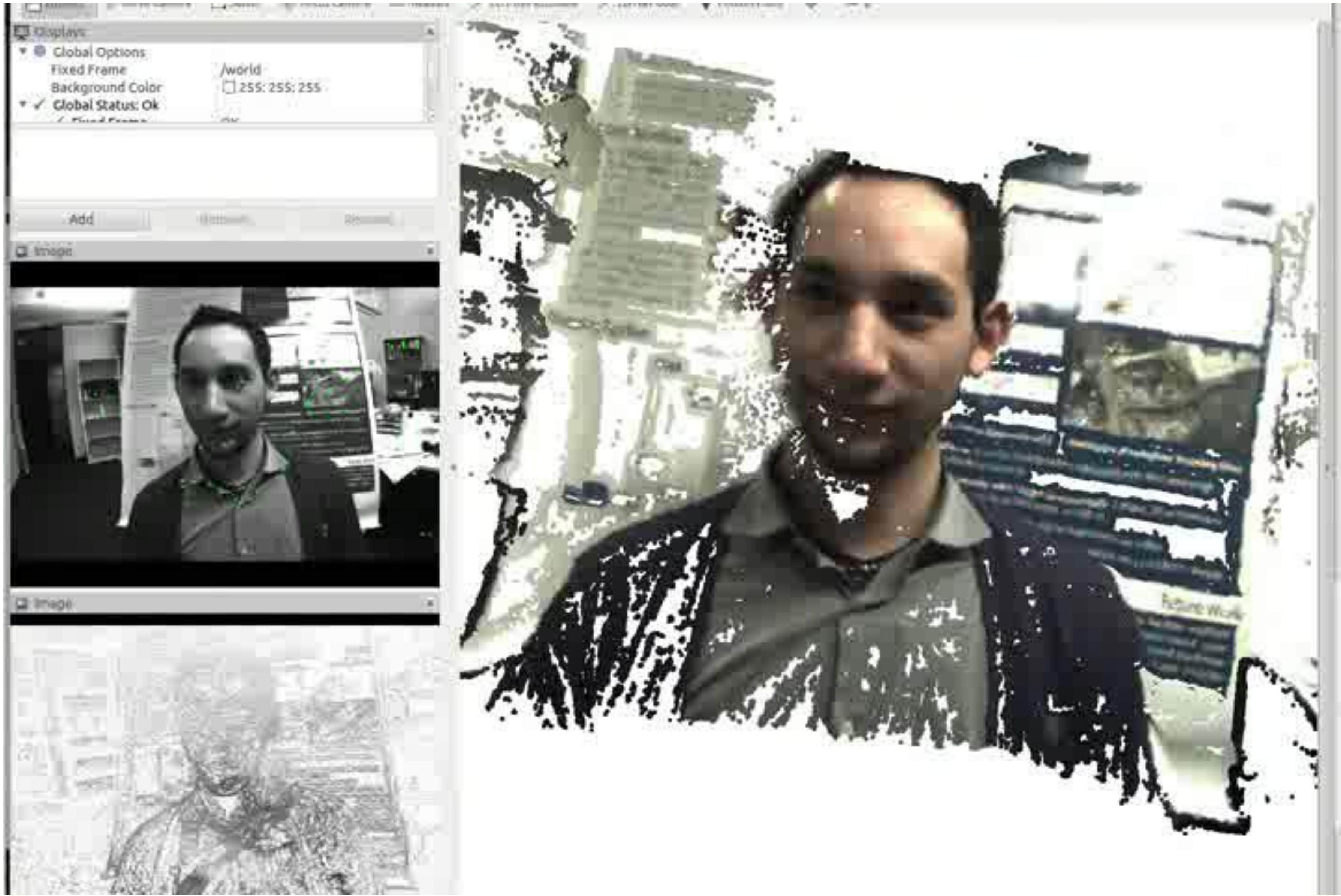


REMODE:
Regularized Monocular Dense Reconstruction

[M. Pizzoli, C. Forster, D. Scaramuzza, REMODE: Probabilistic, Monocular Dense Reconstruction in Real Time, IEEE International Conference on Robotics and Automation 2014]

Open source: *https://github.com/uzh-rpg/rpg_open_remode*

REMODE: Probabilistic, Monocular Dense Reconstruction in Real Time, ICRA'14, by Pizzoli, Forster, Scaramuzza



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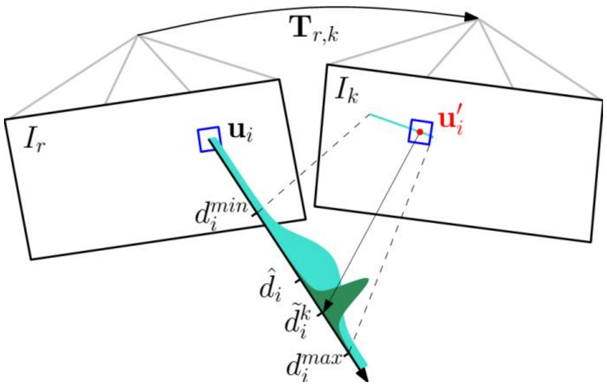
Monocular dense reconstruction
in real-time from a hand-held camera

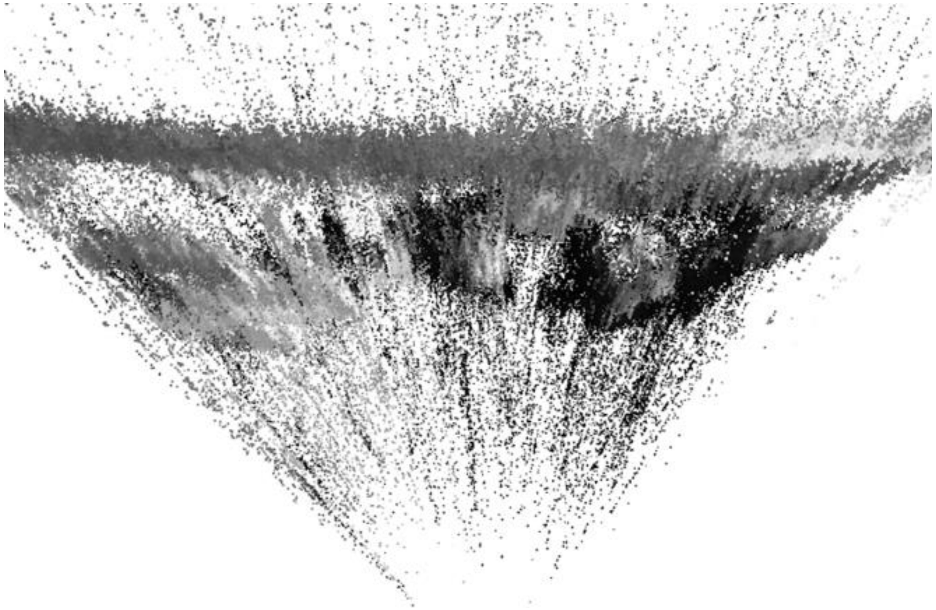
Stage-set from Gruber et al., "The City of Sights", ISMAR'10.

[M. Pizzoli, C. Forster, D. Scaramuzza, REMODE: Probabilistic, Monocular Dense Reconstruction in Real Time, ICRA'14]

REMODE: Probabilistic, Monocular Dense Reconstruction in Real Time, ICRA’14, by Pizzoli, Forster, Scaramuzza

- Tracks every pixel (like DTAM) but **Probabilistically**
- Runs live on video streamed from MAV (50 Hz on GPU)
- Copes well with low texture surfaces





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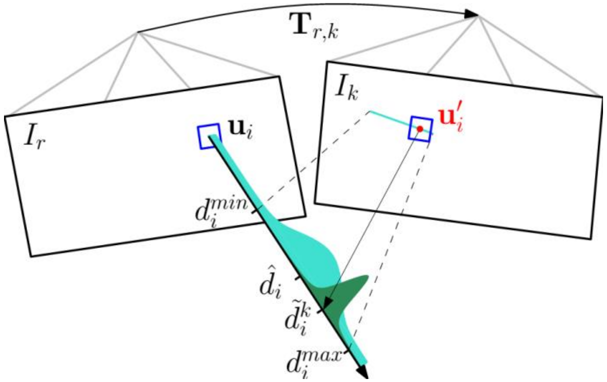

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REMODE applied to autonomous flying 3D scanning

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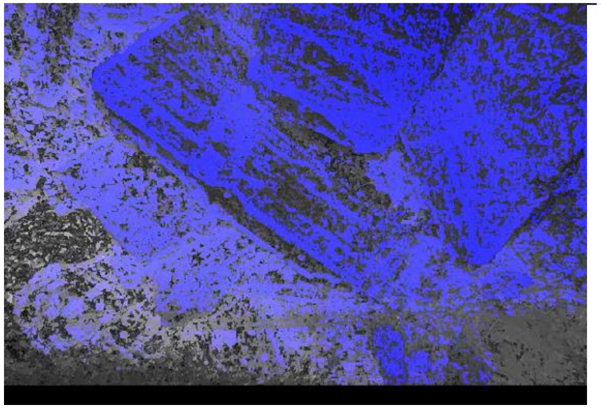
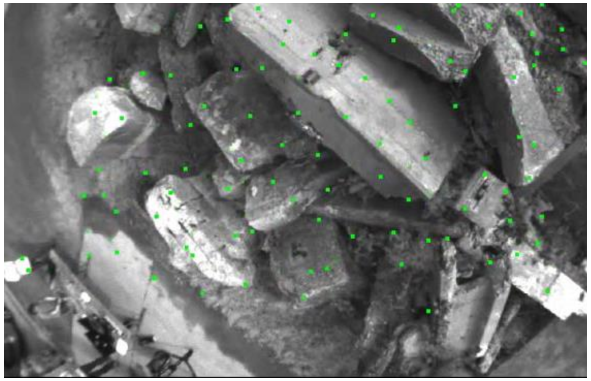
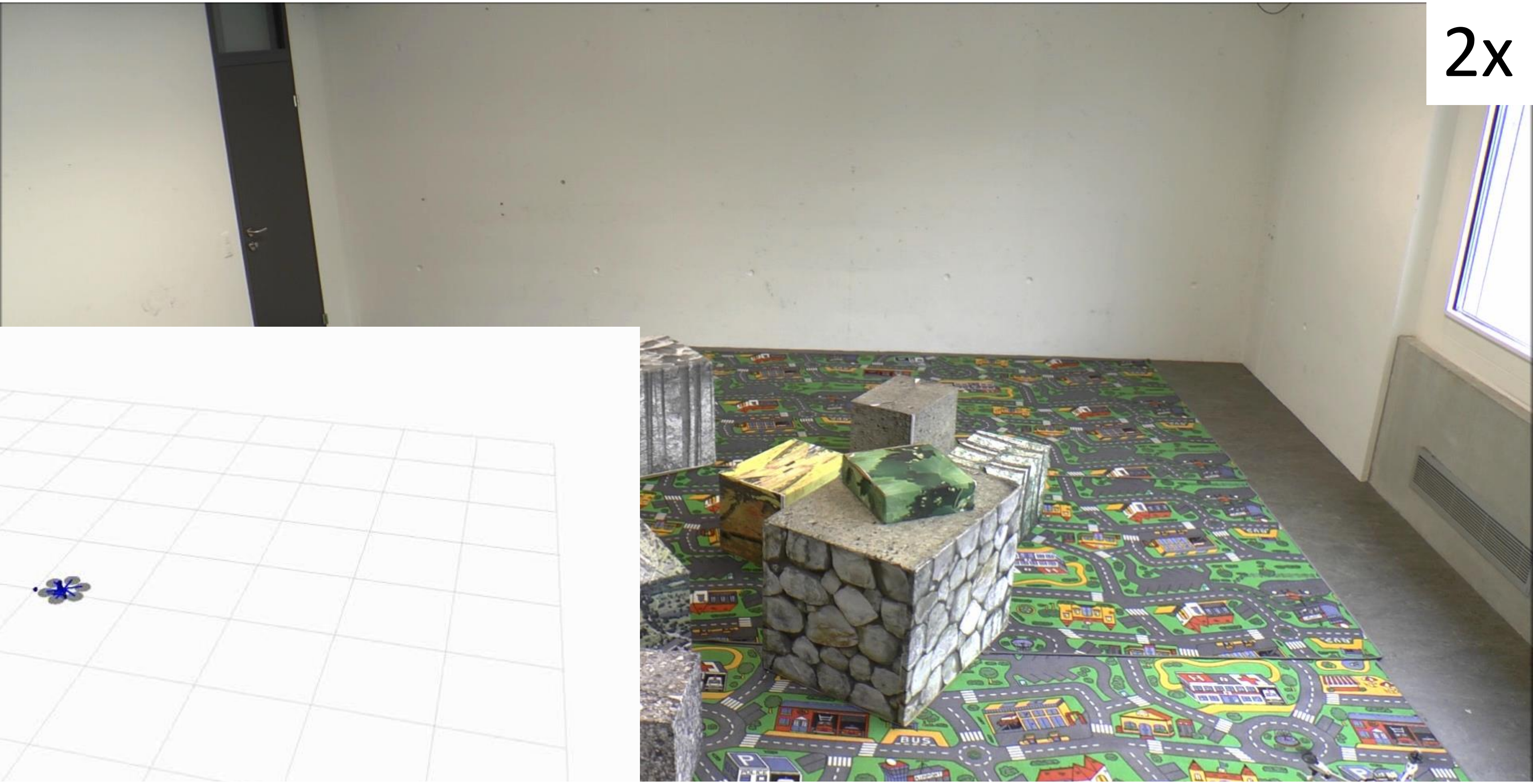




Live demonstration at the Firefighter Training Area of Zurich
Featured on ARTE Tv channel on November 22 and SRF 10vo10

REMODE applied to autonomous flying 3D scanning



Faessler, Fontana, Forster, Mueggler, Pizzoli, Scaramuzza, Autonomous, Vision-based Flight and Live Dense 3D Mapping with a Quadrotor Micro Aerial Vehicle, **Journal of Field Robotics, 2015**.

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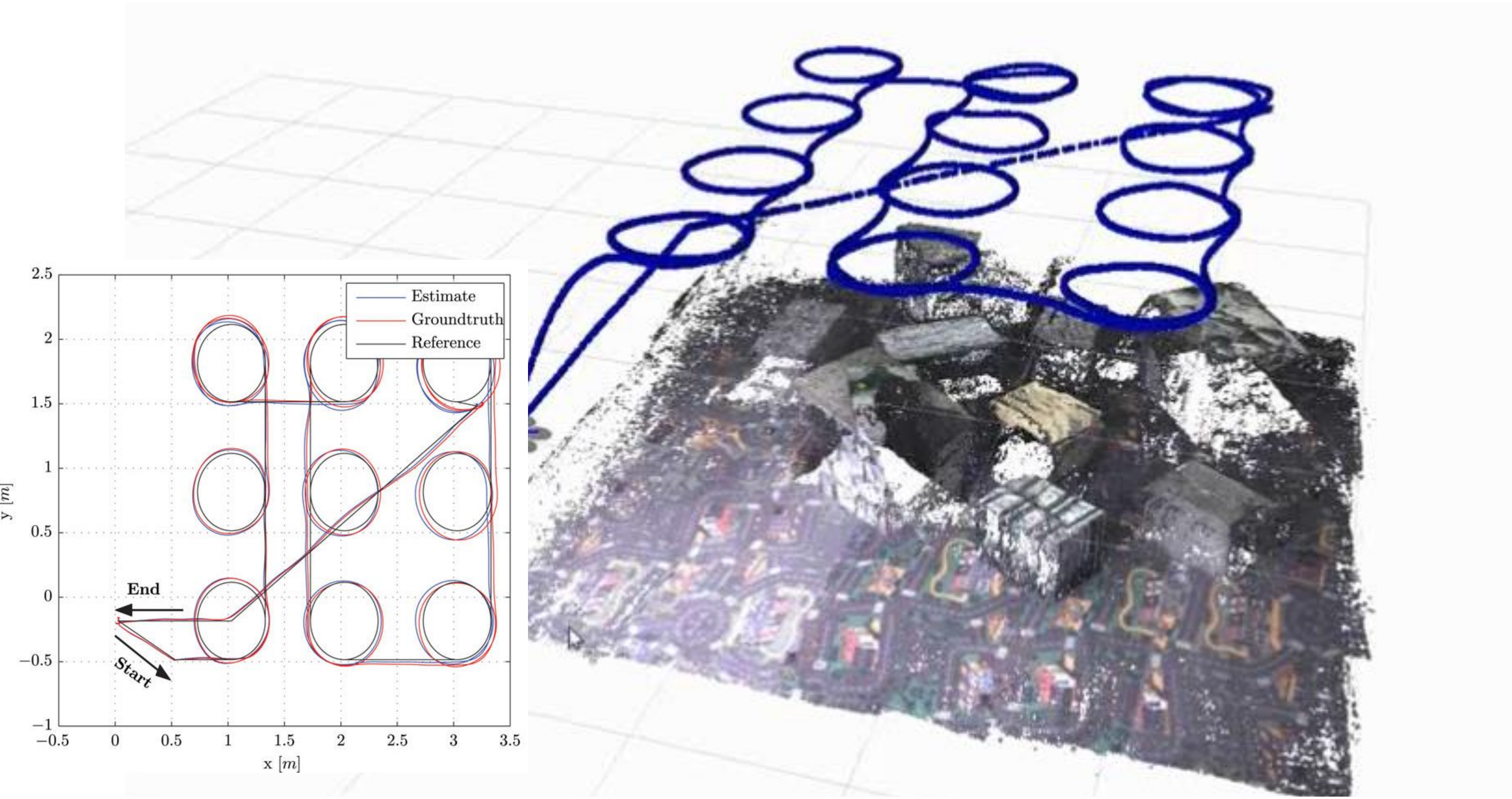

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3DAround iPhone App

Dacuda