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Dense 2D Range-Images

Geometric Computer Vision

GCV v2021.1, Module 3

Alexey Artemov, Spring 2021

Lecture Outline

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§1. Range-images as a basic 3D modality [5 min]

1.1. Range-images as a result of scanning

1.2. Types and properties of range-images

§2. Representing a moving scene [external]

2.1. Rigid body motion

2.2. Camera motion, camera pose (extrinsic parameters)

Lecture Outline

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§3. Perspective projection [external]

3.1. The geometry of perspective projection

3.2. Camera intrinsic parameters

§4. Modeling dense range-images [5 minutes]

4.1. Raycasting

§5. Learning with dense range-images [10 minutes]

5.1. Single depth image: super-resolution, smoothing, …

5.2. Multiple depth images: geometric feature prediction

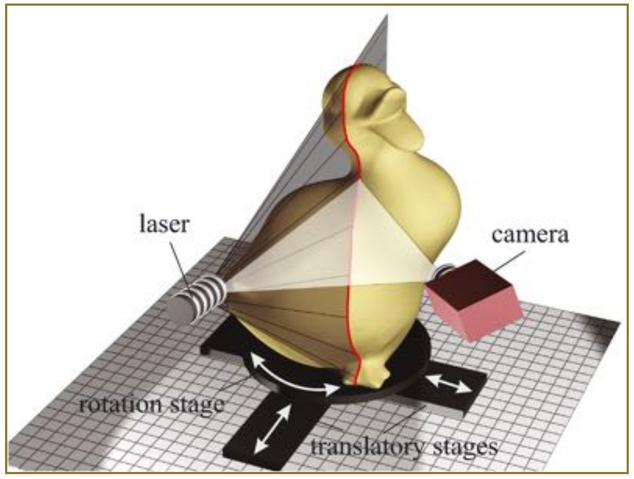
§1. Range-images as a basic 3D modality

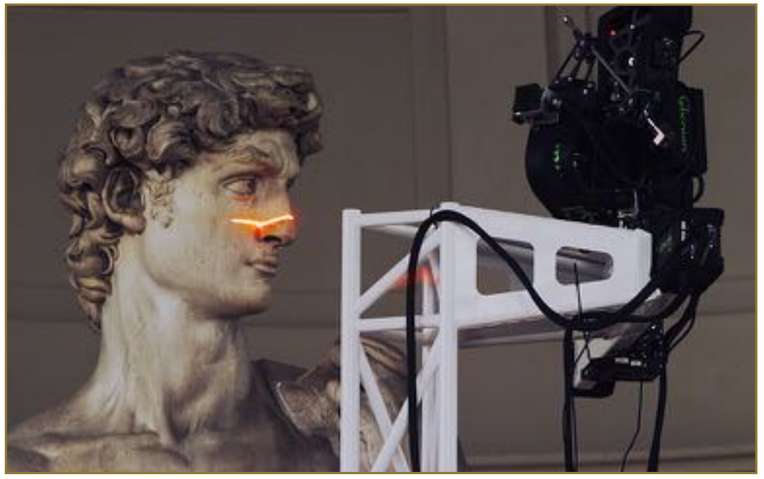
Range-images as a result of scanning

1.1. Range-images as a result of scanning

§1. Range-images as a basic 3D modality

- Captured directly by a large number of 3D sensors:
  - Laser stripes, structured light setups, time-of-flight cameras
- Reconstructed from images by stereo matching, etc.
  - Dense binocular stereo, active stereo, shape-from-X





Types and properties of range-images

1.2. Types of range-images

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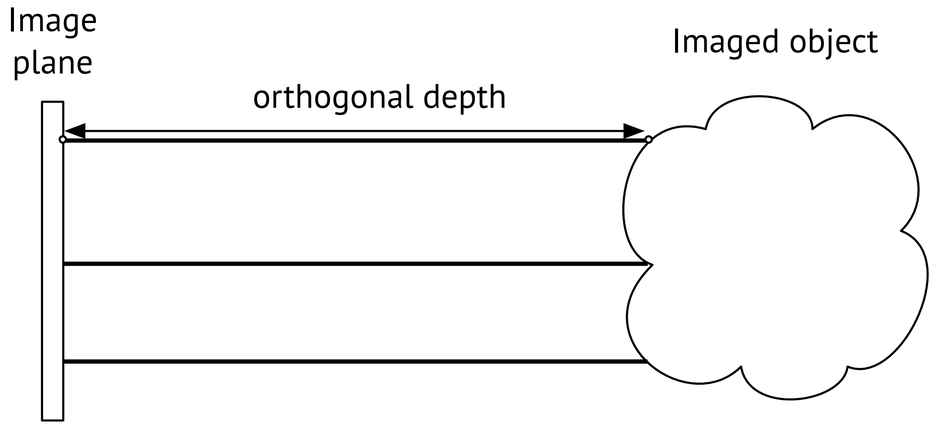
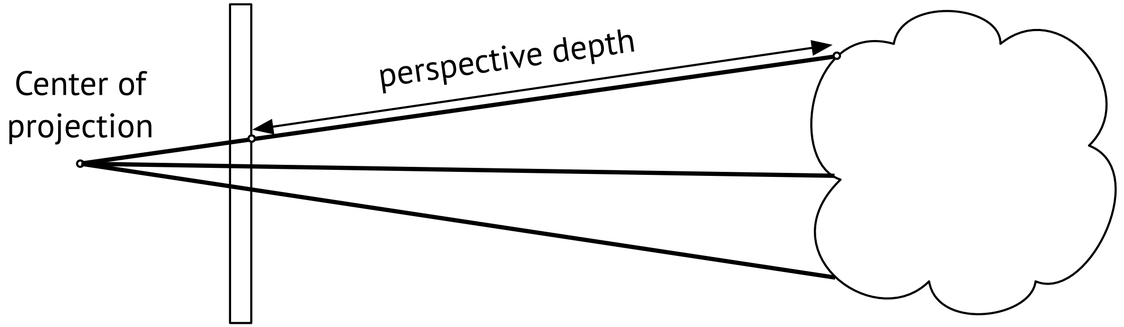
§1. Range-images as a basic 3D modality

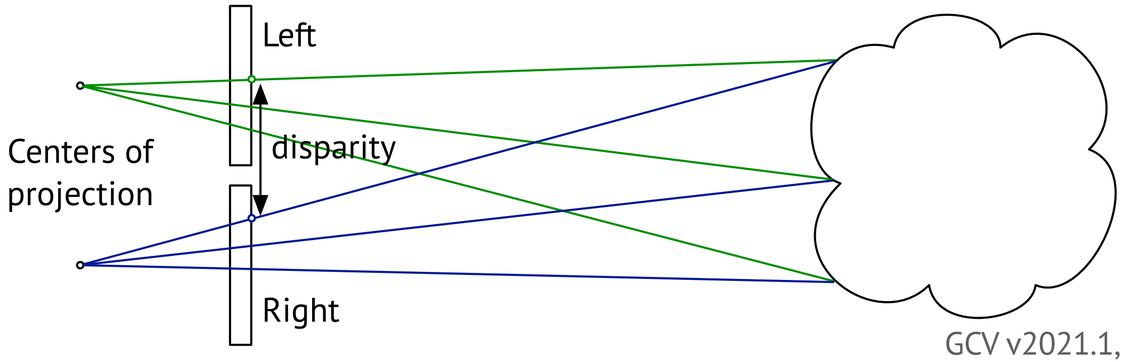
- Orthogonal depth



- Perspective depth



- Disparity: pixel space (left to right)
  - Inversely proportional to depth



1.2. Properties of range-images

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§1. Range-images as a basic 3D modality

- Comparatively low resolution compared to RGB photo-images
  - Intel RealSense D435 (real-time active stereo, 30 FPS):
    depth at 640x480 and RGB at 1920x1080
  - MS Kinect v2 (real-time structured light, 30 FPS):
    depth at 512x424 and RGB at 1920x1080
- **Can we obtain depth at the same spatial resolution as RGB images?**

1.2. Properties of range-images

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§1. Range-images as a basic 3D modality

- High amounts of noise and outliers, relatively low accuracy
  - MS Kinect v2 (real-time structured light, 30FPS): depth accuracy 2.5cm @2m
  - Commonly precision and accuracy proportional to depth value
- **Can we obtain cleaner depth images?**

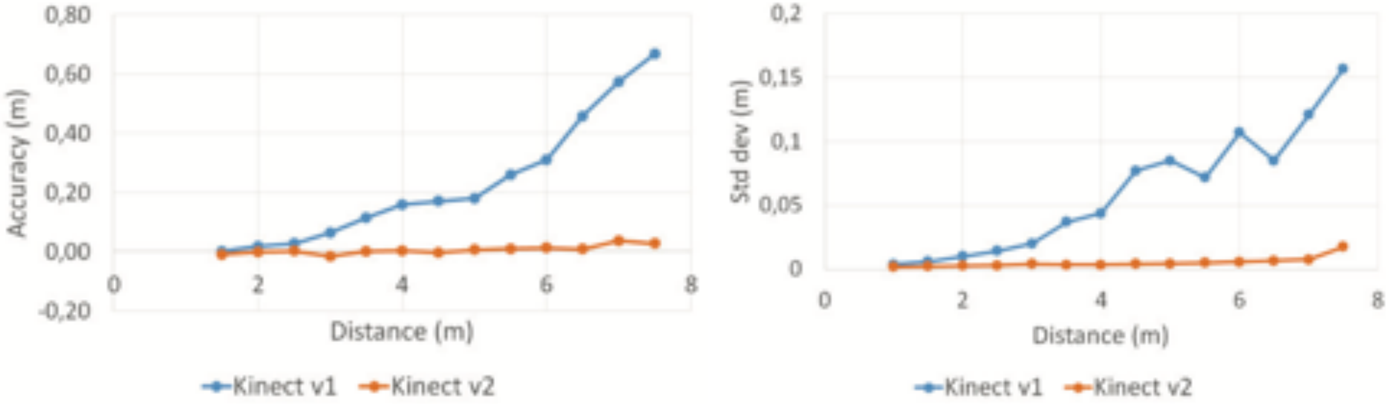
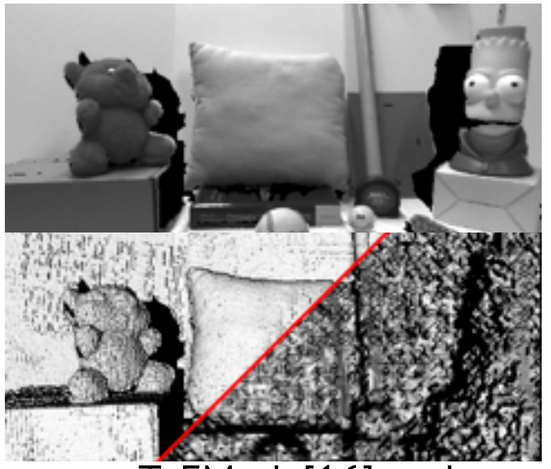


Figure Credit: (Zennaro et al., 2015)

Fig. 9. a) Depth accuracy and b) depth standard deviation of Kinect v1 and v2 at all ranges.

SUN RGBD [15] low-quality real



ToFMark [16] real HQ high-res + super LQ low-res

§2. Representing a moving scene

A lecture on representing a moving scene

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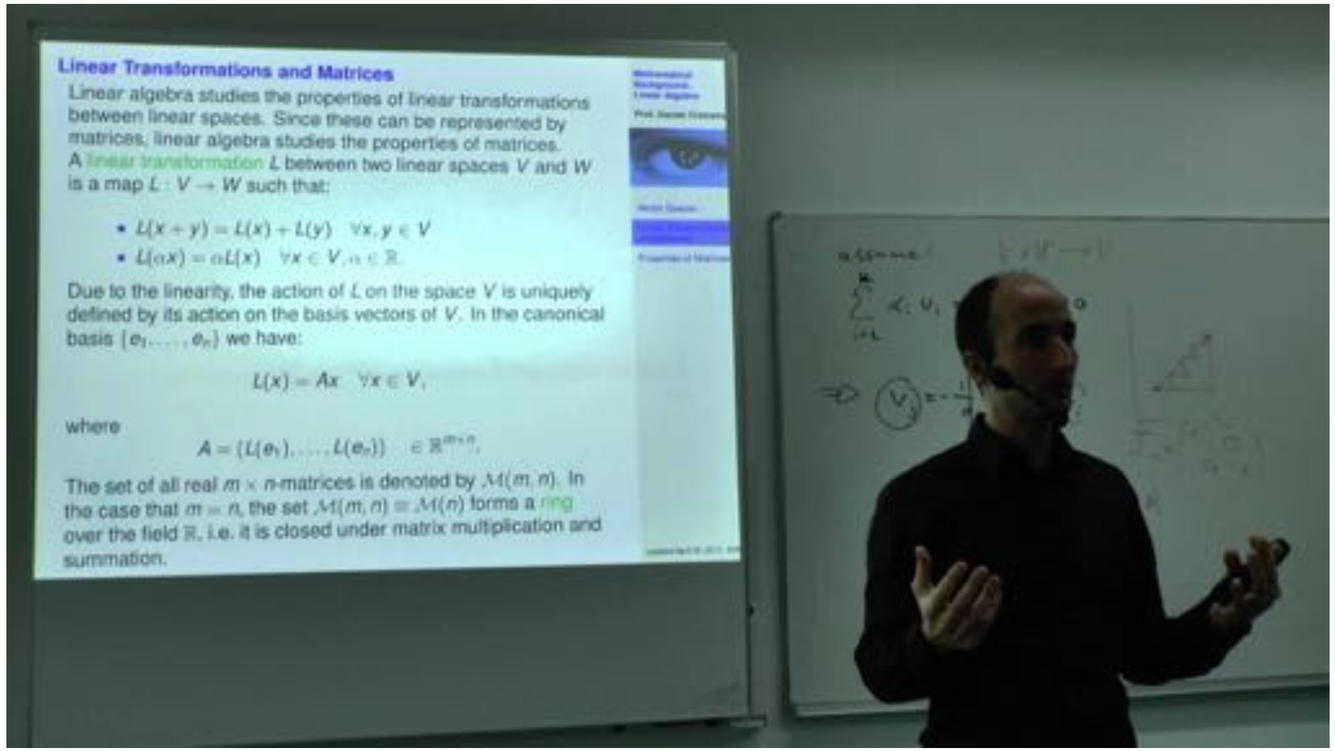
§2. Representing a moving scene

- Prof. D. Cremers: Multiple View Geometry (YouTube playlist with 14 lectures on SfM)



§3. Perspective projection

A lecture on perspective projection

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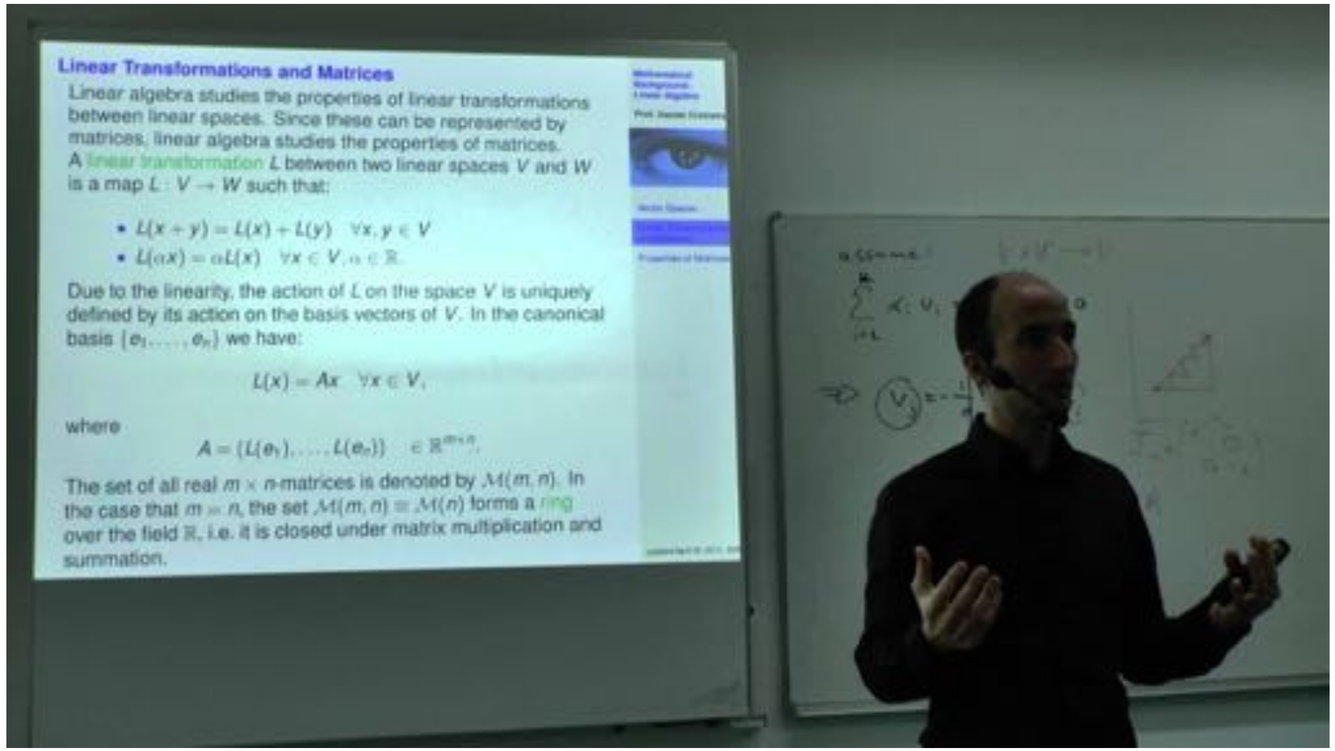
§3. Perspective projection

- Prof. D. Cremers: Multiple View Geometry (YouTube playlist with 14 lectures on SfM)



§4. Modeling dense range-images

Ray-casting

4.1. Ray-casting

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§4. Modeling dense range-images

- Given a 3D scene, compute *(render)* a 2D image of the scene
- This course: model 2D range-images (learning with 3D shapes)
- Basic rendering technique: *ray-casting*
- Created as early as during the late 1970s to replace wireframe renderings of solids

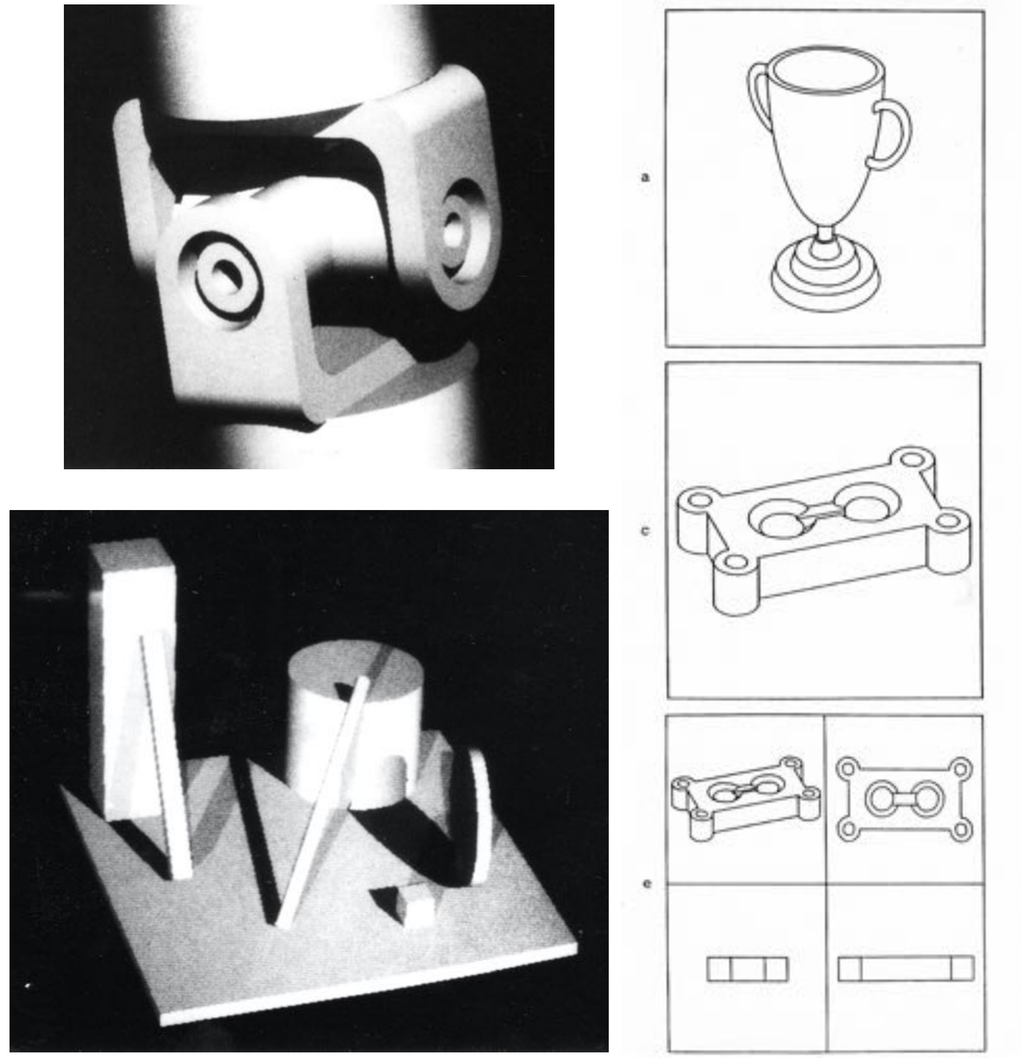

Figure Credit: Wikipedia

4.1. Ray-casting

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§4. Modeling dense range-images

- *Cast* geometric *rays* from the eye though each pixel in the image
- Compute locations of intersection between the ray and each surface point along its path
- Find the closest object blocking the path of each ray
  - Other applications: wireframe drawing, compute volumes, …

4.1. Ray-casting: overview

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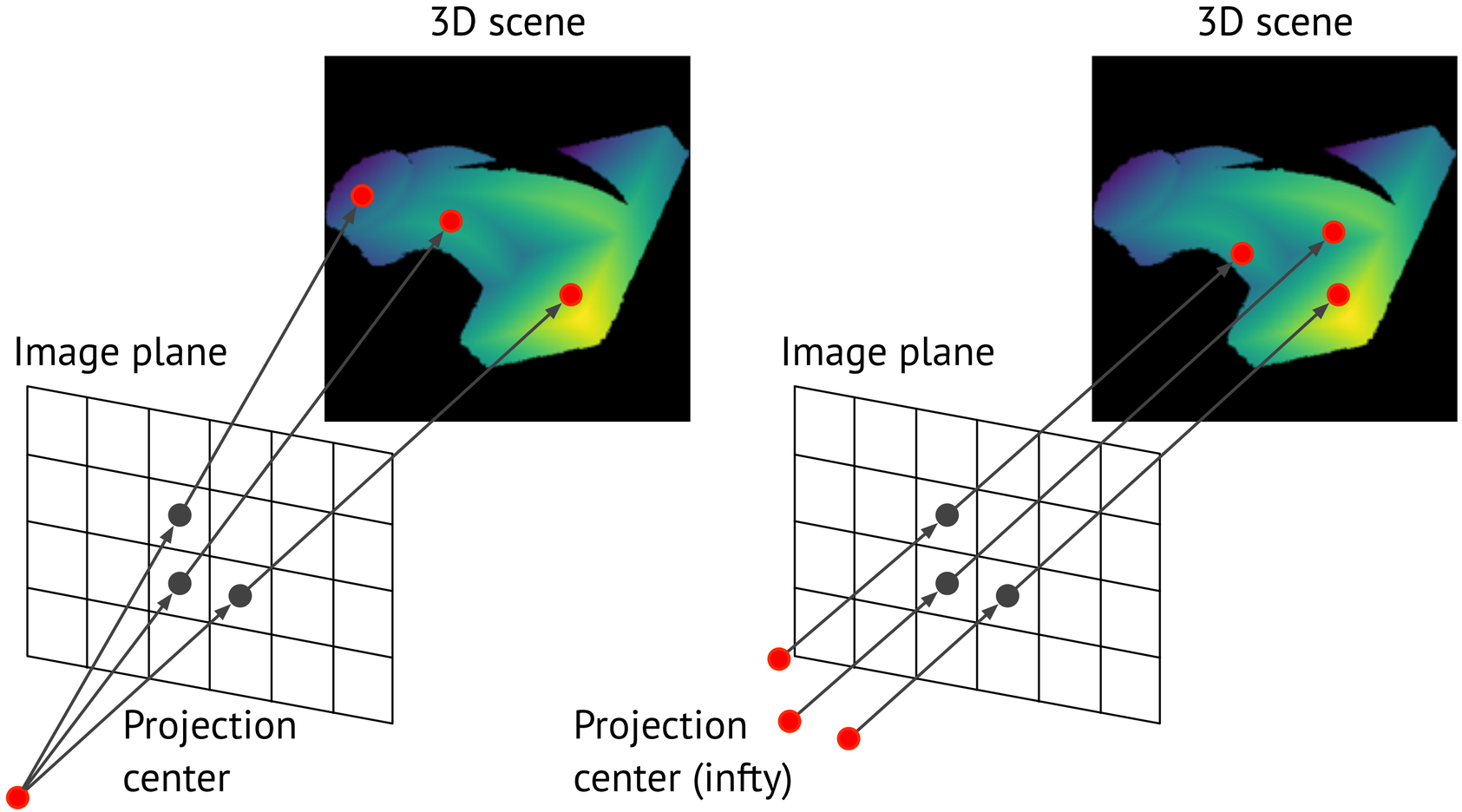
§4. Modeling dense range-images

1. Generation of rays (one per pixel)
2. Intersection with objects in the scene
3. *(For graphics applications)* Shading (aka compute the color of the pixel)



4.1. Ray-casting: intersections

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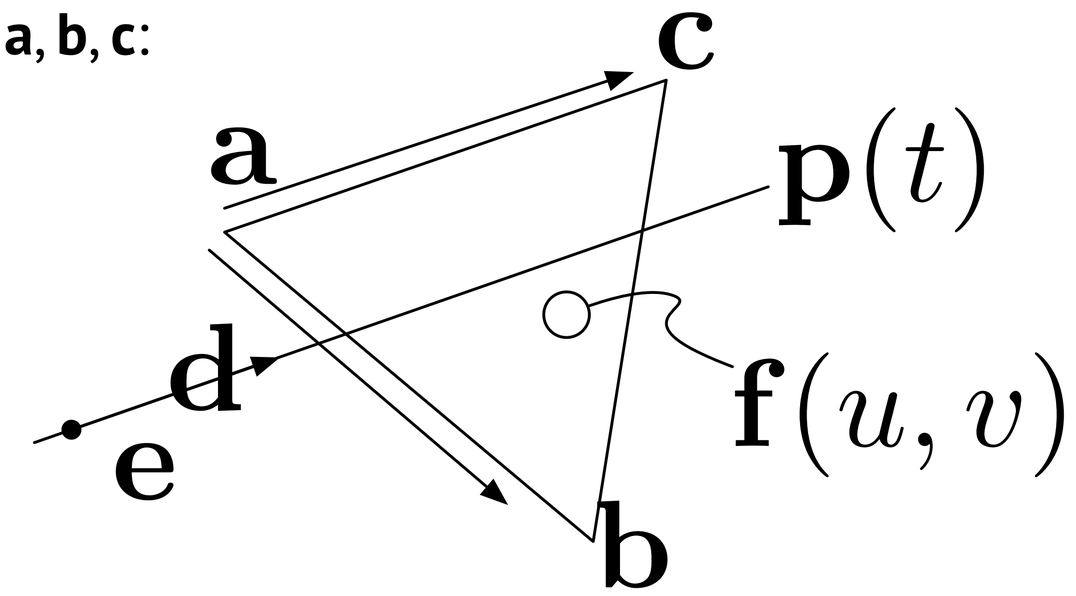
§4. Modeling dense range-images

- This is an expensive operation
- There is a large literature, a good overview is here: http://www.realtimerendering.com/intersections.html
- We will study the one useful case:
  - Triangles (by combining many triangles you can approximate complex surfaces)

4.1. Ray-casting: ray-triangle intersection

§4. Modeling dense range-images

- Explicit parametrization of a triangle with vertices **a**, **b**, **c**:
  $\mathbf{f}(u, v) = \mathbf{a} + u(\mathbf{b} - \mathbf{a}) + v(\mathbf{c} - \mathbf{a})$
- Explicit ray:
  $\mathbf{p}(t) = \mathbf{e} + t\mathbf{d}$
- The ray intersects the triangle if a **t**, **u**, **v** exist s.t.:
  $$\mathbf{f}(u, v) = \mathbf{p}(t),$$
  $$t > 0, \quad 0 \leqslant u, v, \quad u + v \leqslant 1$$
- Solve by yourself to identify appropriate **t**, **u**, **v**



4.1. Ray-casting: intersections

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§4. Modeling dense range-images

- It is simple, intersect it with all of them and only keep the closest intersection
- To speed up computation, you can use a spatial data structure to prune the number of collisions that you need to check

- Bounding volume hierarchy:
  - compute bounding 3D boxes (e.g. AABBs) on sets of objects, group hierarchically
  - quickly discard objects from ray-box intersection checks
- Used by Intel Embree CPU impl.

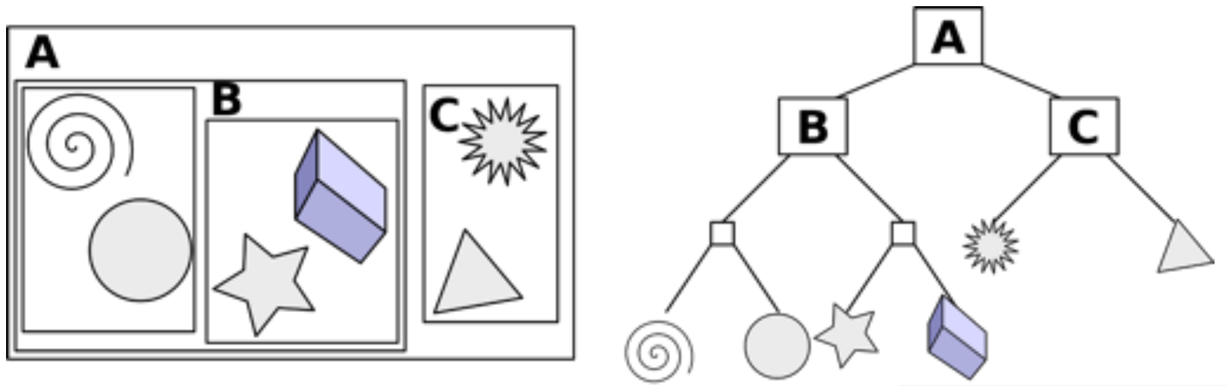

Figure Credit: Wikipedia

Bounding volume hierarchy

Slide Credit: Daniele Panozzo GCV v2021.1, Module 3

4.1. Ray-casting: intersections

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§4. Modeling dense range-images

- Ray-casting: trace rays from the “eye” of the observer into the scene
- Compute intersection locations with scene geometry
- Prune parts of geometry for efficiency

Slide Credit: Daniele Panozzo

§5. Learning with dense range-images

Single depth image

5.1. Single depth image

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§5. Learning with dense range-images

- Range-images: low spatial resolution, sparsity / holes, high noise
- RGB images: high resolution, fully dense, can be made nearly noiseless

- **Can we obtain depth at the same spatial resolution as RGB images?**
- **Can we achieve high degree of noise-suppression in depth images?**
- Common tasks: scene understanding from RGBD (classification, segmentation, retrieval…)

5.1. Single depth image: tasks

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§5. Learning with dense range-images

- **Upsampling/super-resolution**
  - Goal: obtaining depth at a higher spatial resolution
  - Input: low-resolution depth (+possibly high-resolution RGB)
  - Output: high-resolution depth

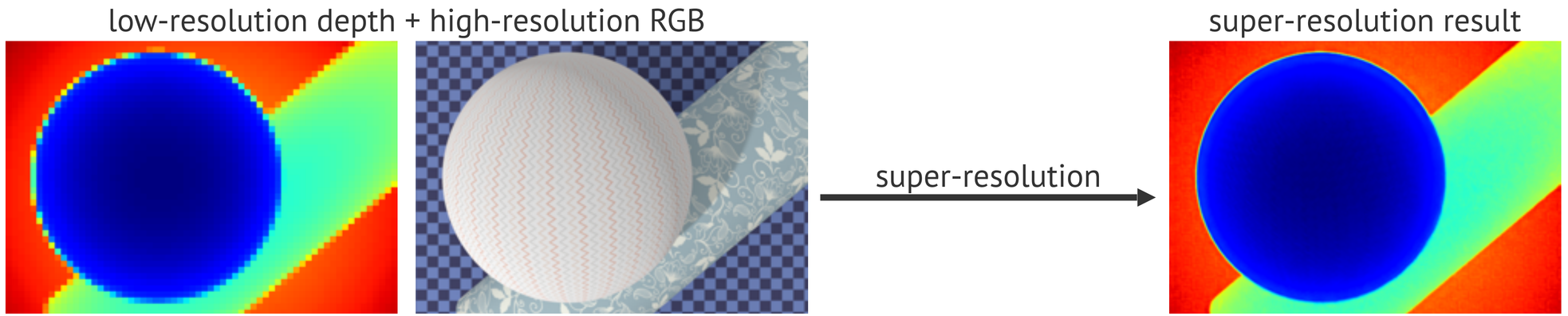

Figure Credit: Voynov et al., 2019

5.1. Single depth image: tasks

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§5. Learning with dense range-images

- **Densification / completion**
  - Goal: obtaining dense depth from sparse samples
  - Input: sparse depth (+possibly high-resolution RGB)
  - Output: dense depth (desirably: high-resolution)

low-resolution depth + high-resolution RGB

densification

densification result

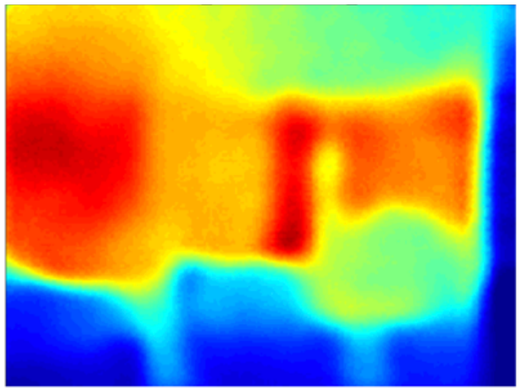

Figure Credit: Ma et al., 2018

5.1. Single depth image: tasks

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§5. Learning with dense range-images

- **Denoising / enhancement**
  - Goal: reducing noise in the depth measurements, depth interpolation
  - Input: noisy/coarse depth (+possibly high-resolution RGB)
  - Output: denoised depth

high-resolution RGB + noisy / quantized depth

denoising

denoising result

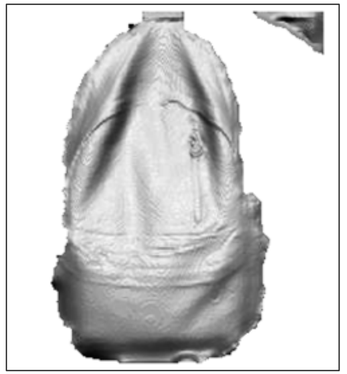

Figure Credit: Yan et al., 2018

5.1. Single depth image: overview

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§5. Learning with dense range-images

- Challenges:
  - Fine structure ambiguity, texture transfer
- Visual cues leveraged in depth processing tasks:
  - RGB guidance, edge-awareness, multi-scale structure/guidance, visual loss functions
- Strategies:
  - Upsample + refine,

5.1. Single depth image: challenges

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§5. Learning with dense range-images

RGB | GT | 8x low-res | SRCNN [1] | MSG-Net [2]

- High-res -> low-res: distortion of fine structures
- Ambiguity in super-resolving fine structures (blurring of the estimated depth map)

Figure Credit: MSG-Net

5.1. Single depth image: visual cues

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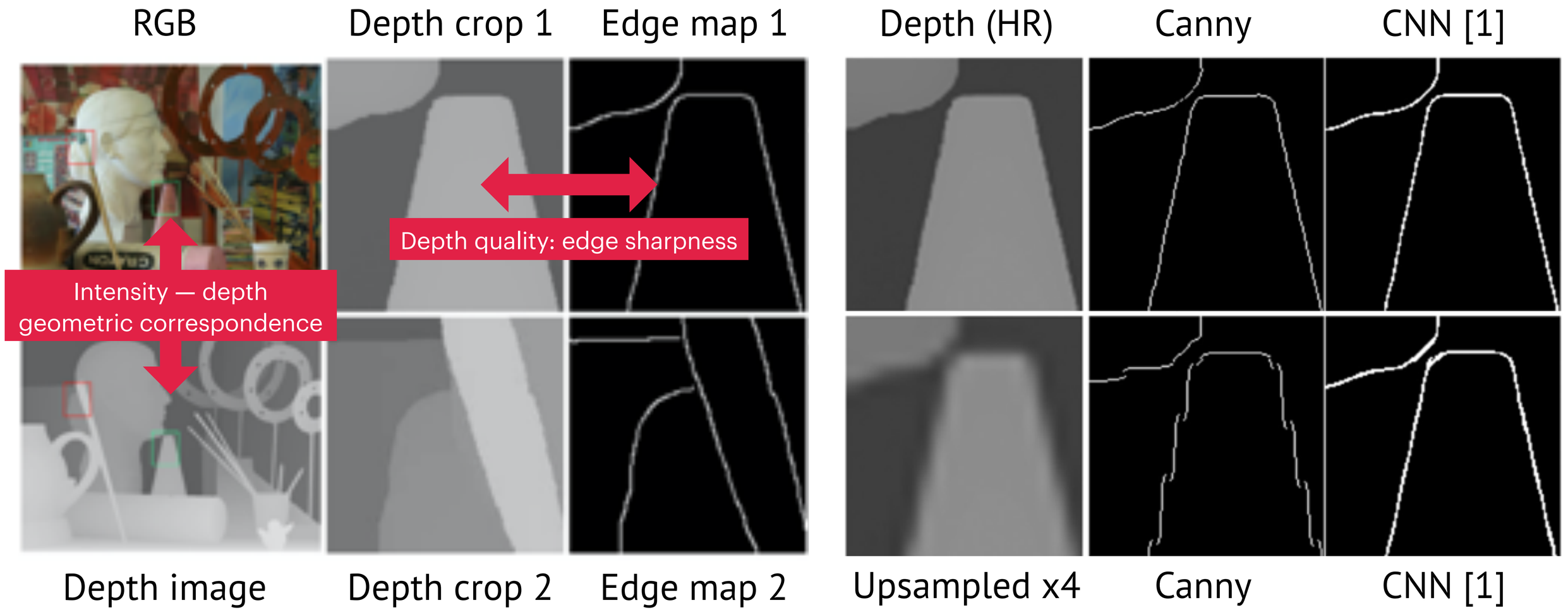
§5. Learning with dense range-images



5.1. Single depth image: challenges

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§5. Learning with dense range-images

- Use intensity (RGB) image to guide upsampling
- Texture artefacts (RGB features transferred into depth images)

Figure Credit: MSG-Net

5.1. Single depth image: visual cues

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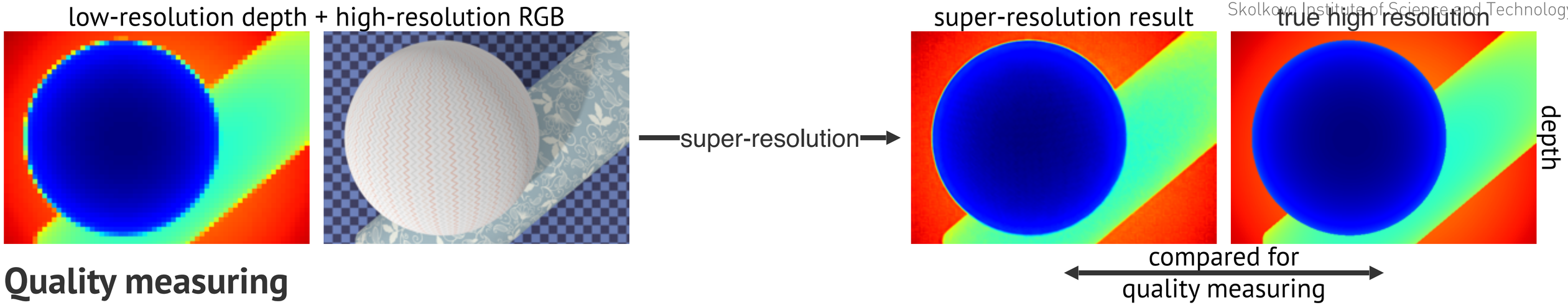
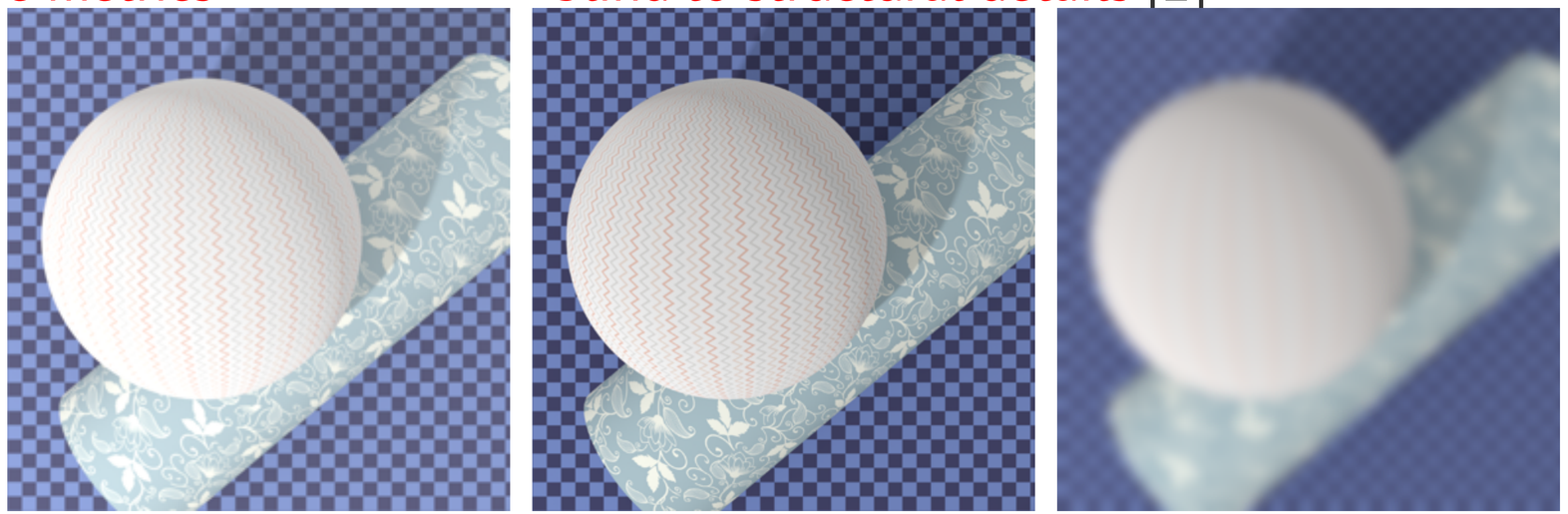


Quality measuring

Common approach: compare depth maps directly with pixel-wise metrics — blind to structural details [2]

Example for photos:

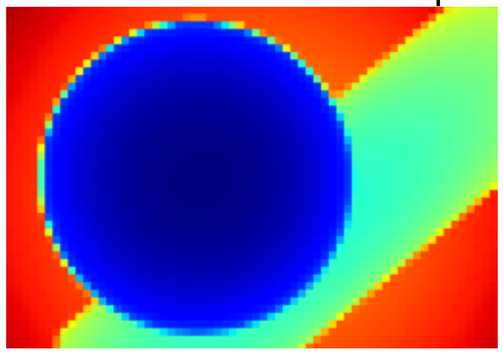
the brighter version is farther from the reference in a pixel-wise metric than the blurred version

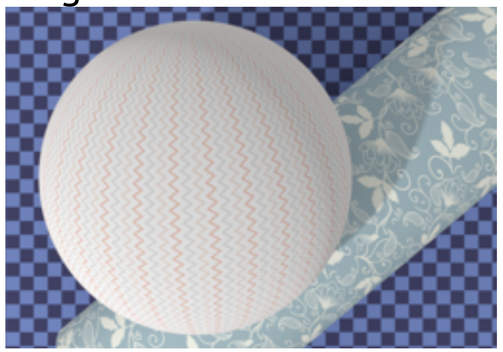


[2] Zhang, R., Isola, P., Efros, A. A., Shechtman, E., & Wang, O. (2018). The unreasonable effectiveness of deep features as a perceptual metric. IEEE Conference on Computer Vision and Pattern Recognition

5.1. Single depth image: visual cues

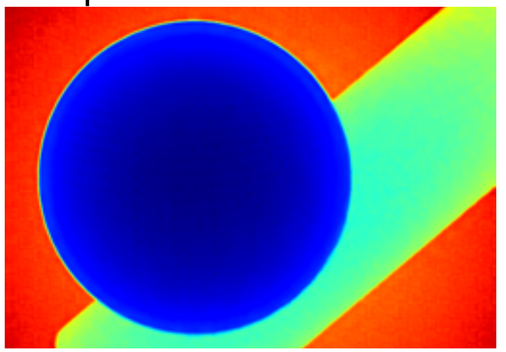
low-resolution depth + high-resolution RGB



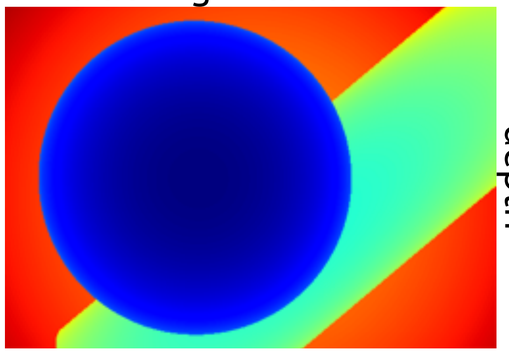


super-resolution

super-resolution result



true high resolution



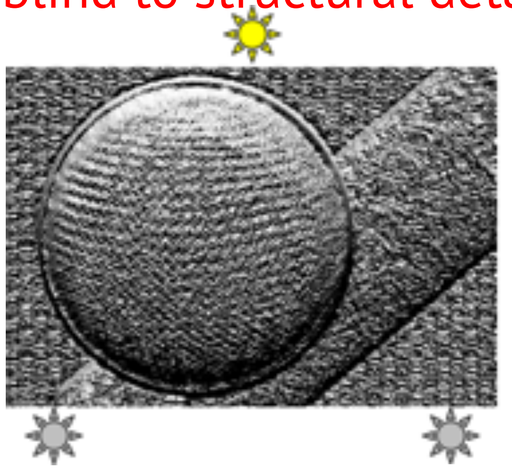
depth

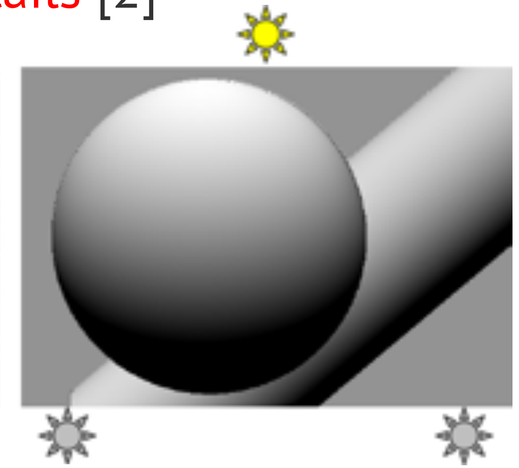
almost identical

Quality measuring

Common approach: compare depth maps directly — blind to surface artefacts [3, 4]
with pixel-wise metrics — blind to structural details [2]

Proposed approach: compare surface visualizations
with perceptual metrics [2]





surface visualization

completely different

[2] Zhang, R., Isola, P., Efros, A. A., Shechtman, E., & Wang, O. (2018). The unreasonable effectiveness of deep features as a perceptual metric. IEEE Conference on Computer Vision and Pattern Recognition
[3] Mechrez, R., Talmi, I., Shama, F., & Zelnik-Manor, L. (2019). Maintaining Natural Image Statistics with the Contextual Loss. Asian Conference on Computer Vision
[4] Xie, J., Feris, R. S., & Sun, M. (2016). Edge-Guided Single Depth Image Super Resolution. IEEE Transactions on Image Processing

5.1. Single depth image: datasets

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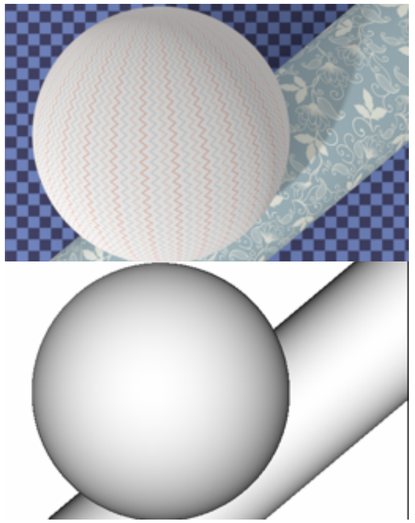
§5. Learning with dense range-images

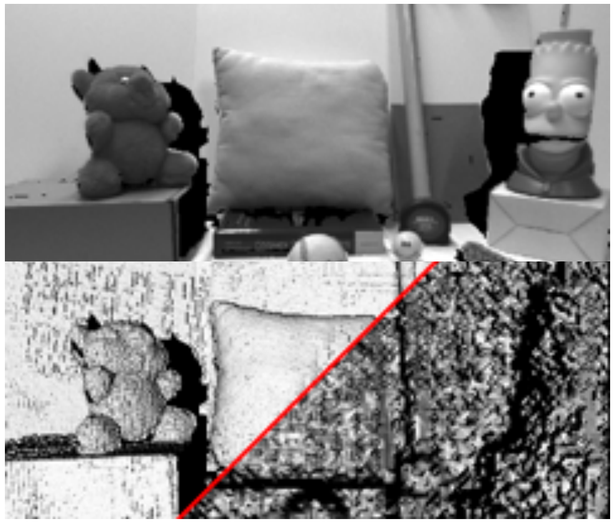


SimGeo
simple synthetic

ICL-NUIM [13]
complex synthetic

Middlebury [14]
high-quality real

SUN RGBD [15]
low-quality real



ToFMark [16] real
HQ high-res + super LQ low-res

- A variety of datasets with range-images:
  - Differ by acquisition method/device, ground-truth, type of scene

[13] Handa, A., Whelan, T., McDonald, J., & Davison, A. J. (2014). A benchmark for RGB-D visual odometry, 3D reconstruction and SLAM. IEEE International Conference on Robotics and Automation
[14] Scharstein, D., Hirschmüller, H., Kitajima, Y., Krathwohl, G., Nešić, N., Wang, X., & Westling, P. (2014). High-resolution stereo datasets with subpixel-accurate ground truth. German Conference on Pattern Recognition
[15] Song, S., Lichtenberg, S. P., & Xiao, J. (2015). Sun rgb-d: A rgb-d scene understanding benchmark suite. IEEE Conference on Computer Vision and Pattern Recognition
[16] Ferstl, D., Reinbacher, C., Ranftl, R., Rüther, M., & Bischof, H. (2013). Image guided depth upsampling using anisotropic total generalized variation. IEEE International Conference on Computer Vision

5.1. Single depth image: recap

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§5. Learning with dense range-images

- Deal with range-image acquisition artefacts (low resolution, holes, sparsity…)
- Commonly use RGB intensity image as guidance
- Visual depth image similarity assessment

Multiple depth images

5.2. Why multiple depth images?

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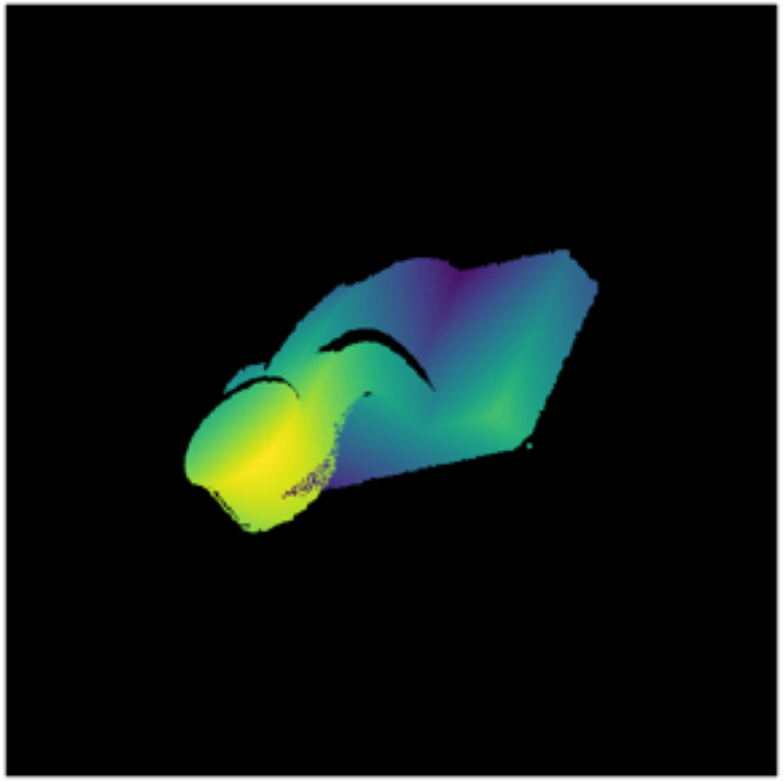
§5. Learning with dense range-images

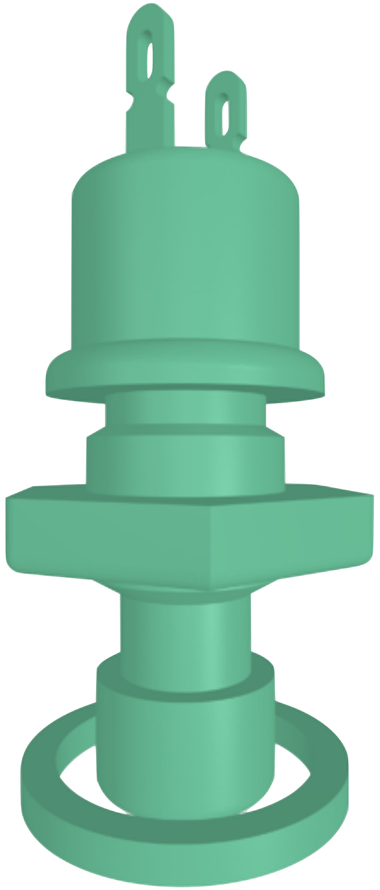
- Range-images: acquired from different (possibly intersecting) views
  - Multiple views provide complementary contexts
  - “Freely” available with standard scanning sequences (e.g. RGBD video, structured light)
- Many applications as range-images are common
  - Depth fusion, feature line estimation, differential quantities (normals / curvature / …), shape segmentation…



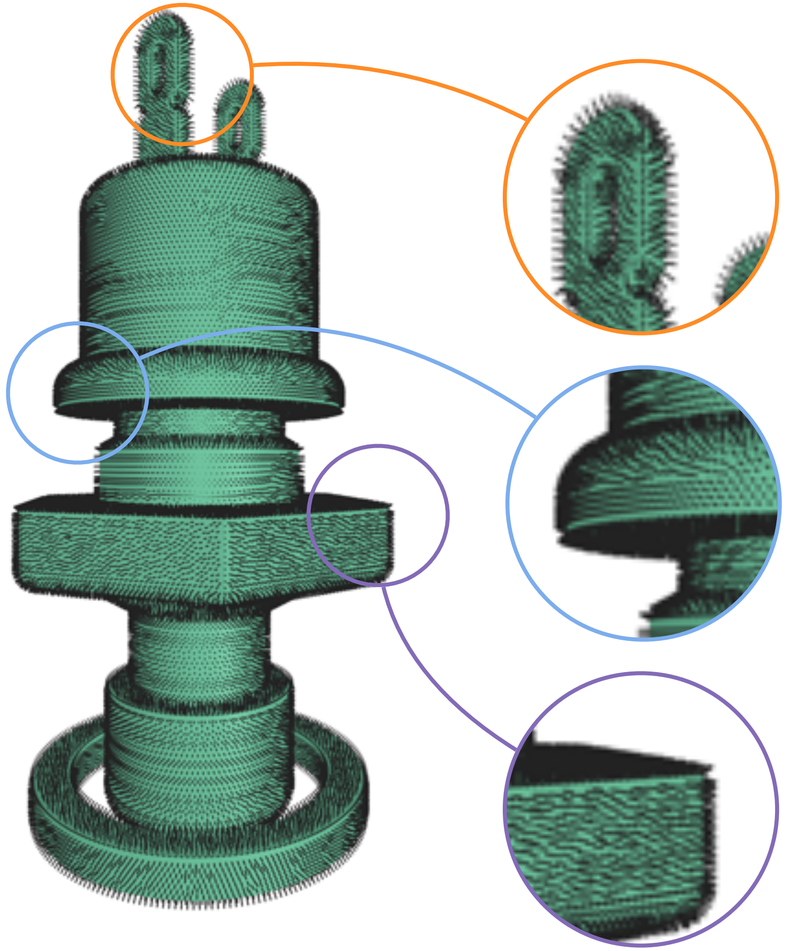
Input: multiple-view range-images

5.2. Multiple depth images: datasets

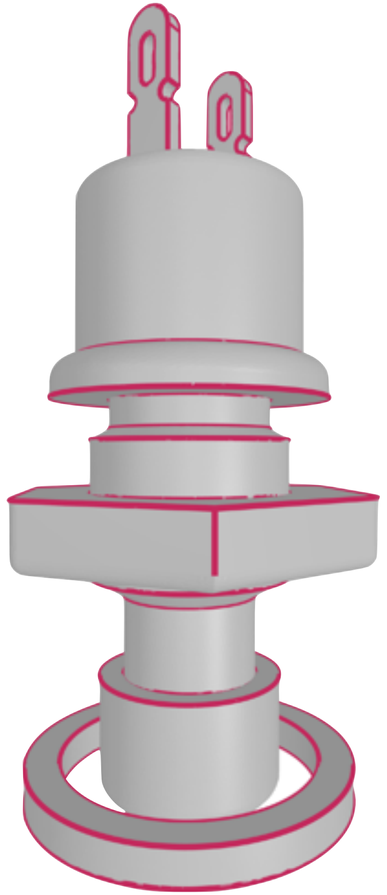
§5. Learning with dense range·



CAD model



Rapid change in normals

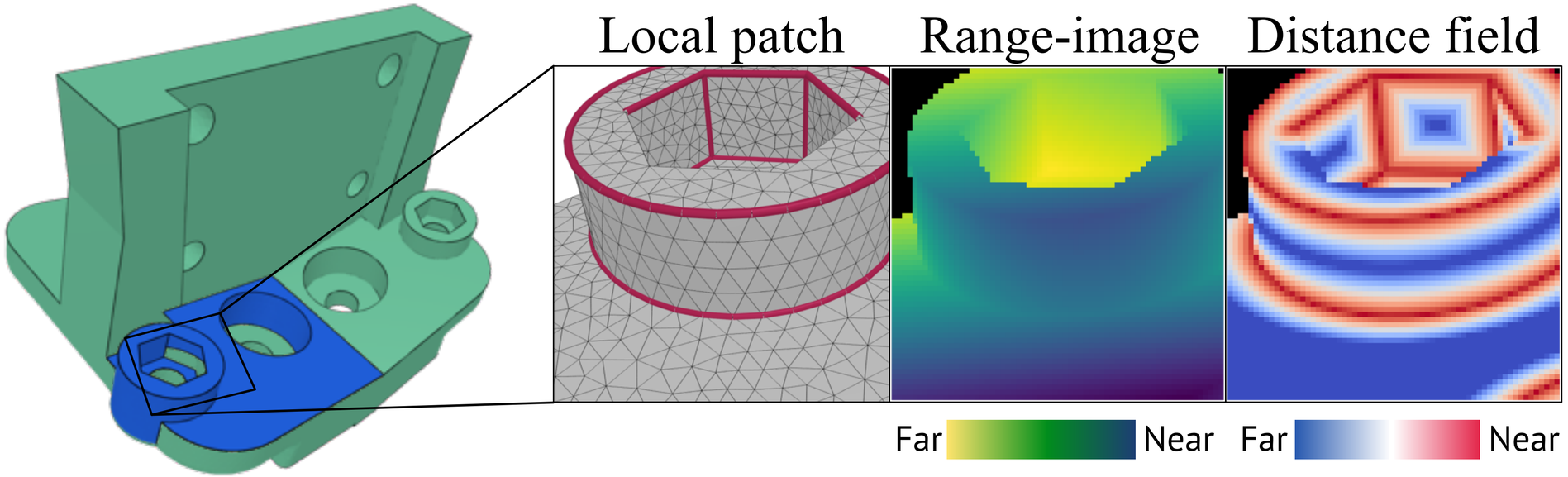


Sharp feature lines

5.2. Multiple depth images: datasets

§5. Learning with dense range-images

3D CAD shapes
+ feature annotations



- Extract local patches → ray-cast and compute range-image → compute distance-to-feature (use closest sharp feature line only)

Figure credit: Matveev, A., Artemov, A., Rakhimov, R., Bobrovskikh, G., Panozzo, D., Zorin, D., & Burnaev, E. (2020). DEF: Deep Estimation of Sharp Geometric Features in 3D Shapes. *arXiv preprint arXiv:2011.15081*.

5.2. Multiple depth images

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§5. Learning with dense range-images

- Common learning scenarios with range-images:
  - **Input:** a dense range-image (+a camera pose and intrinsic parameters)
  - **Output:** per-pixel quantity of interest (e.g., semantic label, distance to geometric feature curve, curvature, normals, …)
- Commonly approached using CNN machinery
- **Challenge:** occlusions would not generally allow accurately predicting for ambiguous regions (e.g. little context, shape boundaries, …)

5.2. Multiple depth images

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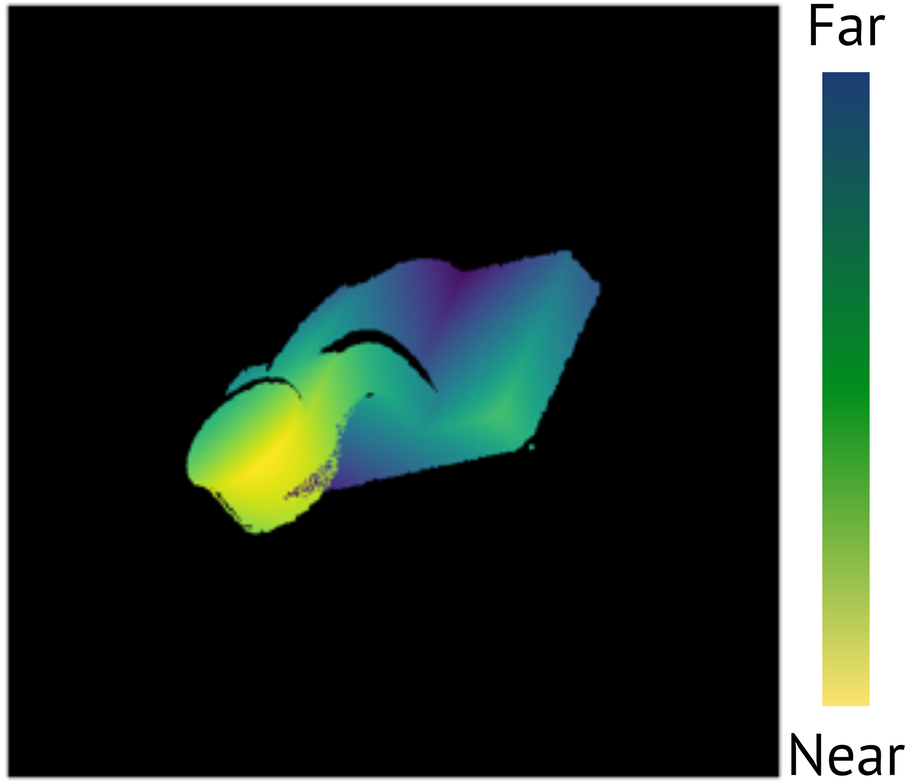
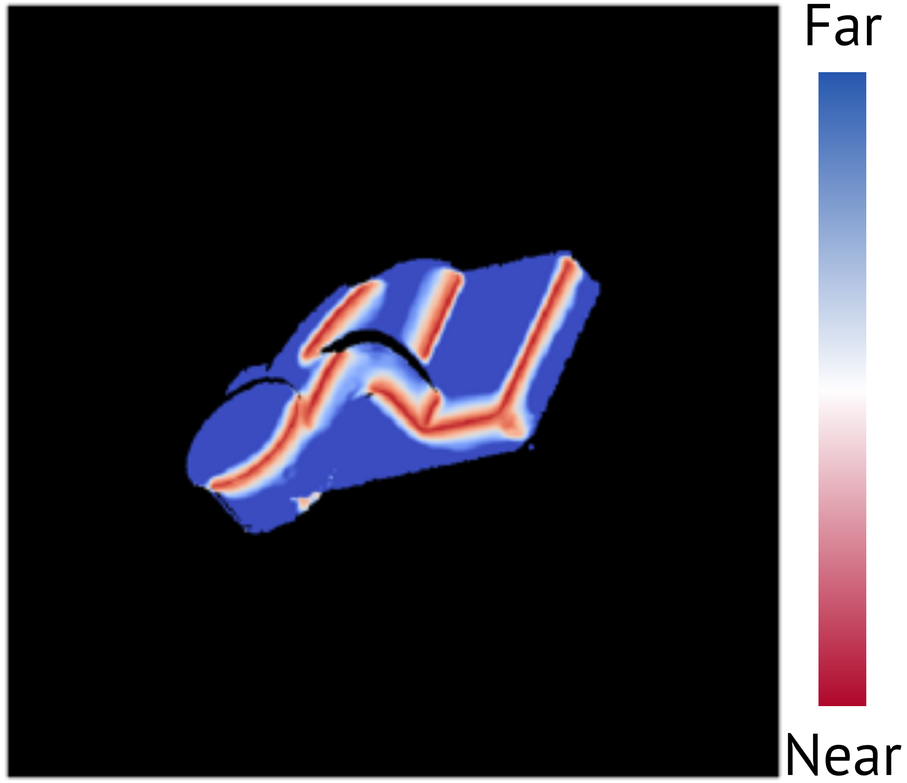
§5. Learning with dense range-images



Input: range-image



Output: distance-to-feature

5.2. Multiple depth images

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§5. Learning with dense range-images

- Leveraging multiple views is possible with:
  - Naive implementation: **“fuse” predictions** from individual views (practice, homework)
  - More advanced: **multiple view consistency** in the scene during training
- Same e.g. for RGB images (e.g., see “Learning Unsupervised Multi-View Stereopsis via Robust Photometric Consistency”)

5.2. Multiple depth images

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§5. Learning with dense range-images

- I_{ref}: a particular (reference) depth image
- $\{I_m\}_{m=1}^M$: additional depth images (views of the same scene)
- $D_{\text{ref}}, \{D_m\}_{m=1}^M$: the quantity of interest (e.g. distance-to-feature annotations)
- u: pixel in I_{ref}, i.e. $I_{\text{ref}}(u)$ represents depth value at u
- K: camera intrinsics (shared across views)
- T_m: relative extrinsic parameters between I_{ref} and I_m

5.2. Multiple depth images

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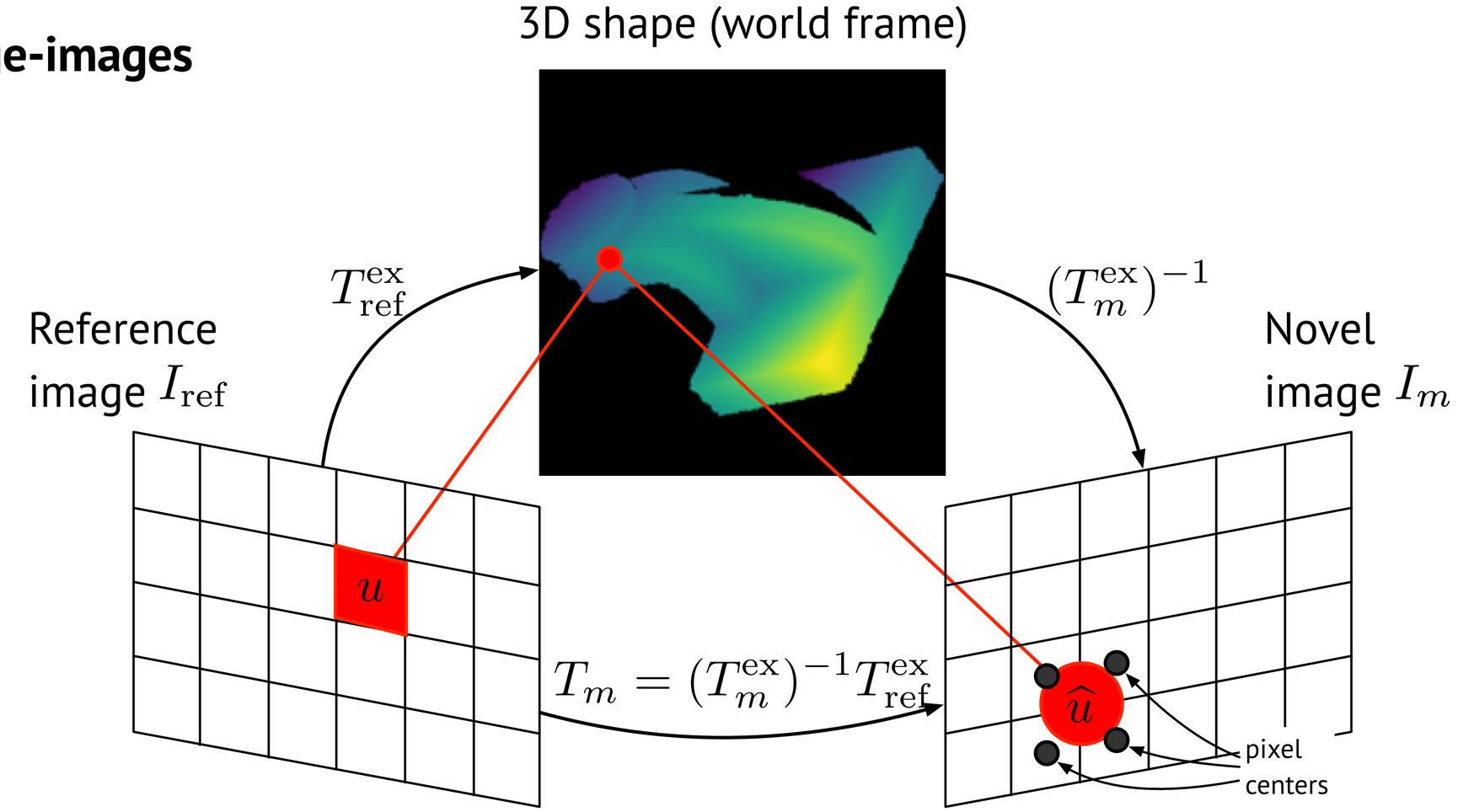
§5. Learning with dense range-images

- 3D coordinates of pixel u in reference image frame:
  $[xyz]_{\text{ref}} = [K^{-1}u; I_{\text{ref}}(u)]$
- Relation between pixel coordinates in two views:
  $\widehat{u} = KT_m[K^{-1}u; I_{\text{ref}}(u)]$
- Note: warped coordinates $\widehat{u}$ need re-sampling on the image grid!



Re-project to 3D + transform from reference to world frame:
$X = T_{\text{ref}}^{\text{ex}}[K^{-1}u; I_{\text{ref}}(u)]$

Transform from world to novel frame + project:
$\widehat{u} = K(T_m^{\text{ex}})^{-1}X$

5.2. Multiple depth images: fusion

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§5. Learning with dense range-images

- **Input:** depth images $I_1, \ldots, I_M$;
  predictions $D_1, \ldots, D_M$ obtained for each view independently (e.g. $D_i = \mathrm{CNN}(I_i)$)
- **Goal:** obtaining predictions that are consistent (approximately the same) across views
- For each pair of views (I_{ref}, I_m) (commonly fix I_{ref}, iterate over I_m):
  - Compute novel view pixel coordinates $\widehat{u} = KT_m[K^{-1}u; I_{\mathrm{ref}}(u)]$ for each pixel u in I_{ref}
  - Computed an interpolated prediction in the pixel space: $\widehat{D}^m_{\mathrm{ref}}(u) = \mathrm{Interp}(D_m(\widehat{u}))$
  - Append $\widehat{D}^m_{\mathrm{ref}}(u)$ and a validity mask $\widehat{V}^m_{\mathrm{ref}}(u)$ to the list of predictions in for each pixel u
- Aggregate by minimizing the pixelwise difference in valid pixels

$$\widehat{D}_{\mathrm{ref}} = \arg\min_{\widehat{D}_{\mathrm{ref}}} \sum_{m=1}^{M} ||(\widehat{D}_{\mathrm{ref}} - \widehat{D}^m_{\mathrm{ref}}) \odot \widehat{V}^m_{\mathrm{ref}}||$$

5.2. Multiple depth images: fusion

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§5. Learning with dense range-images

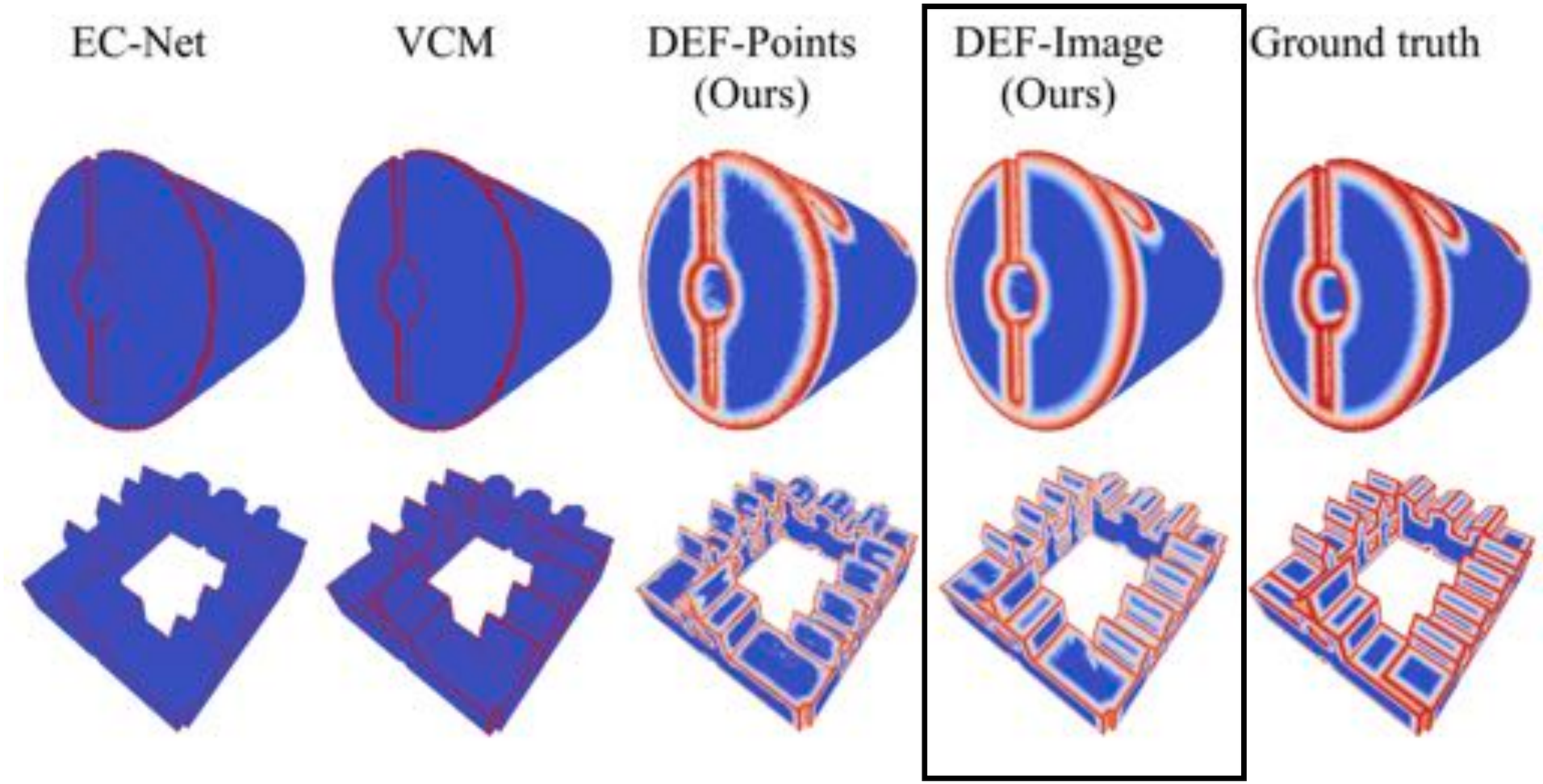

Figure credit: Matveev, A., Artemov, A., Rakhimov, R., Bobrovskikh, G., Panozzo, D., Zorin, D., & Burnaev, E. (2020). DEF: Deep Estimation of Sharp Geometric Features in 3D Shapes. *arXiv preprint arXiv:2011.15081*.

5.2. Multiple depth images: view consistency

§5. Learning with dense range-images

- Virtually the same as the previous slide, but done **during training**
- Predict for each view independently (e.g. $D_i = \mathrm{CNN}(I_i)$)
- Reproject, interpolate, concatenate (all ops must be differentiable!)
- Compute the pixelwise difference in valid pixels (multiple view consistency assumption)

$$L_{\mathrm{reproj}}(\widehat{D}_{\mathrm{ref}}) = \sum_{m=1}^{M} ||(\widehat{D}_{\mathrm{ref}} - \widehat{D}^m_{\mathrm{ref}}) \odot \widehat{V}^m_{\mathrm{ref}}||$$

- Minimize $L_{\mathrm{reproj}}(\widehat{D}_{\mathrm{ref}}) + \text{other losses}$

5.2. Multiple depth images: recap

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§5. Learning with dense range-images

- Multiple views provide complementary contexts
- Boost **method** performance either during **post-processing** by **fusing predictions** in the same spatial positions, visible from different viewpoints
- Boost **network** performance by **training** with **multiple view consistency** assumption

References

1. Botsch, M., Kobbelt, L., Pauly, M., Alliez, P., & Lévy, B. (2010). *Polygon mesh processing*. CRC press.
2. Ma, Y., Soatto, S., Kosecka, J. and Sastry, S.S., 2012. *An invitation to 3-d vision: from images to geometric models* (Vol. 26). Springer Science & Business Media.
3. Hartley, R. and Zisserman, A., 2003. *Multiple view geometry in computer vision*.