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Learning from volumetric depth

Geometric Computer Vision

GCV v2021.1, Module 5

Alexey Artemov, Spring 2021

Lecture Outline

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§1. Volumetric 3D representations [15 min]

1.1. Volumetric 3D shapes

1.2. Connections to other 3D modalities

1.3. Constructing volumetric 3D shapes from range-images

§2. Spatial data structures [15 min]

2.1. Dense volumetric 3D grids

2.2. Sparse data representations

2.3. Octrees

Lecture Outline

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§3. Constructing neural networks on volumetric data [15 min]

3.1. Dense 3D CNNs

3.2. Sparse 3D CNNs

3.3. Octree-based CNNs

§1. Volumetric 3D representations

Volumetric 3D shapes

1.1. Volumetric 3D data

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§1. Volumetric 3D representations

- Dealing with **volumetric representations** of 3D objects and scenes
- **Conceptually simple and most similar** to color 2D images / range-images: defined by sampling a function on a regular grid
- **Fast inside-outside tests** (with distance functions)
- **Fast data modifications** with new information
- **Trivially converted** from different sources of 3D data
  - LIDAR point clouds, RGB-D point clouds, CAD models…
- Acts as a **data source for downstream** tasks (both reconstruction and understanding)
  - Mesh extraction, segmentation / detection / classification, …

1.1. Volumetric 3D functions

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§1. Volumetric 3D representations

- **Occupancy map**: a binary function $\mathrm{OCC}(\mathbf{x}) : \Omega \rightarrow \{0,1\}$
- **Signed distance function** (SDF): an array of signed distance values $\mathrm{SDF}(\mathbf{x}) : \Omega \rightarrow \mathbb{R}$
  - Positive values outsize the shape (free space), negative inside (occupied space)
- **Truncated SDF** (TSDF): $\mathrm{TSDF}(\mathbf{x}) : \Omega \rightarrow [-\sigma, \sigma]$
  - Set max value to a fixed value $\mathrm{TSDF}(\mathbf{x}) = \min(\max(\mathrm{SDF}(\mathbf{x}), -\sigma), \sigma)$

1.1. Volumetric 3D functions

§1. Volumetric 3D representations

Occupancy map | SDF | TSDF

Figure credit: Representing geometry

1.1. Depth images as TSDFs

§1. Volumetric 3D representations

(a) surface

(c) TSDF

Figure credit: SSCnet

1.1. Volumetric 3D computational representations

§1. Volumetric 3D representations

- Sometimes: a **combination of basis functions** $f(\mathbf{x}) = \sum_i c_i b_i(\mathbf{x})$
- **Dense volumetric grid:** a set $\Omega = \{0,\ldots,n_x\} \times \{0,\ldots,n_y\} \times \{0,\ldots,n_z\} \subset \mathbb{R}^3$ **of voxels** (VOlumetric PIXELs: axis aligned cubes)
- **Hierarchical grid (quadtree / octree):** store function values at progressively finer levels
- **Sparse grid / hash grid:** stores only important cells or blocks of volumetric data

1.1. Volumetric 3D functions

§1. Volumetric 3D representations

Occupancy map SDF TSDF

- Dense volumetric grid: need $O(N^3)$ voxels where N is the spatial resolution

Figure credit: Representing geometry

Connections to other 3D modalities

1.2. Connections to other 3D modalities

§1. Volumetric 3D representations

- Volumetric 3D representations can be…
- Built from:
  - Point sets / meshes / CAD models / you name it: **voxelization** (OCC)
  - Surface modalities: **distance-to-surface queries** (SDF, TSDF)
  - **Fusion** of (registered) range-images into a global surface model (OCC, SDF, TSDF)
- Used for:
  - Implicit surface modeling
  - (Explicit) Mesh extraction

1.2. Voxelization

§1. Volumetric 3D representations

- Voxelizing **triangle meshes/CAD models:** all voxels that are intersected by a triangle are set to 1, all others are set to 0
- Voxelizing **point clouds:** occupy a voxel if at least one point of the point cloud is within the voxel
- Surface geometry only (no interior occupancy)

Figure credit: Open3D

1.2. Voxelization: space carving

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§1. Volumetric 3D representations

- Shape-from-silhouette: discard voxels projecting outside silhouette
- Need multiple views of the same shape

Figure credit: A Real-Time System for Full Body Interaction with Virtual Worlds

1.2. Voxelization: space carving

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§1. Volumetric 3D representations

Figure credit: 3DShapeNets

- Useful for sequential tasks (e.g. determining the next-best-view from current reconstructing + a list of previous camera poses)
- Obtain depth maps (raycasting/sensors) → voxelize entire space with several occupancy labels (simplest: free/occupied, but unknown is important, too)

1.2. Distance-to-surface queries: raycasting

§1. Volumetric 3D representations

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

Constructing volumetric 3D shapes from range-images

1.3. Constructing volumetric 3D shapes from range-images

§1. Volumetric 3D representations

- **Input:** a sequence of range-image measurements $d_1, \ldots, d_n$
- **Goal:** to build a single 3D model (preferably a surface) $D(\mathbf{x})$ **(a fused TSDF volume)**
- **Constrains:**
  - Camera poses can be known (frames registered) or unknown (SLAM variant)
  - Dense 3D modeling
  - Real-time performance (e.g. Kinect / RealSense: depth @30FPS)

Figure credit: Andy Zeng

Figure credit: ScanComplete

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations

- Start with range-surfaces (proxy surfaces obtained from range-images)
- Perform rolling averaging in each spatial location on the grid:

$$D_{i+1}(\mathbf{x}) = \frac{W_i(\mathbf{x})D_i(\mathbf{x}) + w_{i+1}(\mathbf{x})d_{i+1}(\mathbf{x})}{W_i(\mathbf{x}) + w_{i+1}(\mathbf{x})}$$

where $W_i(\mathbf{x}), w_i(\mathbf{x})$ represent cumulative and instantaneous weights

$$W_{i+1}(\mathbf{x}) = W_i(\mathbf{x}) + w_i(\mathbf{x})$$

Figure credit: Curless & Levoy

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations

View / camera pose

Current reconstruction

Slide credit: Riegler et al., OctNet

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations

View / camera pose

Current reconstruction

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§1. Volumetric 3D representations

View / camera pose

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View / camera pose

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1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations

View / camera pose

Current reconstruction

Slide credit: Riegler et al., OctNet

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations

- Pros
  - Simple
  - Fast
  - Easy implementation
- Cons
  - Many views required
  - Can not handle outliers
  - No surface completion

Final reconstruction

Slide credit: Riegler et al., OctNet

1.3. Depth fusion: TV-L1

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§1. Volumetric 3D representations

- Obtained by minimizing a surface-shrinking functional during updates

$$\min_{u} \int_{\Omega} |\nabla u| + \lambda \sum_{i \in \mathcal{I}(x)} |u - f_i| \, dx$$

- Pros
  - Prior on surface area
  - Noise reduction
- Cons
  - Simplistic local prior, shrinkage bias
  - Can not complete missing surfaces

Final reconstruction

Slide credit: Riegler et al., OctNet

1.3. Volumetric 3D data: summary

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§1. Volumetric 3D representations

- Generic **regular representation** for 3D data
- **Distance-to-shape function** (or its variants) encoded on a volumetric grid
- Naive implementation **scales cubically** with the required resolution: $O(N^3)$
- Can be constructed with simple procedures from other types of 3D data (e.g., voxelization, space carving, ray-casting, or more complex depth fusion)

§2. Spatial data structures

Dense volumetric 3D grids

2.1. Dense volumetric 3D grids

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§1. Volumetric 3D representations

Occupancy map SDF TSDF

- Dense volumetric grid: need $O(N^3)$ voxels where N is the spatial resolution

Figure credit: Representing geometry

2.1. Dense volumetric 3D grids

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§1. Volumetric 3D representations

Figure credit: NBC News

Figure credit: Despotovic et al., 2010

- "Truly dense" volumetric data is rare (e.g., CT/MRI scans)

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

Point Cloud

Mesh

Slide credit: Riegler et al., OctNet

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

Point Cloud

Voxelized 16^3 Occupancy

4.19%

Slide credit: Riegler et al., OctNet

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

Point Cloud

Voxelized 32^3 Occupancy

2.11%

Slide credit: Riegler et al., OctNet

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

Point Cloud

Voxelized 64^3 Occupancy

1.06%

Slide credit: Riegler et al., OctNet

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

Point Cloud

Voxelized 128^3 Occupancy

0.56%

Slide credit: Riegler et al., OctNet

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

Point Cloud

Voxelized 256^3 Occupancy

0.31%

Slide credit: Riegler et al., OctNet

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

Point Cloud

Voxelized 512^3 Occupancy

0.16%

Slide credit: Riegler et al., OctNet

Sparse data representations

2.2. Sparse data representations

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§2. Spatial data structures

- Storage requirements for volumetric data: $O(N^3)$ where N is the spatial resolution
  - Need $O(N^3)$ for truly volumetric 3D data (e.g., MRI scans)
  - Encoding surfaces: $O(N^2)$
  - Point clouds: inherently sparse $O(N_{\text{points}})$
- Store data only in occupied locations (active values)
  - **Sparse tensor representation**
  - Which format to choose?

2.3. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

Occupancy map

TSDF

- Sparse volumetric grid: need $O(K)$ voxels where K is the number of nonempty voxels

Figure credit: Representing geometry

2.2. Sparse data representations

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§2. Spatial data structures

- Dense array storage

10	20	0	0	0	0
0	30	0	40	0	0
0	0	50	60	70	0
0	0	0	0	0	80

Matrix 6×4

```
[ 10, 20,  0,  0,  0,  0,
   0, 30,  0, 40,  0,  0,
   0,  0, 50, 60, 70,  0,
   0,  0,  0,  0,  0, 80 ]
```

Memory array 24-floats

Example credit: boristhebrave

2.2. Sparse data representations

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§2. Spatial data structures

- Coordinate list storage (COO)

10	20	0	0	0	0
0	30	0	40	0	0
0	0	50	60	70	0
0	0	0	0	0	80

Matrix 6×4

Row	Column	Value
0	0	10
0	1	20
1	1	30
1	3	40
2	2	50
2	3	60
2	4	70
3	5	80

COO

Example credit: boristhebrave

2.2. Sparse data representations

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§2. Spatial data structures

- Compressed sparse row (CSR) and compressed sparse column (CSC)

10	20	0	0	0	0
0	30	0	40	0	0
0	0	50	60	70	0
0	0	0	0	0	80

Matrix 6×4

```
values      = [ 10, 20, 30, 40, 50, 60, 70, 80 ]
col_indices = [  0,  1,  1,  3,  2,  3,  4,  5 ]
row_indptr  = [  0,  2,  4,  7,  8 ]
```

CSR

```
row_idx = 2
col_start = row_indptr[row_idx]  # 4
col_end = row_indptr[row_idx]  # 7
col_idxs = col_indices[col_start:col_end]
vals = values[col_start:col_end]
```

Reading from a CSR

Example credit: boristhebrave

2.2. Sparse data representations

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§2. Spatial data structures

- Compressed sparse fiber (CSF)

Coordinate format.

CSF: conceptual.

CSF: implementation.

Example credit: boristhebrave

Octrees

2.3. Octrees

§2. Spatial data structures

- Memory-efficient data structure for spatial indexing
- Many applications:
  - Efficient 3D spatial indexing at high resolutions
  - Visualization (e.g. level of detail, frustum culling, raycasting)
  - Nearest neighbour search (e.g. needed by ICP)
  - Discrete geometry processing (e.g. meshing)

Figure credit: gifer.com

2.3. Octrees

§2. Spatial data structures

- A search tree with exactly 8 children in each node
- Recursively subdivide space into 8 octants at each spatial scale
- Point-region and matrix-based

- Insertion: $O(\log N)$
- Nearest-neighbour search: $O(\log N)$

Figure credit: Wikipedia

2.3. Octrees

§2. Spatial data structures

Occupancy map SDF TSDF

- Quadtree/octree voxel grid: adaptively subdivide space to accommodate active sites

Figure credit: Representing geometry

2.3. Octrees

§2. Spatial data structures

- Quadtree/octree voxel grid: resolution changes/dynamics

Figure credit: Representing geometry

2.3. Spatial data structures: summary

§2. Spatial data structures

- **Dense volumetric grid:** a set $\Omega = \{0,\ldots,n_x\} \times \{0,\ldots,n_y\} \times \{0,\ldots,n_z\} \subset \mathbb{R}^3$ **of voxels**
  - Simplest, off-the-shelf, easy to use
  - Memory and computationally inefficient
- **Hierarchical grid (quadtree / octree):** store function values at progressively finer levels
  - Fast insertion and search: $O(\log N)$
  - Maintain a separate data structure, still pointwise-constant approximation
- **Sparse grid / hash grid:** stores only important cells or blocks of volumetric data
  - Removes redundancy be not storing / computing values in empty voxels
  - Separate sparse data-structures (e.g. COO-formatted sparse tensors)

§3. Constructing neural networks on volumetric data

Dense 3D CNNs

3.1. Dense 3D CNNs

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§3. Constructing neural networks on volumetric data

- 2D convolutions: mainstream tool for processing signals
  - Images, video, RGBD, …
- Dense 3D volumetric data: directly extend 2D convolutions to 3rd dimension
  - No-brainer (add another loop into the code for convolution computation)

3.1. Dense 3D CNNs: understanding 3D scans

§3. Constructing neural networks on volumetric data

Slide credit: Matthias Niessner

3.1. Dense 3D CNNs: Deep Learning in 3D

§3. Constructing neural networks on volumetric data

(binary) Voxel Grid

Implicit Function

Slide credit: Matthias Niessner

3.1. Dense 3D CNNs: 3D Semantic Segmentation

§3. Constructing neural networks on volumetric data

CVPR'17 (spotlight) [Dai et

3.1. Dense 3D CNNs: 3D Semantic Segmentation

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3.1. Dense 3D CNNs: 3D Reconstructions

TOG'17 [Dai et al.]: Bu

Slide credit: Matthias Niessner

3.1. Dense 3D CNNs: Incomplete Scan Geometry

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TOG'17 [Dai et al.]: Bu

3.1. Dense 3D CNNs: Completing 3D Shapes

§3. Construct l networks on volumetric data

3.1. Dense 3D CNNs: Data-driven Shape Completion

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CVPR'17 (spotlight) [Dai et al.]

Slide credit: Matthias Niessner

3.1. Dense 3D CNNs: Data-driven Shape Completion

§3. Cor

CVPR'17 (spotlight) [Dai et al.]

3.1. Dense 3D CNNs: Shape Completion Results

§3. Constructing ne

Input

Completion

Ground Truth

Results on ShapeNet [Chang et al. 15]

CVPR'17 (spotlight) [Dai et al.]

Slide credit: Matthias Niessner

3.1. What about Entire Scenes and Domain Transfer?

§3. Constructing neural networks on volumes

Slide credit: Matthias Niessner

3.1. Spatial Extent: Fully Convolutional for Arbitrary Sizes

§3. Constructing neural networks on volumetric data

Train on crops of scenes

Train Block Input Partial Scan

Train Block Complete Target

Test on entire scenes

CVPR'18 [Dai et al.]: Sc

3.1. Dense 3D CNNs: ScanComplete: Scene Completion

§3. Constructing metric data

CVPR'18 [Dai et al.]: Sc

Slide credit: Matthias Niessner

3.1 Dense 3D CNNs: ScanComplete

§3.

CVPR'18 [Dai et al.]: Sc

Slide credit: Matthias Niessner

3.1. Dense 3D CNNs: memory requirements

§3. Constructing neural networks on volumetric data

- Network evaluation with batch size 32 (Voxelized ModelNet10 meshes)

Riegler et al., OctNet - 5

3.1. Naive 3D CNNs: summary

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§3. Constructing neural networks on volumetric data

- Dense 3D CNNs: directly extend 2D convolutions to 3rd dimension
- **Computationally inefficient** (scale cubically with spatial resolution)
  - Process low-resolution shapes only (e.g., 32^3 or 64^3) or use shallower NNs
  - Many applications can leverage low-resolution volumes (e.g. semantic segmentation, scene completion…)
- **Sample inefficient** (perform worse compared to 2D CNNs)

Octree-based CNNs

3.3. Octree-based CNNs

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§3. Constructing neural networks on volumetric data

- **Goal:** train **deep architectures** at **high spatial resolutions**
  - Deeper models → higher learning efficiency
  - Higher resolution → more detail in input 3D shapes/scenes

3.3. Octree-based CNNs: effect of resolution

§3. Constructing neural networks on volumetric data

Voxelized 8^3

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: effect of resolution

§3. Constructing neural networks on volumetric data

Voxelized 16^3

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: effect of resolution

§3. Constructing neural networks on volumetric data

Voxelized 32^3

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: effect of resolution

§3. Constructing neural networks on volumetric data

Voxelized 64^3

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: grid of octrees

§3. Constructing neural networks on volumetric data

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: grid of octrees

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§3. Constructing neural networks on volumetric data

A. Miller et al. "Real-time rendering and dynamic updating of 3-d volumetric data". In: **GPGPU**. 2011.

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: grid of octrees

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3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data

Slide credit: Riegler et al., OctNet

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Slide credit: Riegler et al., OctNet

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3.3. Octree-based CNNs: convolution

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3.3. Octree-based CNNs: pooling

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3.3. Octree-based CNNs: pooling

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3.3. Octree-based CNNs: pooling

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3.3. Octree-based CNNs: pooling

§3. Constructing neural networks on volumetric data

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: experiments

§3. Constructing neural networks on volumetric data

Network evaluation with batch size 32
Voxelized ModelNet10 meshes

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: experiments

§3. Constructing neural networks on volumetric data

Network evaluation with batch size 32
Voxelized ModelNet10 meshes

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: experiments

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D. Maturana and S. Scherer. "VoxNet: A 3D Convolutional Neural Network for real-time object recognition". In: **IROS**. 2015.

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: experiments

§3. Constructing neural networks on volumetric data

ModelNet10

ModelNet40

D. Maturana and S. Scherer. "VoxNet: A 3D Convolutional Neural Network for real-time object recognition". In: **IROS**. 2015.

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: summary

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§3. Constructing neural networks on volumetric data

- Define a convolutional / pooling operators on top of octree data structure
- Capability to train deeper architectures at higher spatial resolutions