Local-Level 3D Deep Learning

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Matching 3D Data

Image Credits: Song and Xiao, Tevs et al.
Matching 3D Data

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Matching 3D Data

- Reconstruction
- Shape retrieval
- Object pose estimation
- Aligning deformable shapes

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Matching 3D Data

Establish 3D geometric correspondences
Matching 3D Data

Establish 3D geometric correspondences

Find interesting 3D features

Match 3D features
Matching 3D Features in Scanning Data is Hard

Partial and noisy scan data
Matching 3D Features in Scanning Data is Hard

Partial and noisy scan data

Viewpoint variance
Matching 3D Features in Scanning Data is Hard

Partial and noisy scan data

Viewpoint variance
Matching 3D Features in Scanning Data is Hard

Partial and noisy scan data
Viewpoint variance

Traditional hand-crafted 3D feature descriptors do not work well!
Solution: Let the data speak for itself!
Solution: Let the data speak for itself!

http://3dmatch.cs.princeton.edu/

**3DMatch**: 3D ConvNet that recognizes correspondences in 3D scan data
3D Data Representation

Use truncated distance fields (TDF)

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3D Data Representation

Use truncated distance fields (TDF)

Intermediate 3D Representation

Image Credits: Song and Xiao
3D Data Representation

Use truncated distance fields (TDF)

Intermediate 3D Representation

Enables 3D Convolution

Image Credits: Song and Xiao
3D Data Representation
3D Data Representation
Metric Network vs. L2 Distance
Metric Network vs. L2 Distance
Metric Network vs. L2 Distance

Use metric network for **accuracy**, use L2 distance for **speed**
Generating Training Data Automatically

Manually label geometric correspondences? Too much work!
Generating Training Data Automatically

Manually label geometric correspondences? Too much work!

“Think of all those maps that we've built using large-scale SLAM and all those correspondences that these systems provide — isn’t that a clear path for building terascale image-image "association" datasets which should be able to help deep learning?”

“The basic idea is that today's **SLAM systems are large-scale correspondence engines** which can be used to generate large-scale datasets, precisely what needs to be fed into a deep ConvNet.”

Newcombe’s Proposal: Use SLAM to help Deep Learning

Image Credits: Malisiewicz et al.
Generating Training Data Automatically

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“The basic idea is that today’s SLAM systems are large-scale correspondence engines which can be used to generate large-scale datasets, precisely what needs to be fed into a deep ConvNet.”

Newcombe’s Proposal: Use SLAM to help Deep Learning
Tomasz Malisiewicz’s Computer Vision Blog
ICCV’s Future of Real-Time SLAM Workshop

Solution: Use existing 3D reconstructions to fuel correspondence labels!
Generating Training Data Automatically

Solution: Use existing 3D reconstructions to fuel correspondence labels!

Microsoft 7 Scenes RGB-D dataset

Image Credits: Shotton et al.
3DMatch for Reconstruction
3DMatch for Loop Closures
3DMatch for Loop Closures
3DMatch for Loop Closures
3DMatch for Loop Closures
3DMatch for 3D Reconstruction
3DMatch for Other Applications

Shape retrieval
Object pose estimation
Evaluation: 3DMatch vs. Others

Correspondence
Evaluation: 3DMatch > Others

Correspondence

Geometric Registration
Keypoint Selection Does Not Matter
Keypoint Selection Does Not Matter

The choice of keypoints do not matter much.
Conclusion
3DMatch
http://3dmatch.cs.princeton.edu/
3D ConvNet that recognizes correspondences in 3D scan data