Learning 3D Reconstruction in Function Space

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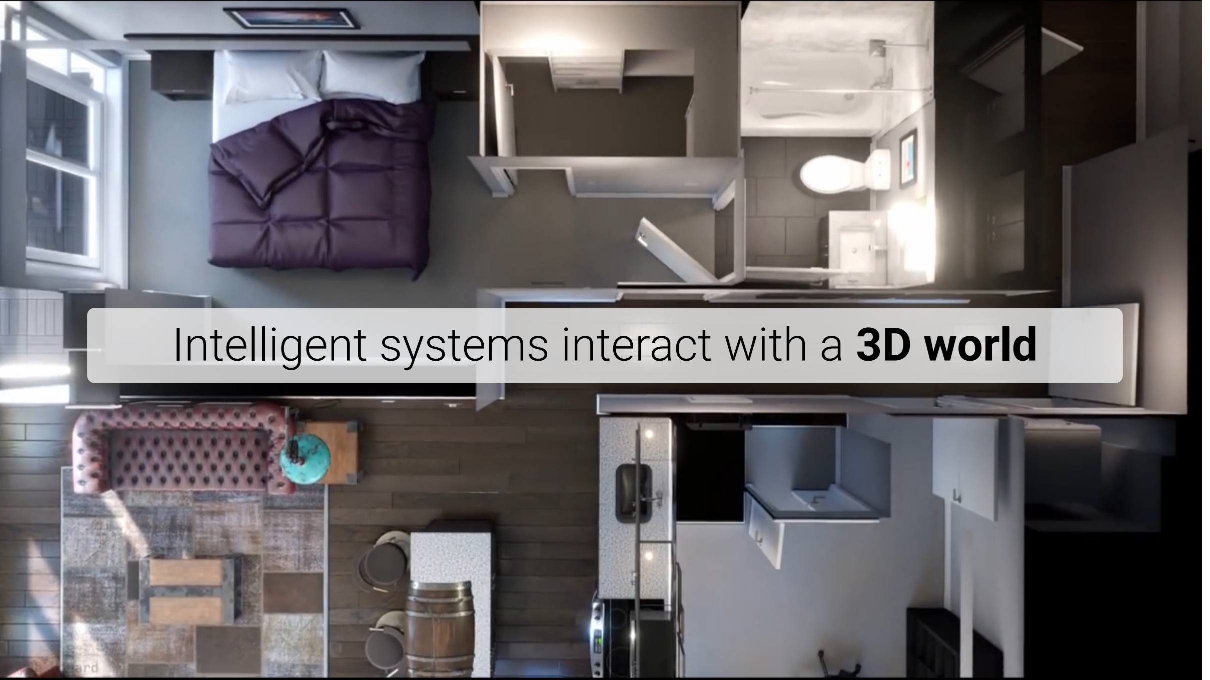
University of Tübingen
MPI for Intelligent Systems

Autonomous Vision Group

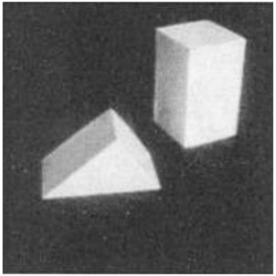
Our goal is to make **intelligent systems** more autonomous, robust and safe

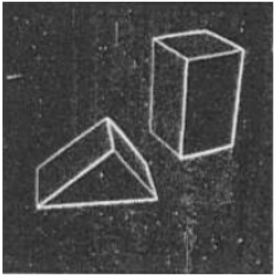


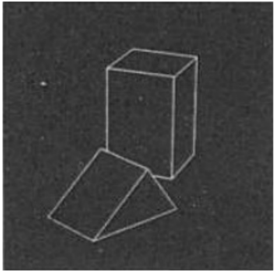
Intelligent systems interact with a **3D world**

3D reconstruction is a hard problem

1963: Blocks World



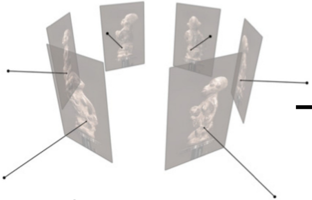




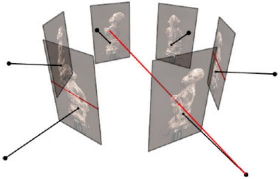
Larry Roberts: Machine Perception of Three-Dimensional Solids. PhD Thesis, MIT, 1963.

Traditional 3D Reconstruction Pipeline

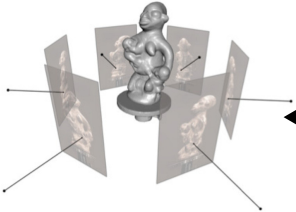
Input Images



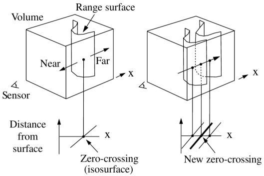
Camera Poses



Dense Correspondences



3D Reconstruction



Depth Map Fusion

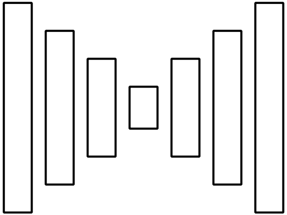
Depth Maps

Humans recognize 3D from a **single** 2D image

Can we **learn** to infer 3D **from a 2D image**?

3D Reconstruction from a 2D Image

Input Images



Neural Network

3D Reconstruction

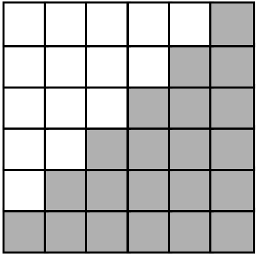
What is a good **output** representation?

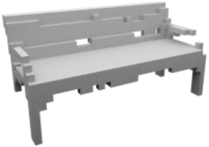
3D Representations

Voxels:

- **Discretization** of 3D space into grid
- Easy to process with neural networks
- Cubic memory $O(n^3) \Rightarrow$ limited resolution
- Manhattan world bias

[Maturana et al., IROS 2015]



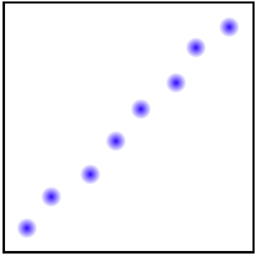


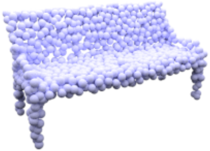
3D Representations

Points:

- **Discretization** of surface into 3D points
- Does not model connectivity / topology
- Limited number of points
- Global shape description

[Fan et al., CVPR 2017]



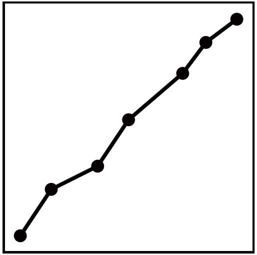


3D Representations

Meshes:

- **Discretization** into vertices and faces
- Limited number of vertices / granularity
- Requires class-specific template – or –
- Leads to self-intersections

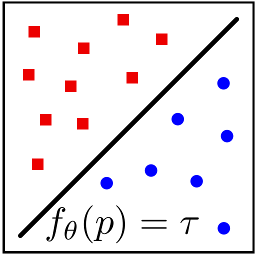
[Groueix et al., CVPR 2018]



3D Representations

This work:

- Implicit representation $\Rightarrow$ **No discretization**
- Arbitrary topology & resolution
- Low memory footprint
- Not restricted to specific class



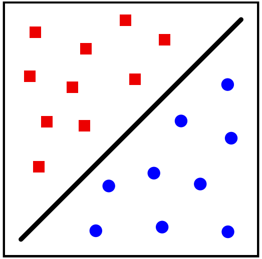
Occupancy Networks

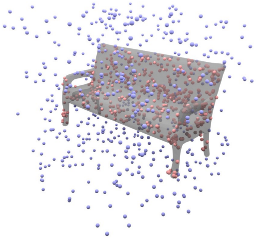
Key Idea:

- Do not represent 3D shape explicitly
- Instead, consider surface **implicitly** as **decision boundary** of a non-linear classifier:

$$f_\theta : \mathbb{R}^3 \times \mathcal{X} \rightarrow [0, 1]$$

3D Location
Condition (eg, Image)
Occupancy Probability



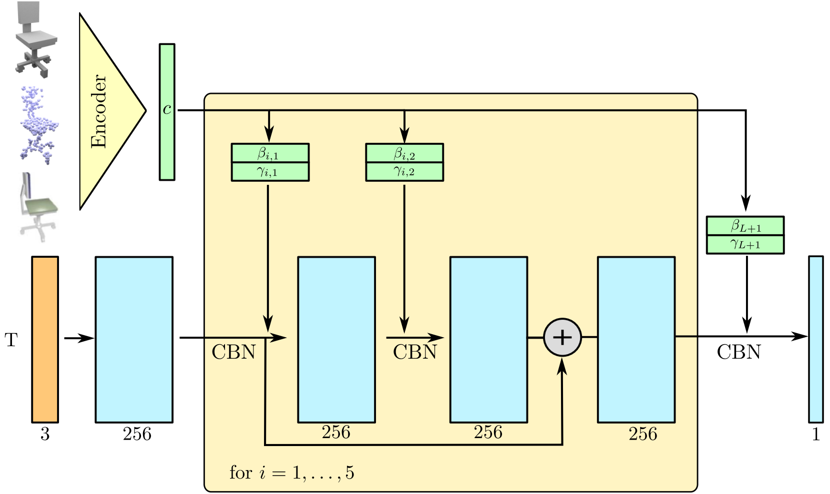


Concurrent work:

- DeepSDF [Park et al., CVPR 2019]
- IM-NET [Chen et al., CVPR 2019]

Mescheder, Oechsle, Niemeyer, Nowozin and Geiger: Occupancy Networks: Learning 3D Reconstruction in Function Space. CVPR, 2019.

Network Architecture



Mescheder, Oechsle, Niemeyer, Nowozin and Geiger: Occupancy Networks: Learning 3D Reconstruction in Function Space. CVPR, 2019.

Training Objective

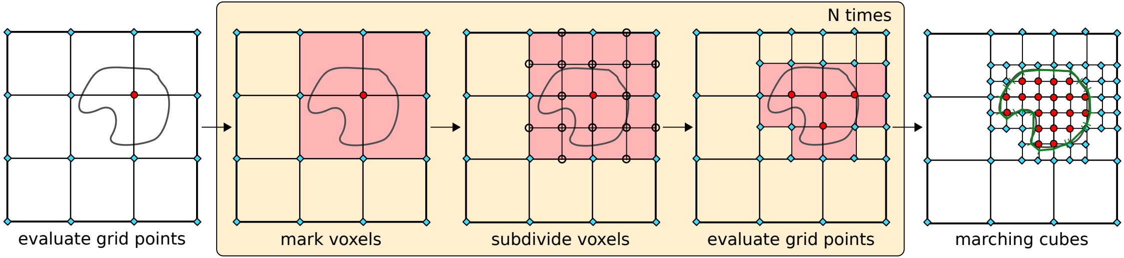
Occupancy Network:Variational Occupancy Encoder:

$$\mathcal{L}(\theta, \psi) = \sum_{j=1}^{K} \text{BCE}(f_\theta(p_{ij}, z_i), o_{ij}) + KL\left[q_\psi(z|(p_{ij}, o_{ij})_{j=1:K}) \,\|\, p_0(z)\right]$$

- K: Randomly sampled 3D points ($K = 2048$)
- BCE: Cross-entropy loss
- q_ψ: Encoder

Mescheder, Oechsle, Niemeyer, Nowozin and Geiger: Occupancy Networks: Learning 3D Reconstruction in Function Space. CVPR, 2019.

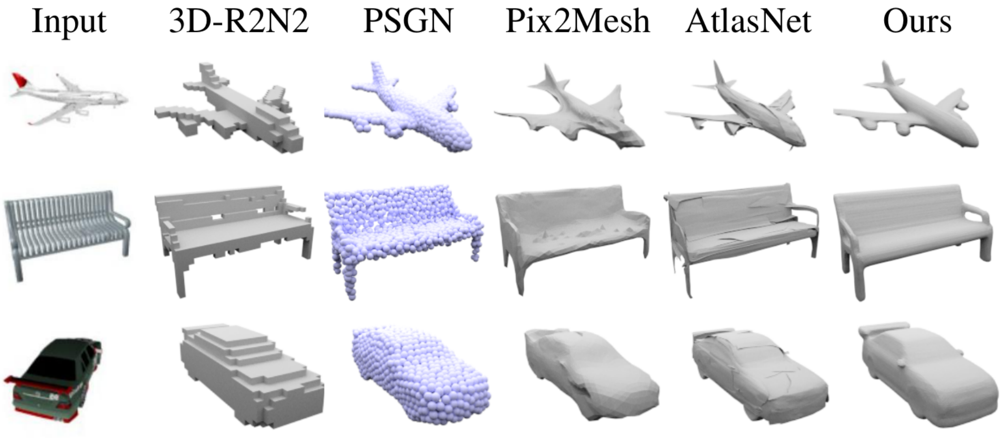
Occupancy Networks



Multiresolution IsoSurface Extraction (MISE):

- Build octree by incrementally querying the occupancy network
- Extract triangular mesh using marching cubes algorithm (1-3 seconds in total)

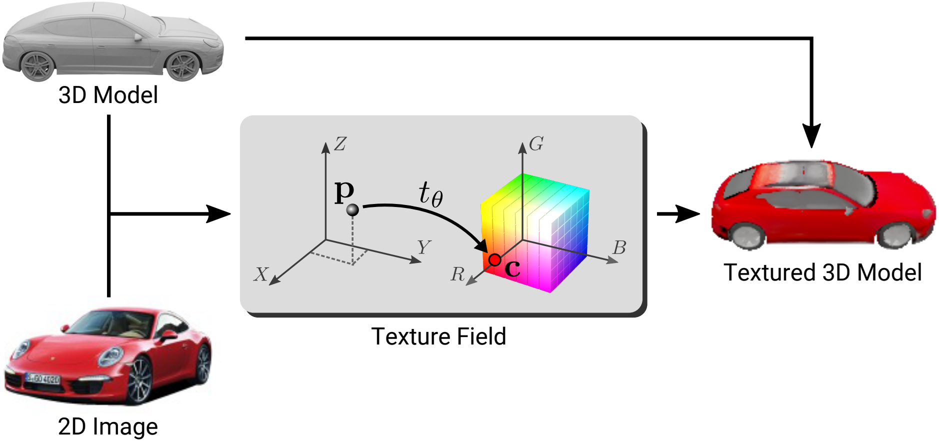
Results



Mescheder, Oechsle, Niemeyer, Nowozin and Geiger: Occupancy Networks: Learning 3D Reconstruction in Function Space. CVPR, 2019.

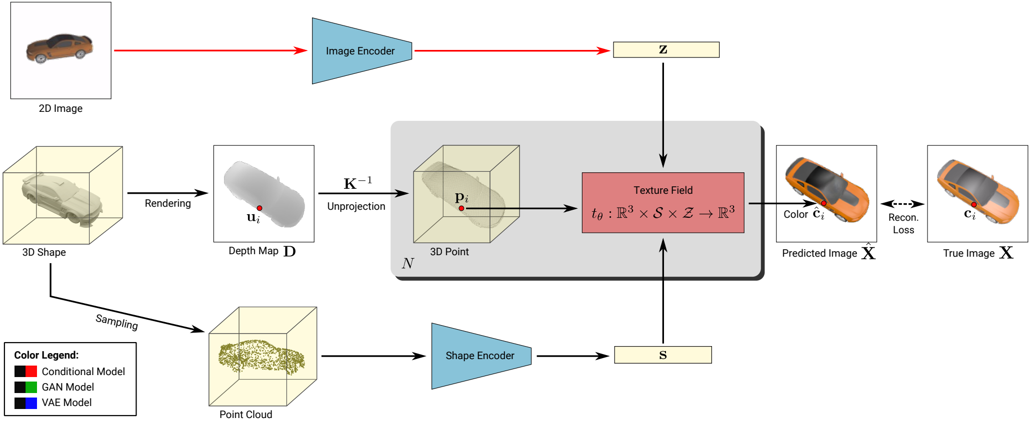
Can we also learn about object **appearance**?

Texture Fields



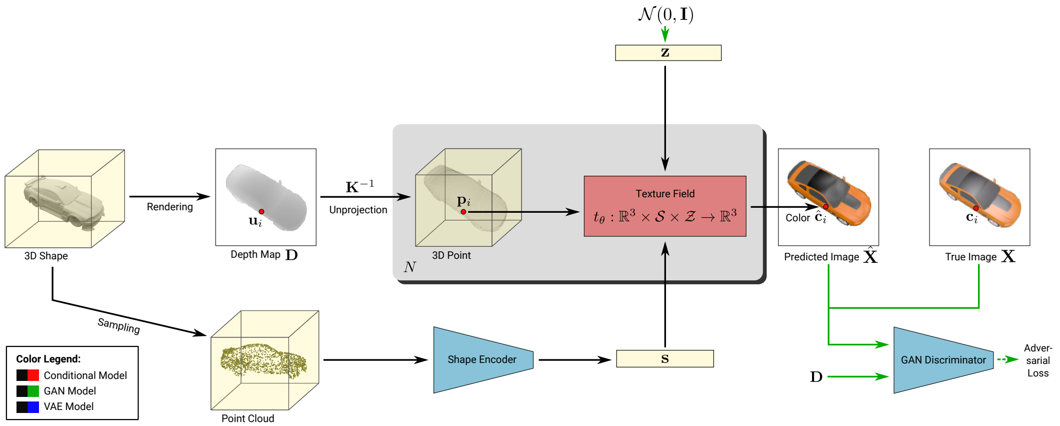
Oechsle, Mescheder, Niemeyer, Strauss and Geiger: Texture Fields: Learning Texture Representations in Function Space. ICCV, 2019.

Texture Fields

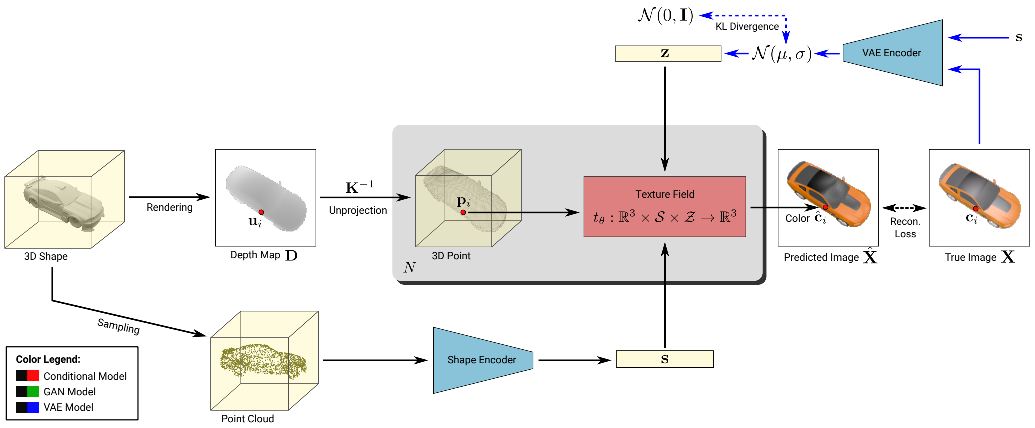


Oechsle, Mescheder, Niemeyer, Strauss and Geiger: Texture Fields: Learning Texture Representations in Function Space. ICCV, 2019.

Texture Fields



Texture Fields



Oechsle, Mescheder, Niemeyer, Strauss and Geiger: Texture Fields: Learning Texture Representations in Function Space. ICCV, 2019.

Representation Power

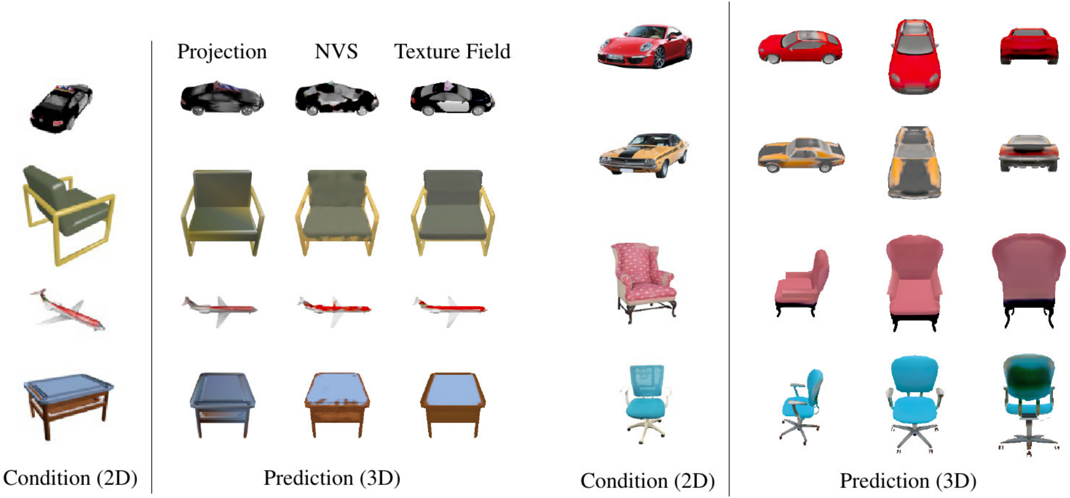
- Ground truth vs. Texture Field vs. Voxelization

Oechsle, Mescheder, Niemeyer, Strauss and Geiger: Texture Fields: Learning Texture Representations in Function Space. ICCV, 2019.

Representation Power (Fit to 10 Models)

Oechsle, Mescheder, Niemeyer, Strauss and Geiger: Texture Fields: Learning Texture Representations in Function Space. ICCV, 2019.

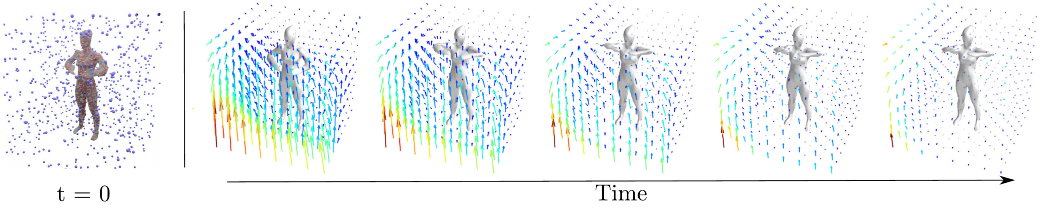
Results



Oechsle, Mescheder, Niemeyer, Strauss and Geiger: Texture Fields: Learning Texture Representations in Function Space. ICCV, 2019.

What about object **motion**?

Occupancy Flow

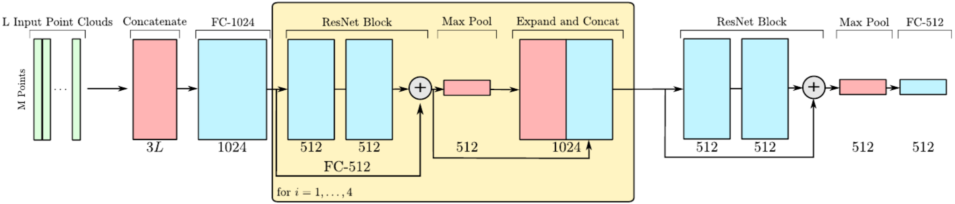


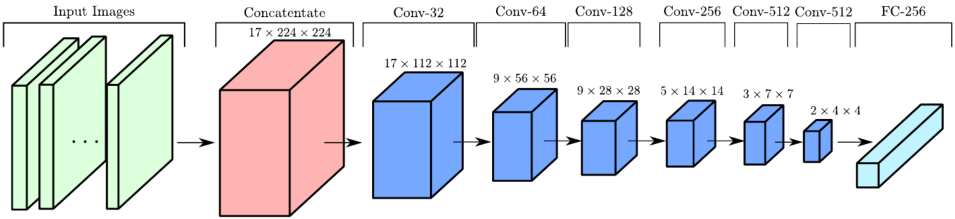
- Extending Occupancy Networks to 4D is hard (curse of dimensionality)
- Represent shape at $t = 0$ using a 3D Occupancy Network
- Represent motion by temporally and spatially continuous vector field
- Relationship between 3D trajectory $\mathbf{s}$ and velocity $\mathbf{v}$ given by (differentiable) ODE:

$$\frac{\partial \mathbf{s}(t)}{\partial t} = \mathbf{v}(\mathbf{s}(t), t)$$

Niemeyer, Mescheder, Oechsle and Geiger: Occupancy Flow: 4D Reconstruction by Learning Particle Dynamics. ICCV, 2019.

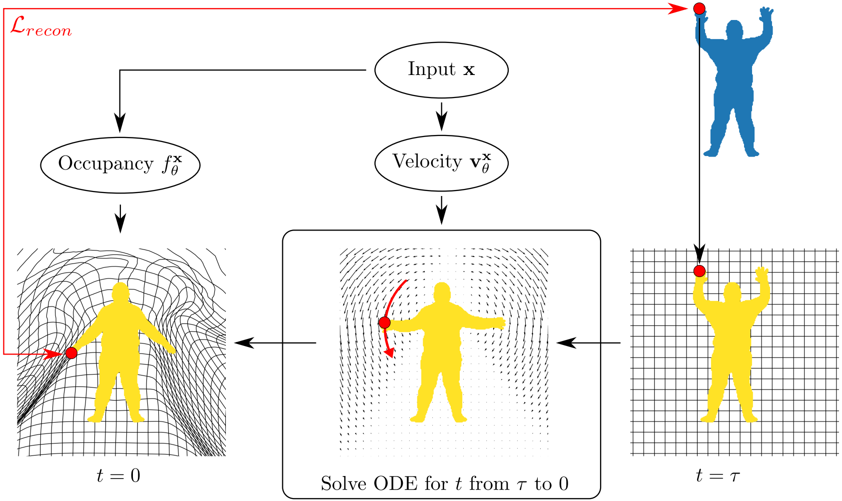
Temporal Encoder





Niemeyer, Mescheder, Oechsle and Geiger: Occupancy Flow: 4D Reconstruction by Learning Particle Dynamics. ICCV, 2019.

Occupancy Flow



Niemeyer, Mescheder, Oechsle and Geiger: Occupancy Flow: 4D Reconstruction by Learning Particle Dynamics. ICCV, 2019.

Loss Functions

Reconstruction Loss:

$$\mathcal{L}_{recon}\left(\theta, \hat{\theta}\right) = \frac{1}{|\mathcal{B}|} \sum_{(\mathbf{p},\tau,\mathbf{x},o)\in\mathcal{B}} \text{BCE}(\hat{o}_{\theta,\hat{\theta}}(\mathbf{p},\tau,\mathbf{x}), o)$$

Correspondence Loss:

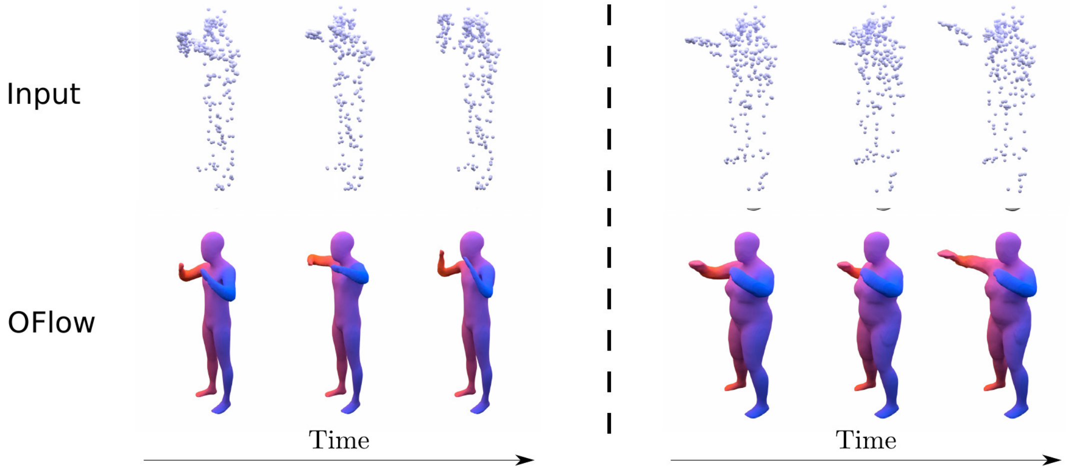
$$\mathcal{L}_{corr}\left(\hat{\theta}\right) = \frac{1}{|\mathcal{B}|} \sum_{(\mathbf{s},\tau,\mathbf{x})\in\mathcal{B}} \left\|\Phi_{\hat{\theta}}^{\mathbf{x}}(\mathbf{s}(0),\tau) - \mathbf{s}(\tau)\right\|_2$$

Neat feat:

- The correspondence loss is optional
- Correspondences are implicitly established by our model!

Niemeyer, Mescheder, Oechsle and Geiger: Occupancy Flow: 4D Reconstruction by Learning Particle Dynamics. ICCV, 2019.

Results

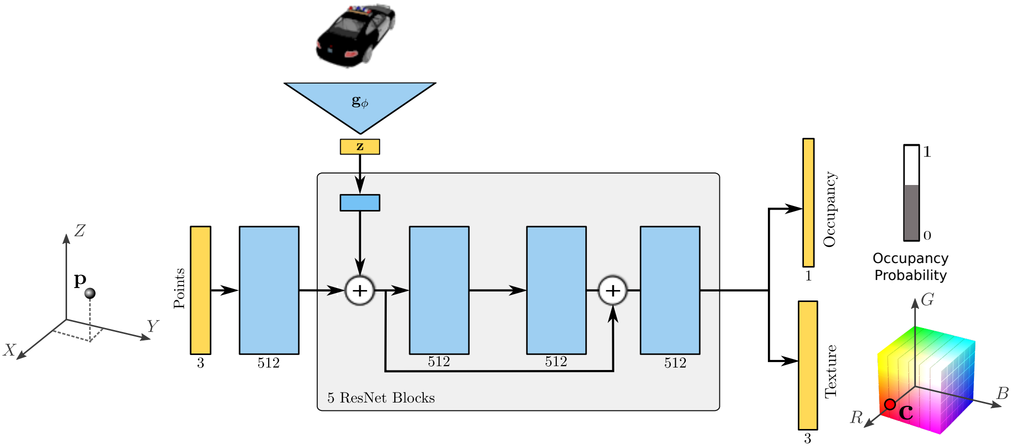


- No correspondences needed $\Rightarrow$ implicitly established by our model!

Niemeyer, Mescheder, Oechsle and Geiger: Occupancy Flow: 4D Reconstruction by Learning Particle Dynamics. ICCV, 2019.

Can we **learn** implicit representations **from images**?

Architecture



Niemeyer, Mescheder, Oechsle and Geiger: Differentiable Volumetric Rendering: Learning Implicit 3D Representations without 3D Supervision. CVPR, 2020.

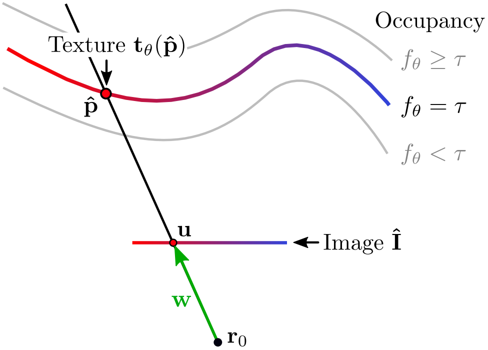
Forward Pass

(Rendering)

Differentiable Volumetric Rendering

Forward Pass:

- For all pixels $\mathbf{u}$
- Find surface point $\hat{\mathbf{p}}$ along ray $\mathbf{w}$ via ray marching and root finding
- Evaluate texture field $\mathbf{t}_\theta(\hat{\mathbf{p}})$ at $\hat{\mathbf{p}}$
- Insert color $\mathbf{t}_\theta(\hat{\mathbf{p}})$ at pixel $\mathbf{u}$



Backward Pass

(Differentiation)

Differentiable Volumetric Rendering

Backward Pass:

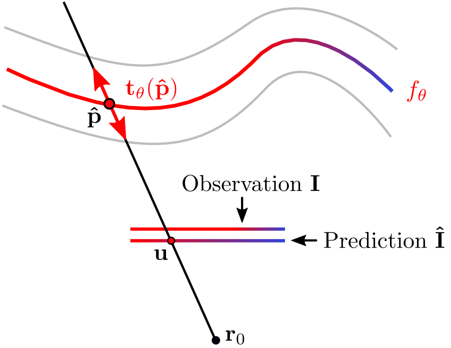
- Image Observation $\mathbf{I}$
- Loss $\mathcal{L}(\hat{\mathbf{I}}, \mathbf{I}) = \sum_{\mathbf{u}} \|\hat{\mathbf{I}}_{\mathbf{u}} - \mathbf{I}_{\mathbf{u}}\|$
- Gradient of loss function:

$$\frac{\partial \mathcal{L}}{\partial \theta} = \sum_{\mathbf{u}} \frac{\partial \mathcal{L}}{\partial \hat{\mathbf{I}}_{\mathbf{u}}} \cdot \frac{\partial \hat{\mathbf{I}}_{\mathbf{u}}}{\partial \theta}$$

$$\frac{\partial \hat{\mathbf{I}}_{\mathbf{u}}}{\partial \theta} = \frac{\partial \mathbf{t}_\theta(\hat{\mathbf{p}})}{\partial \theta} + \frac{\partial \mathbf{t}_\theta(\hat{\mathbf{p}})}{\partial \hat{\mathbf{p}}} \cdot \frac{\partial \hat{\mathbf{p}}}{\partial \theta}$$

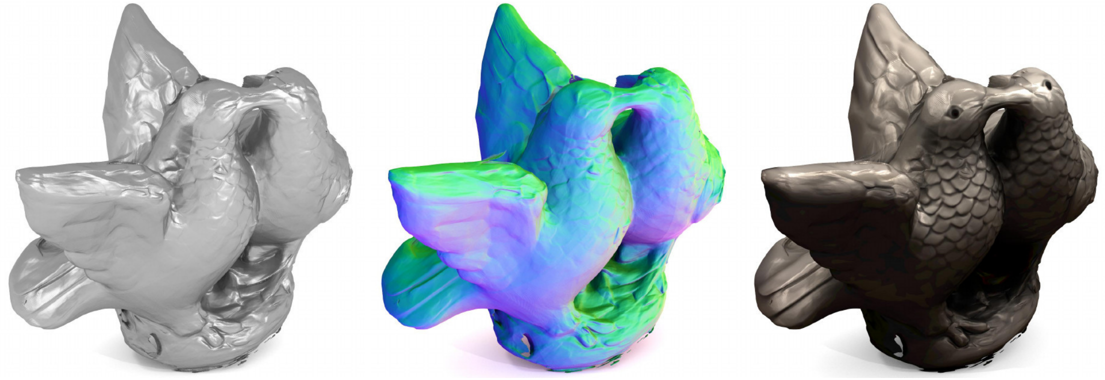
- Differentiation of $f_\theta(\hat{\mathbf{p}}) = \tau$ yields:

$$\frac{\partial \hat{\mathbf{p}}}{\partial \theta} = -\mathbf{w} \left(\frac{\partial f_\theta(\hat{\mathbf{p}})}{\partial \hat{\mathbf{p}}} \cdot \mathbf{w} \right)^{-1} \frac{\partial f_\theta(\hat{\mathbf{p}})}{\partial \theta}$$



$\Rightarrow$ **Analytic solution** and **no need** for storing **intermediate results**

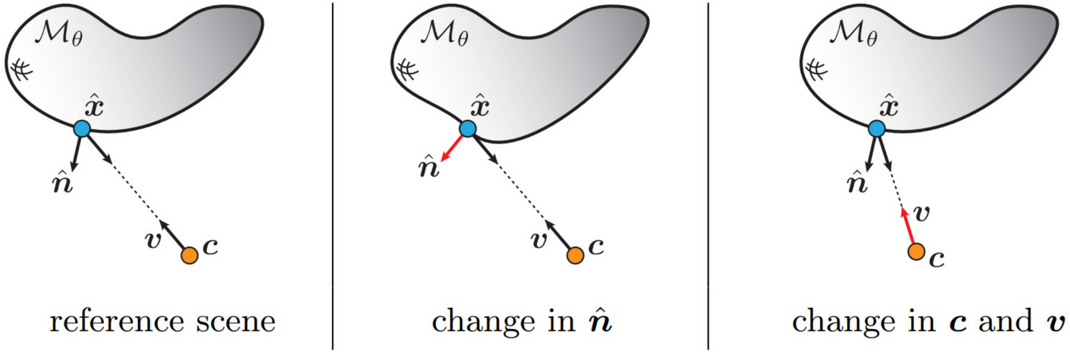
Results



Niemeyer, Mescheder, Oechsle and Geiger: Differentiable Volumetric Rendering: Learning Implicit 3D Representations without 3D Supervision. CVPR, 2020.

Very Recent Results

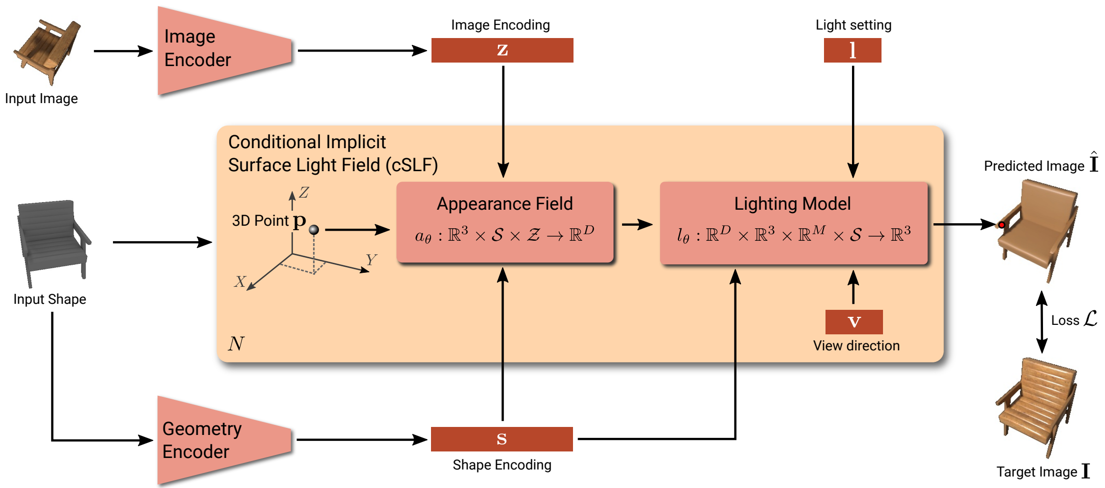
Universal Differentiable Renderer for Implicit Neural Representations



$$L(\hat{\boldsymbol{x}}, \boldsymbol{w}^o) = L^e(\hat{\boldsymbol{x}}, \boldsymbol{w}^o) + \int_{\Omega} f^r(\hat{\boldsymbol{x}}, \hat{\boldsymbol{n}}, \boldsymbol{w}^i, \boldsymbol{w}^o) L^i(\hat{\boldsymbol{x}}, \boldsymbol{w}^i)(\hat{\boldsymbol{n}} \cdot \boldsymbol{w}^i)\, d\boldsymbol{w}^i$$

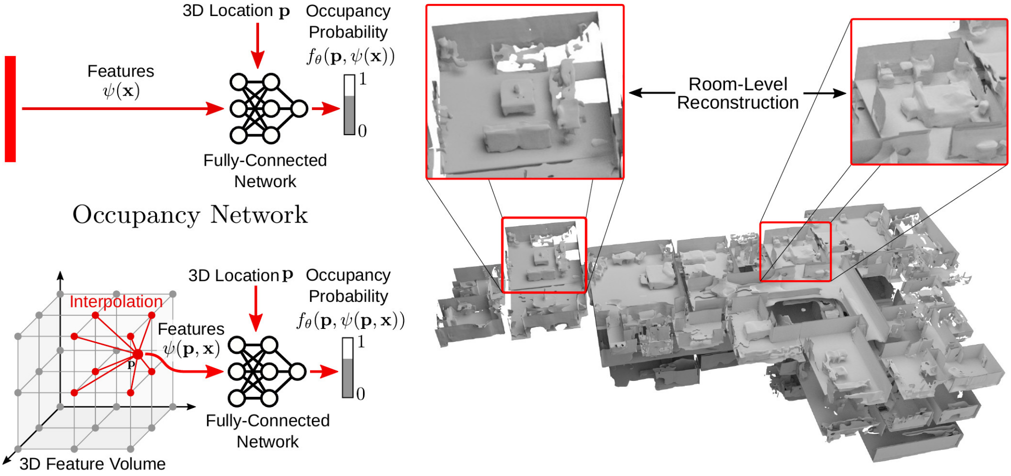
Yariv, Atzmon and Lipman: Universal Differentiable Renderer for Implicit Neural Representations. Arxiv, 2020.

Learning Implicit Surface Light Fields



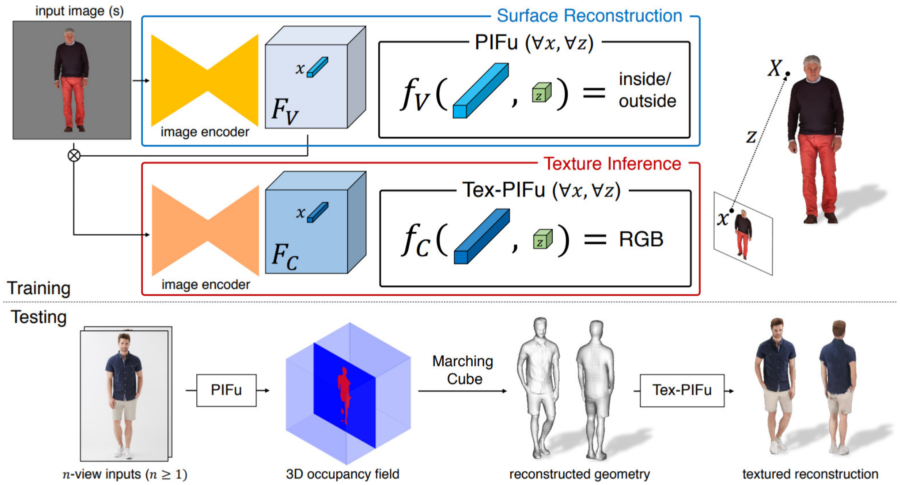
Oechsle, Niemeyer, Mescheder, Strauss and Geiger: Learning Implicit Surface Light Fields. Arxiv, 2020.

Convolutional Occupancy Networks



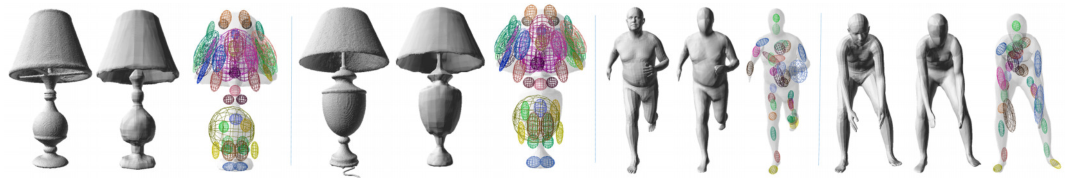
Reconstruction on Matterport3D [1]

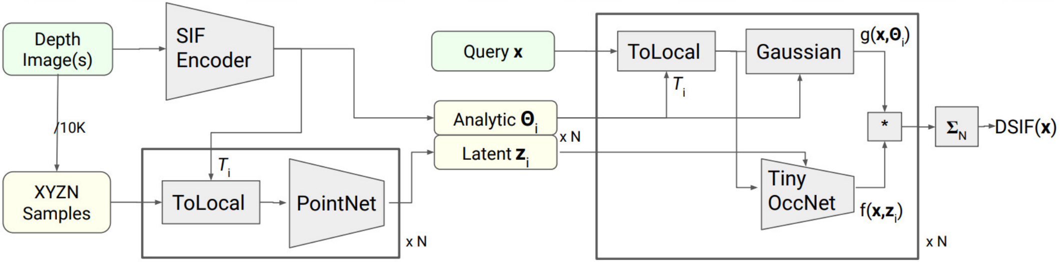
PIFu: Pixel-Aligned Implicit Function



Saito, Huang, Natsume, Morishima, Kanazawa and Li: PIFu: Pixel-Aligned Implicit Function for High-Resolution Clothed Human Digitization. ICCV, 2019.

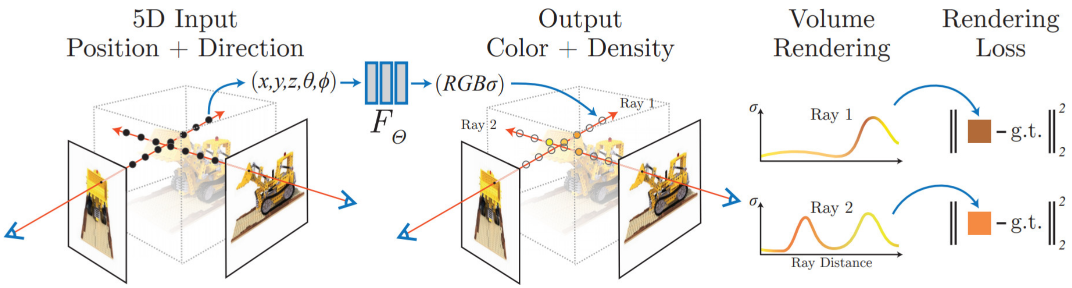
Deep Structured Implicit Functions





Genova, Cole, Sud, Sarna and Funkhouser: Deep Structured Implicit Functions. CVPR, 2020.

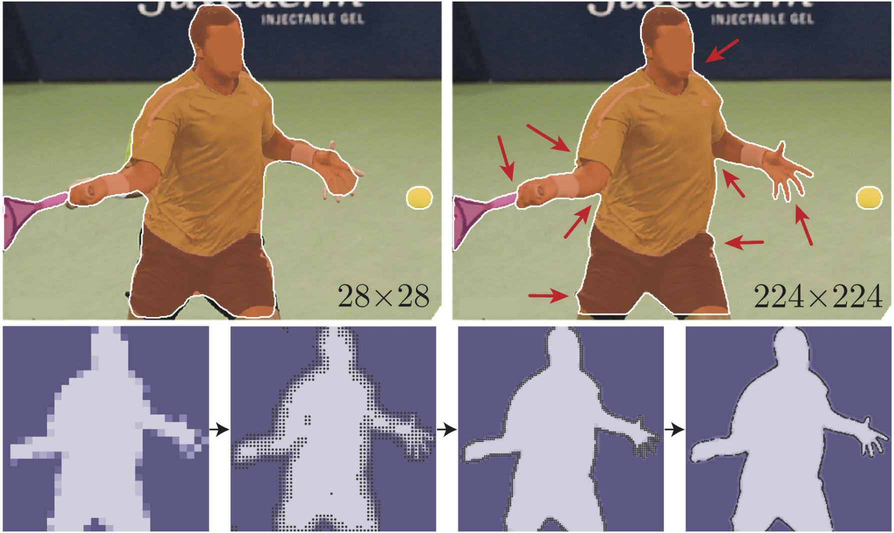
NeRF: Representing Scenes as Neural Radiance Fields



$$C(\mathbf{r}) = \int_{t_n}^{t_f} \underbrace{\exp\left(-\int_{t_n}^{t_f} \sigma(\mathbf{r}(s))ds\right)}_{\text{Transmittance}} \underbrace{\sigma(\mathbf{r}(t))}_{\text{Density}} \underbrace{\mathbf{c}(\mathbf{r}(t),\mathbf{d})}_{\text{Color}} dt$$

Midenhall, Srinivasan, Tancik, Barron, Ramamoorthi and Ng: NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. Arxiv, 2020.

PointRend: Image Segmentation as Rendering



Kirillov, Wu, He and Girshick: PointRend: Image Segmentation as Rendering. CVPR, 2020.

Take-Home Messages

Take-Home Messages

Neural Implicit Models:

- Effective output representation for shape, appearance, material, motion, etc.
- No discretization, model arbitrary topology
- Can be learned from images via differentiable rendering
- Many applications: reconstruction, view synthesis, segmentation, etc.

However:

- Geometry must be extracted in post-processing step (3 sec for ONet)
- Extension to 4D not straightforward (curse of dimensionality)
- Fully connected architecture and global condition lead to oversmooth results
- Promising: Local features (ConvONet, PiFU), Better input encoding (NeRF)

Thank you!

http://autonomousvision.github.io

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