Occupancy Networks: Learning 3D Reconstruction in Function Space

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Differentiable Volumetric Rendering: Learning Implicit 3D Representations without 3D Supervision

[Niemeyer, Mescheder, Oechsle & Geiger, In Review]

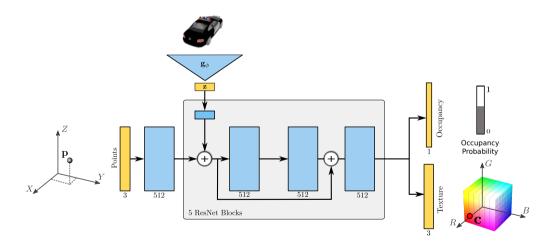








Architecture

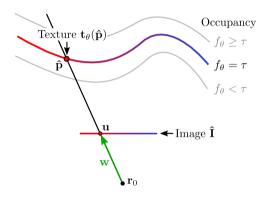


Forward Pass (Rendering)

Differentiable Volumetric Rendering

Forward Pass:

- ► For all pixels **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

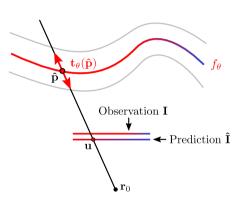
Backward Pass:

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

$$\begin{array}{lcl} \frac{\partial \mathcal{L}}{\partial \theta} & = & \displaystyle \sum_{\mathbf{u}} \frac{\partial \mathcal{L}}{\partial \hat{\mathbf{l}}_{\mathbf{u}}} \cdot \frac{\partial \hat{\mathbf{l}}_{\mathbf{u}}}{\partial \theta} \\ \\ \frac{\partial \hat{\mathbf{l}}_{\mathbf{u}}}{\partial \theta} & = & \displaystyle \frac{\partial \mathbf{t}_{\theta}(\hat{\mathbf{p}})}{\partial \theta} + \frac{\partial \mathbf{t}_{\theta}(\hat{\mathbf{p}})}{\partial \hat{\mathbf{p}}} \cdot \frac{\partial \hat{\mathbf{p}}}{\partial \theta} \end{array}$$

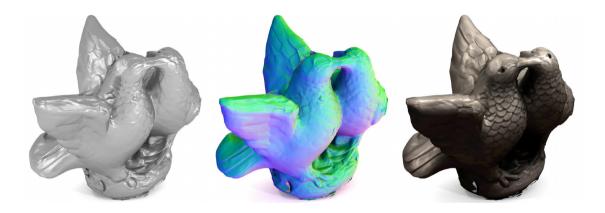
▶ Differentiation of $f_{\theta}(\hat{\mathbf{p}}) = \tau$ yields:

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



⇒ Analytic solution and no need for storing intermediate results

Results



Thank you!

http://autonomousvision.github.io











