

NeRF in the Wild Neural Radiance Fields for Unconstrained Photo Collections, CVPR 2021 (Oral)

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5D Input





Learns both density and emitted radiance simultaneously





















Constrained camera motion



Static environment lighting





Photos. Photos. Photos.

What if we can train NeRF to learn the scene representation of certain place, so that we can freely move around in the reconstructed scene?



Structure from Motion + Multi View Stereo = 3D Model

Image: Building Rome in a Day, Agarwal et al., ICCV 2010

Back in 2010...















Photometric variation

Time of day & atmospheric conditions directly impact the illumination



Photometric variation

Time of day & atmospheric conditions directly impact the illumination

Transient objects

Real-world landmarks are usually occluded by other objects

cf. landmark(s) = static object(s)

 $\ell^{(a)}$

appearance embedding

 $\theta \phi$

viewing direction

XYZ position



 $\ell^{(\tau)}$

transient embedding

Three, instead of one





Generative Latent Optimization (GLO)

 $\{\ell_i^{(a)} | i = 1, ..., N\}$

Real-valued appearance embedding vector

Allows radiance fields to have different color values for different images









Models the appearance of the static object

Interpolation between learned embeddings

Intuition: Image Compositing

Intuition: Image Compositing

Image: https://graphicdesign.stackexchange.com/questions/27507/how-can-i-create-and-batch-this-3d-planes-effect

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Toggle visibility of that layer!

 $\hat{\mathbf{C}}_{i}(\mathbf{r}) = \sum_{k=1}^{n} T_{i}(t_{k}) \Big(\alpha(\sigma(t_{k})\delta_{k})\mathbf{c}_{i}(t_{k}) + \alpha\Big(\sigma_{i}^{(\tau)}(t_{k})\delta_{k}\Big)\mathbf{c}_{i}^{(\tau)}(t_{k}) \Big)$ k=1

where $T_i(t_k) = \exp\left(-\sum_{k'=1}^{k-1} \left(\sigma(t_{k'}) + \sigma_i^{(\tau)}(t_{k'})\right)\delta_{k'}\right)$

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Static radiance field

Static object density

"alpha compositing"

 $\hat{\mathbf{C}}_{i}(\mathbf{r}) = \sum_{k=1}^{n} T_{i}(t_{k}) \Big(\alpha(\sigma(t_{k})\delta_{k})\mathbf{c}_{i}(t_{k}) + \alpha \Big(\sigma_{i}^{(\tau)}(t_{k})\delta_{k}\Big)\mathbf{c}_{i}^{(\tau)}(t_{k}) \Big)$ ald Transient radiance field

Transient object density

(a) Static

 $\mathbf{c}_i(t)$ $\sigma(t)$

(b) Transient

(c) Composite

 $\mathbf{c}_{i}^{(\tau)}(t)$ $\sigma^{(au)}(t)$

 $\alpha(\sigma(\cdot))\mathbf{c}_i + \alpha(\sigma^{(\tau)}(\cdot))\mathbf{c}_i^{(\tau)}$

Transient embeddings $\{\mathcal{C}_{i}^{(\tau)}\}_{i=1}^{N}$

are learned just like appearance embeddings

These embeddings are then decoded to:

- 1. RGB color
- 2. Density
- of transient components

(a) Static

(b) Transient

Just like NeRF, network parameters are optimized by minimizing the pixel-wise distance

(c) Composite

(d) Image

(a) Static

(b) Transient

To get nice and clear image of the landmark, render static image only!

Network for modeling appearance of static object

Network for modeling appearance of static object

Network for modeling density (i.e., geometry) of a scene

Network for modeling appearance of static object

Network for modeling density (i.e., geometry) of a scene

Network for modeling appearance of transient object(s)

Experimental Results

Old Town Square Braue, Czech Fepublic

Generative Latent Optimization (GLO)

Disentangled Scene Representation (Static / Transient)

Thank You