
Continuous 3D Scene Representations with Implicit Functions

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ENPC's Imagine Seminars 16/12/2020

Outline

- I. Implicit functions: an illustration with 3D surface representation**
- 2. Neural Radiance Field (NeRF)**

Explicit vs Implicit Representation (2D)

Explicit:

$$\mathbf{f}(\alpha) = (r \cos(\alpha), r \sin(\alpha))^T$$

Domain: $[0, 2\pi]$

Implicit:

$$F(x, y) = \sqrt{x^2 + y^2} - r$$

Domain: $(x, y) \in \mathbb{R}^2$

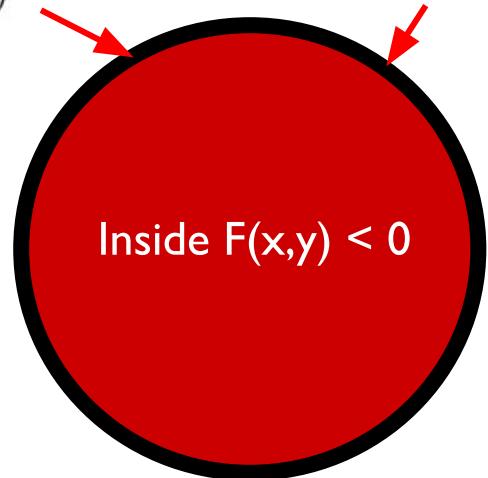
\implies Circle is implicitly defined by $\{(x, y) | F(x, y) = 0\}$

$\mathbf{f}(\alpha)$ defines the interface

$F(x, y)$ defines the **Signed Distance Function** of the circle

$$\mathbf{f}([0, 2\pi])$$

$$\text{Interface } F(x, y) = 0$$



$$\text{Outside } F(x, y) > 0$$

Explicit vs Implicit Representation (3D)

Explicit:

$$\mathbf{f}(\alpha, \beta) = (r \sin(\alpha) \cos(\beta), -r \cos(\alpha) \sin(\beta), r \sin(\alpha) \sin(\beta))$$

Domain: $\alpha \in [0; 2\pi], \beta \in [0; \pi]$

Implicit:

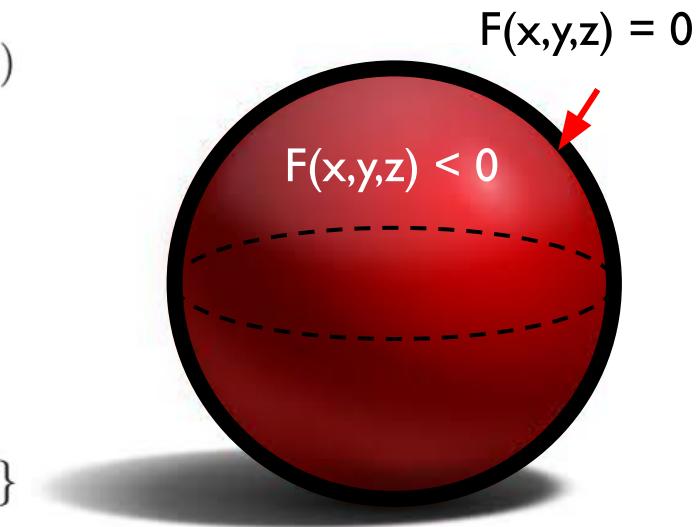
$$F(x, y, z) = \sqrt{x^2 + y^2 + z^2} - r$$

Domain: $(x, y, z) \in \mathbb{R}^3$

\implies Sphere is implicitly defined by $\{(x, y, z) | F(x, y, z) = 0\}$

$\mathbf{f}(\alpha, \beta)$ defines the 3D surface

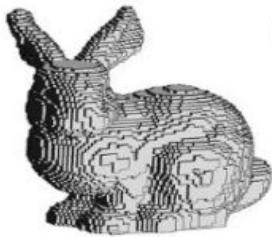
$F(x, y, z)$ defines the **Signed Distance Function** of the sphere



$$F(x, y, z) > 0$$

Representing 3D surfaces

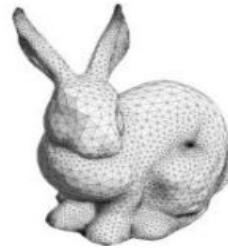
Explicit:



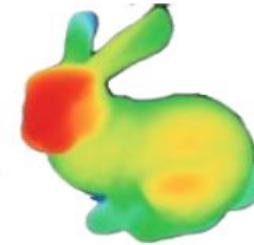
Voxels



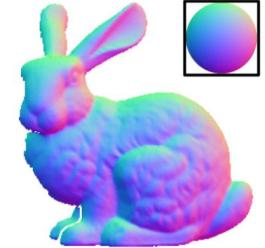
Point clouds



Mesh

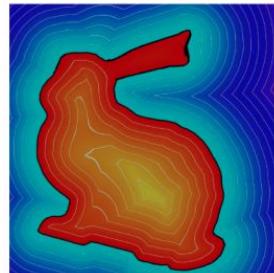


Depth



Surface Normals

Implicit:



Signed distance field



Mixture of primitives
(e.g gaussian mixtures)

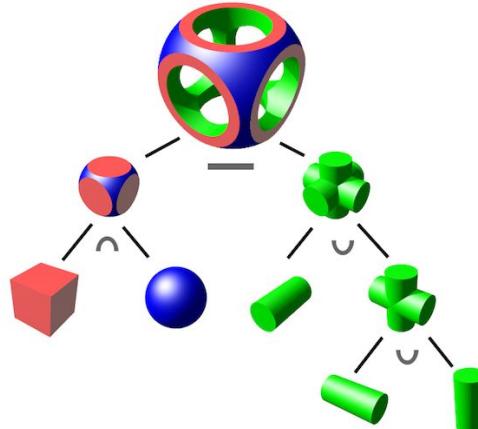
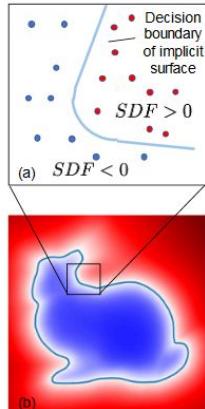
Thomas Funkhouser's talk at 3DGV seminar

Signed Distance Field (SDF)

- Maps each 3D points p to its signed distance from to the object surface S

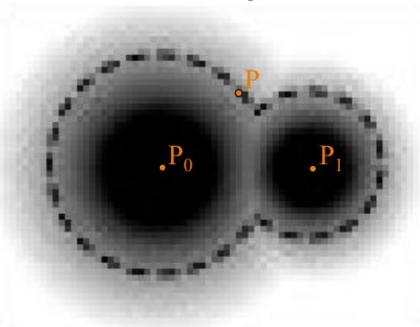
$$SDF(p) = \text{sign}(p) \cdot \min_{q \in S} \|p - q\|$$

- Sign indicates whether the point p is inside (-) or outside (+) of the shape
- Shape's boundary as the zero-level-set of SDF
- Allows for Constructive Solid Geometry (CSG) through boolean operations



Mixture of Gaussians

- Represents a shape as a mixture of local implicit functions (3D gaussians)



$$F(\mathbf{x}, \Theta) = \sum_{i \in [N]} f_i(\mathbf{x}, \theta_i)$$

$$f_i(\mathbf{x}, \theta_i) = c_i \exp \left(\sum_{d \in \{x, y, z\}} \frac{-(\mathbf{p}_{i,d} - \mathbf{x}_d)^2}{2\mathbf{r}_{i,d}^2} \right)$$

- Shape's boundary is defined as an iso-level of the **global** implicit function



[1] Genova19
[2] Genova20

Representing 3D surfaces with Implicit Functions

Pros:

- Compared to **point clouds**: clearly defines the (iso-)surface
- Compared to **meshes**: can continuously adapt to arbitrary topology
- Compared to **voxels**: can be represented with **few parameters** (e.g. mixture of simple implicit functions)
- They are **continuous** in 3D
- Can give analytic normals, can be applied with boolean operations, etc

Representing 3D surfaces with Implicit Functions

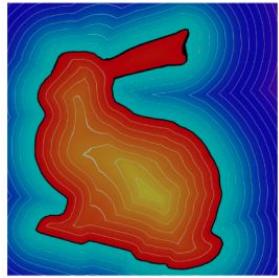
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Cons:

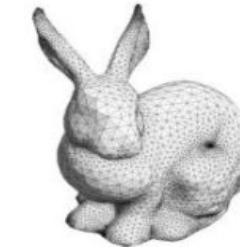
- SDF is well-defined for only watertight meshes (there is an interior and an exterior)
- Need extra steps to visualize

Converting Implicit Surfaces to meshes



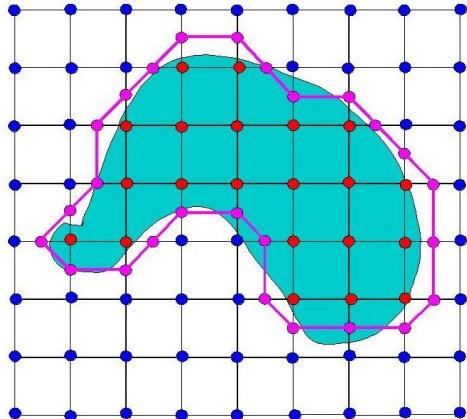
Implicit function

Extract (zero-level) iso-surface

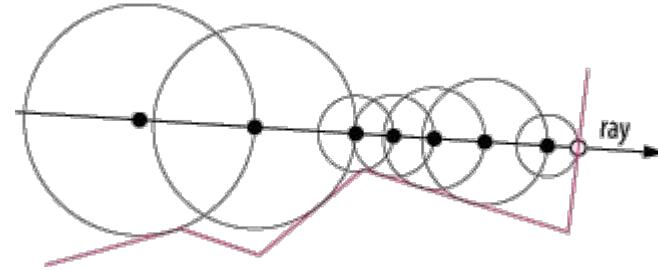


Mesh

Marching Cubes



Ray marching



Representing 3D surfaces with Implicit Functions

Pros:

- Compared to **point clouds**: clearly defines the (iso-)surface
- Compared to **meshes**: can continuously **adapt to arbitrary topology**
- Compared to **voxels**: can be represented with few parameters (e.g. mixture of simple implicit functions)
- They are **continuous** in 3D
- Can give analytic normals, can be applied with boolean operations, etc

Cons:

- Implicit functions is well-defined for only watertight meshes (there is an interior and an exterior)
- Need extra steps to visualize
- Not all complex shapes can be efficiently / accurately represented with simple primitives

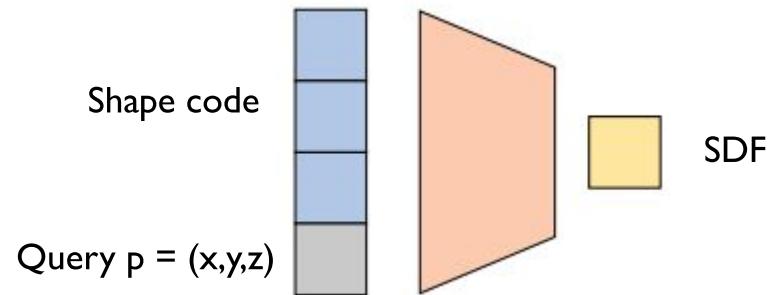
Representing 3D surfaces

DeepSDF: Efficiently representing complex shapes by learning their SDF

Idea: Learn a **continuous** representation of 3D implicit surfaces

Query $p = (x, y, z)$, Shape latent code \mathbf{Z}

$$F(p; \mathbf{Z}) = \text{SDF}(p, \mathcal{M})$$

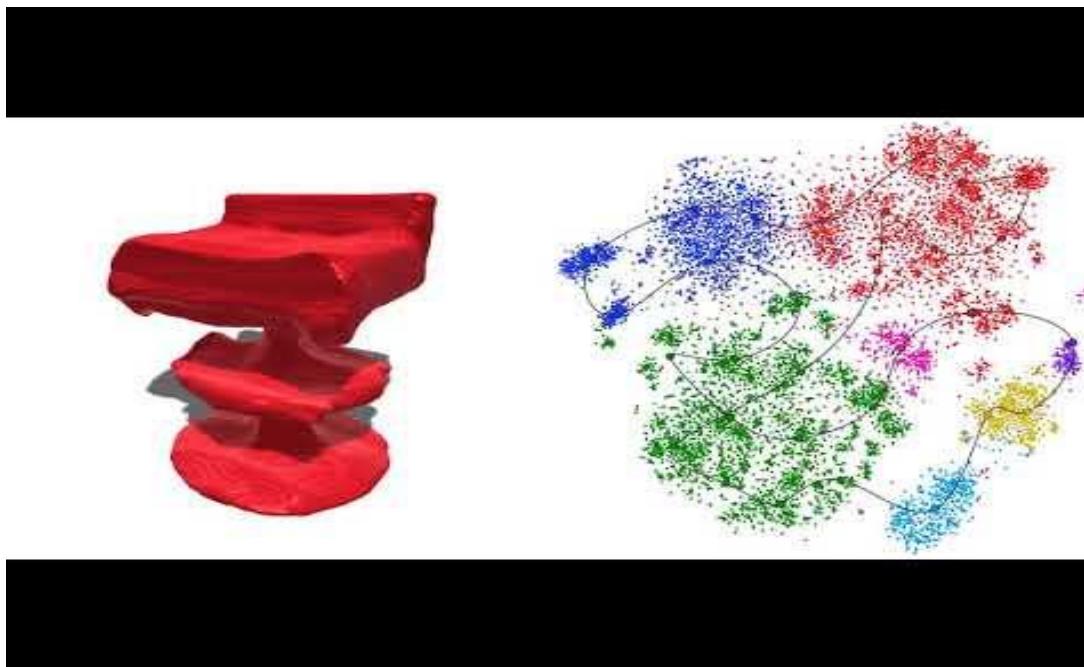


=> **Continuity** in 3D space AND shapes space

[3] Park19

Representing 3D surfaces

DeepSDF: Representing complex shapes by learning their SDF

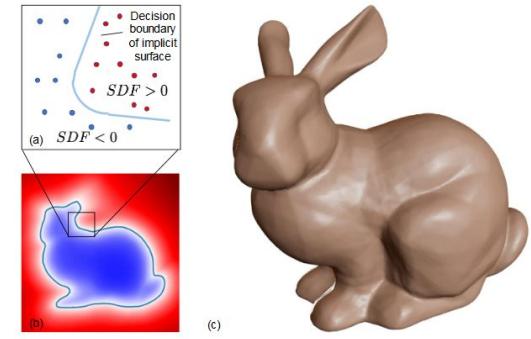


Take home message on Implicit Functions

Representation of a continuous field

Learned implicit functions:

- Can represent complex shapes
- Are **continuous mappings** because they use **MLPs**
- Are applicable to N-D data: 2D images, 3D shapes, radiance fields

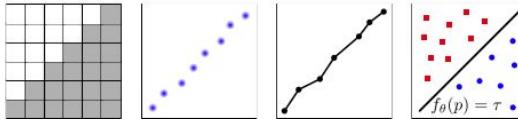


Visualization of implicit functions is done by extracting iso-surfaces:

1. Running inference for multiple queries in input space
2. Rendering the result by combining the queries

More works on Implicit Functions for 3D shape

- Occupancy Networks



[4] Mescheder19



- PiFu and PiFuHD



[5] Saito19

[6] Saito20

References

- [1] Genova et al., [Learning Shape Templates with Structured Implicit Functions](#), ICCV 2019
- [2] Genova et al., [Local Deep Implicit Functions for 3D Shape](#), CVPR 2020
- [3] Park et al., [DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation](#), CVPR 2019
- [4] Mescheder et al., [Occupancy Networks: Learning 3D Reconstruction in Function Space](#), CVPR 2019
- [5] Saito, Huang, Natsume et al., PIFu: [Pixel-Aligned Implicit Function for High-Resolution Clothed Human Digitization](#), ICCV 2019
- [6] Saito et al., [PIFuHD: Multi-Level Pixel-Aligned Implicit Function for High-Resolution 3D Human Digitization](#), CVPR 2020

Courses and Seminars

Lecture on [Implicit geometry](#)

Lecture on [Implicit surface](#)

Lecture on [Explicit & Implicit Surfaces](#)

[Thomas Funkhouser's talk](#) at 3DGV seminar

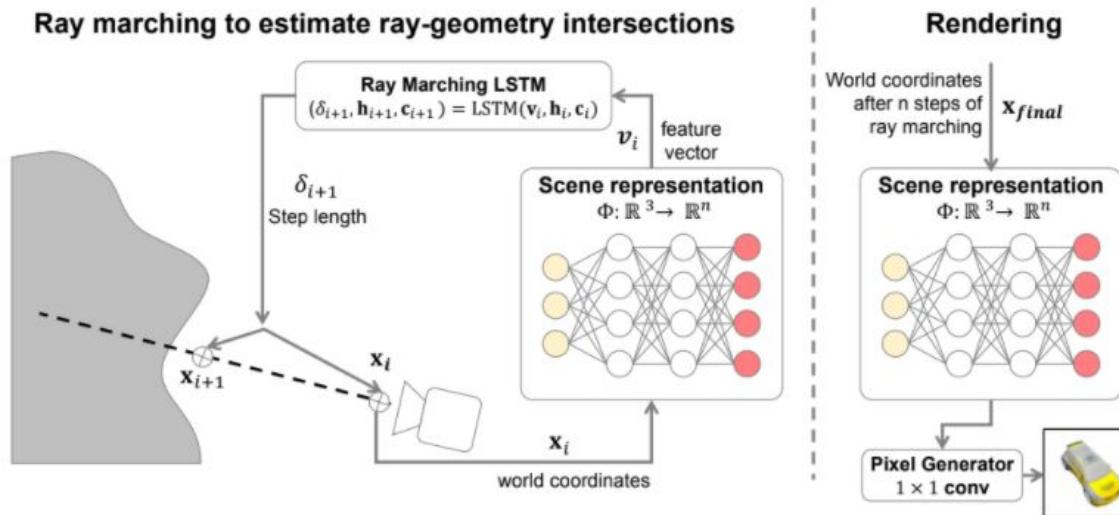
Princeton COS 426, Spring 2014 on [Implicit Surfaces & Solid Representations](#)

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- I. Implicit functions: an illustration with 3D surface representation
2. Neural Radiance Field (**NeRF**)

Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations

- One of the first relevant works on scene **geometry and appearance** representation, also benchmark for most of NeRF's paper



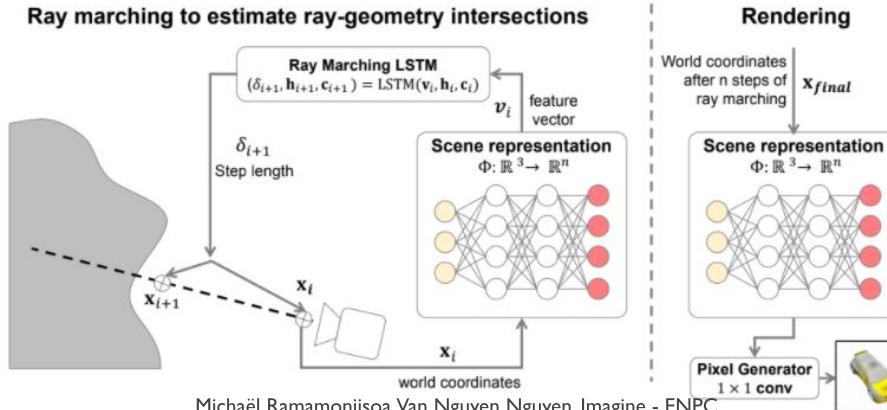
[7] Sitzmann | 9

Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations

- Represent a scene as a function Φ which maps a spatial location x to a feature representation v

$$\Phi : \mathbb{R}^3 \rightarrow \mathbb{R}^n, \quad x \mapsto \Phi(x) = v.$$

- v may encode:
 - visual information: **surface color** or reflectance
 - geometry: signed distance of x
- Then learn a differentiable renderer to render v (using LSTM)



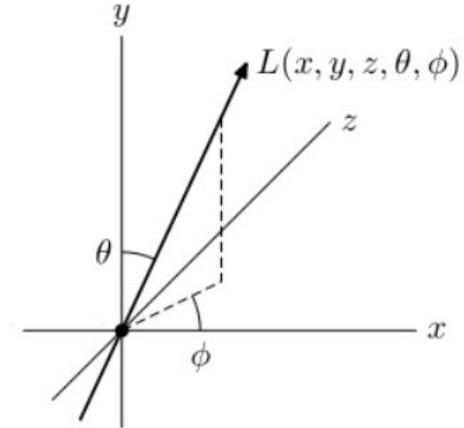
[7] Sitzmann | 9

Definition of radiance field

- Radiance field is a 5-dimensional function which maps a 3D location \underline{x} and a direction in 3D sphere \underline{d} to a color (r, g, b) :

$$L : \mathbb{R}^3 \times S^2 \rightarrow \mathbb{R}^3$$

$$L(\underline{x}, \underline{d}) = (r, g, b)$$

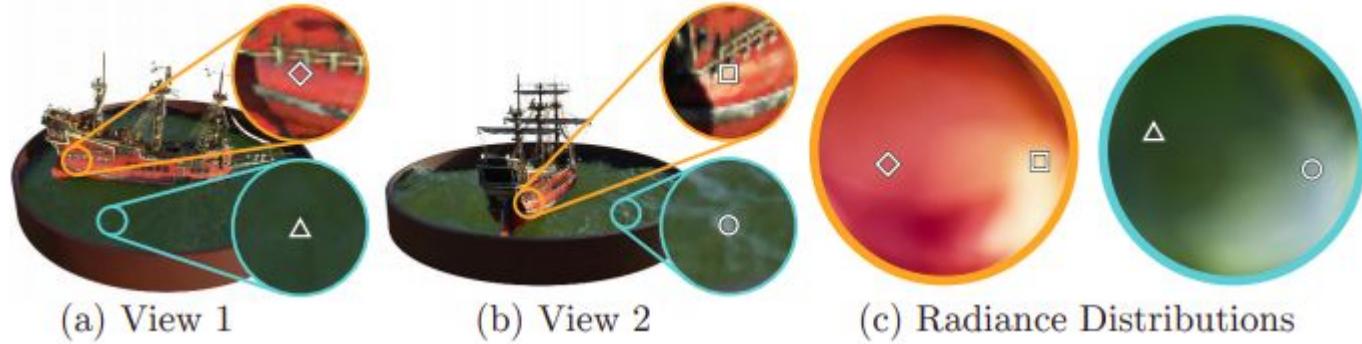


- Intuitively, “radiance” is the amount of light energy passing through a given point in space, heading in a given direction
- In NeRF, there is an additional output is volume density $\sigma \in \mathbb{R}$

$$L(\underline{x}, \underline{d}) = (r, g, b, \sigma)$$

Definition of radiance field

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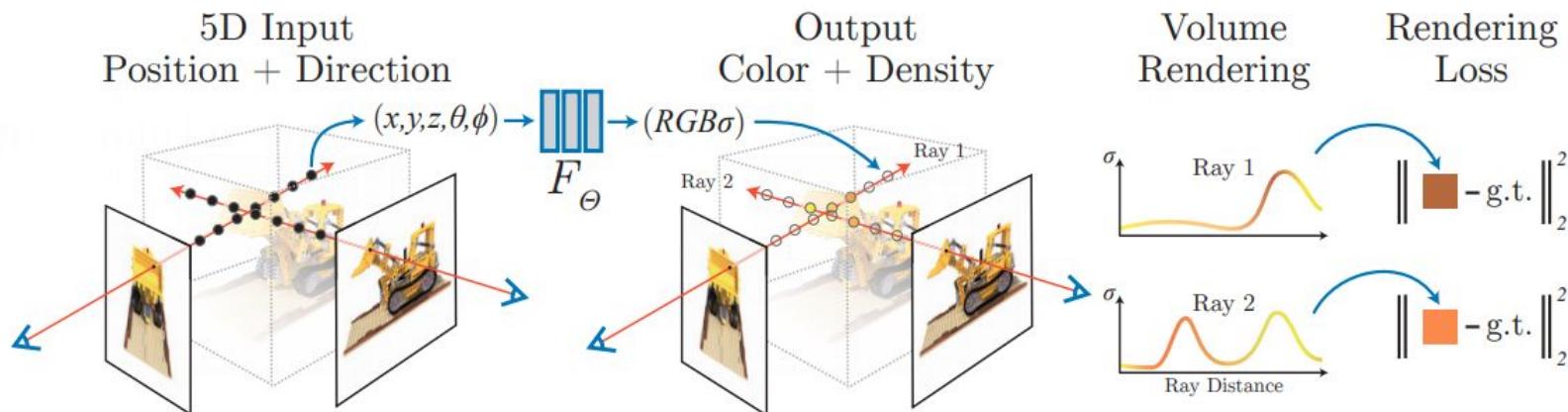
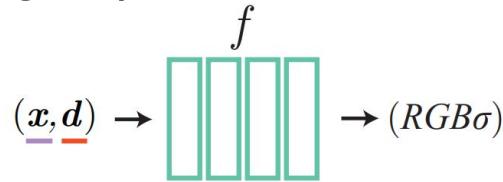


[8] Mildenhall20

Neural Radiance field (NeRF)

Idea:

- Continuous neural networks as a view-dependent volumetric scene representation ($xyz +$ view direction d)
- Using volumetric rendering to synthesize new views



Neural Radiance field (NeRF)

Volumetric rendering with ray tracing:

$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t) \sigma(\mathbf{r}(t)) \mathbf{c}(\mathbf{r}(t), \mathbf{d}) dt, \text{ where } T(t) = \exp\left(-\int_{t_n}^t \sigma(\mathbf{r}(s)) ds\right)$$

Opacity Predicted colors
 ↓
 Volume density

Rendering model for ray $\mathbf{r}(t) = \mathbf{o} + \mathbf{td}$:

$$C \approx \sum_{i=1}^N T_i \alpha_i c_i$$

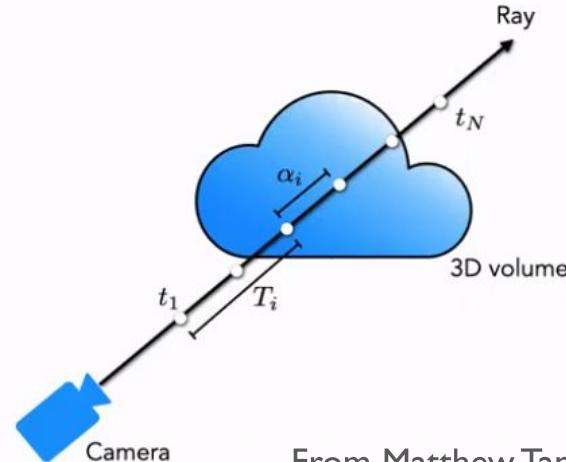
↓
 colors
 ↓
 Opacity

How much light is blocked earlier along ray:

$$T_i = \prod_{j=1}^{i-1} (1 - \alpha_j)$$

How much light is contributed by ray segment i :

$$\alpha_i = 1 - e^{-\sigma_i \delta t_i}$$



From Matthew Tancik @Tübingen AVG
[8] Mildenhall20

Neural Radiance field (NeRF)

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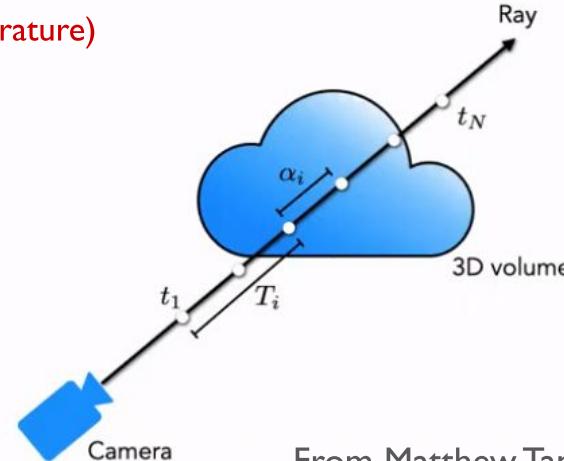
Opacity Predicted colors
Volume density

Rendering model for ray $\mathbf{r}(t) = \mathbf{o} + \mathbf{td}$:

$$C \approx \sum_{i=1}^N T_i \alpha_i c_i$$

colors
Opacity

(approximation with numerical quadrature)



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Opacity Predicted colors
 Volume density

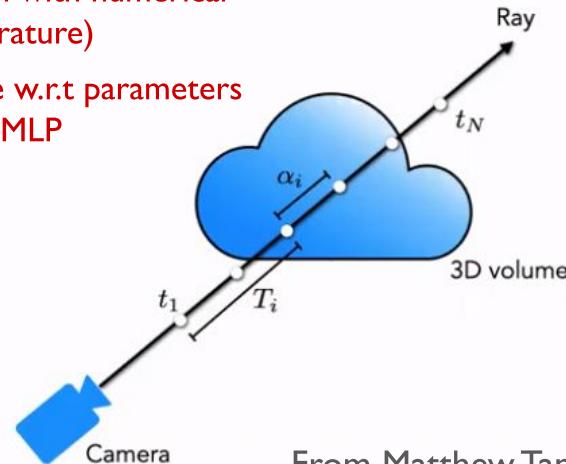
Rendering model for ray $\mathbf{r}(t) = \mathbf{o} + \mathbf{td}$:

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Opacity colors

(approximation with numerical quadrature)

-> differentiable w.r.t parameters of MLP



How much light is blocked earlier along ray:

$$T_i = \prod_{j=1}^{i-1} (1 - \alpha_j)$$

How much light is contributed by ray segment i :

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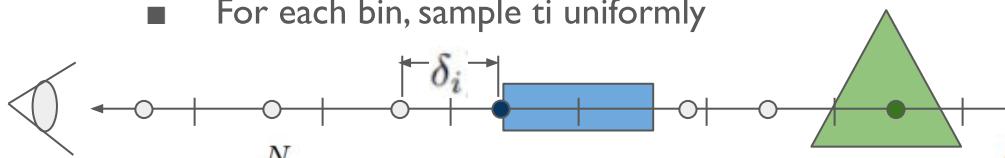
From Matthew Tancik @Tübingen AVG
[8] Mildenhall20

Neural Radiance field (NeRF)

Tricks:

- **Hierarchical Sampling: coarse to fine importance sampling**

- First sample coarsely along the ray with stratified sampling
 - Create N_c bins between t_n and t_f
 - For each bin, sample t_i uniformly

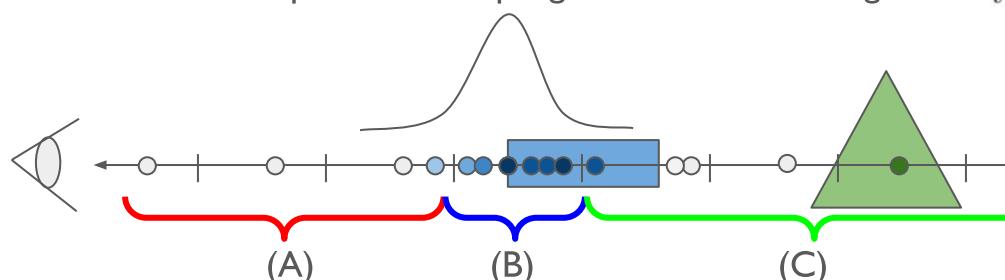


(Ray-)Volume rendering

$$\hat{C}(\mathbf{r}) = \sum_{i=1}^N T_i (1 - \exp(-\sigma_i \delta_i)) \mathbf{c}_i, \text{ where } T_i = \exp\left(-\sum_{j=1}^{i-1} \sigma_j \delta_j\right)$$

\mathbf{w}_i

- Then do importance sampling based on color weight \mathbf{w}_i



(A) $T_i \approx 1, \sigma_i \approx 0$
 $\mathbf{w}_i \approx 0$

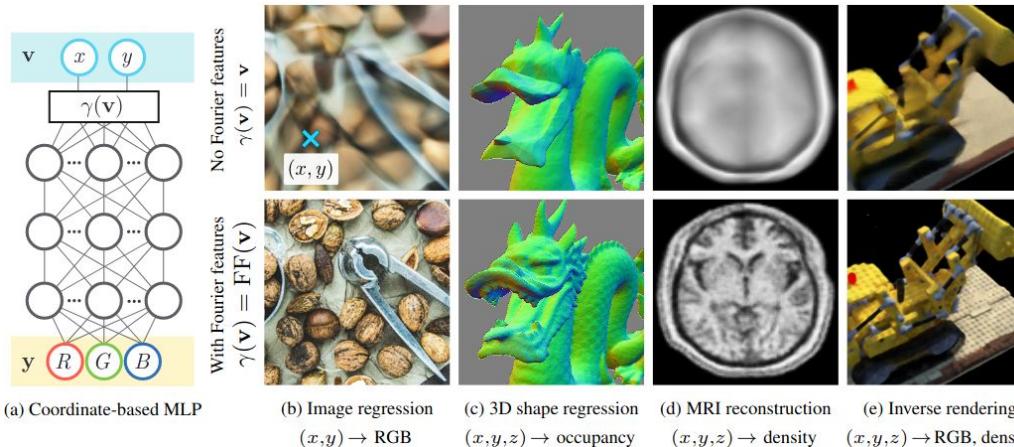
(B) $T_i > 0, \sigma_i > 0$
 $\mathbf{w}_i > 0$

(C) $T_i \approx 0 \quad \mathbf{w}_i \approx 0$

Neural Radiance field (NeRF)

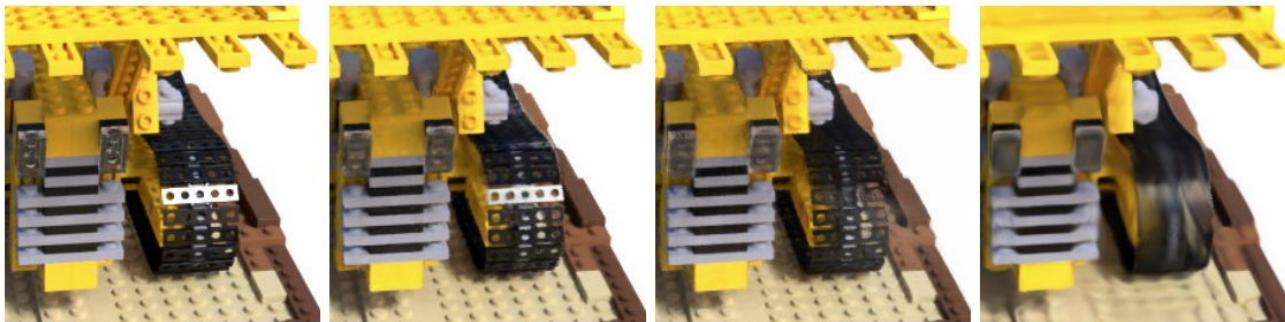
Tricks:

- **Positional encoding** to map each input 5D coordinate into a higher dimensional space
 - Learning in high-frequency mappings is difficult to learn
$$\gamma(p) = (\sin(2^0\pi p), \cos(2^0\pi p), \dots, \sin(2^{L-1}\pi p), \cos(2^{L-1}\pi p))$$
 - Fourier Basis feature mapping allocates neurons to different spatial frequency bands (frequency disentangling)



Neural Radiance field (NeRF)

| | Input | #Im. | L | (N_c , N_f) | PSNR↑ | SSIM↑ | LPIPS↓ |
|-----------------------|-----------------|------|-----|-------------------|--------------|--------------|--------------|
| 1) No PE, VD, H | xyz | 100 | - | (256, -) | 26.67 | 0.906 | 0.136 |
| 2) No Pos. Encoding | $xyz\theta\phi$ | 100 | - | (64, 128) | 28.77 | 0.924 | 0.108 |
| 3) No View Dependence | xyz | 100 | 10 | (64, 128) | 27.66 | 0.925 | 0.117 |
| 4) No Hierarchical | $xyz\theta\phi$ | 100 | 10 | (256, -) | 30.06 | 0.938 | 0.109 |
| 5) Far Fewer Images | $xyz\theta\phi$ | 25 | 10 | (64, 128) | 27.78 | 0.925 | 0.107 |
| 6) Fewer Images | $xyz\theta\phi$ | 50 | 10 | (64, 128) | 29.79 | 0.940 | 0.096 |
| 7) Fewer Frequencies | $xyz\theta\phi$ | 100 | 5 | (64, 128) | 30.59 | 0.944 | 0.088 |
| 8) More Frequencies | $xyz\theta\phi$ | 100 | 15 | (64, 128) | 30.81 | 0.946 | 0.096 |
| 9) Complete Model | $xyz\theta\phi$ | 100 | 10 | (64, 128) | 31.01 | 0.947 | 0.081 |



Ground Truth Complete Model No View Dependence No Positional Encoding

| Method | Diffuse Synthetic 360° [41] | | | Realistic Synthetic 360° | | | Real Forward-Facing [28] | | |
|-----------|-----------------------------|--------------|--------------|--------------------------|--------------|--------------|--------------------------|--------------|--------------|
| | PSNR↑ | SSIM↑ | LPIPS↓ | PSNR↑ | SSIM↑ | LPIPS↓ | PSNR↑ | SSIM↑ | LPIPS↓ |
| SRN [42] | 33.20 | 0.963 | 0.073 | 22.26 | 0.846 | 0.170 | 22.84 | 0.668 | 0.378 |
| NV [24] | 29.62 | 0.929 | 0.099 | 26.05 | 0.893 | 0.160 | - | - | - |
| LLFF [28] | 34.38 | 0.985 | 0.048 | 24.88 | 0.911 | 0.114 | 24.13 | 0.798 | 0.212 |
| Ours | 40.15 | 0.991 | 0.023 | 31.01 | 0.947 | 0.081 | 26.50 | 0.811 | 0.250 |

[8] Mildenhall20

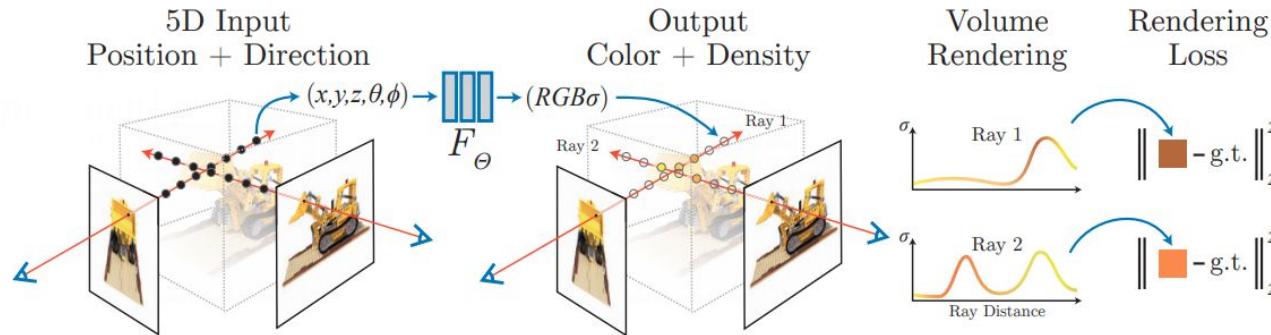
Neural Radiance field (NeRF)



[8] Mildenhall20

Neural Radiance field (NeRF)

NeRF in a nutshell:



- Learn the radiance field of a scene based on a collection of calibrated images
 - Use an MLP to learn continuous geometry and view-dependent appearance
- Use fully differentiable volume rendering with reconstruction loss
- Combines importance sampling and Fourier-basis encoding of 5D query to produce **high-fidelity novel view synthesis results**
- Allows efficient storage of scenes ($\times 3000$ gain over voxelized representations)

Neural Radiance field (NeRF)

Remaining challenges

- Handling dynamic scenes when acquiring calibrated views
- One network trained per scene - no generalization

Neural Radiance field (NeRF)

Remaining challenges

- Handling dynamic scenes when acquiring calibrated views
 - D-NeRF: Neural Radiance Fields for Dynamic Scenes
 - Deformable Neural Radiance Fields
- One network trained per scene - no generalization

D-NeRF: Neural Radiance Fields for Dynamic Scenes

NeRF

- Only applicable to rigid scenes
- 5D continuous function
- Requiring multiple views of a rigid scene



[12] Pumarola20

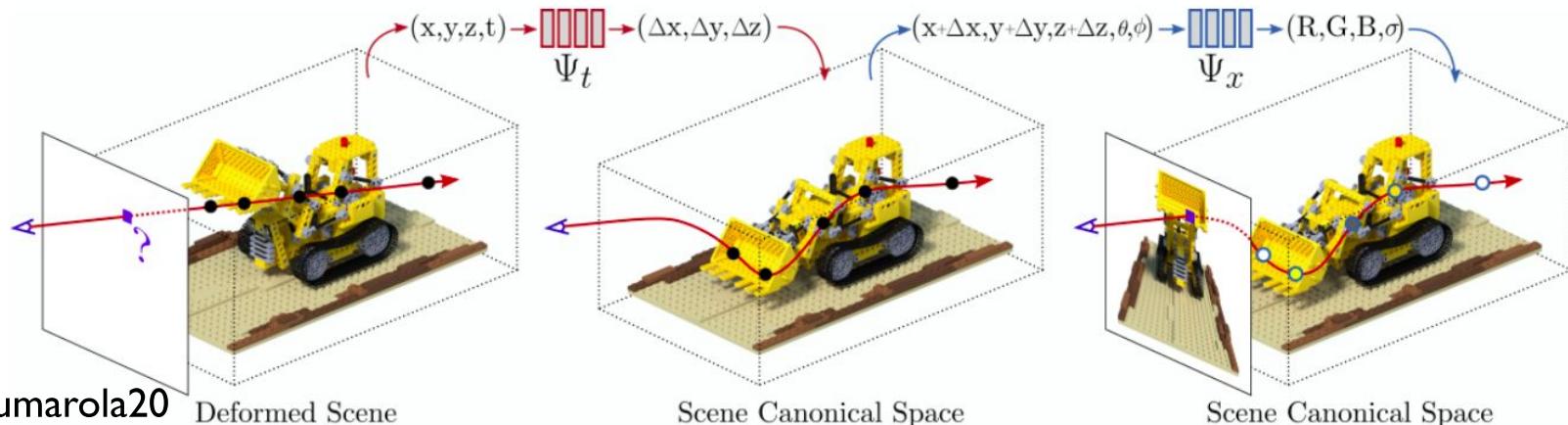
D-NeRF: Neural Radiance Fields for Dynamic Scenes

- **Deformation network** Ψ_t : to predict deformation field between the scene at time instant t and the scene in canonical space ($t=0$)

$$\Psi_t(\mathbf{x}, t) = \begin{cases} \Delta\mathbf{x}, & \text{if } t \neq 0 \\ 0, & \text{if } t = 0 \end{cases}$$

- **Canonical network** Ψ_x : to predict color and density in canonical configuration

$$\Psi_x(\mathbf{x}, \mathbf{d}) \mapsto (\mathbf{c}, \sigma)$$



[12] Pumarola20

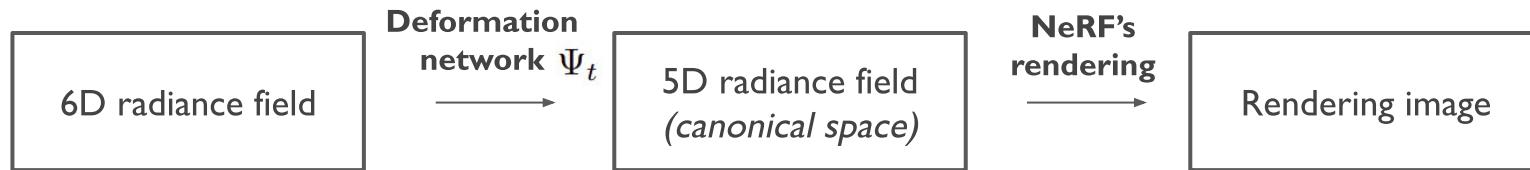
Deformed Scene

Scene Canonical Space

Scene Canonical Space

D-NeRF: Neural Radiance Fields for Dynamic Scenes

Volumetric rendering is the same as NeRF in **canonical space**:



$$C(p, t) = \int_{h_n}^{h_f} \mathcal{T}(h, t) \sigma(\mathbf{p}(h, t)) \mathbf{c}(\mathbf{p}(h, t), \mathbf{d}) dh$$

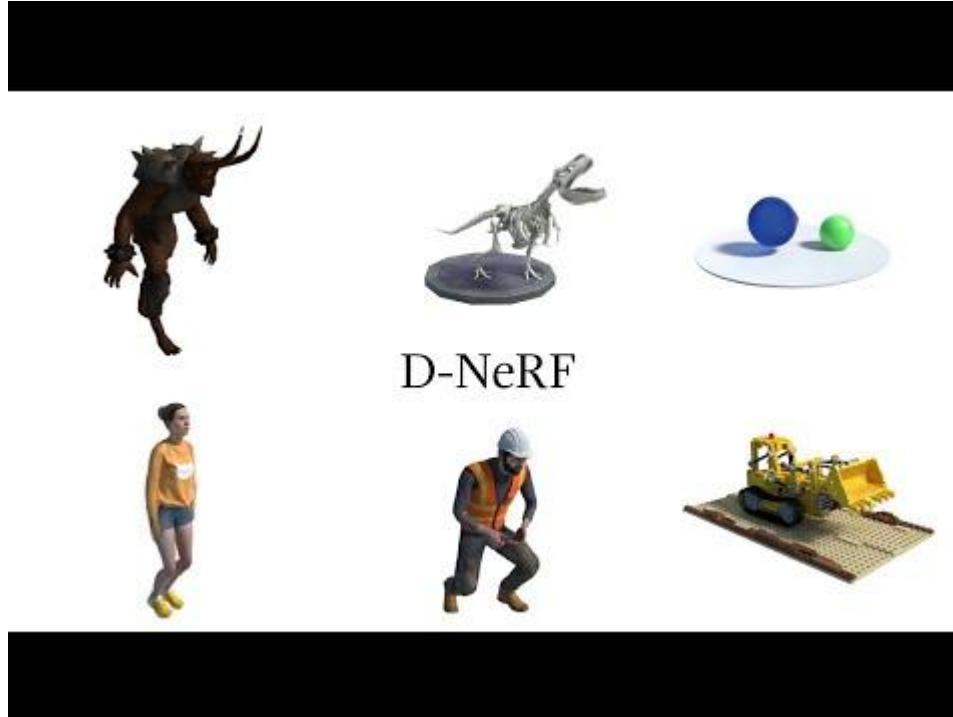
Opacity

Predicted colors

Volume density

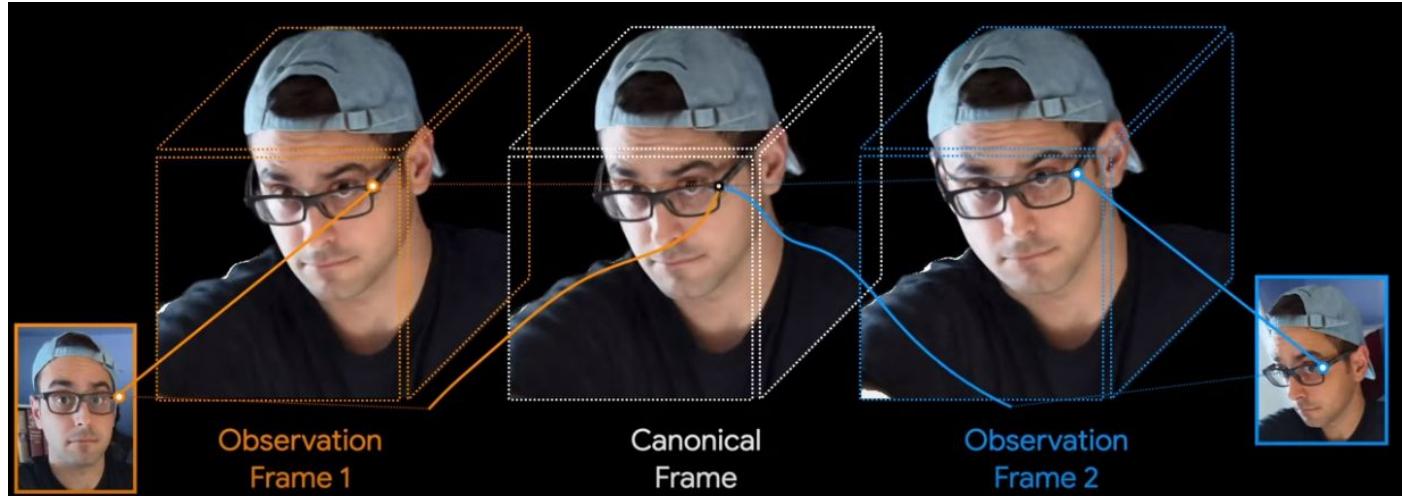
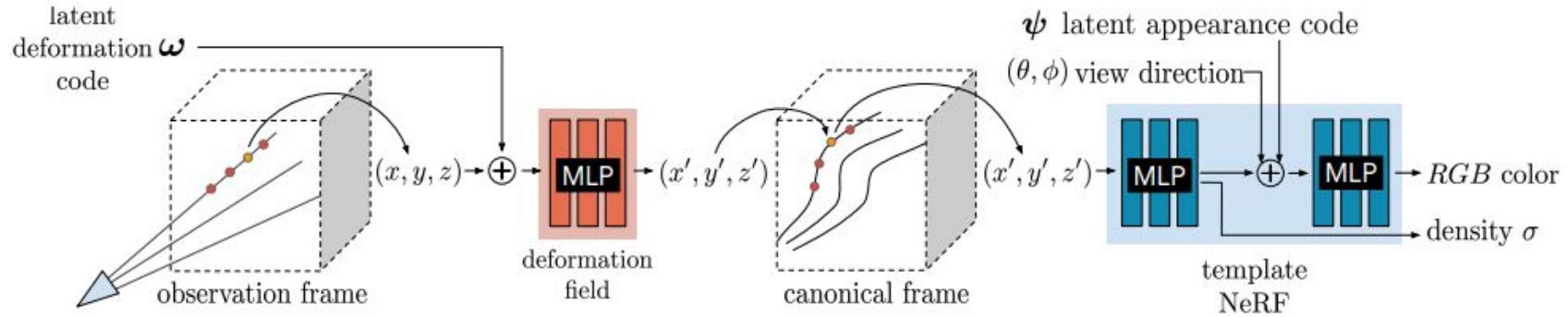
$$\text{where } \mathbf{p}(h, t) = \mathbf{x}(h) + \Psi_t(\mathbf{x}(h), t),$$
$$[\mathbf{c}(\mathbf{p}(h, t), \mathbf{d}), \sigma(\mathbf{p}(h, t))] = \Psi_x(\mathbf{p}(h, t), \mathbf{d}),$$
$$\text{and } \mathcal{T}(h, t) = \exp \left(- \int_{h_n}^h \sigma(\mathbf{p}(s, t)) ds \right).$$

D-NeRF: Neural Radiance Fields for Dynamic Scenes



[12] Pumarola20

Deformable Neural Radiance Fields



[13] Park20

Deformable Neural Radiance Fields



[13] Park20

Deformable Neural Radiance Fields vs D-NeRF

Deformable Neural Radiance Fields

Submission history

From: Keunhong Park [[view email](#)]

[v1] Wed, 25 Nov 2020 18:55:04 UTC (47,887 KB)

[v2] Thu, 26 Nov 2020 01:52:45 UTC (47,887 KB)

We present the first method capable of photorealistically reconstructing a non-rigidly deforming scene using photos/videos captured casually from mobile phones. Our approach – D-NeRF – augments neural radiance fields (NeRF)

- + Works on real data
- Relies on pretrained foreground dynamic object segmentation
- + Formulation of elastic deformation regularization
- Does not explore time dependency



D-NeRF

Submission history

From: Albert Pumarola [[view email](#)]

[v1] Fri, 27 Nov 2020 19:06:50 UTC (16,352 KB)

ages. In this paper we introduce **D-NeRF**, a method that extends neural radiance fields to a dynamic domain, allowing to reconstruct and render novel images of objects under rigid and non-rigid motions from a single camera moving around the scene. For this purpose we consider time as an

- Works on synthetic data
- Works on scenes with isolated object
- + Time as input

Neural Radiance field (NeRF)

Remaining challenges

- Handling dynamic scenes when acquiring calibrated views
- One network trained per scene - no generalization
 - PixelNeRF (CVPR'21 submission)
 - General radiance field (ICLR'21 submission)

PixelNeRF: Neural Radiance Fields from One or Few Images

NeRF

[8] Mildenhall20

- Optimizing NeRF of each scene independently
- Requiring many calibrated views
- Using canonical coordinate frame

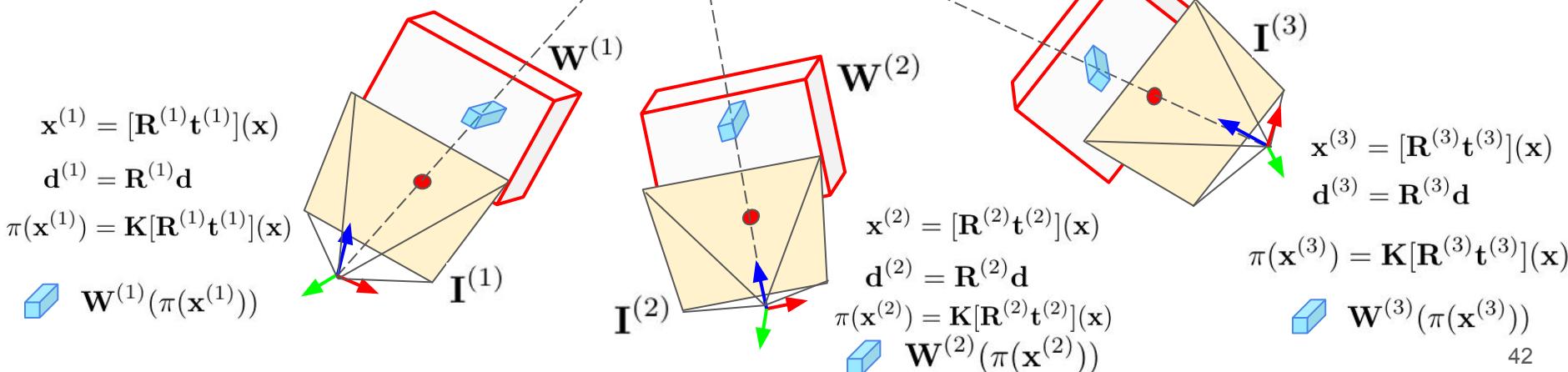
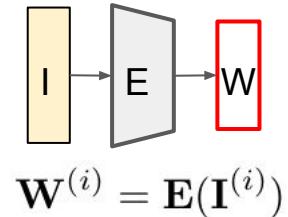
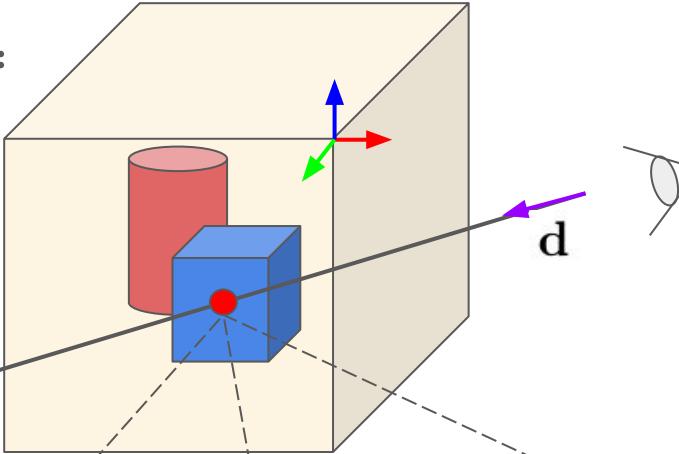
PixelNeRF

[10]
Yu20

- + Training across multiple scenes to learn a scene prior
- + Address few-shot view synthesis task with sparse set of views
- + Predicting a NeRF representation in the camera coordinate system
- + **Incorporate a variable number of posed input views**

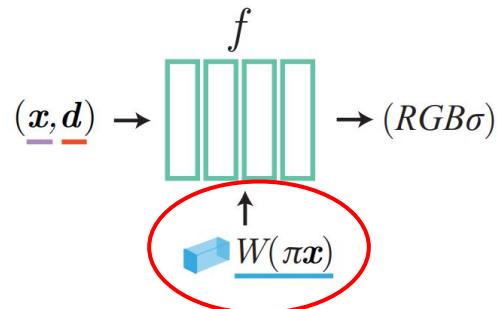
PixelNeRF: Neural Radiance Fields from One or Few Images

Incorporating multiple views:

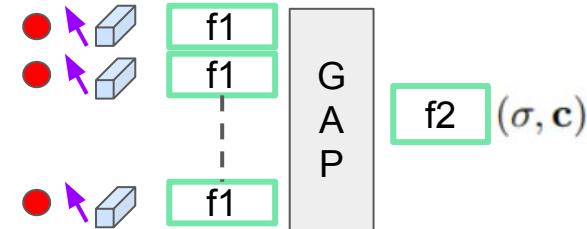


PixelNeRF: Neural Radiance Fields from One or Few Images

Incorporating multiple views:



- First, transform 5D input into coordinate system of each view given camera transform
- Then, calculate intermediate feature vector for each view:
$$\mathbf{V}^{(i)} = f_1 \left(\gamma(\mathbf{x}^{(i)}), \mathbf{d}^{(i)}; \mathbf{W}^{(i)}(\pi(\mathbf{x}^{(i)})) \right)$$
- Finally, aggregate with the average pooling operator ψ and passed into a the final layer
$$(\sigma, \mathbf{c}) = f_2 \left(\psi \left(\mathbf{V}^{(1)}, \dots, \mathbf{V}^{(n)} \right) \right)$$



PixelNeRF: Neural Radiance Fields from One or Few Images

| | 1-view | | | 2-view | | |
|---------|--------------|--------------|--------------|--------------|--------------|--------------|
| | ↑ PSNR | ↑ SSIM | ↓ LPIPS | ↑ PSNR | ↑ SSIM | ↓ LPIPS |
| – Local | 20.39 | 0.848 | 0.196 | 21.17 | 0.865 | 0.175 |
| – Dirs | 21.93 | 0.885 | 0.139 | 23.50 | 0.909 | 0.121 |
| Full | 23.43 | 0.911 | 0.104 | 25.95 | 0.939 | 0.071 |

Table 3: **Ablation studies for ShapeNet chair reconstruction.**
We show the benefit of using local features over a global code to condition the NeRF network (–Local vs Full), and of providing view directions to the network (–Dirs vs Full).

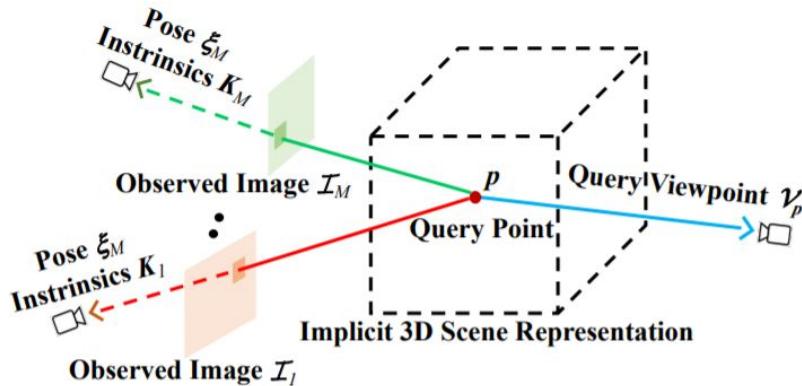
[10]
Yu20

PixelNeRF: Neural Radiance Fields from One or Few Images



[10]
Yu20

GRF: Learning a General Radiance Field for 3D Scene Representation and Rendering



GRF

- [v1] Fri, 9 Oct 2020 14:21:43 UTC (7,696 KB)
- [v2] Sun, 29 Nov 2020 06:33:25 UTC (25,183 KB)

ICLR21 submission

[OpenReview](#) grades: 7, 6, 5, 4

[11] Trevithick20

PixelNeRF

[v1] Thu, 3 Dec 2020 18:59:54 UTC (9,768 KB)

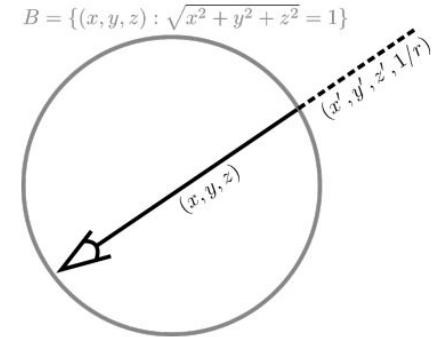
IEEE International Conference on Neural Radiance Fields (ICNeRF)

Related Work

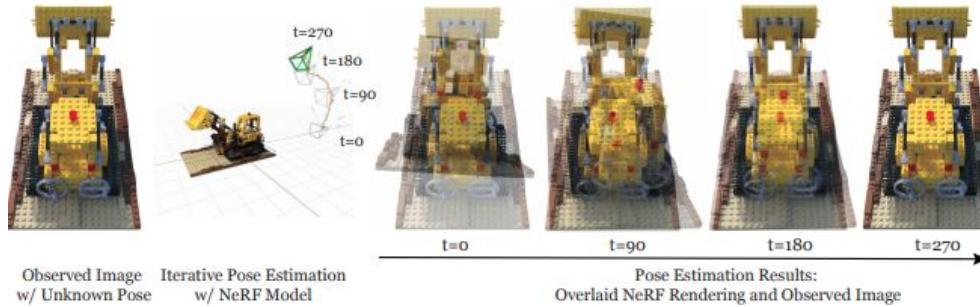
Lastly, note that concurrent work [42] adds image features to NeRF. A key difference is that we operate in view rather than canonical space, which makes our approach applicable in more general settings.

Moreover, we extensively demonstrate our method's performance in few-shot view synthesis, while GRF shows very limited quantitative results for this task.

More works on NeRF



- NeRF++:Analyzing and Improving Neural Radiance Fields [15] Zhang20
- iNeRF: Inverting Neural Radiance Fields for Pose Estimation [16] Yen-Chen20



- NeRF in the Wild [14] Ricardo20...

References

- [7] Sitzmann et al., [Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations](#), NeurIPS 2019
- [8] Mildenhall, Srinivasan, Tancik et al., [NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis](#), ECCV 2020
- [9] Tancik, Srinivasan, Mildenhall et al., [Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains](#), NeurIPS 2020
- [10] Yu et al., [PixelNeRF: Neural Radiance Fields from One or Few Images](#), Arxiv preprint 2020
- [11] Trevithick and Yang, [GRF: Learning a General Radiance Field for 3D Scene Representation and Rendering](#), Arxiv preprint 2020
- [12] Pumarola et al., [D-NeRF: Neural Radiance Fields for Dynamic Scenes](#), Arxiv preprint 2020
- [13] Park et al., [Deformable Neural Radiance Fields](#), Arxiv preprint 2020
- [14] Ricardo et al., [NeRF in the Wild: Neural Radiance Fields for Unconstrained Photo Collections](#), Arxiv preprint
- [15] Zhang et al., [NeRF++:Analyzing and improving neural radiance fields](#), Arxiv preprint
- [16] Yen-Chen et al., [iNeRF: Inverting Neural Radiance Fields for Pose Estimation](#), Arxiv preprint

Matthew Tancik's 1h [talk](#) at Tübingen seminar of the Autonomous Vision Group

Awesome Neural Radiance Fields: <https://github.com/yenchenlin/awesome-NeRF>

NeRF papers with code: <https://paperswithcode.com/method/nerf>