清華大學
Tsinghua University

基于NeRF的三维视觉
年度进展报告

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清华大学
2023-6-14

背景介绍：三维表征与可微渲染

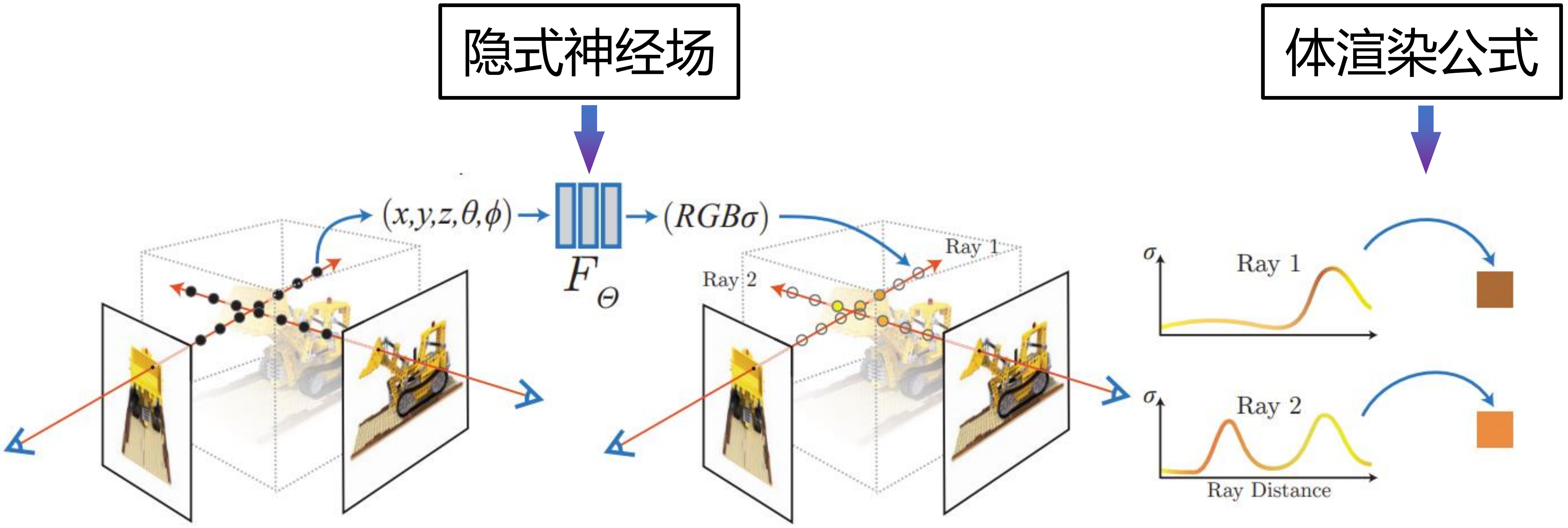
□ NeRF：基于可微体渲染和神经场三维表征的新视点生成方法

不同场景自由视点渲染

螺旋视角渲染　固定视角渲染

基本概念：NeRF的两个核心要素

- 隐式神经场：用基于坐标的全连接网络表达颜色场与体密度场
- 体渲染公式：将颜色场与体密度场渲染为图像



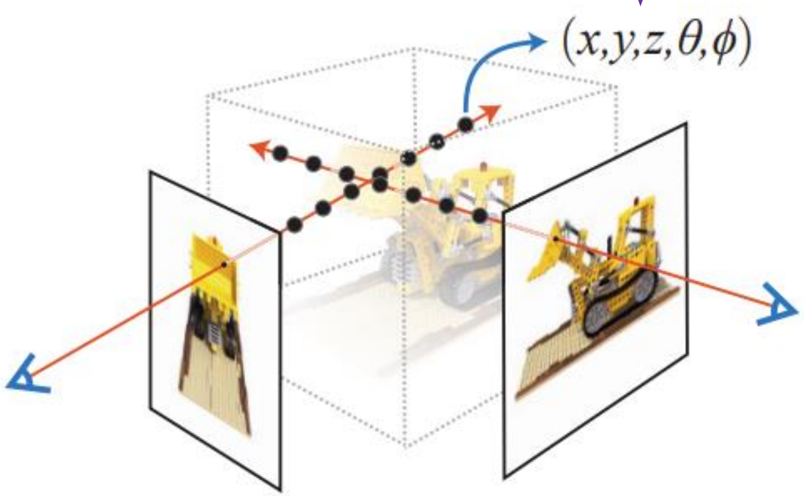
Mildenall et al. NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV 2020.

基本概念：NeRF的渲染与优化过程

- **确定一条光线$\vec{r}(t)=\vec{o}+t\vec{d}$，沿该光线采样$\vec{r}_i=\vec{r}(t_i)$**

$(x_i, y_i, z_i) = \vec{r}_i = \vec{r}(t_i)$

(θ, ϕ)为光线方向$\vec{d}$



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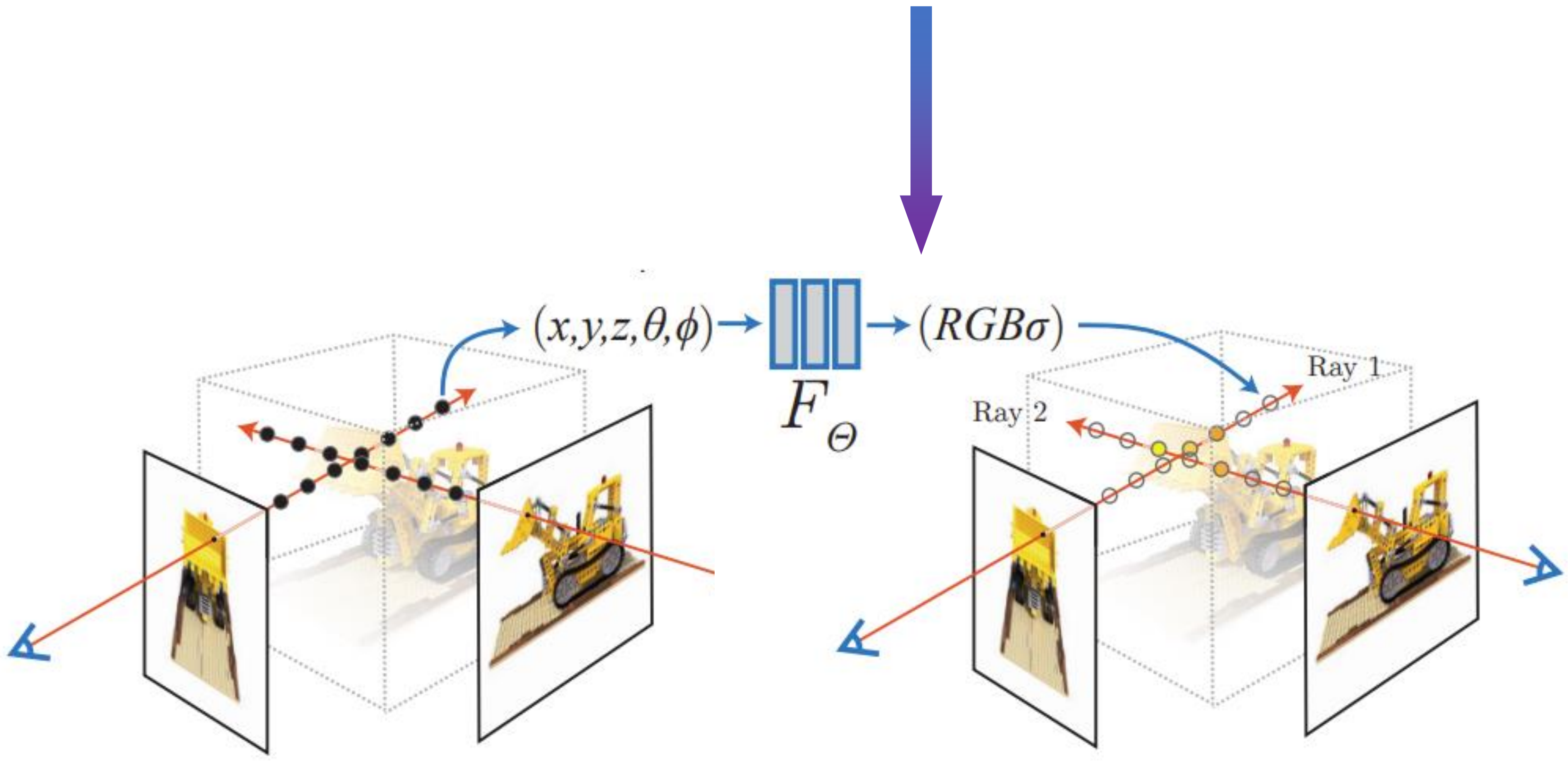
- 通过隐式神经场查询每个采样点的颜色与体密度c_i, σ_i



Mildenall et al. NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV 2020.

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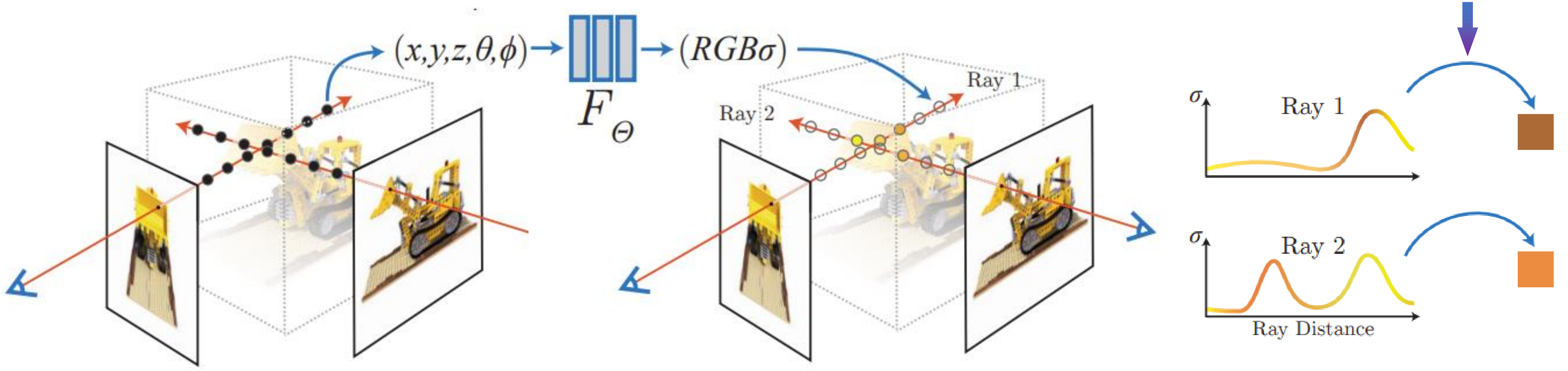
- 通过隐式神经场查询每个采样点的颜色与体密度c_i, σ_i
- 通过体渲染公式得到沿该光线可观测到的最终颜色

$C = \sum_{i=1}^{N} \prod_{j=1}^{i-1}(1-\alpha_j)\,\alpha_i c_i$，其中$\alpha_j = (1 - e^{-\sigma_j(t_{i+1}-t_i)})$为该处的不透明度



Mildenall et al. NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV 2020.

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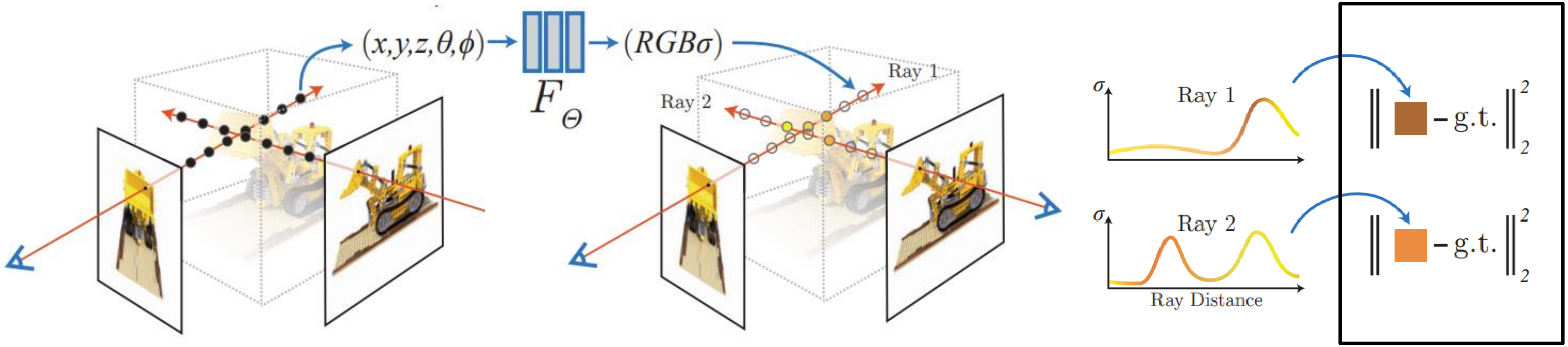
- 确定一条光线$\vec{r}(t) = \vec{o} + t\vec{d}$，沿该光线采样$\vec{r}_i = \vec{r}(t_i)$
- 通过隐式神经场查询每个采样点的颜色与体密度c_i, σ_i
- 通过体渲染公式得到沿该光线可观测到的最终颜色
- 通过渲染结果与图片的误差进行梯度下降优化神经辐射场



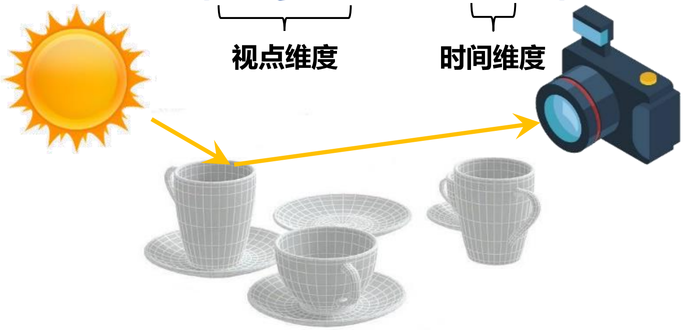
Mildenall et al. NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV 2020.

NeRF与三维视觉

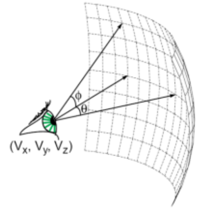
- NeRF：基于二维图像，通过神经网络还原全光函数
  - 核心优化手段：端到端可微渲染 (紧致-高效的三维视觉信息表达)
  - 从更本质的角度建立二维图像与三维世界的联系

[Adelson 91]

$$L = P(\underbrace{x, y, z}_{\text{视点维度}}, \overbrace{\theta, \varphi}^{\text{空间维度}}, \underbrace{t}_{\text{时间维度}}, \overbrace{\lambda}^{\text{光谱维度}})$$



7维全光函数,现实世界的视觉信息（结构、材质、运动、光照、相机）



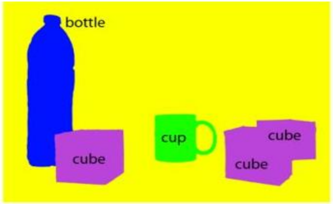
$$I(x,y) = \int \cdots \int \underbrace{L(x', y', \theta_x, \theta_y, \lambda, \ldots, t)}_{\text{Most of this gets lost}}\, d\mathbf{A}\, d\boldsymbol{\omega}\, d\lambda \cdots dt$$

成像过程是全光函数离散下采样，滤波等

二维视觉

二维图像

模式识别



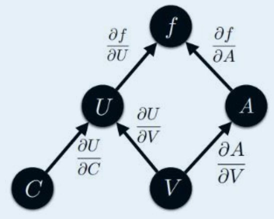
场景理解

三维视觉（NeRF）建模了视觉成像机理，更接近视觉世界本质

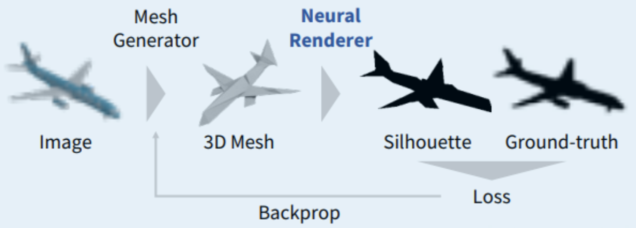
背景介绍：三维表征与可微渲染

三维表征与可微渲染的发展（NeRF前）

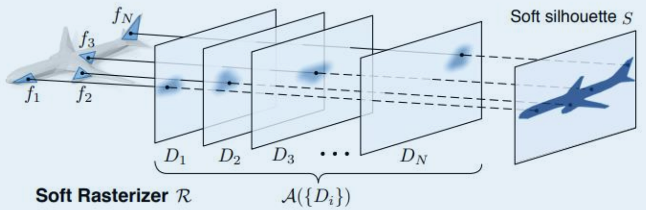
显式曲面



OpenDR [ECCV 2014]



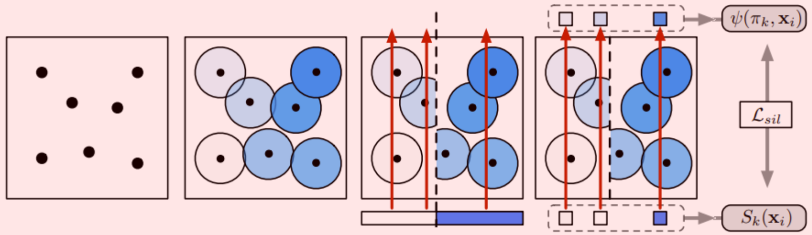
NMR [CVPR 2018]



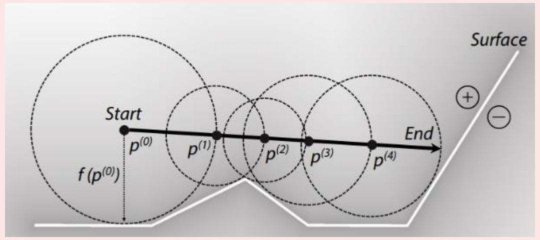
SoftRasterizer [ICCV 2019]

传统渲染可微化

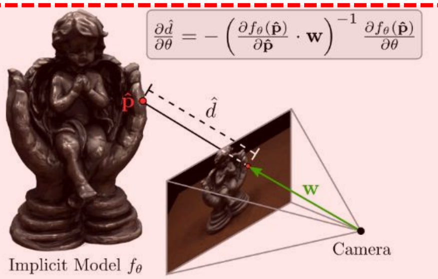
隐式几何场



Liu et al. [NeuIPS 2019]



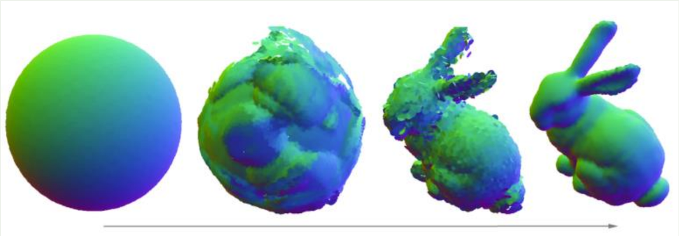
DIST [CVPR 2020]



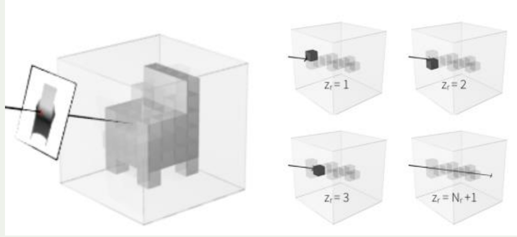
DVR [CVPR 2020]

几何拓扑灵活化

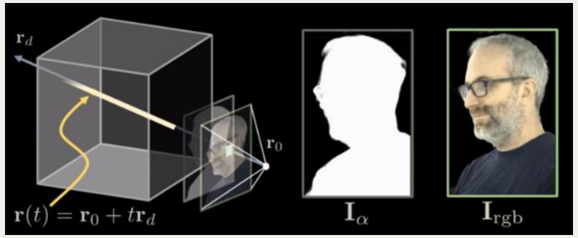
点云与体素



DSS [TOG 2019]



DRC [CVPR 2017]



Neural Volumes [TOG 2019]

渲染操作高效化

背景介绍：三维表征与可微渲染

◻ NeRF：结合体渲染和隐式神经表征

显式曲面

- ✓ 高效、渲染管线成熟
- × 拓扑固定，一般需要已知几何或模板
- × 梯度仅从表面传回，不利于优化

隐式几何场（距离场、示性函数场）

- ✓ 拓扑灵活、表达连续
- × 使用时需显式提取表面信息
- × 计算低效

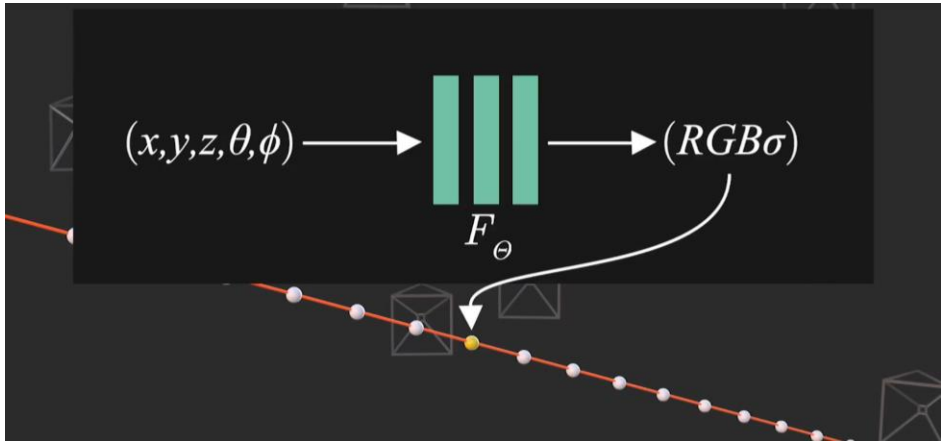
点云

- ✓ 灵活、高效
- × 不连续
- × 无结构性

体素

- ✓ 高效
- × 存储占用高
- × 分辨率受限

NeRF：神经辐射场



连续五维全光函数场

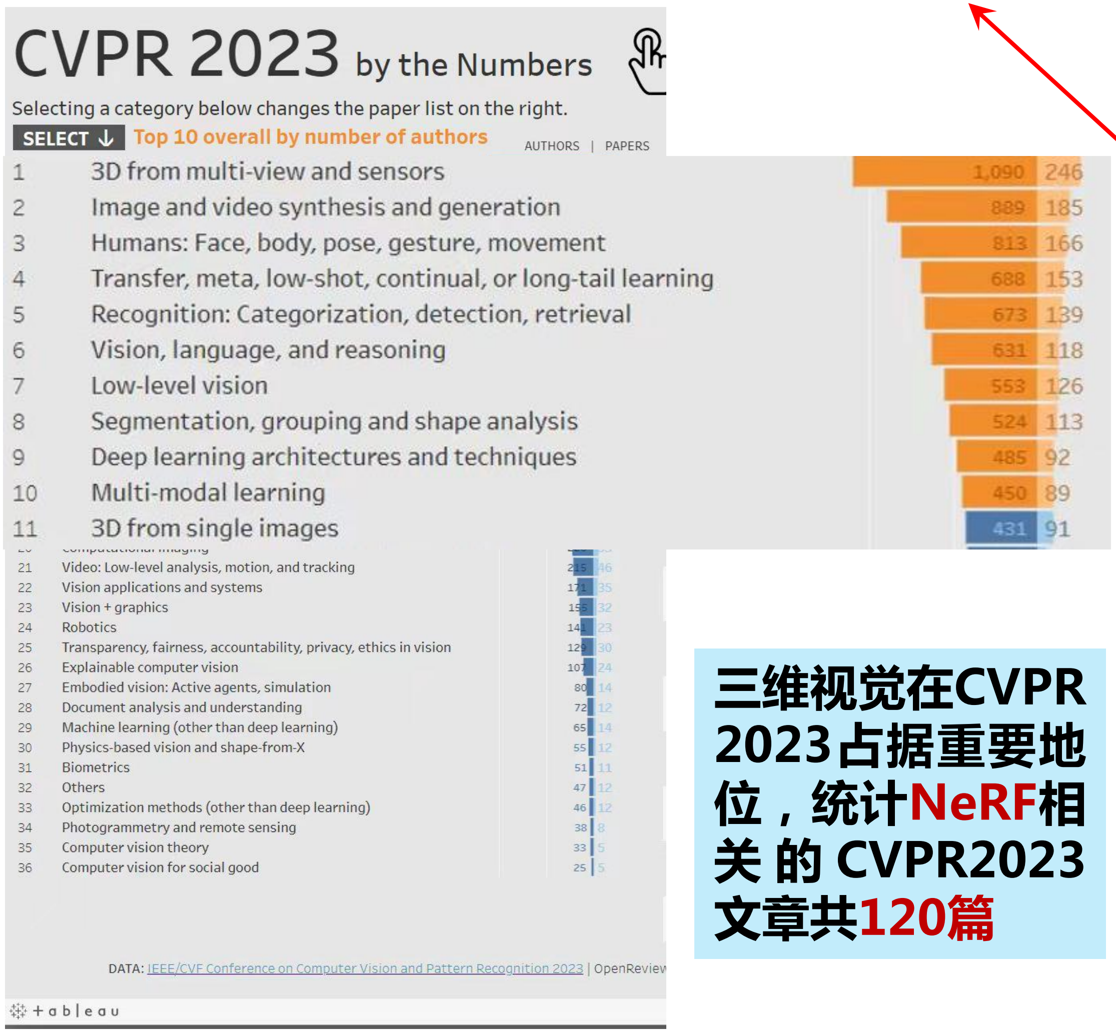
- ✓ 使用体渲染，支持半透明等复杂场景
- ✓ 体渲染公式自然可微，梯度优化性质好
- ✓ 引入视角依赖性，可建模高光
- ✓ 连续神经辐射场表征，支持任意分辨率高效学习
- ✓ 位置编码表征高频细节

Mildenhall et al. NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV 2020 Oral - Best Paper Honorable Mention.

背景介绍：学术影响力

◘ 学术影响力逐年攀升

2020年发表至今已引用超过3000次



三维视觉在CVPR 2023占据重要地位，统计NeRF相关的CVPR2023文章共120篇

Nerf: Representing scenes as neural radiance fields for view synthesis

B Mildenhall, PP Srinivasan, M Tancik… - Communications of the …, 2021 - dl.acm.org

We present a method that achieves state-of-the-art results for synthesizing novel views of complex scenes by optimizing an underlying continuous volumetric scene function using a sparse set of input views. Our algorithm represents a scene using a fully connected (nonconvolutional) deep network, whose input is a single continuous 5D coordinate (spatial location (x, y, z) and viewing direction (θ, ϕ)) and whose output is the volume density and view-dependent emitted radiance at that spatial location. We synthesize views by querying …

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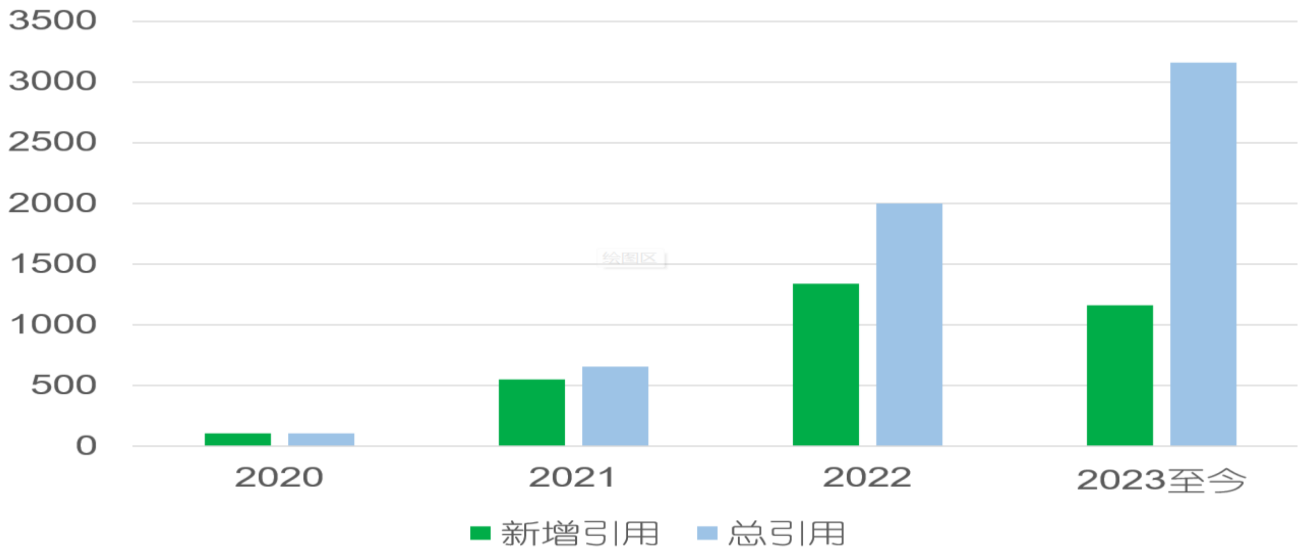
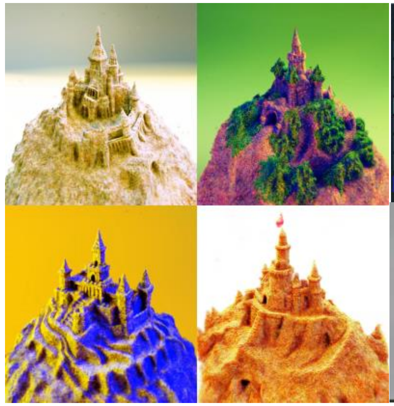


背景介绍：应用价值

三维内容生成与编辑



ProlificDreamer
[arXiv 2023]

IDE-3D
[TOG 2022]

三维重建与渲染

Urban Radiance Ffields [CVPR 2022]

城市级别街景地图

BungeeNeRF [ECCV 2022]

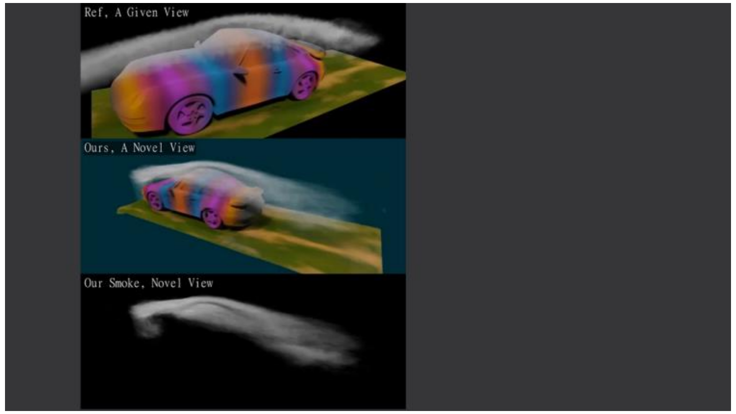
机器人视觉定位与导航

RNR-Map [CVPR 2023]

真实感可驱动数字人

AvatarRex [SIGGRAPH 2023]

物理模拟



PI-NeRF [TOG 2022]

NeRF研究进展概括

- 自2020年被提出以来，NeRF的研究百家争鸣
  - 已成为三维视觉领域的**基本研究范式**之一
  - 推动了三维视觉的**重建**、**渲染**、**定位**、**生成**、**理解**等任务的发展

效率优化：Overview

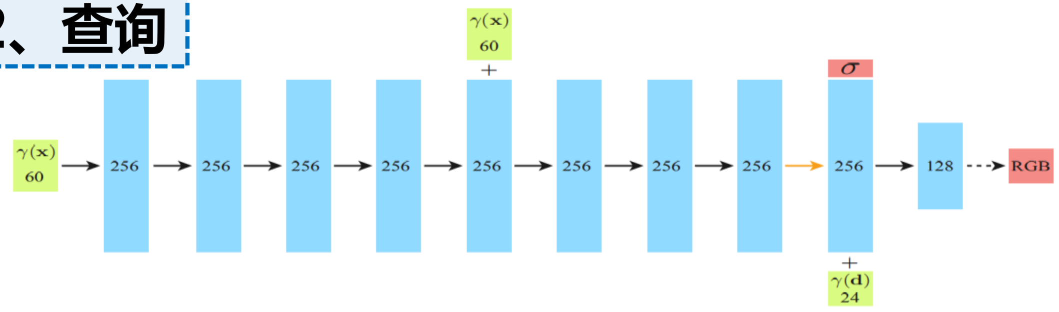
- 研究动机：朴素的NeRF训练久（数十个小时）、渲染时间长

计算瓶颈：复杂度≈单个采样点网络查询时间×采样点数量

- 原生NeRF渲染过程：

1、采样 $(x_i, y_i, z_i) = \vec{\boldsymbol{r}}_i = \vec{\boldsymbol{r}}(\boldsymbol{t}_i)$

2、查询



3、整合

$$C = \int_{t_n}^{t_f} T(t)\sigma(\vec{r}(t))c(\vec{r}(t), \vec{d})dt$$

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

深层网络推理耗时较长

需密集采样近似积分

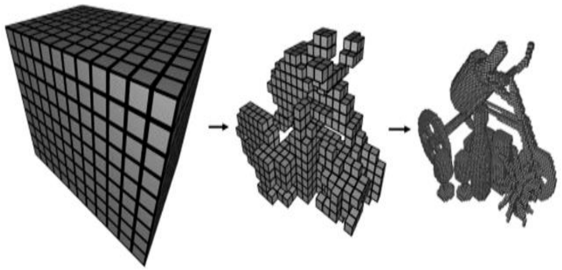
直接存储颜色与密度特征？ → 体素及其分解、哈希网络轻量化

跳过无积分贡献空间？ → 稀疏几何表达

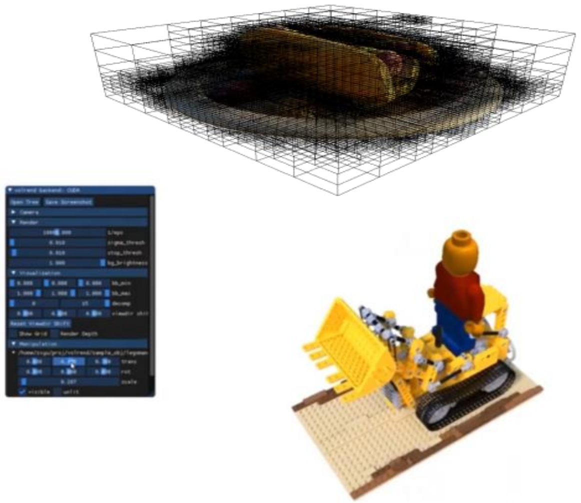
效率优化：利用稀疏几何表达

- 研究动机：为逼近体渲染公式的积分，NeRF渲染时需对光线密集采样
- 解决思路：利用稀疏几何表达（稀疏体素、八叉树、曲面等）排除对积分无贡献的采样区域，减少采样数
  - NSVF, SNeRG, Plenoxels, Plenoctrees：删去无几何区域体素，细化物体表面附近体素，得到稀疏体素或八叉树表达
  - MobileNeRF: 将NeRF提取到三角网格曲面的稀疏几何上，可利用光栅化在移动端实时渲染

Plenoxels



NSVF



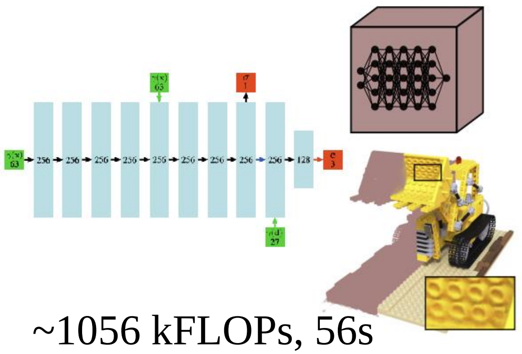
PlenOctrees

MobileNeRF

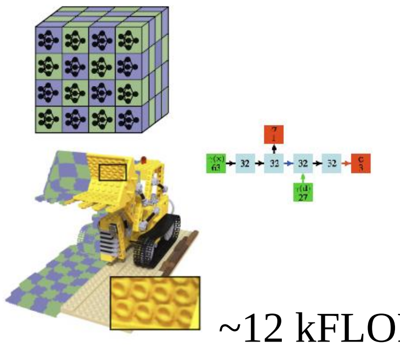
Liu et al. Neural Sparse Voxel Fields. NeurIPS 2020.
Fridovich-Keil et al. Plenoxels: Radiance Fields without Neural Networks. CVPR 2022.
Yu et al. PlenOctrees for Real-time Rendering of Neural Radiance Fields. ICCV 2021.
Chen. MobileNeRF: Exploiting the Polygon Rasterization Pipeline for Efficient Neural Field Rendering on Mobile Architectures. CVPR 2023.

效率优化：体素化

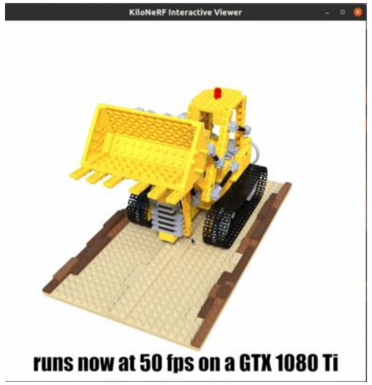
- 研究动机：原生NeRF将坐标映射为高维特征，每个查询点都需网络推理
- 解决思路：使用体素网格存储高维特征或轻量化网络，实现低复杂度查询
  - KiloNeRF：空间体素化，每个体素用轻量网络，显著降低运算量并加快渲染约数千倍
  - DVGO：通过体素网格低密度初始化、插值后激活等训练策略直接优化体素表达的NeRF密度场与颜色特征场，实现分钟级别的训练收敛

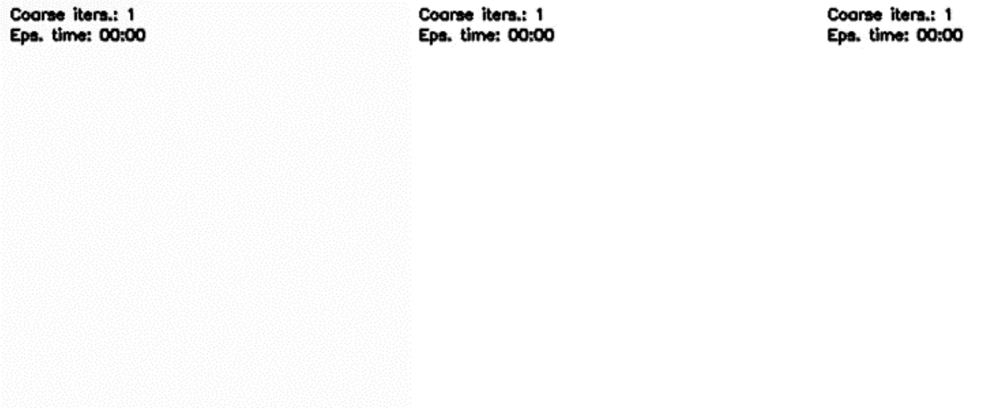


~1056 kFLOPs, 56s



~12 kFLOPs, 0.02s



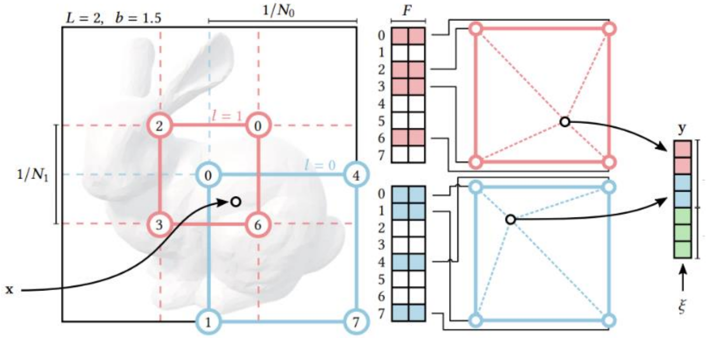


NeRF [ECCV 2020]　　KiloNeRF [ICCV 2021]　　DVGO [CVPR2022]

Mildenall et al. NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV 2020.
Reiser et al. KiloNeRF: Speeding up Neural Radiance Fields with Thousands of Tiny MLPs. ICCV 2021.
Sun, et al. Direct Voxel Grid Optimization: Super-fast Convergence for Radiance Fields Reconstruction. CVPR 2022.

效率优化：体素压缩（哈希表）

- 研究动机：体素表达空间复杂度高，可表达的分辨率受限
- 解决思路：使用哈希技术压缩高分辨率的体素网格存储
  - InstantNGP：建立多尺度体素网格存储高维特征，将高分辨率网格用哈希压缩，可在低复杂度的条件下实现高分辨率（$2^9 \sim 2^{19}$）与快速渲染（秒级收敛速度）



多尺度网格　哈希表压缩

Instant NGP [SIGGRAPH 2022]

Müller et al. Instant Neural Graphics Primitives with a Multiresolution Hash Encoding. SIGGRAPH 2022.

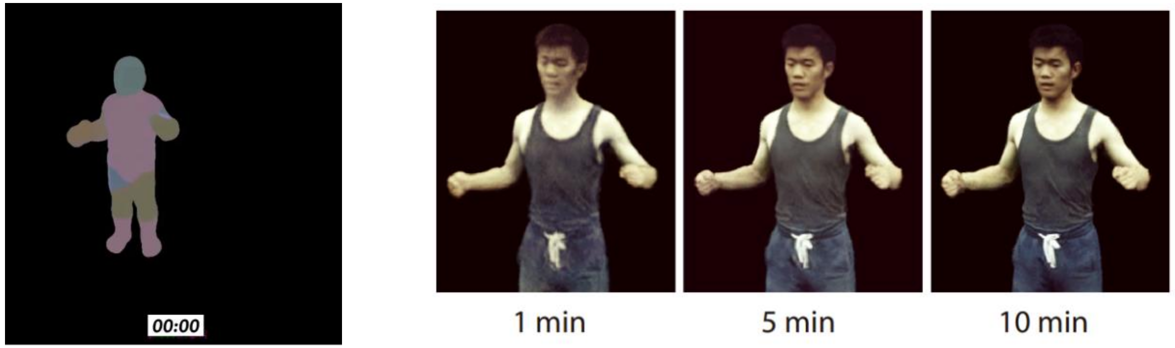
效率优化：体素压缩（哈希表）

◻ Instant NGP为NeRF等三维表征提供了极大提升效率的方法

INSTA [CVPR 2023]

HQ3DAvatar [arXiv 2023]

静态场景收敛：5分钟
动态场景收敛：20秒/帧



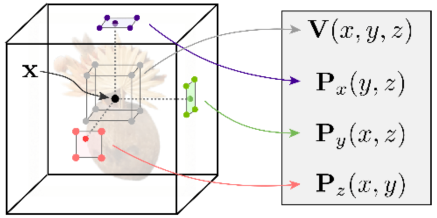
Geng et al. [CVPR 2023]

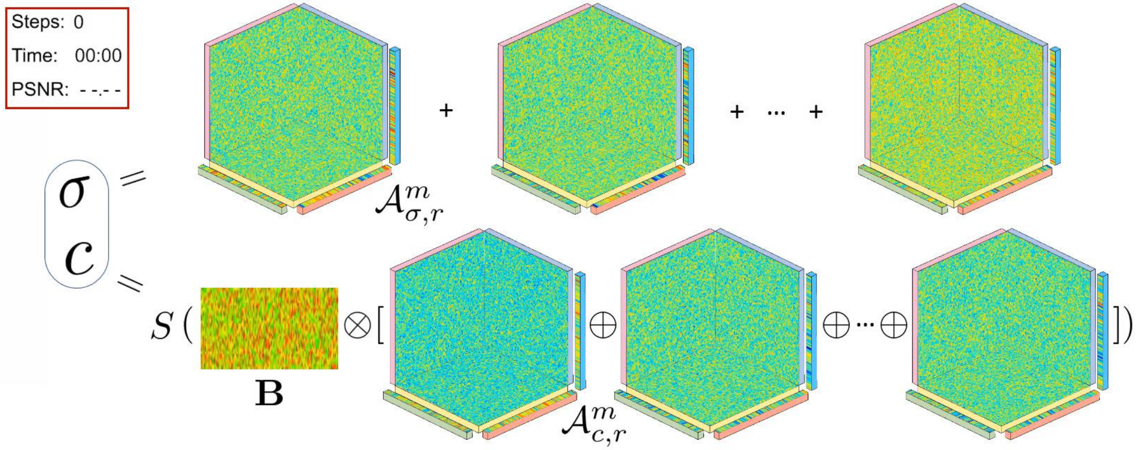
NeuS2 [Arxiv 2022]

Zielonka et al. Instant Volumetric Head Avatars. CVPR 2023.
Teotia et al. HQ3DAvatar: High Quality Controllable 3D Head Avatar. arXiv 2023.
Geng et al. Learning Neural Volumetric Representations of Dynamic Humans in Minutes. CVPR 2023
Wang et al. NeuS2: Fast Learning of Neural Implicit Surfaces for Multi-view Reconstruction. Arxiv 2022.

效率优化：体素分解

- 研究动机：体素表达虽时间高效，但空间占用为立方级，难以提高分辨率
- 解决思路：体素网格分解为低维平面网格表达，空间占用降为平方级
  - EG3D：将三维坐标对应的体素特征定义为三个正交投影平面的特征
  - TensoRF：将体素网格分解为“向量-平面”张量积形式的低秩张量之和
  - MeRF：低分辨率体素+高分辨率平面投影





TensoRF [ECCV 2022]

MeRF [SIGGRAPH 2023]

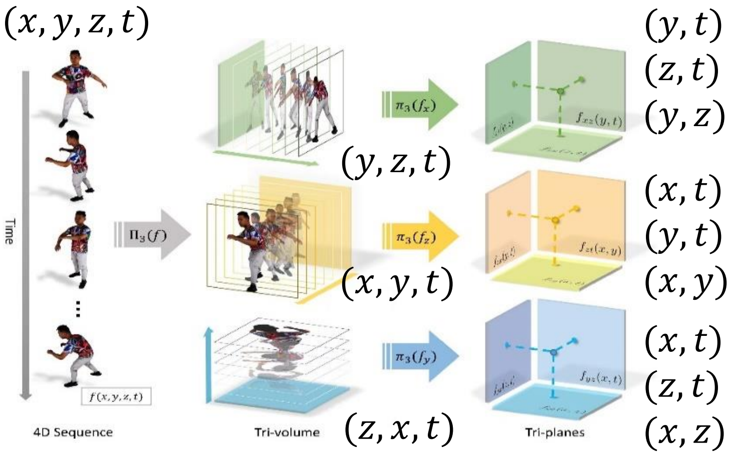
Chan et al. Efficient Geometry-aware 3D Generative Adversarial Networks. CVPR 2022.

Chen et al. TensoRF Tensorial Radiance Fields. ECCV 2022.

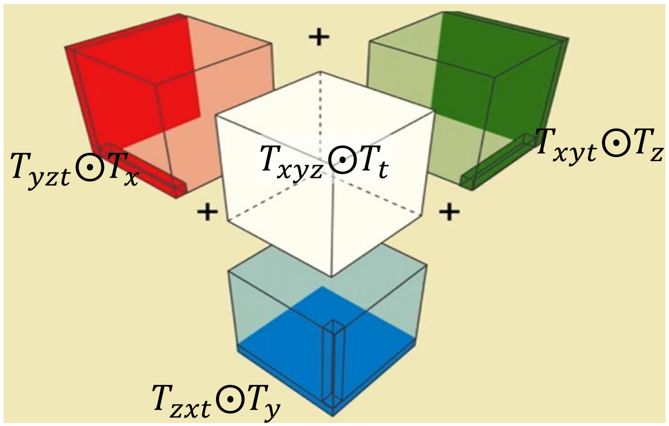
Reiser et al. MERF: Memory-Efficient Radiance Fields for Real-time View Synthesis in Unbounded Scenes. SIGGRAPH 2023.

效率优化：体素分解（4D推广）

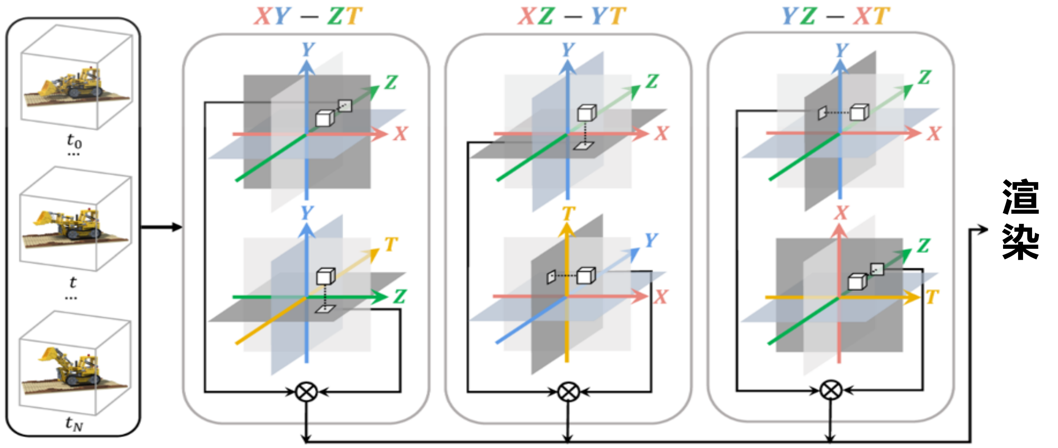
- 研究动机：使用体素建模时序(4D)时，需额外考虑时间维度，复杂度高
- 解决思路：沿用3D->2D的分解思路，进行4D->2D的分解
  - Tensor4D：4D网格 -> 3个3D网格 -> 3x3=9个2D网格
  - HumanRF：4D网格 -> 4个3D网格与1D网格的张量积，其中3D网格使用哈希压缩
  - HexPlane， K-Planes：4D网格 -> (x, y, z, t)坐标两两组合得到的六个2D网格



Tensor4D [CVPR 2023]



HumanRF [TOG 2023]



HexPlane [CVPR 2023]

Shao et al. Tensor4D: Efficient Neural 4D Decomposition for High-fidelity Dynamic Reconstruction and Rendering. CVPR 2023.
Işık et al. HumanRF: High-Fidelity Neural Radiance Fields for Humans in Motion. TOG 2023.
Cao et al. HexPlane: A Fast Representation for Dynamic Scenes. CVPR 2023.
Fridovich-Keil et al. K-Planes Explicit Radiance Fields in Space, Time, and Appearance. CVPR 2023.

效率优化：体素分解（4D推广）

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Tensor4D [CVPR 2023]

HumanRF [TOG 2023]

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Shao et al. Tensor4D: Efficient Neural 4D Decomposition for High-fidelity Dynamic Reconstruction and Rendering. CVPR 2023.
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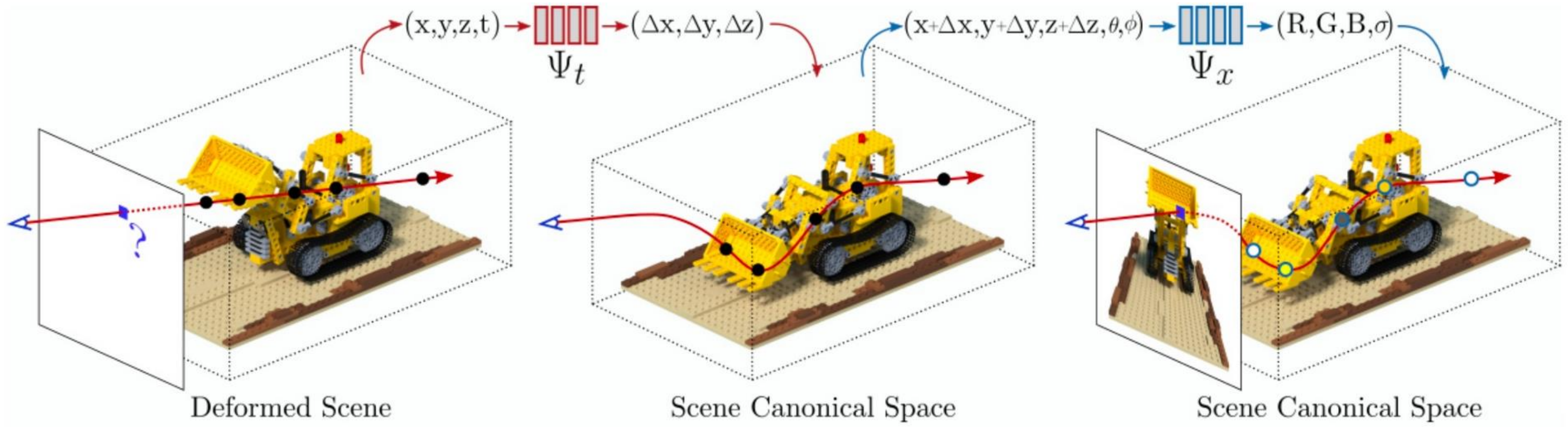
Cao et al. HexPlane: A Fast Representation for Dynamic Scenes. CVPR 2023.
Fridovich-Keil et al. K-Planes Explicit Radiance Fields in Space, Time, and Appearance. CVPR 2023.

动态建模: Overview

- 研究动机：扩展NeRF表征非静态内容，允许对动态场景进行新视点合成
- 早期工作：D-NeRF, Nerfies, Hyper-NeRF
- 解决思路：将动态场景建模为标准空间和变形场，利用变形场将不同帧观测到的外观信息观映射至标准空间，实现外观与运动信息的解耦

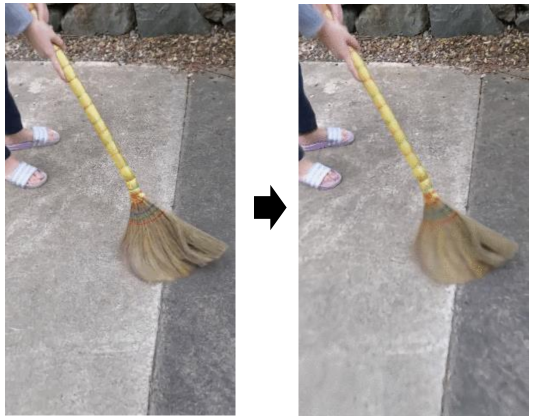


[1] Pumarola, Albert, et al. "D-nerf: Neural radiance fields for dynamic scenes." *CVPR*. 2021.
[2] Park, Keunhong, et al. "Nerfies: Deformable neural radiance fields." *ICCV*. 2021.
[3] Park, Keunhong, et al. "HyperNeRF: a higher-dimensional representation for topologically varying neural radiance fields." *TOG.2021*.

动态建模: Overview

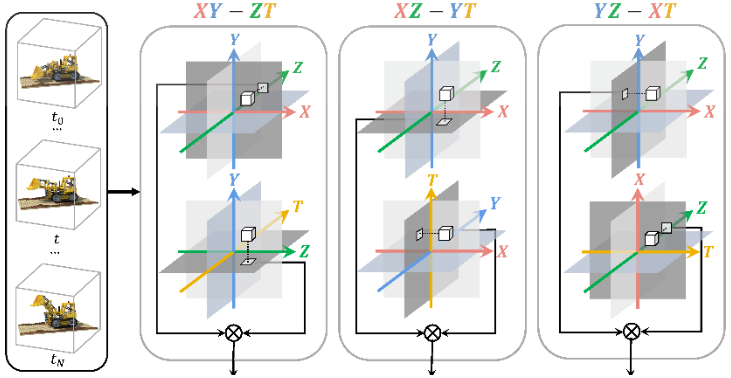
现有局限和改进方向：

变形场缺少监督，难以刻画自然场景大幅度运动。	计算效率低，建模和推理速度慢。	未充分挖掘时空相关性，稀疏视角观测时效果较差。
动态前景感知	**体素化**	**时空一致表达**
准确运动解耦，提升动态纹理	分钟级别建模，实时高清渲染	低秩张量分解，紧致高效表达



FSDNeRF, NeRFPlayer …

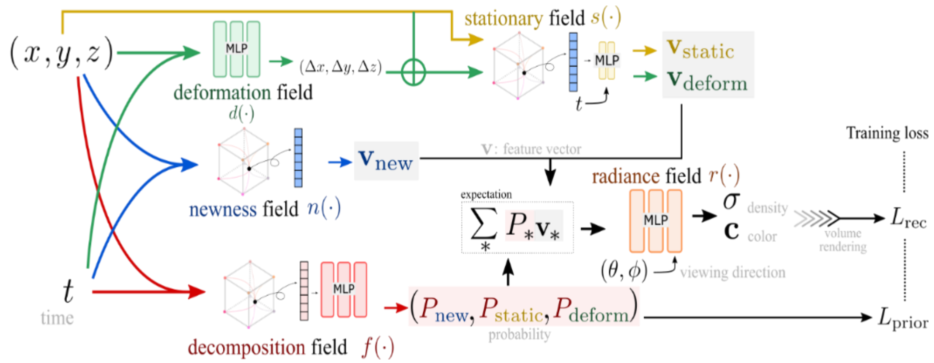
Tineuvox, Fourier plenoctrees …



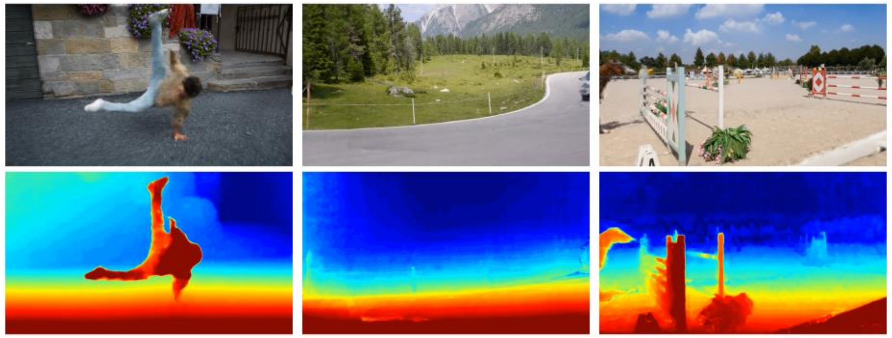
Tensor4D, Hexplane …

动态建模: 动态前景感知

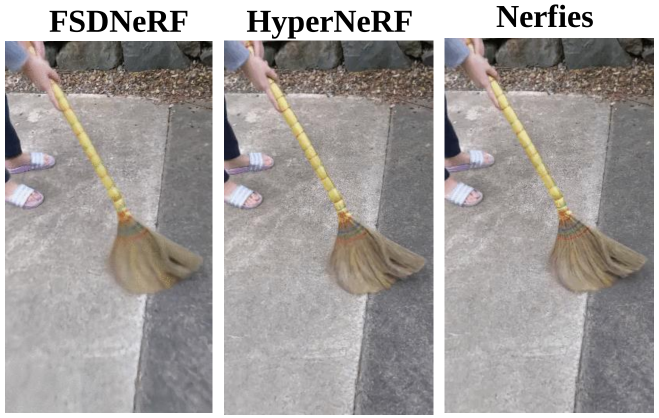
- 研究动机：对于单目相机拍摄的含较大运动变形的真实场景，现有基于变形场的动态表征方法无法准确解耦物体运动，难以恢复高质量动态纹理
- 解决思路：通过改变表征或引入额外信息来增强NeRF对于动态前景的感知能力
  - FSDNeRF：构建隐式速度场的表征方法，引入单目预测帧间光流信息，为速度场施加时域正则化
  - Nerfplayer：设计时域相关的动态残差NeRF，减少运动信息与动态纹理的耦合
  - RoDynRF：引入动态NeRF显式建模前景分割，并通过联合相机位姿优化增强合成外观质量



Nerfplayer [TVCG 2023]



RoDynRF [CVPR 2023]

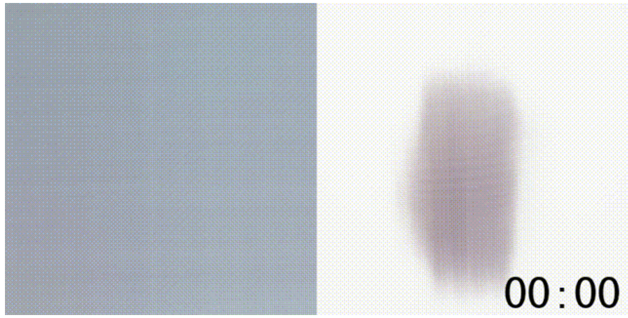


FSDNeRF [CVPR 2023]

[1] Wang, Chaoyang, et al. "Flow supervision for Deformable NeRF." CVPR. 2023.
[2] Song, Liangchen, et al. "Nerfplayer: A streamable dynamic scene representation with decomposed neural radiance fields." TVCG.2023.
[3] Liu, Yu-Lun, et al. "Robust Dynamic Radiance Fields." CVPR.2023.

动态建模: 体素化

- 研究动机：朴素的动态NeRF表征方法建模优化速度慢，动态场景建模需耗费几十小时，渲染512分辨率图片耗时数十秒
- 解决思路：使用体素存储高维特征或轻量网络，实现分钟级动态建模和高清实时渲染。
  - TineuVox：将标准空间NeRF改造为基于体素的显式表征，利用多尺度特征采样策略确保优化过程中体素全局感知能力
  - Fourier Plenoctrees：结合离散傅里叶变换，使用FT参数建模逐帧体素场辐射参数
  - Dynamic MLP masps：由体素级别局部轻量网络组合表征3D场景，结合2D超参数卷积网络高效生成动态逐帧MLP网络参数



TineuVox [SIGGRAPH Asia 2022]

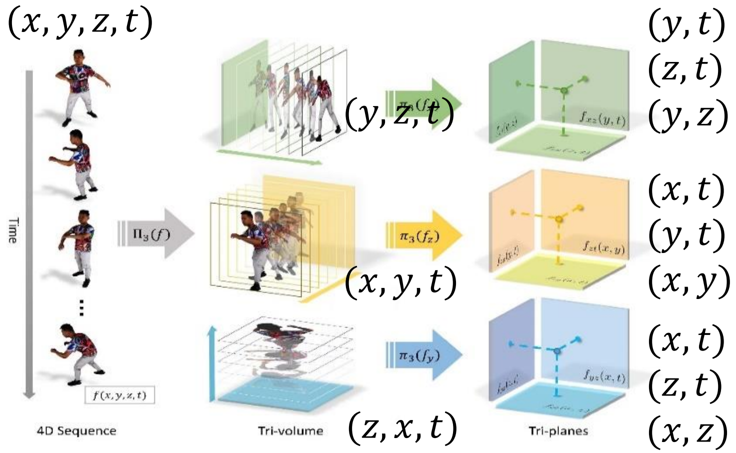
Dynamic MLP Maps [CVPR 2023]

Fourier Plenoctrees [CVPR 2022]

[1] Fang, Jiemin, et al. "Fast dynamic radiance fields with time-aware neural voxels." SIGGRAPH Asia 2022 Conference Papers.
[2] Wang, Liao, et al. "Fourier plenoctrees for dynamic radiance field rendering in real-time." CVPR. 2022.
[3] Peng, Sida, et al. "Representing Volumetric Videos as Dynamic MLP Maps." CVPR. 2023.

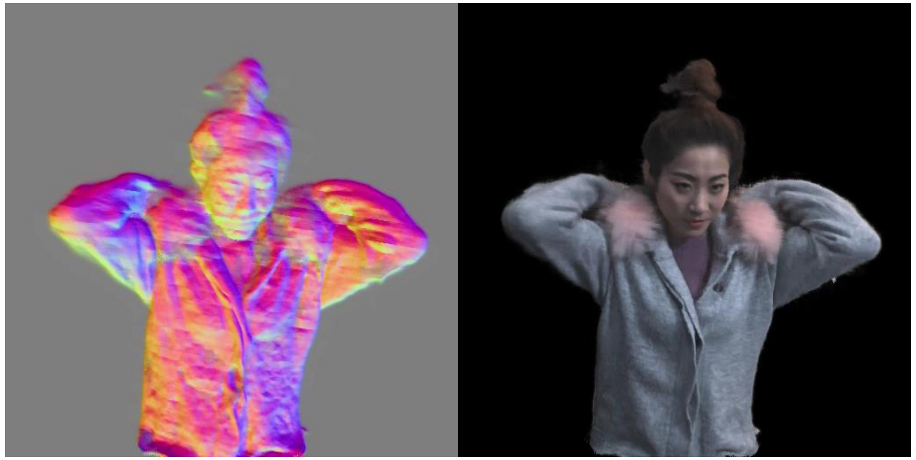
动态建模：时空张量分解

- **研究动机：现有动态表征方法未能充分利用帧间的时域相关性，难以处理稀疏视角下的大尺度运动**
- **解决思路：将4D大尺度运动压缩至多个低秩特征平面，提出紧致高效的时空NeRF表征**
  - **Tensor4D：4D网格 -> 3个3D网格 -> 3x3=9个2D网格**
  - **HumanRF：4D网格 -> 4个3D网格与1D网格的张量积，其中3D网格使用哈希压缩**



Tensor4D [CVPR 2023]

四视点重建



Tensor4D [CVPR 2023]

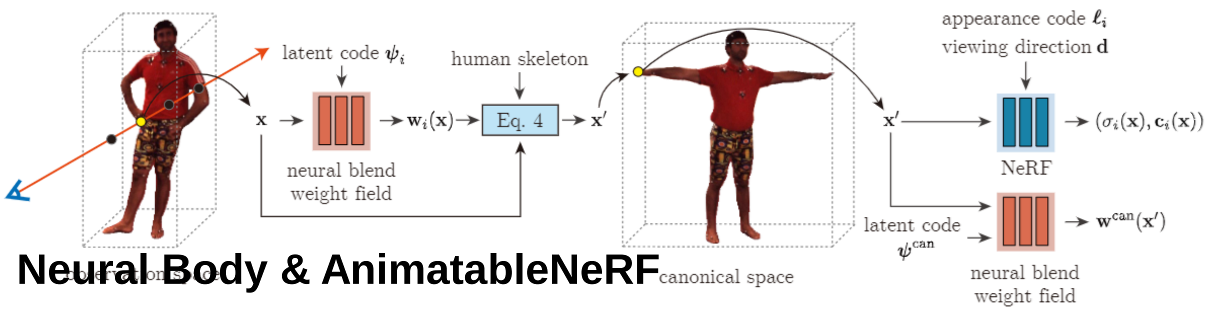
密集视点重建

HumanRF [SIGGRAPH 2023]

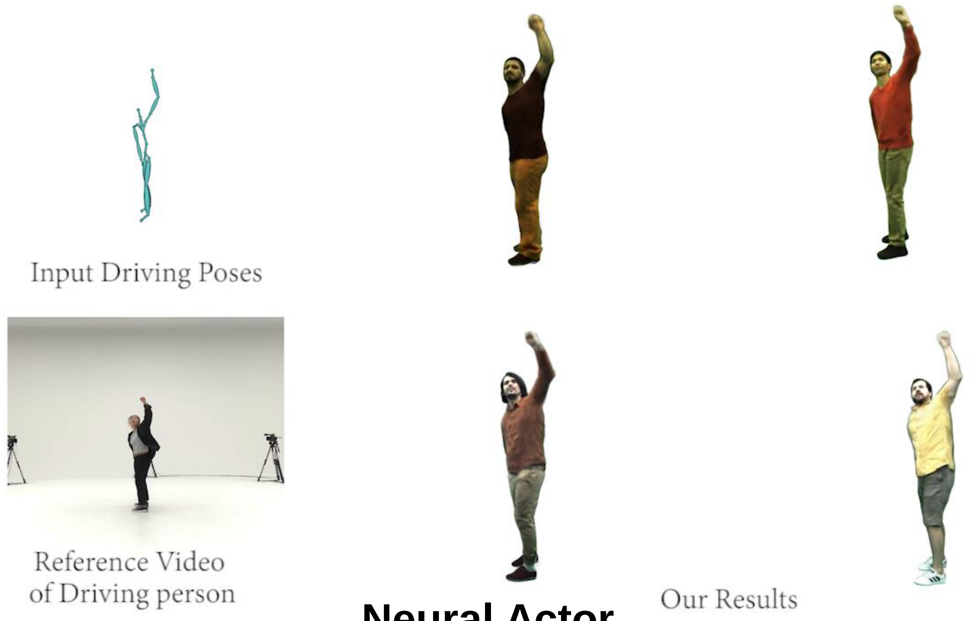
[1] Shao, Ruizhi, et al. "Tensor4d: Efficient neural 4d decomposition for high-fidelity dynamic reconstruction and rendering." CVPR. 2023.
[2] Fridovich-Keil, Sara, et al. "K-planes: Explicit radiance fields in space, time, and appearance." CVPR. 2023.
[3] Cao, Ang, and Justin Johnson. "Hexplane: A fast representation for dynamic scenes." CVPR. 2023.
[4] Işık, Mustafa, et al. "HumanRF: High-Fidelity Neural Radiance Fields for Humans in Motion." SIGGRAPH.2023.

人体重建与化身生成：动态人体化身

- 研究动机：动态NeRF建模方法难以适用于人体大范围运动的场景
- 早期工作：以人体参数化模型SMPL为先验，建立帧间大尺度骨架运动联系，同时优化非刚性变形场与标准姿势下的NeRF

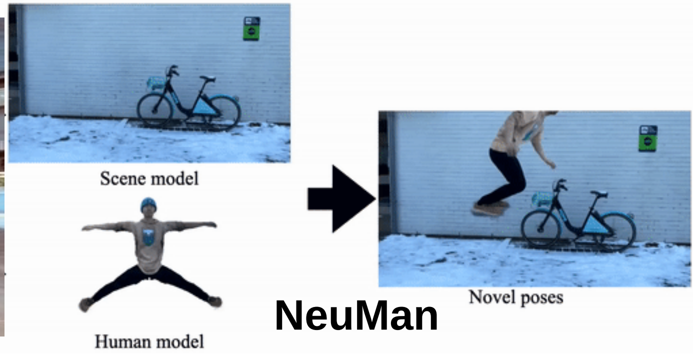


Neural Body & AnimatableNeRF



Neural Actor

HumanNeRF

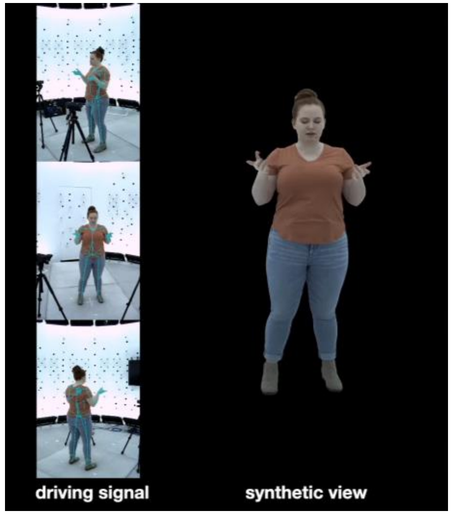


NeuMan

[1] Peng et al. Animatable Neural Radiance Fields for Modeling Dynamic Human Bodies. ICCV 2021.
[2] Peng et al. Neural Body: Implicit Neural Representations with Structured Latent Codes for Novel View Synthesis of Dynamic Humans. CVPR 2021.
[3] Weng et al. HumanNeRF: Free-viewpoint Rendering of Moving People from Monocular Video. CVPR 2022.
[4] Liu et al. Neural Actor: Neural Free-view Synthesis of Human Actors with Pose Control. TOG 2021.
[5] Jiang et al. NeuMan: Neural Human Radiance Field from a Single Video. ECCV 2022.

人体重建与化身生成：动态人体化身

- 研究动机：动态NeRF建模方法难以适用于人体大范围运动的场景
- 近期路线：更高质量的可驱动数字人，关注动态衣物细节的建模
  - Remelli et al.：引入额外图像驱动信号，提供更丰富的外观信息
  - AvatarReX：提出局部神经辐射场以及局部特征块以编码细粒度人体衣物细节
  - PoseVocab：提出姿势表征库以编码不同姿态下的人体外观高频变化



Remelli et al.

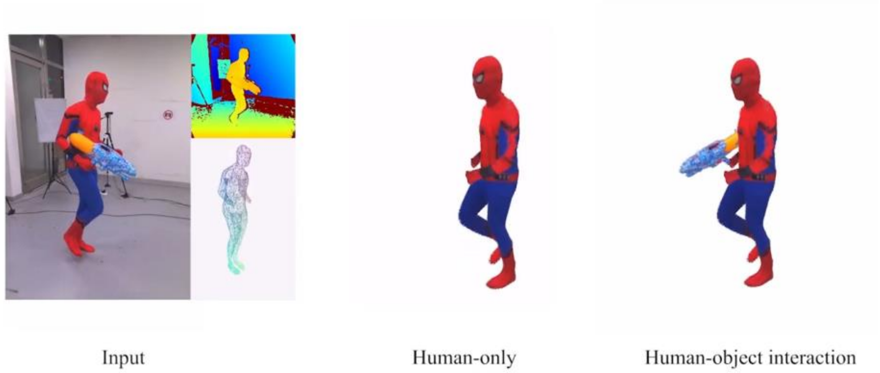
AvatarReX

PoseVocab

[1] Remelli et al. Drivable Volumetric Avatars using Texel-Aligned Features. SIGGRAPH 2022.
[2] Zheng et al. AvatarReX: Real-time Expressive Full-body Avatars. SIGGRAPH 2023.
[3] Li et al. PoseVocab: Learning Joint-structured Pose Embeddings for Human Avatar Modeling. SIGGRAPH 2023.

人体重建与化身生成：人与物体、场景交互

- 研究动机：人与物体、场景的交互，关注自然交互与重建
- 解决方案：
  - Instant-NVR：结合非刚性跟踪以及Instant-NGP实现人和物体NeRF的在线重建
  - HOSNeRF：引入状态隐编码以表征人和物体、场景的不同交互状态
  - Hou et al.：引入人和物体的隐编码以解耦人和物体的接触关系，合成新姿态下人和物体的交互



Instant-NVR

HOSNeRF

Hou et al.

[1] Jiang et al. Instant-NVR: Instant Neural Volumetric Rendering for Human-objectInteractions from Monocular RGBD Stream. CVPR 2023.
[2] Liu et al. HOSNeRF: Dynamic Human-Object-Scene Neural Radiance Fields from a Single Video. arXiv 2023.
[3] Hou et al. Compositional 3D Human-Object Neural Animation. arXiv 2023.

人体重建与化身生成：数字人生成

- **研究动机：基于文本描述或随机采样，生成虚拟数字人**
- **解决方案：SMPL+NeRF+(GAN/Diffusion)**
  - **AvatarCLIP：以CLIP为先验，分别生成静态数字人以及运动序列**
  - **EVA3D：提出组合式人体NeRF，在标准空间中学习三维人体GAN**
  - **DreamAvatar：以Stable Diffusion为先验，约束基于NeRF渲染的图像满足语义输入**

A tall and skinny female soldier that is arguing.

A tall and fat Iron Man that is running.

AvatarCLIP

EVA3D

DreamAvatar

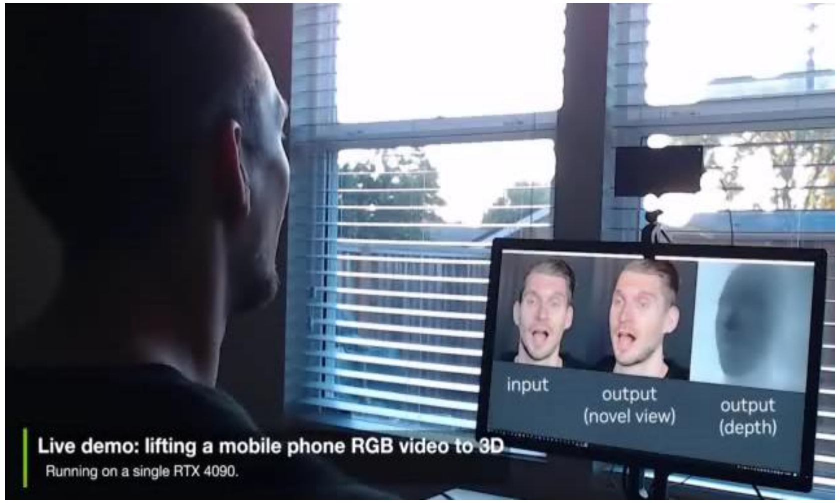
[1] Hong et al. AvatarCLIP: Zero-Shot Text-Driven Generation and Animation of 3D Avatars. SIGGRAPH 2022.

[2] Hong et al. EVA3D: Compositional 3D Human Generation from 2D Image Collections. ICLR 2023.

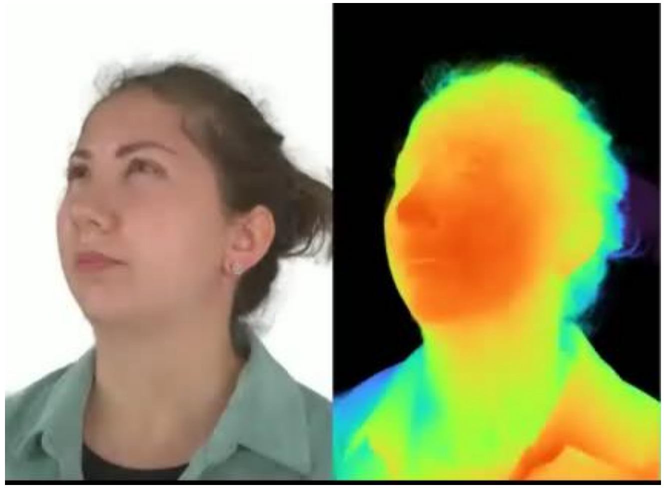
[3] Cao et al. DreamAvatar: Text-and-Shape Guided 3D Human Avatar Generation via Diffusion Models. arXiv 2023.

人脸重建与化身生成：稀疏视点重建

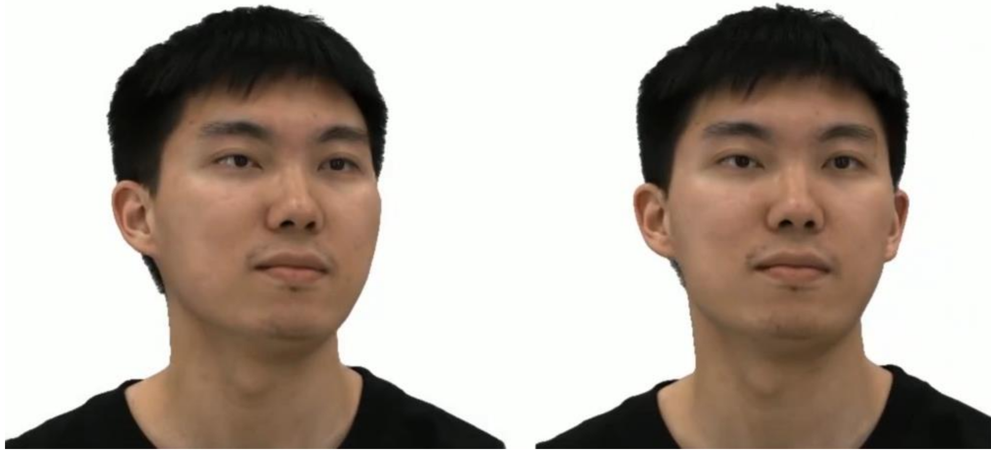
- 研究动机：稀疏视点人脸重建，NeRF容易过拟合到每个视点，新视点合成出现伪影
- 解决方案：引入人脸大数据、关键点和人脸模板等先验，优化NeRF重建质量
  - LP3D(静态+实时)：使用EG3D生成的人脸数据训练，输入单图像，推理三平面表达的NeRF
  - HAvatar(动态化身)：采用3DMM投影的三平面神经辐射场约束，实现高质量人头动态化身
  - NeRSemble(动态)：引入3DMM表情参数，构建带表情语义空间变形场，拟合复杂表情动态



LP3D：单相机，512分辨率，实时



NeRSemble：16相机，1k分辨率



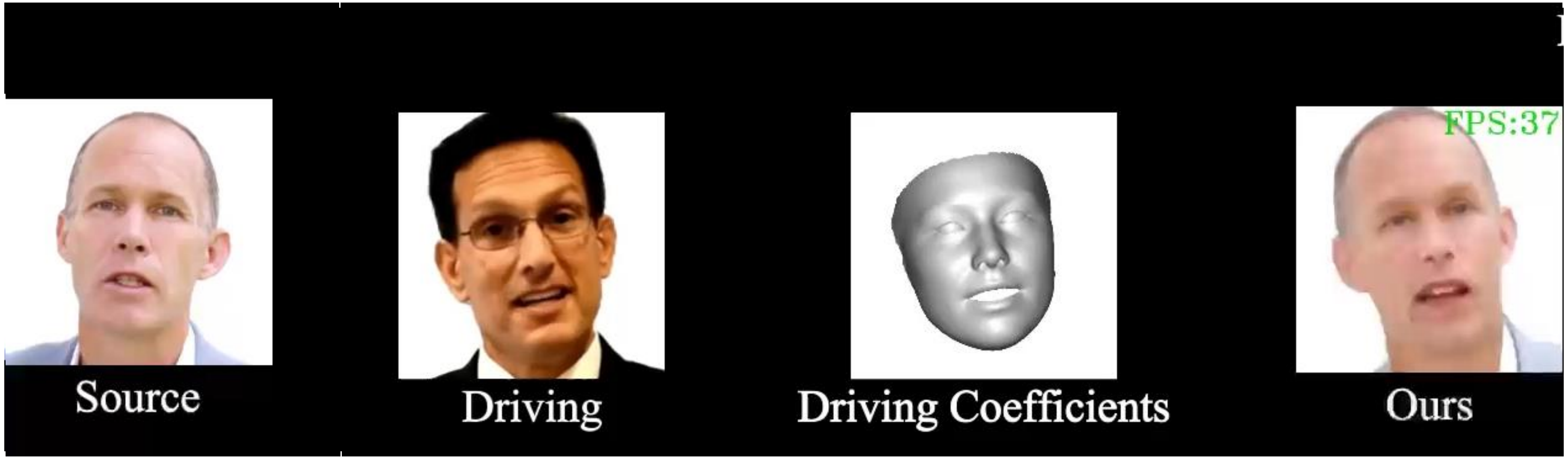
HAvatar：6相机，512分辨率

[1] Tobias Kirschstein, et al. NeRSemble: Multi-view Radiance Field Reconstruction of Human Heads. SIGGRAPH 2023.
[2] Alex Trevithick et al. Live 3D Portrait: Real-Time Radiance Fields for Single-Image Portrait View Synthesis. SIGGRAPH 2023.
[3] Zhao et al. Havatar: High-fidelity Head Avatar via Facial Model Conditioned Neural Radiance Field. 2023

人脸重建与化身生成：人脸化身生成

- 研究动机：动态NeRF重建方法，无法通过音视频对人脸模型进行后续表情、嘴型驱动
- 近期研究：引入预训练模型扩展到单图像重建；更好的NeRF表达方式和表情表达方式
  - Huang et al.：从语音学习隐式表情参数，相比于传统3DMM表情，具备更强的表达能力
  - OTAvatar：无需视频作为训练，仅输入单帧图像，通过预训练EG3D生成可驱动NeRF模型

Huang et al. ：单视频，512分辨率



OTAvatar：单帧，256分辨率

[1] Weichuang Li et al. One-Shot High-Fidelity Talking-Head Synthesis with Deformable Neural Radiance Field. CVPR 2023.
[2] Ricong Huang et al. Parametric Implicit Face Representation for Audio-Driven Facial Reenactment. CVPR 2023.
[3] Zhiyuan Ma et al. OTAvatar : One-shot Talking Face Avatar with Controllable Tri-plane Rendering. CVPR 2023.

人脸重建与化身生成：化身生成加速

- 研究动机：从视频学习一个高质量的基于NeRF的人脸化身需要数十小时的训练时间
- 近期研究：结合成熟的静态NeRF加速技术体素化，实现分钟级的训练速度
  - INSTA：构建体素网格表达的静态NeRF模型，再使用人脸模板引导空间变形进而实现表情驱动
  - AvatarMAV：用体素网格表达表情相关的动态变形，具体而言，将表情相关的动态变形表达为，以模板表情参数为权重，体素网格基底的加权组合

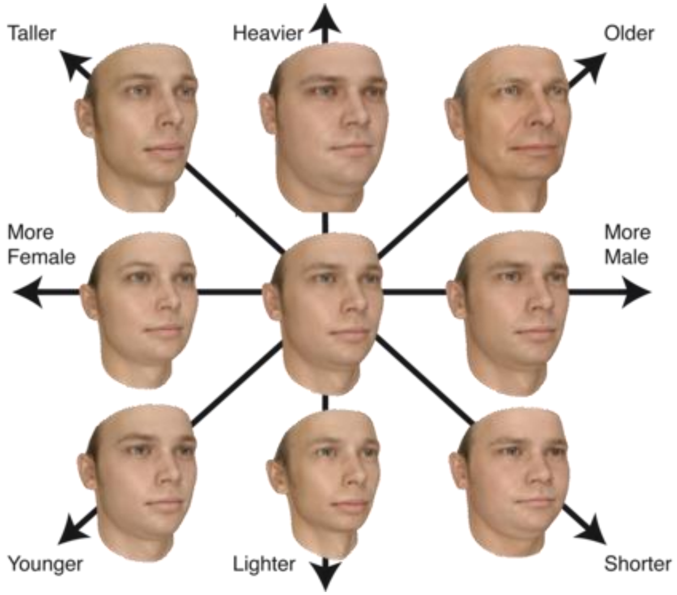
INSTA：单视点，256分辨率

AvatarMAV：单视点，256分辨率

[1] Wojciech Zielonka et al. INSTA - Instant Volumetric Head Avatars. CVPR 2023.
[2] Xu et al. AvatarMAV: Fast 3D Head Avatar Reconstruction Using Motion-Aware Neural Voxels. SIGGRAPH 2023.
[3] Gao et al. Reconstructing Personalized Semantic Facial NeRF Models From Monocular Video. SIGGRAPH Asia 2022.

人脸重建与化身生成：通用人脸模板

- 研究动机：传统基于Mesh的3DMM人脸模板过于粗糙，难以表达头发、胡须等，缺少细节，且真实感不足
- 近期路线：借助NeRF强大的表达能力，利用大规模人脸数据集训练基于NeRF的隐式人脸模板——全头建模；精细纹理；高真实感



传统3DMM模板

NeRF模板：MetaHead

NeRF模板：HeadNeRF

[1] Yang Hong et al. HeadNeRF: A Real-time NeRF-based Parametric Head Model. CVPR 2022.
[2] Yiyu Zhuang et al. MoFaNeRF:Morphable Facial Neural Radiance Field. ECCV 2022.
[3] Dingyun Zhang et al. MetaHead: An Engine to Create Realistic Digital Head. arXiv. 2023

人脸重建与化身生成：头发重建和驱动

- 研究动机：头发几何结构和物理运动的复杂性，动态重建任务极具挑战性
- 解决方案：针对头发的新表征方式，使用发丝结构作为头发及运动的粗糙表达
  - HVH：首先使用发丝结构(左)表达头发，其次在每根发丝构建固定其上的立方体单元(中)，最后在每一个立方体单元中构建一个局部NeRF，最后通过体渲染得到图像(右）
  - NeuWigs：为了实现跨身份的头发驱动，对发丝结构加入物理约束

HVH

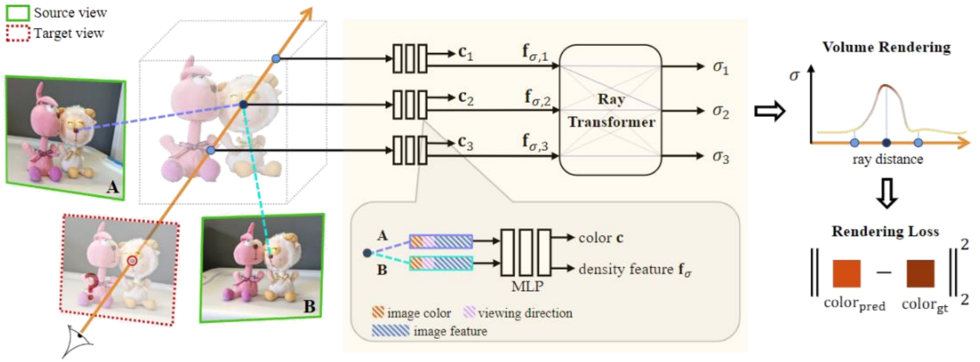
NeuWigs

[1] Ziyan Wang et al. NeuWigs: A Neural Dynamic Model for Volumetric Hair Capture and Animation. CVPR 2023.
[2] Ziyan Wang et al. HVH: Learning a Hybrid Neural Volumetric Representation for Dynamic Hair Performance Capture. CVPR 2022.
[3] Radu Alexandru Rosu et al. Neural Strands: Learning Hair Geometry and Appearance from Multi-View Images. ECCV 2022.

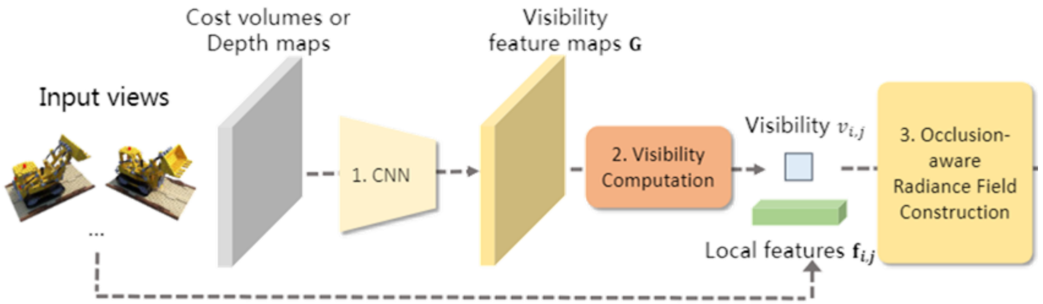
可泛化NeRF重建：Overview

- 研究动机：朴素的NeRF需要对每个物体或场景进行密集的拍摄以及独立的训练，因此希望实现从稀疏视点图像中直接推理得到NeRF
- 早期工作：从大规模数据中学习图像特征空间对齐的NeRF

IBRNet



Liu et al.



DoubleField

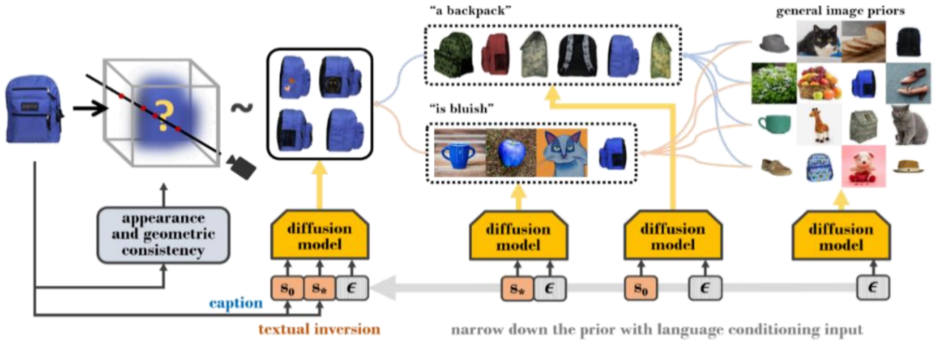
pixelNeRF

不可见区域重建相对模糊

[1] Yu et al. pixelNeRF: Neural Radiance Fields from One or Few Images. CVPR 2021.
[2] Wang et al. IBRNet: Learning Multi-View Image-Based Rendering. CVPR 2021.
[3] Liu et al. Neural Rays for Occlusion-aware Image-based Rendering. CVPR 2022.
[4] Shao et al. DoubleField: Bridging the Neural Surface and Radiance Fields for High-fidelity Human Reconstruction and Rendering. CVPR 2022.

可泛化NeRF重建：基于扩散模型重建

- 研究动机：朴素的NeRF需要对每个物体或场景进行密集的拍摄以及独立的训练，因此希望实现从稀疏视点图像中直接推理得到NeRF
- 近期路线：基于扩散模型的单图像NeRF重建
  - NeRDi：从预训练的latent diffusion model中获得输入图像的语义信息，并约束新视点渲染图像符合语义信息
  - GeNVS：提出3D-aware扩散模型，以体渲染得到的特征图为条件进行去噪过程
  - Make-It-3D：提出NeRF到点云的两阶段优化方法，进一步提升纹理质量



NeRDi

GeNVS

Make-It-3D

[1] Deng et al. NeRDi: Single-View NeRF Synthesis with Language-Guided Diffusion as General Image Priors. CVPR 2023.
[2] Chan et al. GeNVS: Generative Novel View Synthesis with 3D-Aware Diffusion Models. arXiv 2023.
[3] Tang et al. Make-It-3D: High-Fidelity 3D Creation from A Single Image with Diffusion Prior. arXiv 2023.
[4] Melas-Kyriazi et al. RealFusion: 360◦ Reconstruction of Any Object from a Single Image. CVPR 2023.

3D生成: Overview

- 研究动机：利用大规模2D图像先验，获得对象的生成式先验模型，以支持稀疏视点重建和各类编辑任务
- 近期路线：类别对象3D生成→GAN，通用对象3D生成→Diffusion

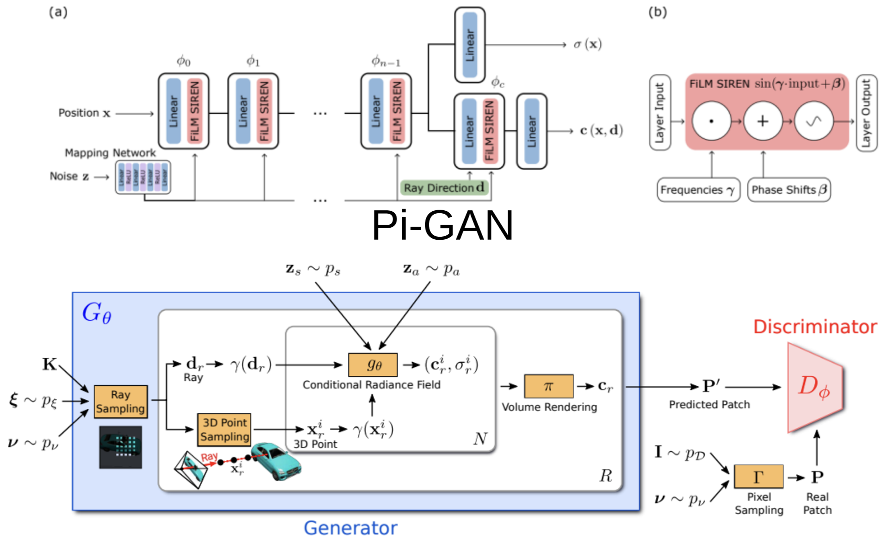
EG3D

Dreamfusion

[1] Chan, Eric R., et al. "Efficient geometry-aware 3D generative adversarial networks." *CVPR* 2022.
[2] Poole, Ben, et al. "Dreamfusion: Text-to-3d using 2d diffusion." *arXiv preprint arXiv:2209.14988* (2022).

3D生成: 3D GAN类别对象生成

- 研究动机：NeRF具有可微渲染的特点，可以从2D图片的监督中优化网络参数，因此将NeRF与GAN结合，构建生成式神经辐射场，学习3D内容生成
- 解决方案: 基于神经辐射场的MLP网络，利用GAN的对抗式训练策略从2D图片中学习生成式神经辐射场，通过随机噪声产生隐式编码控制其几何与纹理



Pi-GAN

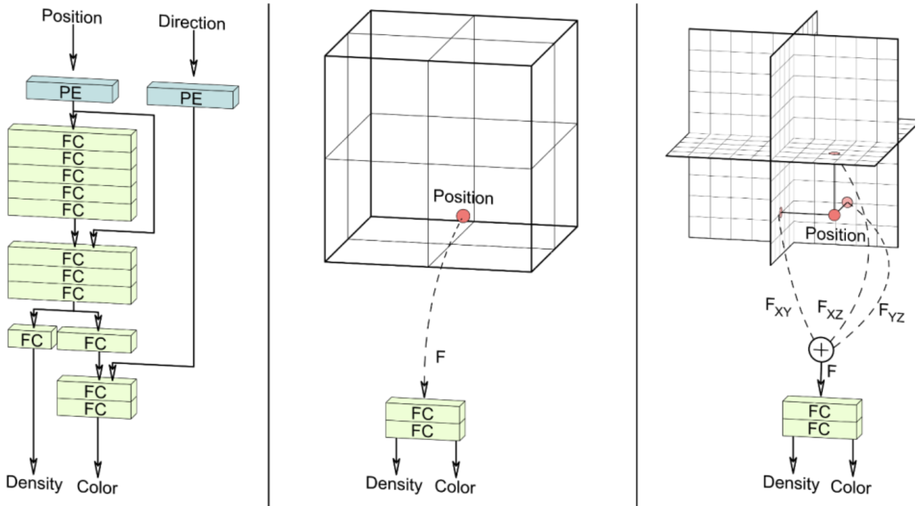
GRAF


Pi-GAN

[1] Schwarz, Katja, et al. "Graf: Generative radiance fields for 3d-aware image synthesis." NeurIPS 2020.
[2] Chan, Eric R., et al. "pi-gan: Periodic implicit generative adversarial networks for 3d-aware image synthesis." *CVPR* 2021.
[3] Niemeyer et al.. "Giraffe: Representing scenes as compositional generative neural feature fields." *CVPR* 2021.
[4] Deng, Yu, et al. "Gram: Generative radiance manifolds for 3d-aware image generation." *CVPR* 2022.

3D生成： 3D GAN类别对象生成(三平面改进)

- 研究动机：3D GAN受限于MLP的显存消耗和表达能力，生成结果分辨率低
- 解决方案和创新性：提出基于三平面的三维表达，将神经辐射场的高频信号存储在三平面上从而轻量化MLP网络，在不损失表达能力的同时，大大降低显存消耗和提升渲染速率；利用高效的2D styleGAN生成具有高频细节的triplane，从而提升生成质量；利用2D超分辨提高渲染分辨率



(a) NeRF (Implicit) (b) Voxels (Explicit or Hybrid) (c) Ours (Hybrid)

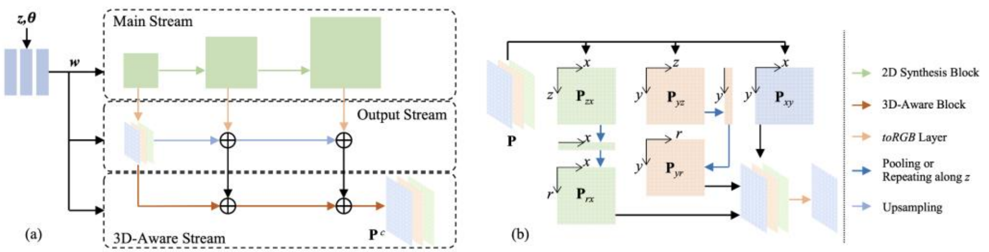
EG3D

PanoHead

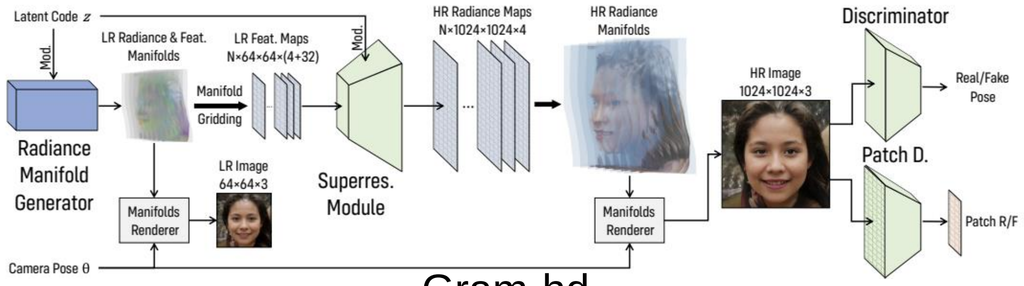
[1] Chan, Eric R., et al. "Efficient geometry-aware 3D generative adversarial networks." *CVPR* 2022.
[2] An, Sizhe, et al. "PanoHead: Geometry-Aware 3D Full-Head Synthesis in 360deg." *CVPR* 2023.

3D GAN类别对象生成(超分辨)

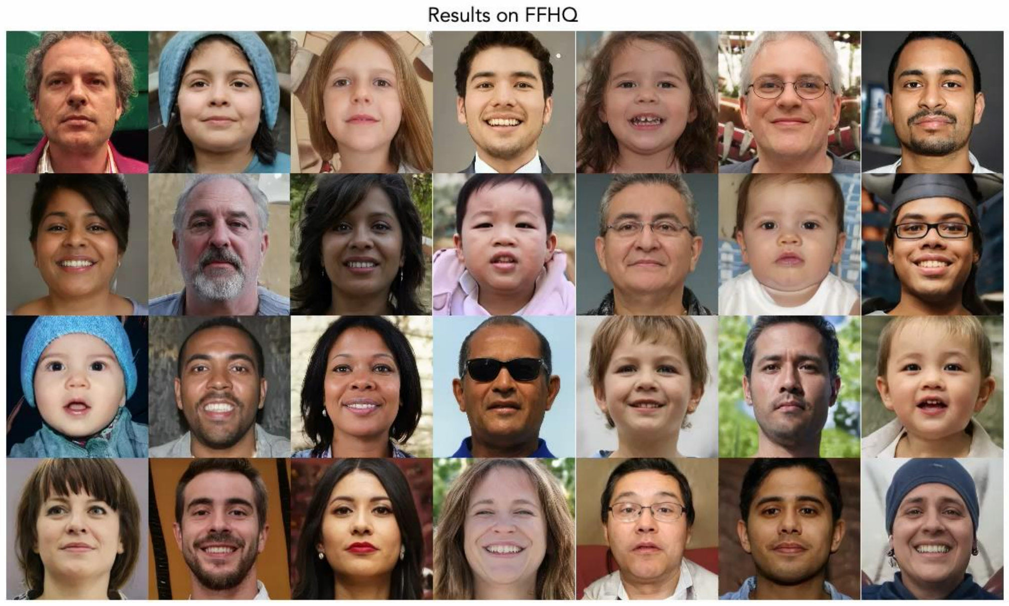
- **研究动机：2D超分辨网络将视角信息和图像特征耦合，破坏了三维一致性**
- **解决方案和创新性：用3D超分辨代替2D超分辨**
  - **Gram-hd：在神经辐射场中设置一组隐式曲面流形，并对曲面流形进行超分；**
  - **Mimic3D: 通过让生成器的3D渲染分支合成的图像模仿其2D超分辨率分支生成的图像，使3D GAN能够生成高质量的图像，同时保持其严格的3D一致性**



Mimic3D



Gram-hd



Mimic3D

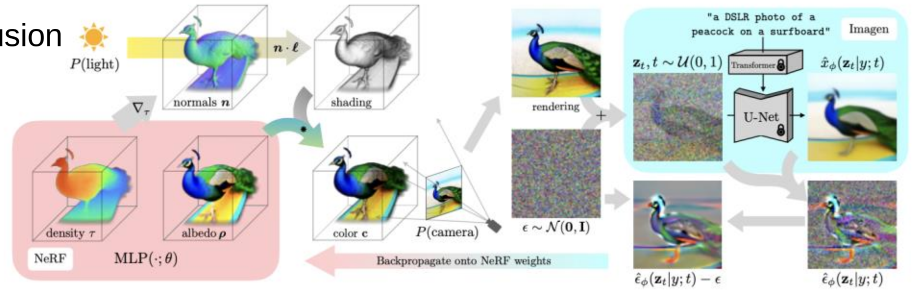
[1] Xiang, et al. "Gram-hd: 3d-consistent image generation at high resolution with generative radiance manifolds." *arXiv* 2022.

[2] Chen, Xingyu, Yu Deng, and Baoyuan Wang. "Mimic3D: Thriving 3D-Aware GANs via 3D-to-2D Imitation." *arXiv* 2023.

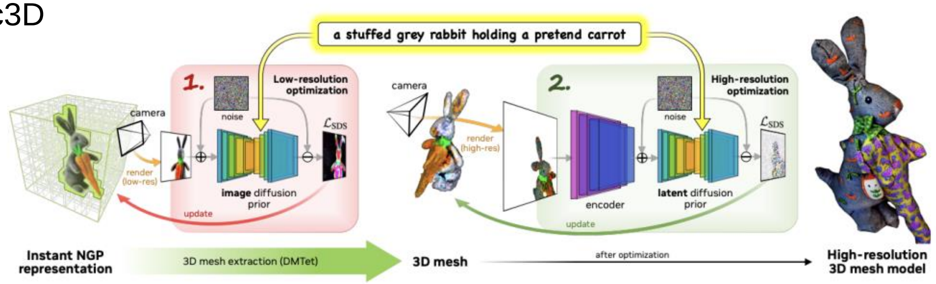
3D生成：通用3D对象生成 (2D升维)

- **研究动机： 2D生成式大模型具有强大的文本生成图片能力；NeRF具有表征连续复杂三维对象的能力，并且其渲染方式一种可微逆渲染，因此可通过2D监督反向优化辐射场的网络参数，实现通用物体或场景的三维生成**
- **解决方案：将预训练 2D生成式大模型作为先验，利用得分蒸馏采样（SDS）损失，最小化NeRF可微渲染图与扩散模型生成图像之间分布的KL散度，优化NeRF参数，实现文本到三维的生成。代表工作：Dreamfusion, Magic3D，Fantasia3D**

Dreamfusion



Magic3D



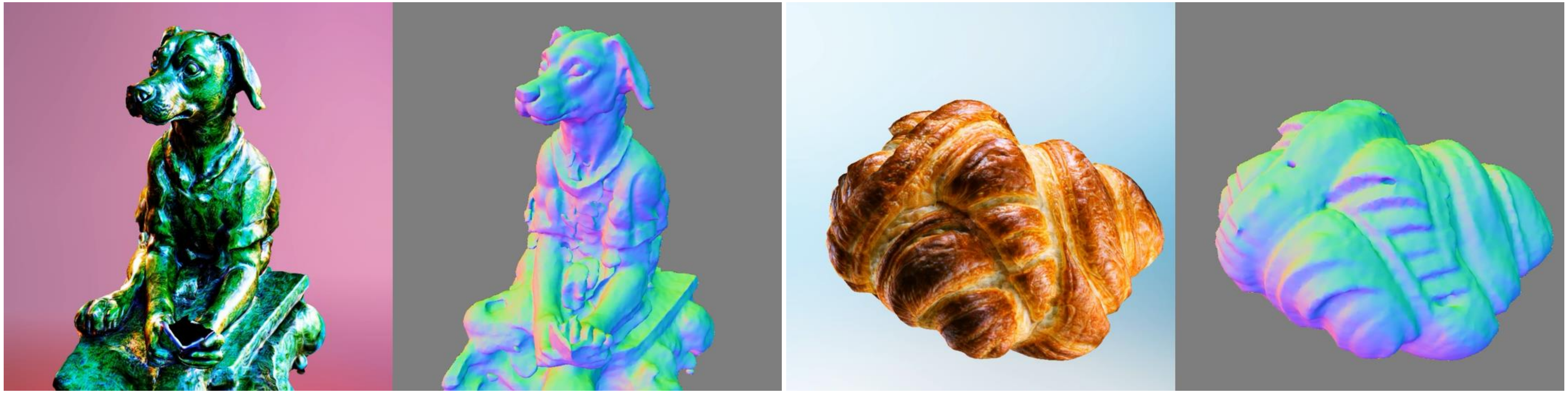
Dreamfusion

Fantasia3d

[1] Poole, Ben, et al. "Dreamfusion: Text-to-3d using 2d diffusion." *arXiv preprint arXiv:2209.14988* (2022).
[2] Lin, Chen-Hsuan, et al. "Magic3d: High-resolution text-to-3d content creation." *CVPR* 2023.
[3] Chen, Rui, et al. "Fantasia3d: Disentangling geometry and appearance for high-quality text-to-3d content creation." *arXiv* 2023

3D生成：通用3D对象生成 (2D升维)

- 研究动机：得分蒸馏采样（SDS）的优化目标是让单个NeRF的渲染图满足给定文本下预训练模型的图片分布的似然最大值；使得该NeRF被优化成符合该图片分布的某个最值：生成的三维模型过饱和、过平滑，且缺少多样性
- 解决方案：给定文本下预训练模型的图片分布对应一组（大于等于一）NeRF的分布，从概率角度下对NeRF参数进行变分推断。变分得分蒸馏采样（VSD）将优化的目标从单点的NeRF改为NeRF的分布；用粒子建模 NeRF的分布，通过迭代优化这些粒子，使得其渲染图片分布接近预训练模型的分布，因此生成的三维模型的多样性和细节质量更高



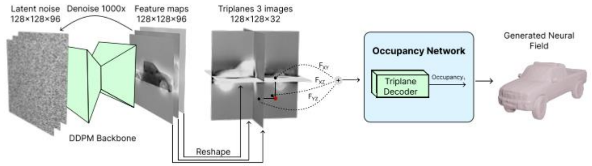
ProlificDreamer

[1] Wang et al. "ProlificDreamer: High-Fidelity and Diverse Text-to-3D Generation with Variational Score Distillation." *arXiv* 2023

3D生成：类别对象3D生成（原生3D）

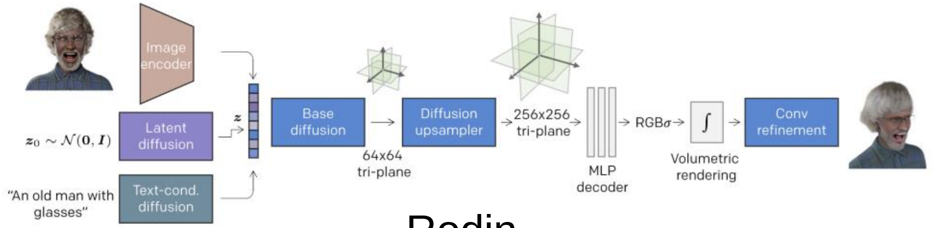
- 研究动机: 利用Diffusion优化NeRF的方法（2D升维）费时（小时级）；神经辐射场中的MLP网络没有显式的结构，无法直接基于diffusion对其进行优化；3D diffusion所需的内存存储与计算开销几乎无法承受
- 解决方案：构建具有三维感知的扩散模型：将神经辐射场表征为显式的三平面结构（Rodin, NFD, SSDNeRF），体素网格（DiffRF），通过学习神经辐射场的去噪过程，可以直接从噪声中生成神经辐射场，无需优化。目前仅支持类别对象生成。

DiffRF



NFD

NFD



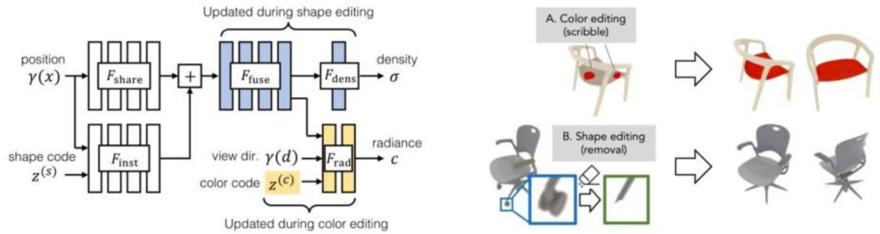
Rodin

Rodin

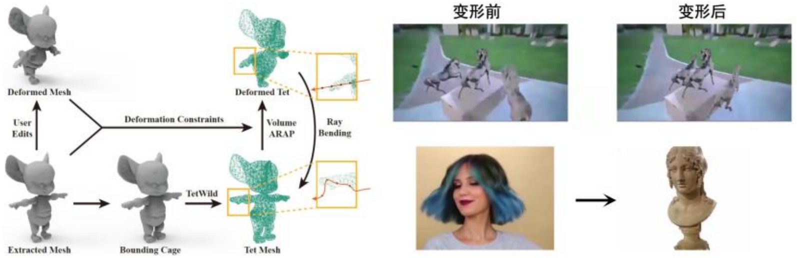
[1] Wang, Tengfei, et al. "Rodin: A generative model for sculpting 3d digital avatars using diffusion." *CVPR* 2023.
[2] Shue, J. Ryan, et al. "3d neural field generation using triplane diffusion." *CVPR* 2023.
[3] Müller, Norman, et al. "Diffrf: Rendering-guided 3d radiance field diffusion." *CVPR* 2023.
[4] Chen et al. “Single-Stage Diffusion NeRF: A Unified Approach to 3D Generation and Reconstruction”. arXiv 2023.

3D编辑： 物体/场景NeRF的编辑

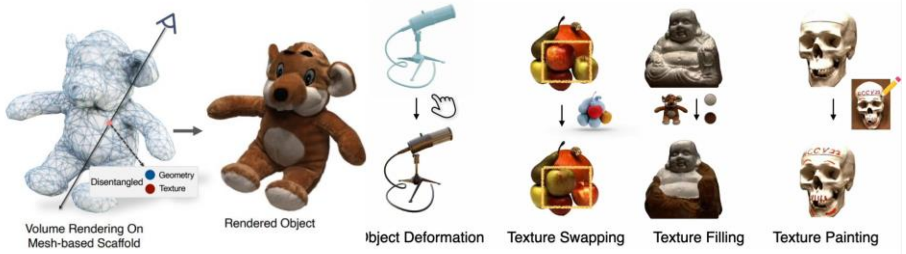
- 研究动机: 传统神经辐射场拟合或生成场景或物体，无法对其编辑
- 解决方案：利用不同的网络和隐含向量解耦形状和外观；用户在二维渲染图片上编辑，利用网络和隐含向量进行反向传播优化或前向编辑
- 早期工作：EditNeRF, NeRF-Editing, NeuMesh，ARF



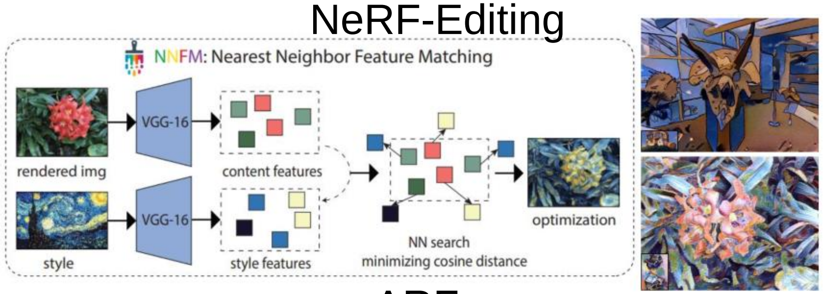
EditNeRF



NeRF-Editing



NeuMesh



ARF

[1] Liu, Steven, et al. "Editing conditional radiance fields." ICCV 2021.

[2] Yuan, Yu-Jie, et al. "NeRF-editing: geometry editing of neural radiance fields." *CVPR* 2022.

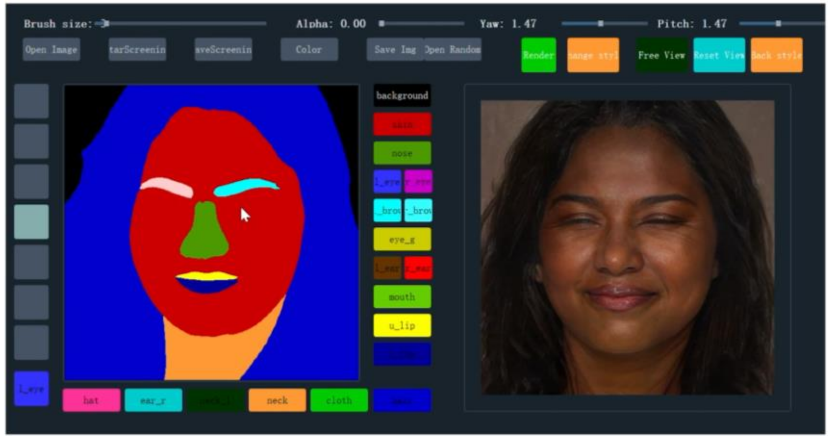
[3] Yang, et al. "Neumesh: Learning disentangled neural mesh-based implicit field for geometry and texture editing." *ECCV 2022*.

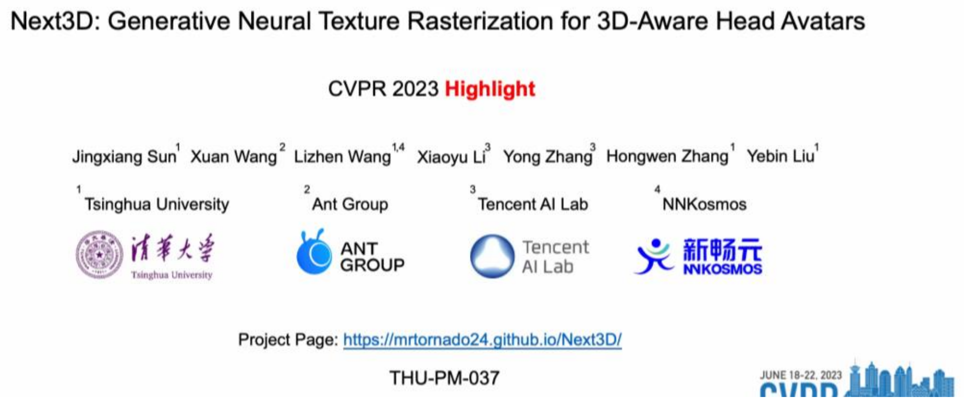
[4] Zhang, Kai, et al. "Arf: Artistic radiance fields." *ECCV 2022*.

3D编辑： 基于GAN的NeRF编辑

- 研究动机: PiGAN, GRAF等3D GAN生成丰富的三维人脸，但无法对其进行细粒度编辑
- 解决方案：将外部信号映射到神经辐射场，对其特征进行编辑
  - IDE3D：提出一个几何和材质解耦的生成式神经语义场，通过在几何分支网络中额外输出语义mask，对齐三维语义和几何；编辑原理是2D语义图编辑映射到语义场，从而编辑三维语义和与其对齐的几何
  - Next3D：提出了一个基于神经纹理贴图的动态三平面表达，驱动表情信号会通过神经纹理光栅化，引起三平面特征形变，进而渲染具有相应表情的图像
- 代表工作：IDE3D, NeRFaceEditing, AnifaceGAN, Next3D

IDE3D





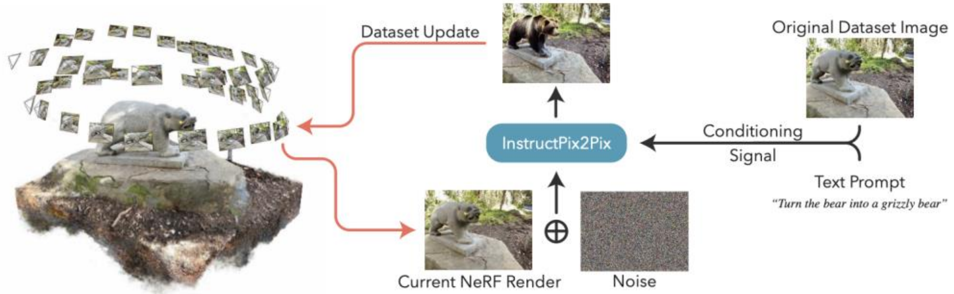
Next3D

[1] Sun, Jingxiang, et al. "Ide-3d: Interactive disentangled editing for high-resolution 3d-aware portrait synthesis." *ACM TOG* 2022.
[2] Jiang, Kaiwen, et al. "NeRFFaceEditing: Disentangled Face Editing in Neural Radiance Fields." SIGGRAPH Asia 2022 Conference Papers. 2022.
[3] Wu, Yue, et al. "Anifacegan: Animatable 3d-aware face image generation for video avatars." arXiv preprint arXiv:2210.06465 (2022).
[4] Sun, Jingxiang, et al. "Next3D: Generative Neural Texture Rasterization for 3D-Aware Head Avatars." *CVPR* 2023.

3D编辑： 基于Diffusion的NeRF编辑

- 研究动机: 基于文生图的扩散模型，利用文本对NeRF实现更直观，交互性更好的3D或4D编辑
- 解决方案：利用扩散模型不断迭代编辑训练集，同时优化神经辐射场参数，使得NeRF渲染结果和给定文本生成的编辑图像趋于一致；
- 代表工作：InstructNeRF2NeRF， Instruct3D-to-3D

InstructPix2Pix



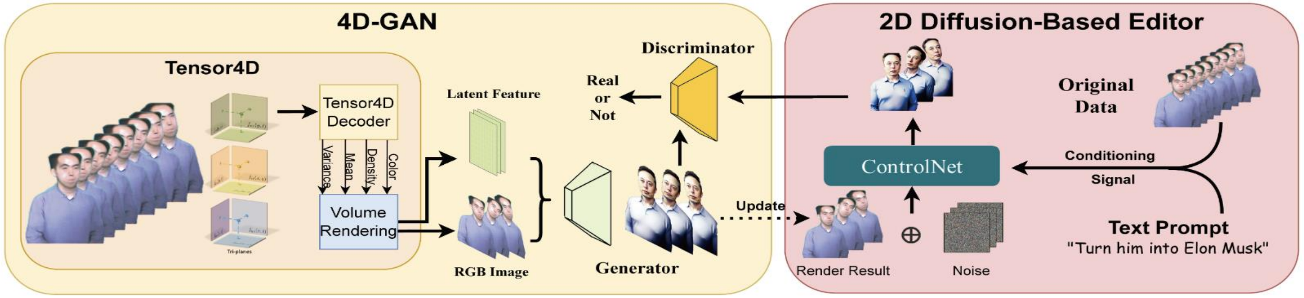
InstructNeRF2NeRF

InstructNeRF2NeRF

[1] Haque, Ayaan, et al. "Instruct-nerf2nerf: Editing 3d scenes with instructions." *arXiv* 2023.
[2] Brooks et al. "Instructpix2pix: Learning to follow image editing instructions." *CVPR* 2023.
[3] Kamata, Hiromichi, et al. "Instruct 3D-to-3D: Text Instruction Guided 3D-to-3D conversion." *arXiv* 2023.

4D生成与编辑： 基于Diffusion动态NeRF生成与编辑

- 研究动机: 现有扩散模型只能编辑生成2D图像，借助动态NeRF可以从2D升维到4D，实现高质量且一致的4D编辑生成
- Control4D：将Tensor4D与GAN结合实现了一个4D GAN，利用4D GAN来学习扩散模型在不同时刻视角生成的图像分布，避免了图像的直接监督从而实现高质量的编辑生成效果，4D GAN判别器产生的监督信号相比扩散模型更加平滑，使得4D场景编辑的时空一致性更好且网络收敛更快

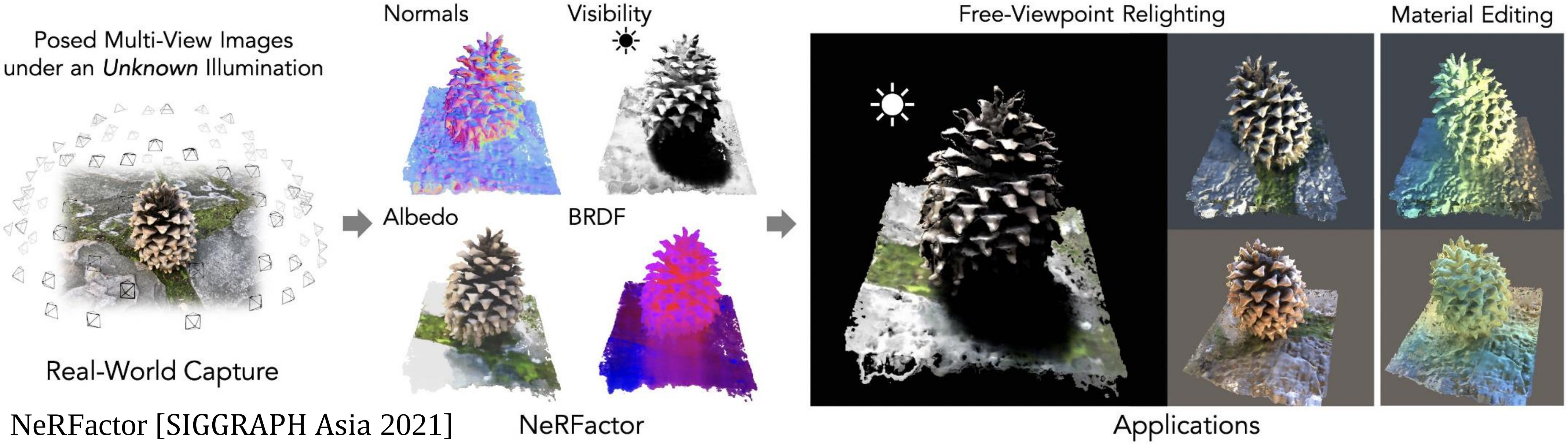


Control4D

[1] Shao et al. "Control4D: Dynamic Portrait Editing by Learning 4D GAN from 2D Diffusion-based Editor." *arXiv* 2023.
[2] Singer, Uriel, et al. "Text-to-4d dynamic scene generation." *arXiv* 2023.

光影编辑: Overview

- 研究动机：扩展NeRF表征材质信息进而实现光影编辑
- 早期工作：NeRFactor, InvRender , PhySG
- 解决思路：将NeRF颜色表征分解为“几何(Normal)+材质(BRDF)+光照(Lighting)”，重新组合渲染实现重光照与材质编辑

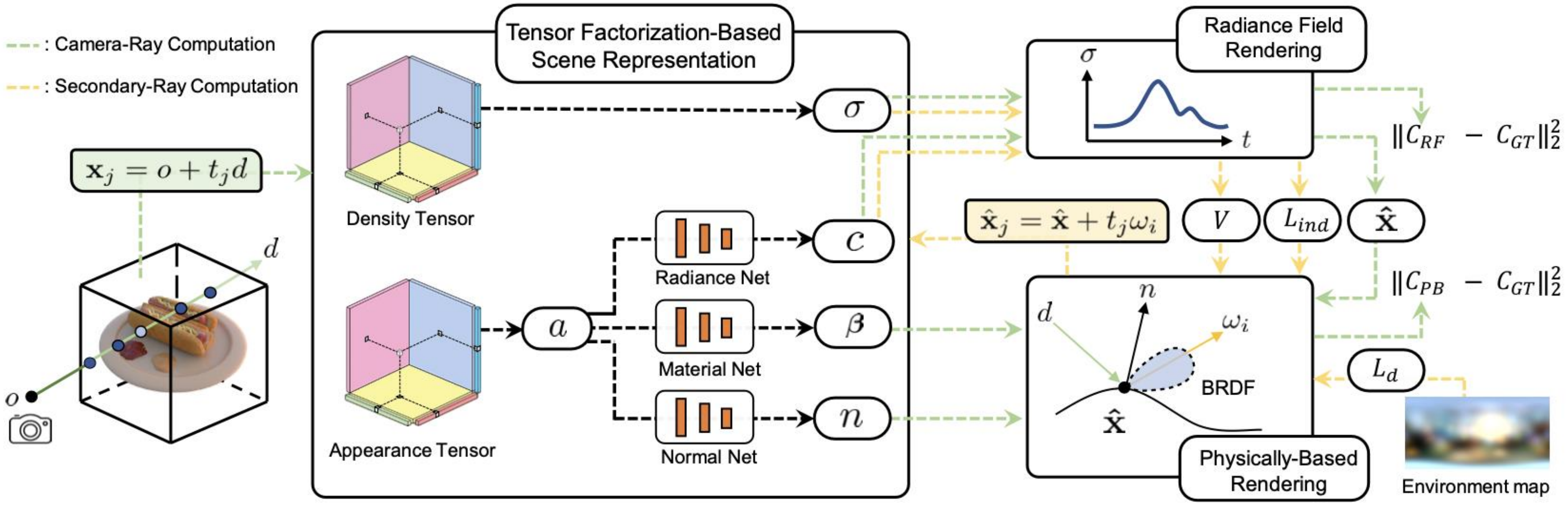


NeRFactor [SIGGRAPH Asia 2021]

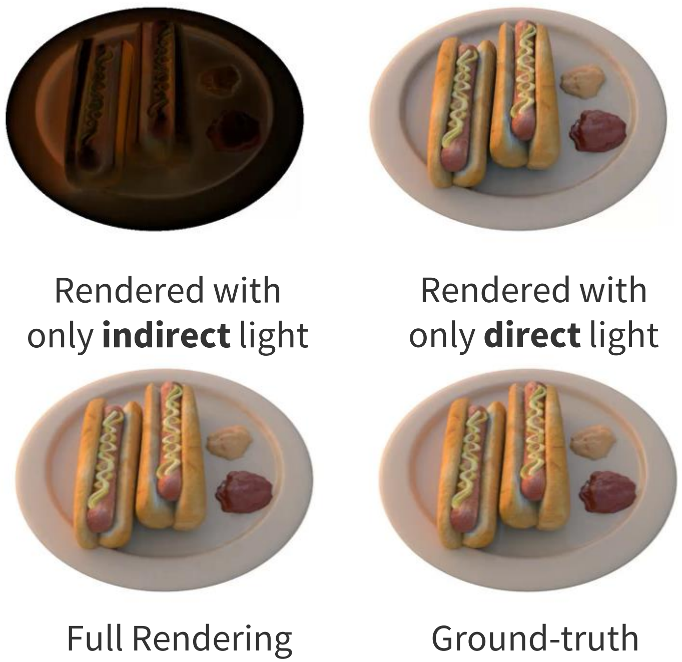
[1] Xiuming Zhang, et al. "NeRFactor: Neural Factorization of Shape and Reflectance Under an Unknown Illumination.SIGGRAPH Asia 2021.
[2] Kai Zhang, et al. " PhySG: Inverse Rendering with Spherical Gaussians for Physics-based Material Editing and Relighting." CVPR 2021.
[3] Yuanqing Zhang, et al. " Modeling Indirect Illumination for Inverse Rendering." CVPR 2022.

光影编辑：间接光模拟

- 研究动机：仅模拟直接光照难以解释复杂光传输效应
- 解决方案和创新性：使用NeRF在不同方向的出射辐照度模拟间接光照，通过模拟光线多次弹射建立更为精细的光照模型，基于物理渲染实现高质量光影编辑
  - TensorIR:提出基于张量分解逆向渲染方法，同时实现基于物理的渲染模型估计和辐射场重建
  - NeFII: 提出端到端逆向渲染管道，结合蒙特卡洛采样与球面高斯函数实现高质量渲染



TensoIR [CVPR 2023]

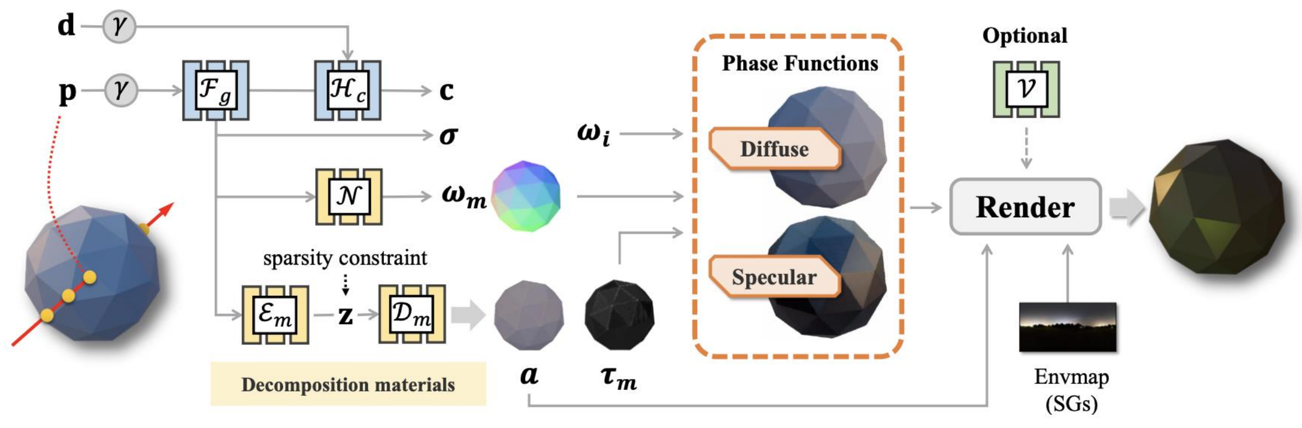


[1] Haian Jin, et al. "TensoIR: Tensorial Inverse Rendering." CVPR 2023.

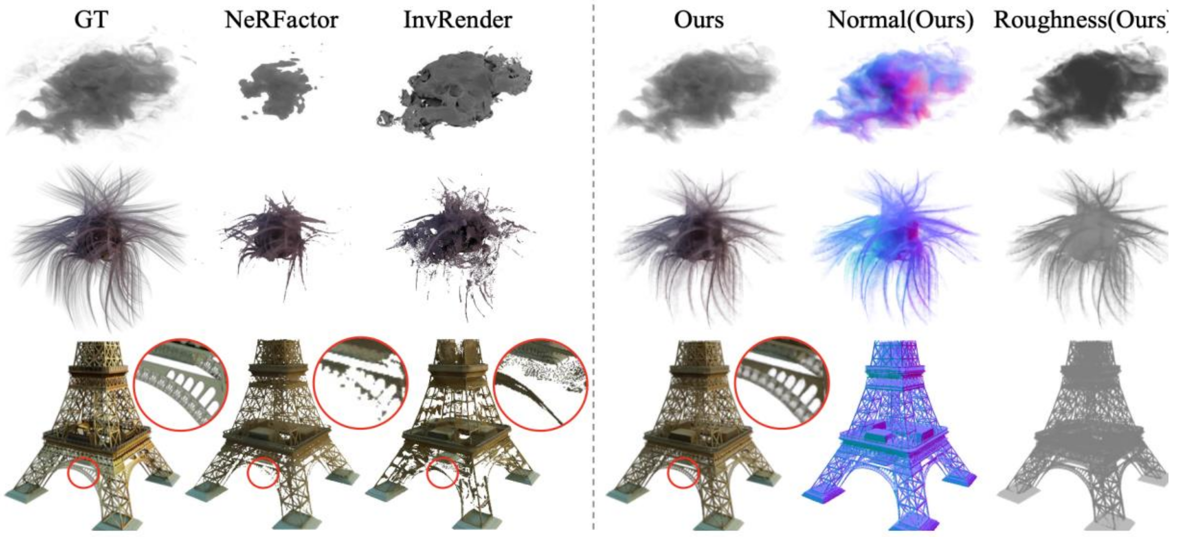
[2] Haoqian Wu, et al. "NeFII: Inverse Rendering for Reflectance Decomposition with Near-Field Indirect Illumination." CVPR 2023.

光影编辑：场景表征

- 研究动机：传统基于表面渲染方法难以模拟复杂几何与透明材质
- 解决方案和创新性：将微平面模型与神经辐射场结合，模拟光线在传输过程中与微平面交互，建立隐式微平面场，使用体渲染实现不依赖于几何表面的高质量渲染
  - NMF:提出微平面反射材质模型，使用蒙特卡洛采样和光线追踪模拟相互反射
  - NeMF: 结合微薄片体积模型与神经辐射场，模拟光线在微薄片处反射与折射效应



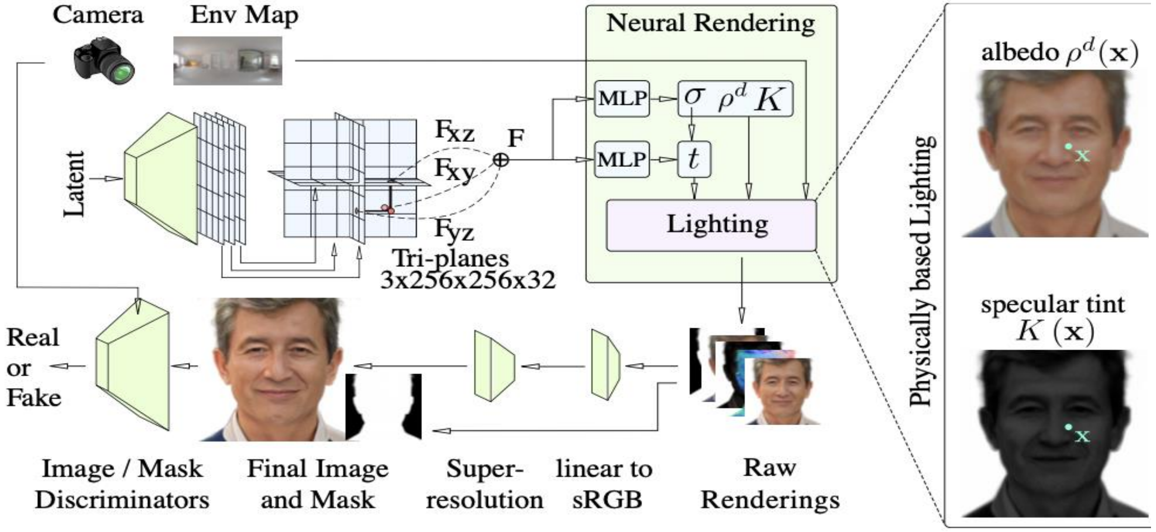
NeMF [Arxiv 2023]



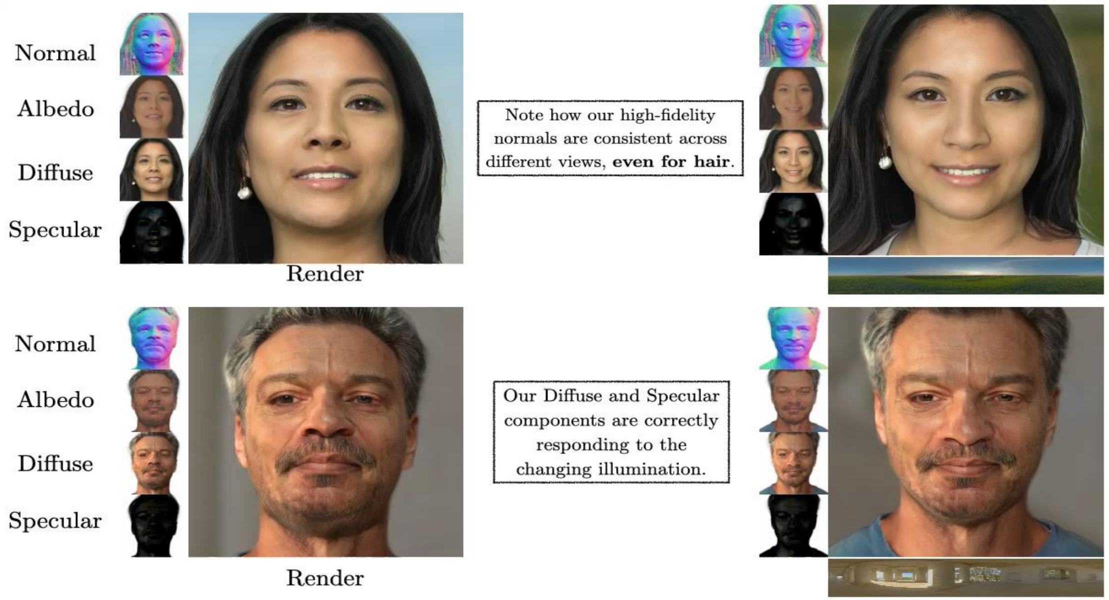
[1] Alexander Mai , et al. “Neural Microfacet Fields for Inverse Rendering .” Arxiv 2023.
[2] Youjia Zhang , et al. “NeMF: Inverse Volume Rendering with Neural Microflake Field .” Arxiv 2023.

光影编辑：生成式模型

- 研究动机：NeRF针对单个场景优化，渲染生成结果缺乏多样性
- 解决方案和创新性：将生成式模型引入NeRF光影编辑，生成三维视角一致的可重光照人像
  - VoLux-GAN: 提出体积HDRI重光照方法，使用数据增强端到端训练三维可重光照人像
  - LumiGAN:以自监督训练方式学习精细几何，建立感知自遮挡的BRDF材质模型



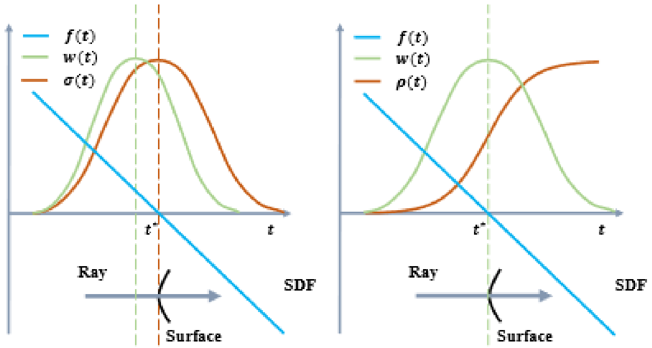
LumiGAN [Arxiv 2023]



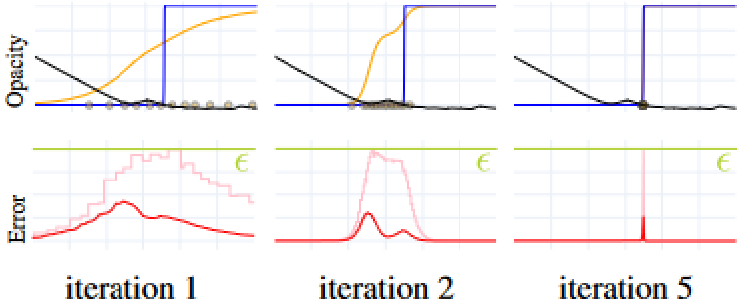
[1] Feitong Tan, et al. “VoLux-GAN: A Generative Model for 3D Face Synthesis with HDRI Relighting.” SIGGRAPH 2022.
[2] Boyang Deng, et al. "LumiGAN: Unconditional Generation of Relightable 3D Human Faces." Arxiv 2023.

表征增强：Overview

- 研究动机：隐式曲面场具有表示几何的优越性，但难以通过NeRF光线步进的方法渲染训练；若使用朴素方法将隐式曲面函数转换为密度函数，光线积分所估计的表面位置会略近于真实表面。
- 早期工作：VolSDF、NeuS、DoubleField、UNISURF
- 解决思路：1）对光线采样点重新分配积分的权重，使最终积分能落在表面；
  2）对光线采样点重采样，使采样点集中在表面。



重新分配采样点的积分权重



采样点重采样

[1] Yariv, Lior, et al. "Volume rendering of neural implicit surfaces." *NeurIPS*. 2021.

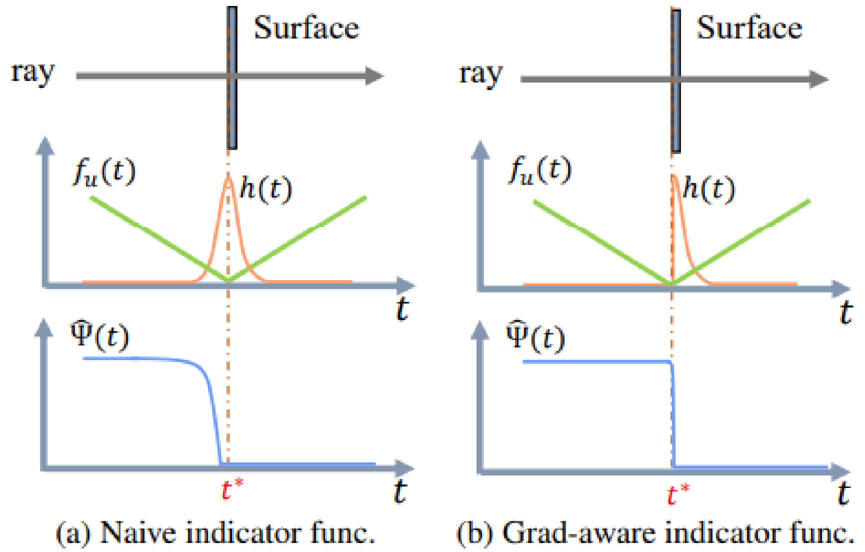
[2] Wang, Peng, et al. "NeuS: Learning Neural Implicit Surfaces by Volume Rendering for Multi-view Reconstruction." *NeurIPS.* 2021.

[3] Shao, Ruizhi, et al. "Doublefield: Bridging the neural surface and radiance fields for high-fidelity human reconstruction and rendering." *CVPR*. 2022.

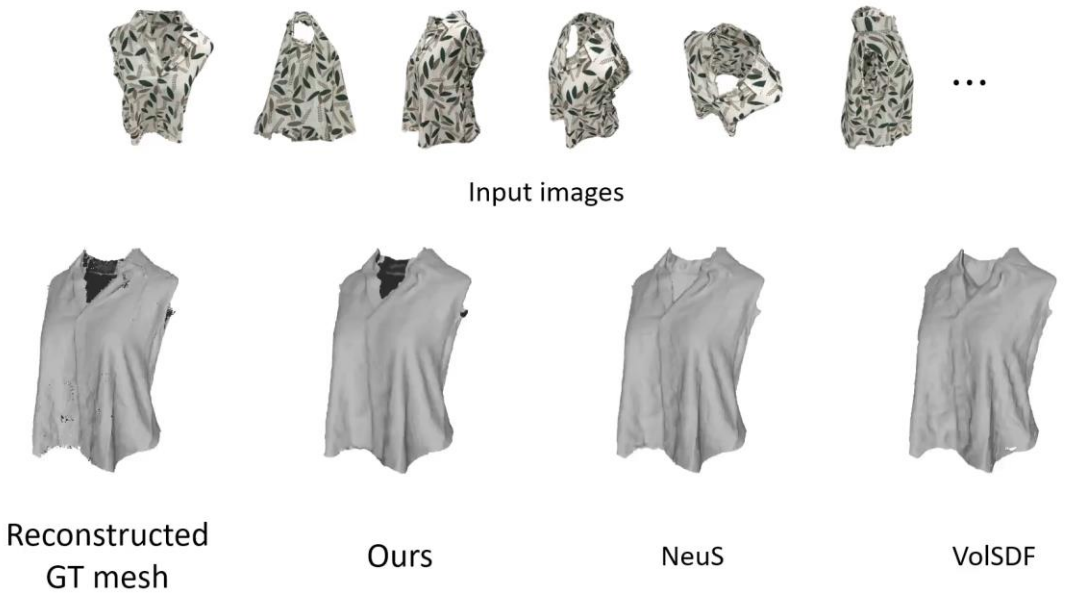
[4] Oechsle, Michael, Songyou Peng, and Andreas Geiger. "Unisurf: Unifying neural implicit surfaces and radiance fields for multi-view reconstruction." *ICCV*. 2021.

表征增强：无符号距离场

- 研究动机：符号距离场（SDF）等闭合曲面函数难以建模衣物等较薄的物体。
- 解决思路：使用无符号距离场（UDF）的开放曲面函数进行建模，提出对应的重权重化策略以训练，实现更合理的曲面重建。



渲染无符号距离场的光线采样点权重分配

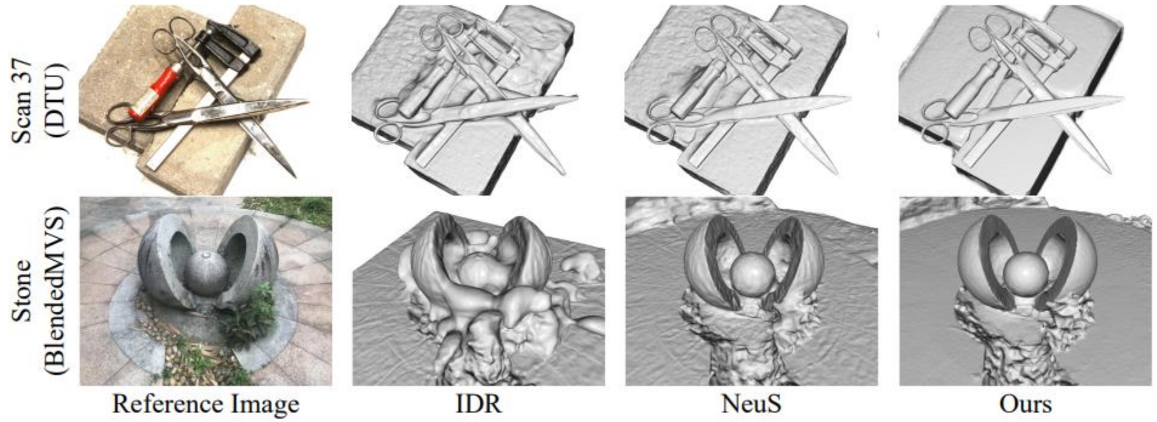


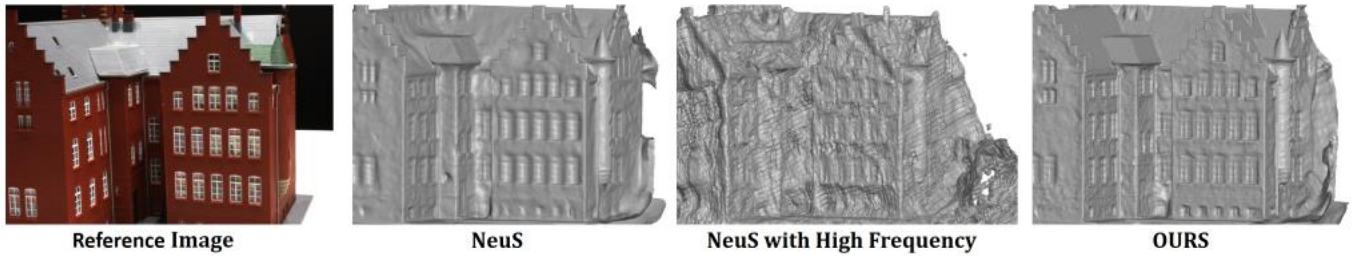
不同曲面表示的重建结果

[1] Long, Xiaoxiao, et al. "Neuraludf: Learning unsigned distance fields for multi-view reconstruction of surfaces with arbitrary topologies." *CVPR*. 2023.

表征增强：高频几何细节

- 研究动机：神经辐射场的几何-辐射歧义性使高频几何细节难以刻画，朴素地添加高频的位置编码会导致不必要的几何噪声。
- 解决思路：使用几何先验（深度图/SfM解算出的表面）对神经隐式曲面进行约束；将SDF场拆解成低频的SDF场和沿表面法向的高频位移，实现由粗到细的几何训练。





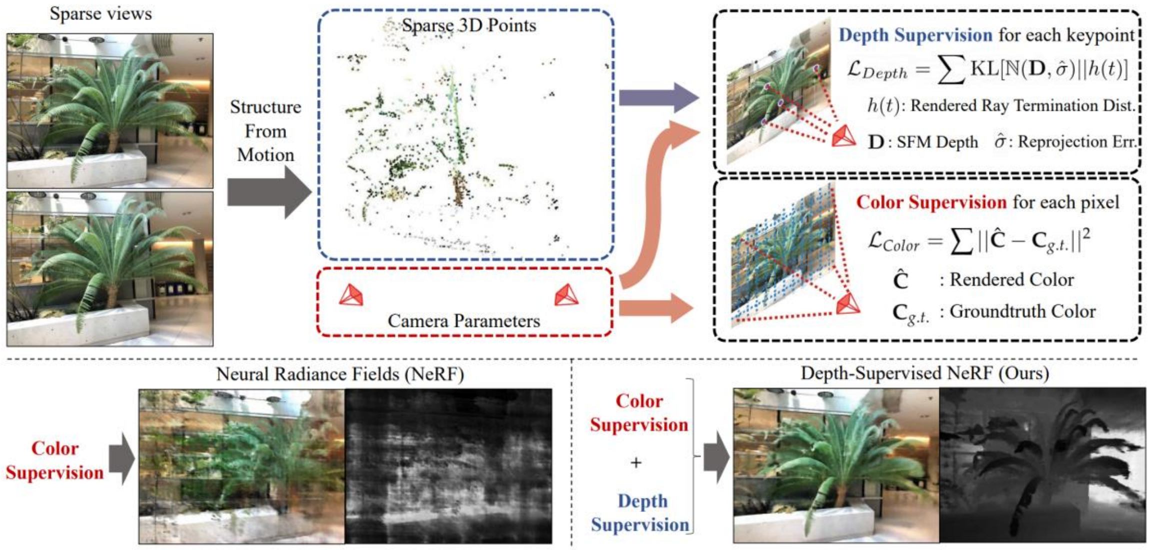
高低频特征分解的几何重建

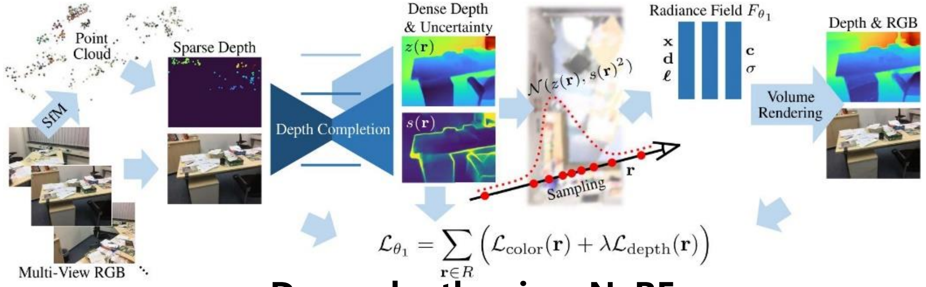
使用SfM表面约束的重建结果对比

[1] Fu, Qiancheng, et al. “Geo-neus: Geometry-consistent neural implicit surfaces learning for multi-view reconstruction.” *NeurIPS.* 2022.
[2] Wang, Yiqun, et al. "Hf-neus: Improved surface reconstruction using high-frequency details." *NeurIPS*. 2022.
[3] Zhu, Bingfan, et al. "Vdn-nerf: Resolving shape-radiance ambiguity via view-dependence normalization." *CVPR*. 2023.

表征增强：深度先验

- 研究动机：朴素的NeRF通常难以直接优化得到合理的几何，导致在稀疏视角下倾向于过拟合到少数输入视点
- 解决思路：使用SfM、MVS或者深度预测网络等工具得到少量或稠密深度值作为场景的约束，提高稀疏视角下的优化效率和鲁棒性





Dense depth priors NeRF

Depth-supervised NeRF

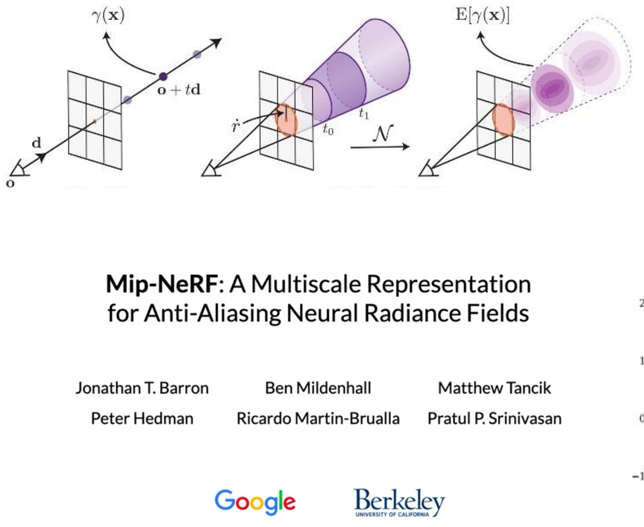
ENeRF

[1] Deng, Kangle, et al. "Depth-supervised nerf: Fewer views and faster training for free." CVPR. 2022.
[2] Roessle, Barbara, et al. "Dense depth priors for neural radiance fields from sparse input views." CVPR. 2022.
[3] Lin, Haotong, et al. "Efficient Neural Radiance Fields for Interactive Free-viewpoint Video." SIGGRAPH Asia. 2022.

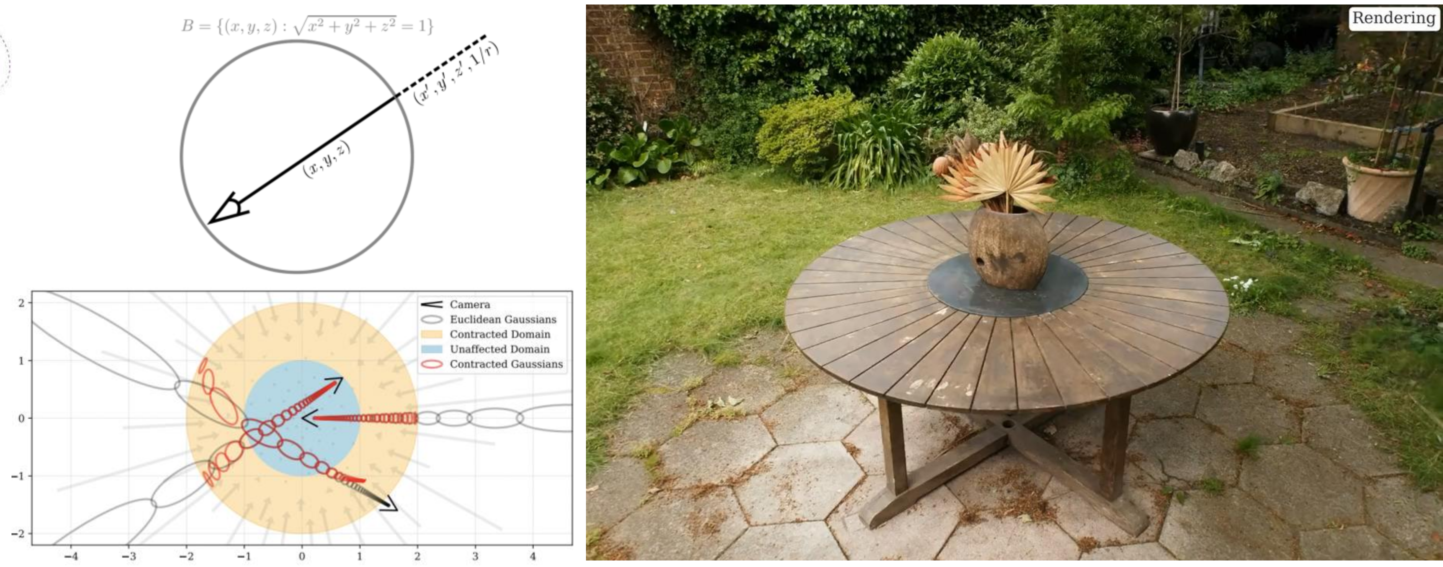
场景建模：Overview

- 研究动机：扩展NeRF表征大场景内容，允许对空间跨度大、几何纹理复杂的非结构化图像集合进行准确重建和新视点合成
- 早期工作：NeRF++、Mip-NeRF、Mip-NeRF 360
- 解决思路：通过引入全空间非线性参数化模型，解决无界3D场景下NeRF建模问题；通过引入考虑采样点高斯区域的集成位置编码，解决NeRF在多尺度重建下模糊和混叠问题

NeRF++



Mip-NeRF

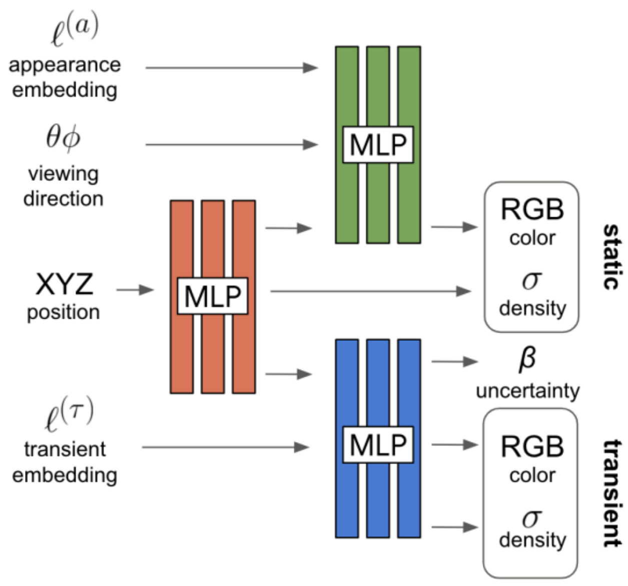


Mip-NeRF 360

[1] Zhang K, Riegler G, Snavely N, et al. Nerf++: Analyzing and improving neural radiance fields. arXiv. 2020.
[2] Barron, Jonathan T., et al. "Mip-nerf: A multiscale representation for anti-aliasing neural radiance fields." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2021.
[3] Barron, Jonathan T., et al. "Mip-nerf 360: Unbounded anti-aliased neural radiance fields." CVPR. 2022.

场景建模：光照编码

- 研究动机：解决受不同日照、天气影响的非结构化图像集合的NeRF重建问题
- 解决方案和创新性：通过引入可学习的表观和瞬态嵌入，生成静态及瞬态颜色、密度和不确定性度量，实现大场景的光照编码和解耦；通过构建双MLP表示，分别建模场景表面颜色和虚拟位置的反射，实现高真实感的大场景NeRF渲染



Nerf in the wild

Scalable neural indoor scene rendering

[1] Martin-Brualla, Ricardo, et al. "Nerf in the wild: Neural radiance fields for unconstrained photo collections." CVPR. 2021.

[2] Li, Quewei, et al. “NeuLighting: Neural Lighting for Free Viewpoint Outdoor Scene Relighting with Unconstrained Photo Collections.” SIGGRAPH Asia. 2022.

[3] Wu, Xiuchao, et al. "Scalable neural indoor scene rendering." TOG. 2022.

场景建模：稀疏观测

- 研究动机：解决室内或局部城市街景下，面对场景复杂和观测稀疏挑战的大场景NeRF重建问题
- 解决方案和创新性：引入LiDAR、点云等几何信息约束NeRF建模，通过融合多模态信息，实现大空间跨度稀疏视角下的城市街景3D重建

URBAN RADIANCE FIELDS

Konstantinos Rematas Andrew Liu Pratul Srinivasan
Jon Barron Andrea Tagliasacchi Tom Funkhouser Vittorio Ferrari

Google Research

Urban Radiance Fields

S-NeRF: Neural Radiance Fields for Street Views

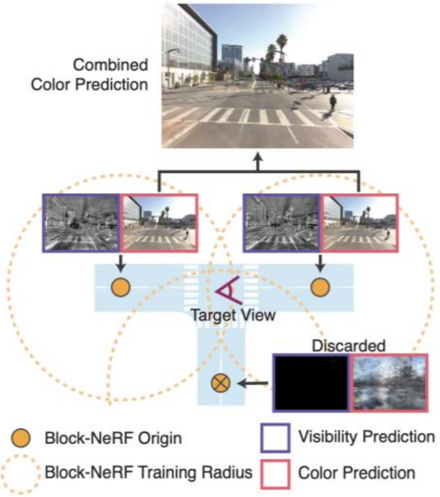
Ziyang Xie*, Junge Zhang*, Wenye Li, Feihu Zhang, Li Zhang
Fudan University

S-NeRF

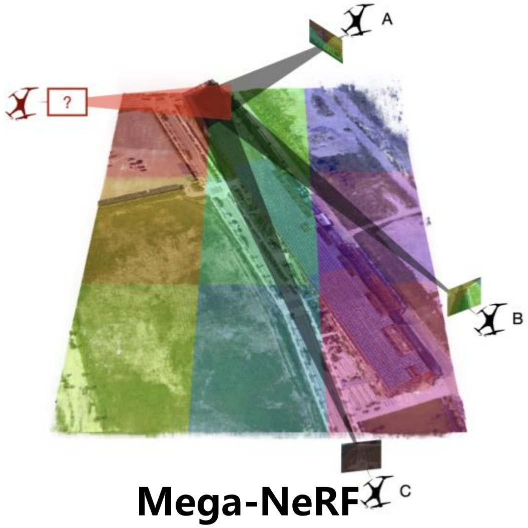
[1] Rematas, Konstantinos, et al. "Urban radiance fields." CVPR. 2022.
[2] Xie, Ziyang, et al. "S-nerf: Neural radiance fields for street views." arXiv. 2023.
[3] Carlson, Alexandra, et al. "Cloner: Camera-lidar fusion for occupancy grid-aided neural representations." IEEE Robotics and Automation Letters. 2023.

场景建模：城市级建模

- 研究动机：解决更大范围甚至整个城市的场景建模
- 解决方案和创新性：针对无人车街景或空中俯拍数据，对场景分块建模，将场景不同区域分配到并行训练的子神经辐射场中，并通过表观匹配(Block-NeRF)，设计门控网络(Switch-NeRF)或设计渐进式增长模型(Bungeenerf)保证整个场景的一致性，实现更大范围场景下平滑的新视点合成



Block-NeRF



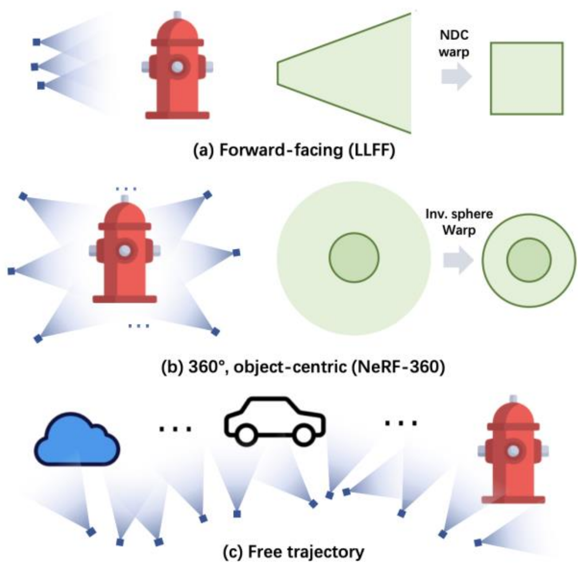
Mega-NeRF

Bungeenerf

[1] Tancik, Matthew, et al. "Block-nerf: Scalable large scene neural view synthesis." CVPR. 2022.
[2] Turki, Haithem, Deva Ramanan, and Mahadev Satyanarayanan. "Mega-nerf: Scalable construction of large-scale nerfs for virtual fly-throughs." CVPR. 2022.
[3] Xiangli, Yuanbo, et al. "Bungeenerf: Progressive neural radiance field for extreme multi-scale scene rendering." ECCV, 2022.
[4] Zhenxing, M. I., and Dan Xu. "Switch-NeRF: Learning Scene Decomposition with Mixture of Experts for Large-scale Neural Radiance Fields." ICLR. 2023.
[5] Reiser, Christian, et al. “Merf: Memory-efficient radiance fields for real-time view synthesis in unbounded scenes.” arXiv. 2023.

场景建模：自由轨迹绘制

- 研究动机：解决无界场景NeRF框架无法处理任意轨迹下自由视点渲染的问题
- 解决方案和创新性： 通过一种新空间变形方法，实现任意虚拟相机轨迹下的NeRF建模；通过同时优化相机位姿和局部NeRF，并动态分配局部辐射场，实现大场景下高质量的自由轨迹图像渲染



F2-NeRF

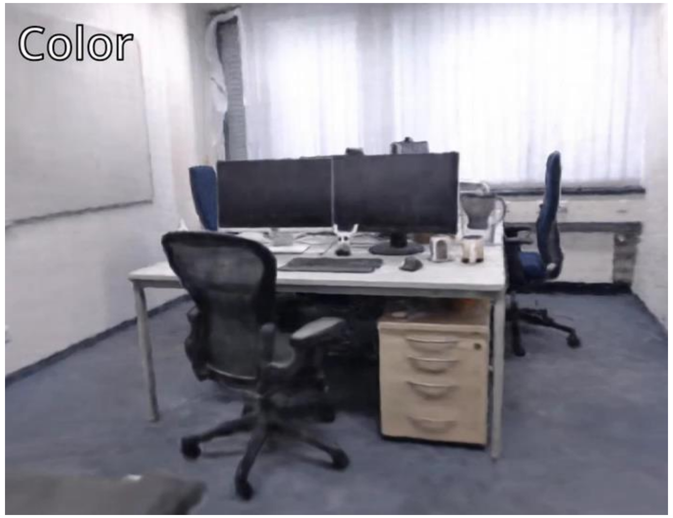
Progressively optimized local radiance fields for robust view synthesis

[1] Wang, Peng, et al. "F2-NeRF: Fast Neural Radiance Field Training with Free Camera Trajectories." CVPR. 2023.

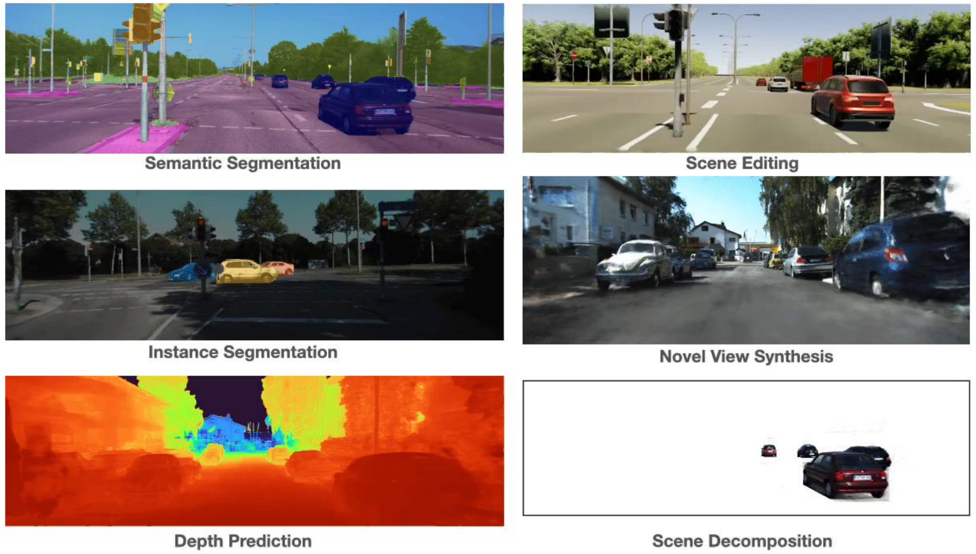
[2] Meuleman, Andreas, et al. "Progressively optimized local radiance fields for robust view synthesis." CVPR. 2023.

场景建模：三维场景理解

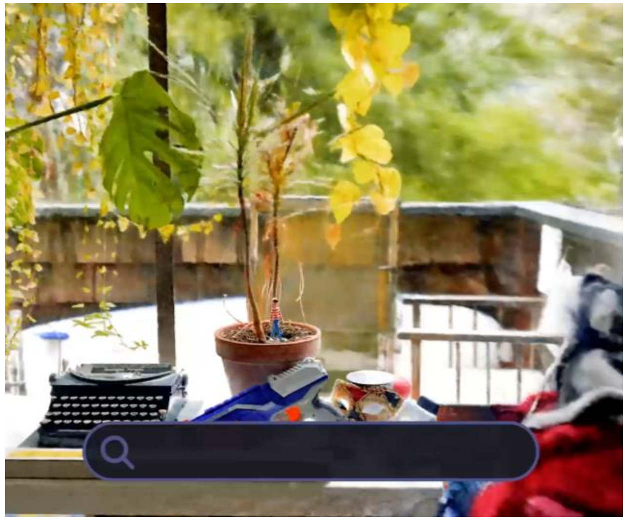
- 研究动机：构建高精度三维场景语义，用于自动驾驶、三维语义建图等场景；通过NeRF三维连续场提升语义分割时空一致性和准确性
- 解决方案和创新性：利用NeRF可微渲染技术，将二维语义嵌入到三维隐式场，构建语义物体感知的神经场景表示，实现全场景的三维理解和检索



Siddiqui et al. 2023



Kundu et al. 2022

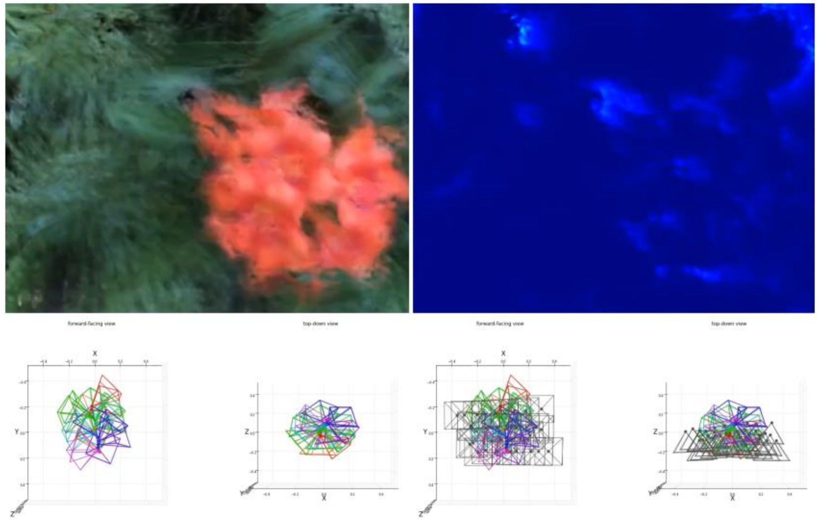


Kerr et al. 2022

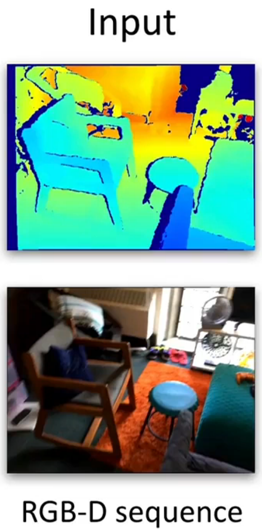
[1] Kundu et al. “Panoptic Neural Fields: A Semantic Object-Aware Neural Scene Representation.” CVPR 2022.
[2] Siddiqui et al. "Panoptic Lifting for 3D Scene Understanding with Neural Fields." CVPR 2023.
[3] Wang et al. “DM-NeRF: 3D Scene Geometry Decomposition and Manipulation from 2D Images.” ICLR 2023.
[4] Kerr et al. “LERF: Language Embedded Radiance Fields”. arXiv 2023.

场景建模：相机姿态估计和SLAM

- 研究动机：精确相机位姿难以获取，联合优化NeRF与相机位姿容易陷入局部极小
- 解决方案和创新性：从图像中估计深度和光流先验，用自监督的方式提取不同视角间的相关关系，约束表面的一致性，结合局部对齐和全局对齐，实现相机姿态的优化



Yu et al. 2023

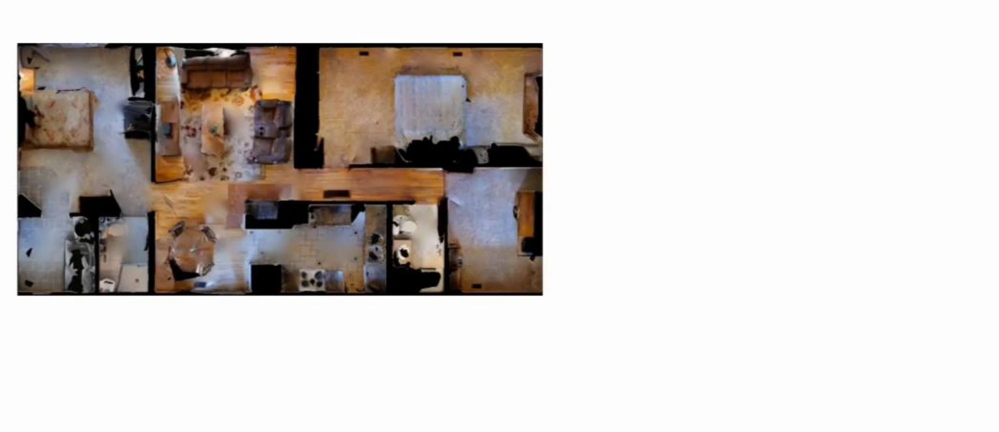


Wang et al. 2023

[1] Chen et al. “L2G-NeRF: Local-to-Global Registration for Bundle-Adjusting Neural Radiance Fields”. CVPR 2023.
[2] Yu et al. “DBARF: Deep Bundle-Adjusting Generalizable Neural Radiance Fields”. CVPR 2023.
[3] Bian et al. “NoPe-NeRF: Optimising Neural Radiance Field with No Pose Prior”. CVPR 2023
[4] Wang et al. “Co-SLAM: Joint Coordinate and Sparse Parametric Encodings for Neural Real-Time SLAM”. CVPR 2023.
[5] Zhu et al. “NICER-SLAM: Neural Implicit Scene Encoding for RGB SLAM”. arXiv 2023.

场景建模：自动驾驶和机器人

- NeRF渲染生成自动驾驶模拟数据集，提升自动驾驶视觉感知泛化能力
- 构建可渲染的辐射场地图，即时查询目标位置，实现视觉导航和定位
- 对机械臂进行位姿扰动，用NeRF同步进行数据视角增广，提升抓取策略鲁棒性



自动驾驶：Xie et al. 2023　　**视觉导航和定位：Kwon et al. 2023**　　**机械臂抓取：Zhou et al. 2023**

[1] Elluswamy, Tesla CVPR 2022 Workshop on Autonomous Driving.
[2] Xie et al. S-NeRF: Neural Radiance Fields for Street Views. ICLR 2023.
[3] Zhou et al. NeRF in the Palm of Your Hand: Corrective Augmentation for Robotics via Novel-View Synthesis. CVPR 2023
[4] Kwon et al. Renderable Neural Radiance Map for Visual Navigation. CVPR 2023.
[5] Lee et al. Uncertainty Guided Policy for Active Robotic 3D Reconstruction using Neural Radiance Fields. RA-L 2022

NeRF年度发展趋势

□ 趋势1：高质量动态建模

- 尽管2022年以前的NeRF方法在静态场景下表现优越，但是对于复杂动态场景的建模效果仍然存在改进空间。本年度大量工作在此方向作出努力，既包括了对于一般动态场景的4D建模改进，也有对于人脸人体的建模改进，部分工作甚至在保证实时性的前提下取得了惊艳的效果。

□ 趋势2：与大模型的结合

- 大模型的落地应用已然势不可挡。本年度有大量工作致力于将生成式大模型与NeRF相结合，从而实现NeRF的生成创作。与大模型结合之后， NeRF不再局限于重建现实物体或场景，而是具备了“无中生有”的创造力。

□ 趋势3：更丰富的信息嵌入

- 2022年以前的NeRF工作主要着眼于新视点渲染，因此只考虑了几何和纹理的建模。本年度的工作中，研究者为NeRF引入了更多的信息，包括丰富的材质属性，以及更高层次的语义内涵。语义信息的引入则进一步拓宽了NeRF的潜在应用场景。

□ 趋势4：应用到其他领域

- 在上一年度，NeRF仅仅在三维视觉领域受到关注。在本年度，NeRF实现了“破圈”，在机器人、自动驾驶、医疗等领域也有了应用，其新视点生成能力能够有效辅助这些领域的数据生成与场景理解。

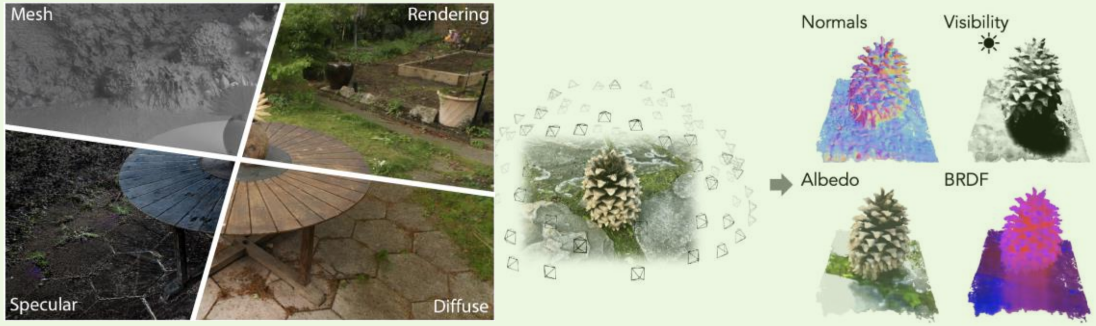
NeRF研究的展望

实时、动态、高精度

如何设计更高效的表征

表征解耦

如何准确分解几何/光照/材质

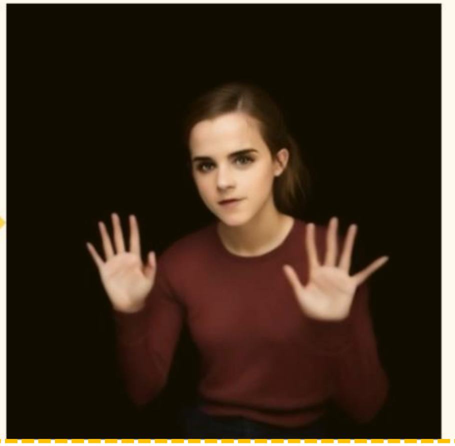


大场景建模

如何同时定位与多尺度场景建模

可控生成

如何联合大模型实现语义一致生成



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□ 开源框架

- https://docs.nerf.studio

□ 论文整理

- https://neuralradiancefields.io
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致谢


郑泽荣


苏肇祺


周玥眉


李哲


赵笑晨


邵睿智


徐乐朗


吉朝南


林思有


孙景翔


陈雨硕


张鸿文

感谢本课题组同学们在文献收集与内容梳理过程中的辛勤付出！

清華大學
Tsinghua University

谢 谢！