# Balanced Spherical Grid for Egocentric View Synthesis

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### EgoNeRF - Motivation & Goal

 NeRF & grid-based NeRFs<sup>1,2,3</sup> can visualize the photorealistic appearance of bounded scenes



#### Goal

- We propose a *practical solution* to reconstruct *large-scale* environments



[1] Anpei Chen et al., Tensorf: Tensorial radiance fields, ECCV 2022
 [2] Cheng Sun et al., Direct voxel grid optimization: Super-fast convergence for radiance fields reconstruction, CVPR 2022
 [3] Thomas Müller et al., Instant neural graphics primitives with a multiresolution hash encoding, ACM ToG 2022

### EgoNeRF - Keys

#### 1. Reconstruct NeRF of large-scale scenes from **egocentric video**





#### egocentric video

free-view rendering



### EgoNeRF - Keys

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- 2. Grid-based NeRF with **balanced spherical grid**





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- 3. Resampling technique for grid-based methods





## EgoNeRF

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### Capturing Large-Scale Scenes

RGB-D Camera<sup>4</sup>

Multi-camera rigs <sup>5, 6</sup>

Omnidirectional Video / Egocentric Video





- X Narrow field-of-view
- X Hard to capture large-scale environments in a short period
- X High-cost
- X Inaccessible to nonexpert users

- ✓ Short capturing time (less than 5s)
- ✓ Portable & low-cost
- ✓ Non-expert can capture easily



[4] Angela Dai et al., ScanNet: Richly-Annotated 3D Reconstruction of Indoor Scenes, CVPR 2017
[5] Michael Broxton et al., Deepview immersive light field video, SIGGRAPH 2020 Immersive Pavilion
[6] Albert Parra Pozo et al., An integrated 6dof video camera and system design, ToG 2019

#### Datasets - OmniBlender





BistroBike



BistroSquare





LoneMonk





PavilionChair

PavilionPond



#### Datasets - Ricoh360





Center

Farm





GalleryChair



GalleryPillar







## EgoNeRF

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### Grid-based Methods in Outward-looking Scene

Inward-facing views vs Outward-looking views





Inward-facing views

Outward-looking views



### Grid-based Methods in Outward-looking Scene

- Cartesian Grid in Outward-looking Scenario
  - Uniform grid size regardless of distance from camera
  - Non-uniform ray-grid hits in outward-looking scenario
- Spherical Grid
  - Resolves aforementioned limitations



Cartesian Grid



o : camera center
○ : camera path
○ : 360° camera
□ : ray-grid hit
→ : camera ray

#### Spherical Grid



### **Balanced Spherical Grid**

Naïve Spherical Grid



Singularity at poles, cause artifacts







### Balanced Spherical Grid



Angular Partition<sup>7</sup>

Yin grid: 
$$\left(\frac{\pi}{4} \le \theta \le \frac{3\pi}{4}\right) \cap \left(-\frac{3\pi}{4} \le \phi \le \frac{3\pi}{4}\right)$$
  
Yang grid:  $\begin{bmatrix} x^{\text{Yin}} \\ y^{\text{Yin}} \\ z^{\text{Yin}} \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x^{\text{Yang}} \\ y^{\text{Yang}} \\ z^{\text{Yang}} \end{bmatrix}$   
Partition:  $\Delta \theta^{y} = \frac{\pi}{2} \frac{1}{N_{\theta}^{y}}, \Delta \phi^{y} = \frac{3\pi}{2} \frac{1}{N_{\phi}^{y}}, y \in \{\text{Yin, Yang}\}$ 

**Radial Partition** 

**Exponential Partition** 

$$r_i^{\mathcal{Y}} = r_0 k^{i-1}$$
,  $R_{\max} = r_0 k^{N_r^{\mathcal{Y}} - 1}$ 



[7] Akira Kageyama and Tetsuya Sato, "yin-yang-grid": An overset grid and spherical geometry, Geochemistry 2004

### Balanced Spherical Grid as a Radiance Field

- Consider Explicit Feature Grids as the Mapping Function instead of MLP
  - Density grid:  $\mathcal{G}_{\sigma} \in \mathbb{R}^{2N_{r}^{y} \times N_{\theta}^{y} \times N_{\phi}^{y}}$
  - Appearance grid:  $\mathcal{G}_a \in \mathbb{R}^{2N_r^y \times N_\theta^y \times N_\phi^y \times C}$
- Querying Density and Color
  - $\sigma(\mathbf{x}) = \mathcal{T}(\mathcal{G}_{\sigma}, \mathbf{x}), c(\mathbf{x}, \mathbf{d}) = f_{\text{MLP}}(\mathcal{T}(\mathcal{G}_{a}, \mathbf{x}), \mathbf{d})$  ( $\mathcal{T}$ : Trilinear Interpolation)





[1] Anpei Chen et al., Tensorf: Tensorial radiance fields, ECCV 2022

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### Resampling Technique

- Sample  $N_c$  coarse points from a coarse grid
  - Don't need to allocate additional memory for coarse grid

 $\mathcal{G}_{\sigma}^{c} = K * \mathcal{G}_{\sigma}, K$ : non-learnable kernel (e.g. avg pool)





### Optimization

Training Objective

$$\hat{C} = \sum_{i=1}^{N} \tau_i (1 - e^{-\sigma(\mathbf{x}_i)\delta_i}) c(\mathbf{x}_i, \mathbf{d}) + \tau_{N+1} c_{\text{env}}(\mathbf{d})$$
$$\mathcal{L} = \frac{1}{|\mathcal{R}|} \|\hat{C}(\mathbf{r}) - C(\mathbf{r})\|$$

– Environment map  ${\cal E}$ 





w/o Env map

w/Env map



### Quantitative Results

- Fast training & rendering time
- High reconstruction quality at large-scale outward-looking scenes





### **Qualitative Results**





[1] Anpei Chen et al., Tensorf: Tensorial radiance fields, ECCV 2022
 [2] Cheng Sun et al., Direct voxel grid optimization: Super-fast convergence for radiance fields reconstruction, CVPR 2022
 [8] Jonathan T. Barron et al., Mip-nerf360: Unbounded anti-aliased neural radiance fields, CVPR 2022

### Conclusion

- EgoNeRF takes casual egocentric video of large scene as input
- EgoNeRF takes adv improved perform

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VISION



s (fast speed) and cal Grid in large scene





code&data

