

Context

Goal: From a **few satellite images**, we want to **recover the BRDF and 3D model** of the scene using deep learning method NeRF (Neural radiance fields), and further generate **synthetic images** under new viewing angle and illumination.

Applications:

- 1) Change detection;
- 2) land cover classification;
- 3) Earth radiation budget for climate studies... ..

SparseSat-NeRF

Workflow:

- 1) Input 2 satellite images;
- 2) Refine image poses with bundle adjustment;
- 3) Get dense depth and uncertainty with SGM scale4;
- 4) Recover 3D model and synthetic image using SparseSat-NeRF.

Preliminary Results

(1.1) Qualitative result, dataset DFC

(1.2) Qualitative result, dataset Dji

- Compared to NeRF and Sat-NeRF, SparseSat-NeRF renders sharper image and more informative DSM.
- Compared to SGM scale1, SparseSat-NeRF is better at reconstructing vegetation and at handling building outlines near occlusions, while SGM is better at roofs and edges.

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Training details:

- 1) For each pixel in an image, we trace a ray from the camera into the scene, and sample points along the ray.
- 2) For each point, we input the position and view direction to SparseSat-NeRF to predict the rgb color and volume density.
- 3) For each ray, we accumulate the points on the ray to get the predicted rgb color and depth of the pixel.

(2) Quantitative result of MAE (mean altitude error):
 *best and second best performing are indicated in blue and magenta.

	MAE _{in} ↓		MAE _{out} ↓
	DFC	Dji	DFC
NeRF	9.51	9.72	13.2
Sat-NeRF	5.89	9.51	11.75
SparseSatNeRF	3.02	1.57	7.77
SGM scale1	2.77	1.15	9.82

MAE_{in}: valid pixels defined by SGM
 MAE_{out}: occluded and poorly textured areas