Assignment 4: Non-line-of-sight imaging

Datasets

The reconstruction algorithm was tested on all the datasets provided with different scene geometries and capture setups. All reconstructed volumes are stored in the *results* folder. To visualize them, run the *show_volume.m* script. The visualization can be adjusted by modifying the parameters in *config.m*.

Basic tests and filtering

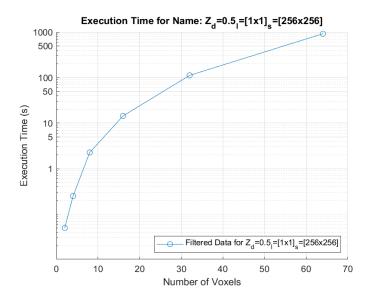
Initial tests were conducted using the *Z* dataset. By varying the voxel grid resolution, it was observed that:

• Reconstruction Time:

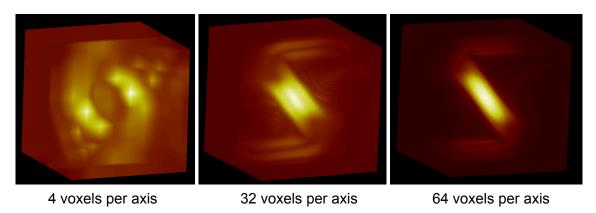
The time increases significantly with higher resolution. For instance, an 16x16x16 grid yields a fast computation but at the expense of image detail, while a denser grid improves quality but requires more computation time.

• Laplacian Filtering:

Applying a Laplacian filter enhances contrast and helps mitigate the inherent blurriness of the back-projection output.

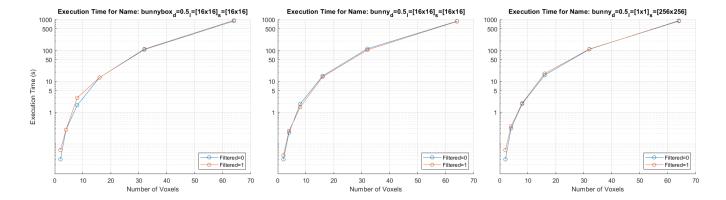


This is crucial since back-projection tends to produce blurred reconstructions due to the accumulation of spread-out energy.

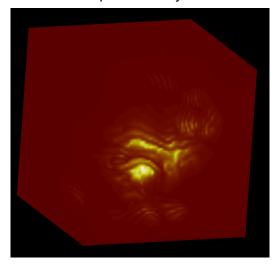


Non-planar geometry

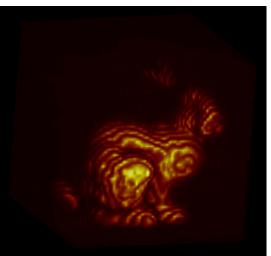
The reconstruction time is affected by both the voxel grid and relay wall capture resolutions. Higher voxelization improves detail but increases computational cost, with doubling resolution roughly increasing time eightfold due to cubic growth. Similarly, higher relay wall resolution leads to a denser dataset and longer processing times, while reducing sampling points can improve efficiency at the expense of accuracy.



Reconstructions with a single laser point and a SPAD grid exhibit less detail and more artifacts due to limited light path diversity, resulting in blurred features. In contrast, combining laser and SPAD grids captures multiple light paths from different angles, enhancing spatial resolution and depth accuracy.



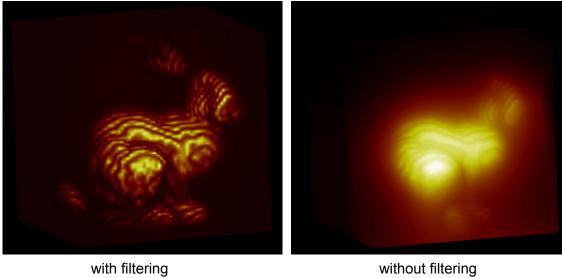
single laser point



multiple laser points

Back-projection reconstructions inherently appear blurry because energy is distributed over multiple voxels, softening edges. Applying a Laplacian filter emphasizes high-frequency details and sharpen edges, although excessive filtering may introduce noise.

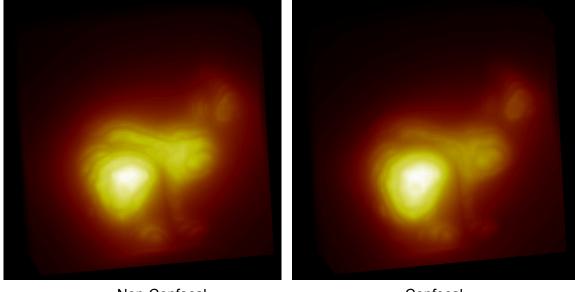
For enclosed scenes like the bunnybox dataset, global illumination from interreflections between the walls and object can improve overall reconstruction completeness but may also cause ghosting or incorrect intensity distributions, necessitating careful filtering to balance these effects.



Back-projection on confocal measurements

| Configuration | Laser Grid | SPAD Grid | Light Paths | Reconstruction Characteristics |
|---|---------------|--------------|--------------------------------------|--|
| Non-Confocal (bunny_d=0.5_l=[16x16] _s=[16x16]) | 16×16 | 16×16 | Multiple paths from different angles | Higher scene coverage, more complete reconstruction |
| Confocal (bunny_d=0.5_c=[256x2 56]) | 256×256 | 256×256 | Single path per laser-SPAD pair | Sharper reconstruction, but limited by directional constraints |

In these experiments, filtering is not used to see the differences more easily:



Non-Confocal

Confocal

Observations and Differences

1. Sharpness and Resolution

Confocal reconstruction is sharper since each measurement corresponds to a specific laser-SPAD pair, reducing signal spread and blurring. In contrast, non-confocal reconstruction distributes energy across multiple voxels, resulting in smoother but sometimes less defined images.

2. Coverage and Information Content

The non-confocal setup benefits from multiple light paths, capturing reflections from different angles and enabling more complete reconstructions, especially in occluded or complex surfaces. In contrast, the confocal setup, by illuminating and measuring from a single viewpoint, captures less indirect light information, potentially missing details in occluded areas.

3. Noise and Artifacts

Confocal reconstructions exhibit fewer artifacts due to the direct nature of light transport but may be less robust in the presence of occlusions. On the other hand, non-confocal reconstructions tend to have more noise and ghosting effects due to the increased number of indirect light paths but achieve better scene completeness.

Attenuation and foreshortening correction

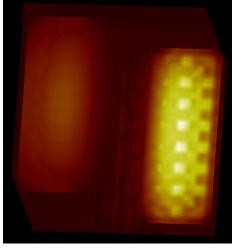
For each voxel x_v , the algorithm applies two corrections:

1. Distance-Based Correction (Quadratic Falloff):

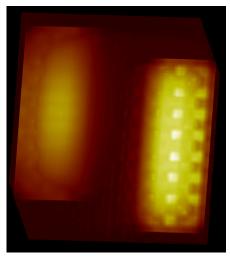
The total optical path (laser \rightarrow wall \rightarrow voxel) is computed. Since light intensity decreases with the square of the distance, a compensation factor

$$I_{\text{corregido}}(x_v) = I(x_v) \cdot d(x_v)^2$$

is applied, where $d(x_v)$ is the total distance.



without Quadratic Falloff



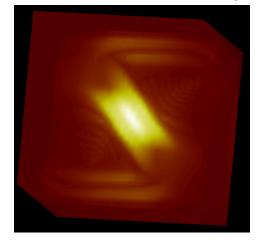
with Quadratic Falloff

2. Cosine Correction (Foreshortening):

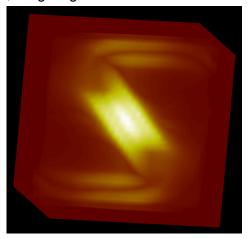
To correct for directional attenuation, the cosine of the incidence angle θ (between the voxel direction and the wall's normal) is used:

$$I_{\text{corregido}}(x_v) = I(x_v) / \cos(\theta)$$

This boosts intensities for voxels at steeper angles, mitigating radial falloff.







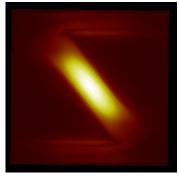
with Foreshortening

Results and Observations:

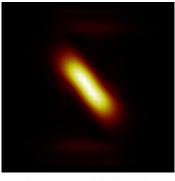
After these corrections, brightness across the reconstructed volume becomes more uniform. In the planes dataset, both depth planes show similar intensity, and the Z scene's peripheral voxels brighten relative to the center. However, extreme corrections may amplify noise in low-signal areas, requiring careful tuning.

Phasor-based filtering

Without phasor filtering, the reconstruction is noisier and contains more high-frequency artifacts due to the direct backprojection of unprocessed temporal signals. Applying the Morlet wavelet filter smooths temporal variations, enhancing reconstruction quality by suppressing undesired frequencies. A small σ ($\lambda_c/2\text{log2}$) results in a sharper response, preserving finer details but potentially allowing more noise. Conversely, a large σ ($2\lambda_c$) yields a stronger smoothing effect, reducing noise but also blurring edges and losing some spatial resolution.



without phasor filtering



sigma = $\lambda_c / (2 \cdot \log 2)$



sigma = $2 \cdot \lambda_c$