

Project RoboSPECT

3D SPECT

Hierarchical Object Definitions

CrystalCamBundle

- CrystalCam[] m_crystalCams
- int m_numOfCrystalCams

- Vector3 m_position
- Vector3 m_orientation

CrystalCam

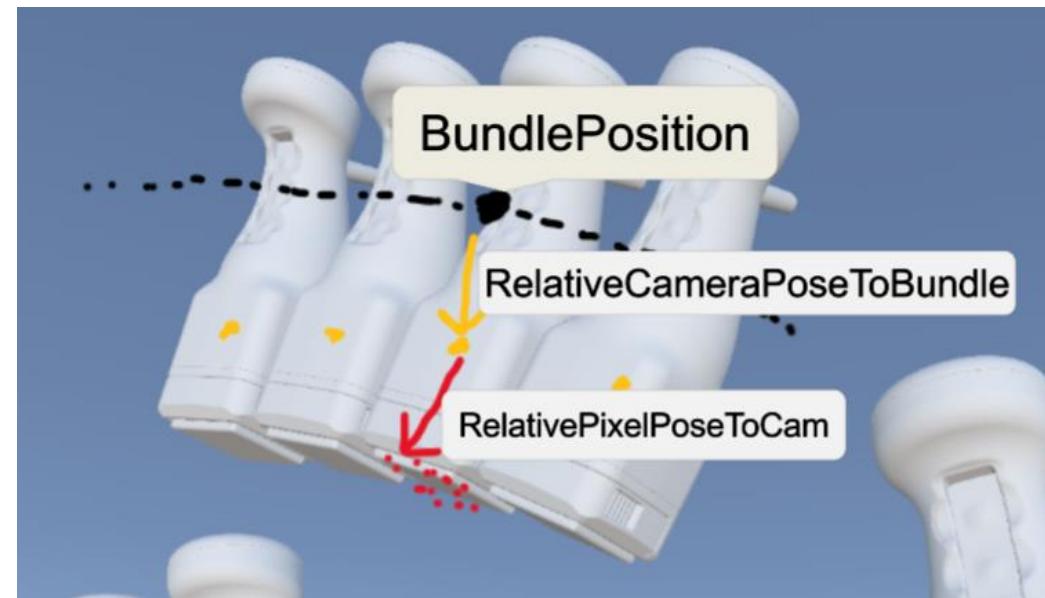
- Pixel[] m_pixels
- int m_numOfPixels

- Vector3 m_relativePositionToParentBundle
- Vector3 m_relativeOrientationToParentBundle

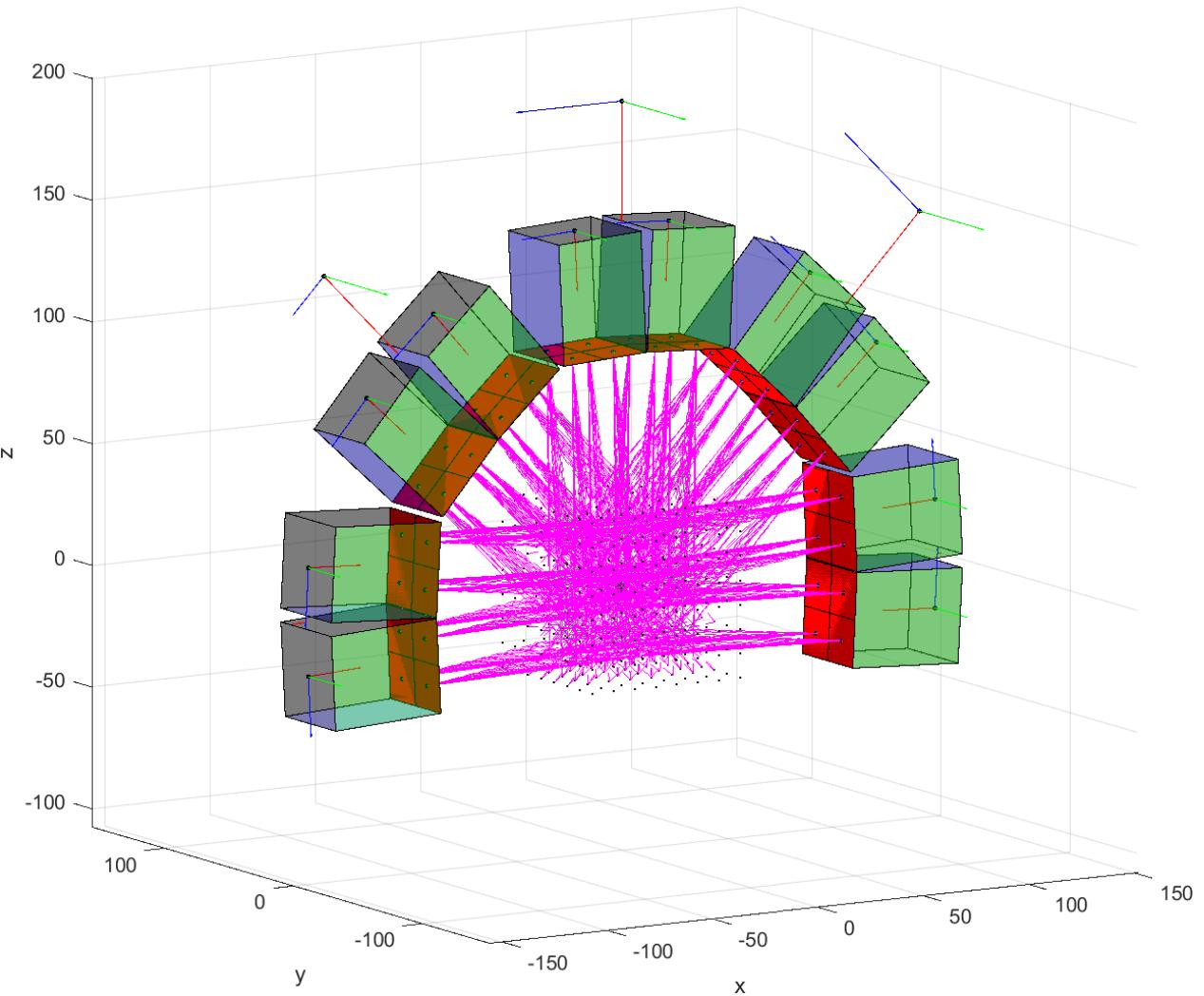
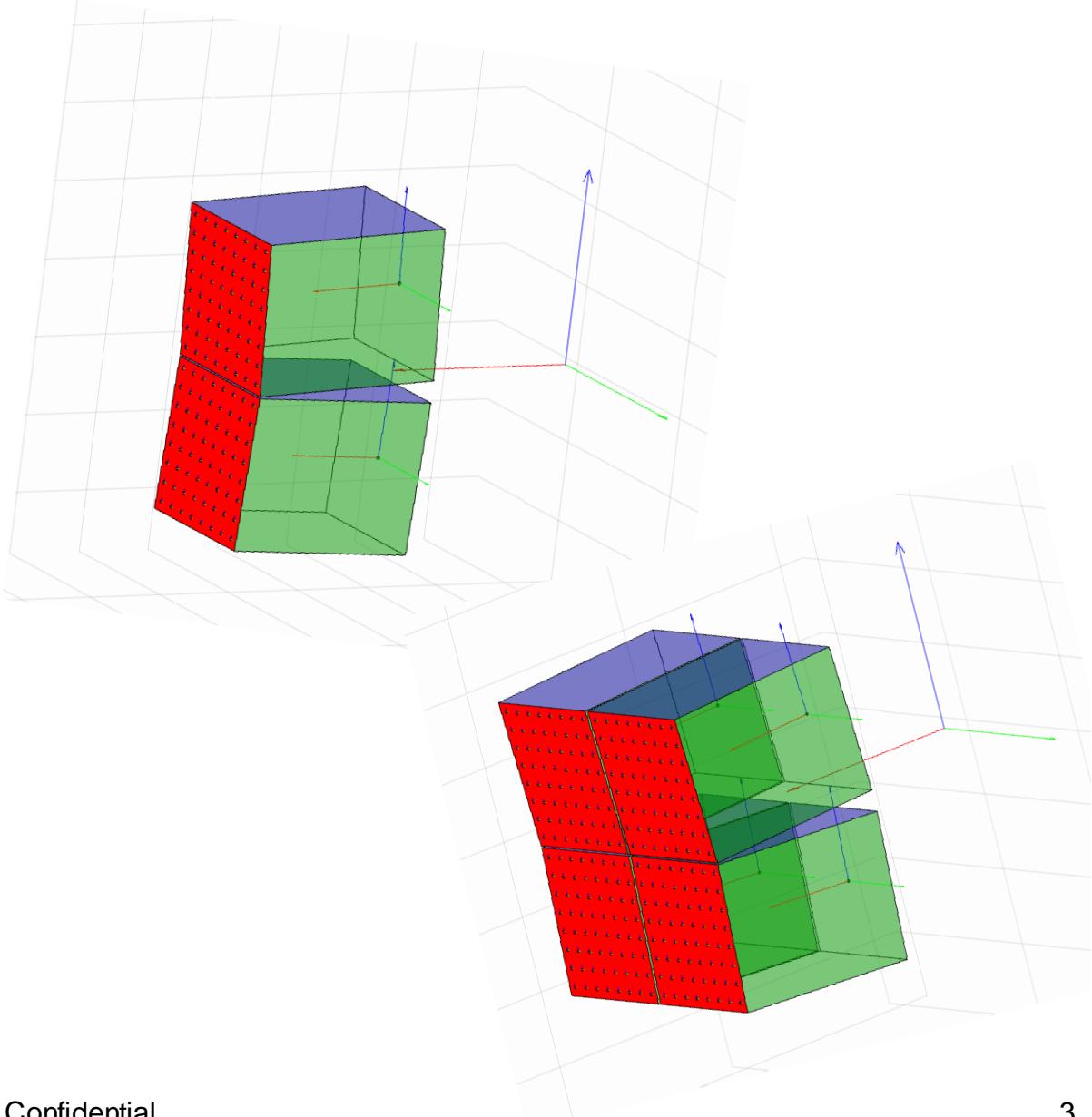
Pixel

- CrystalCam m_parentCrystalCam

- Vector3 m_relativePositionToParentCamera
- Vector3 m_relativeOrientationToParentCamera



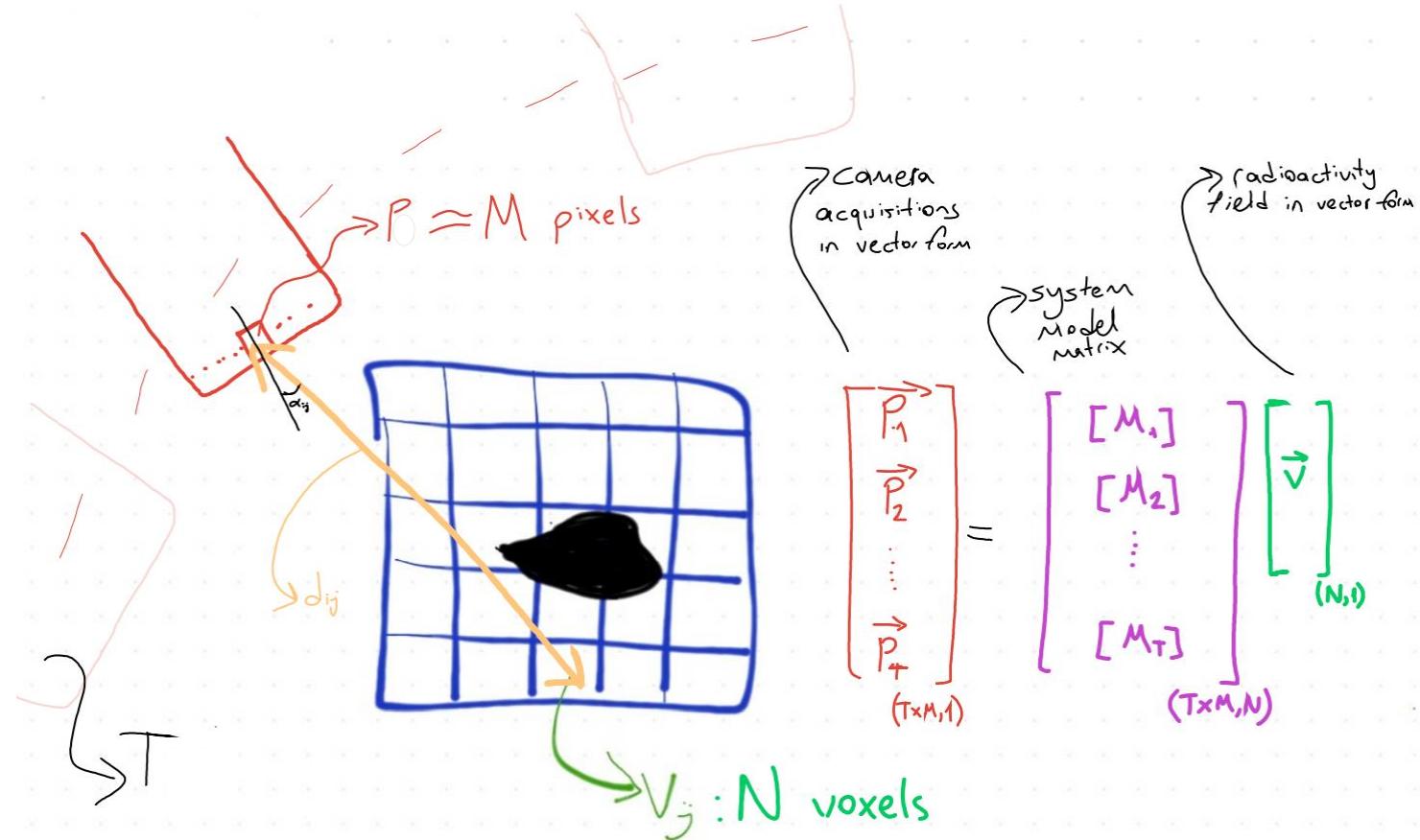
Hierarchical Object Definitions



Some References for 3D SPECT

- [link](#) PhD dissertation - Robotic freehand SPECT Imaging, Jose Francisco Gardiazabal Schilling
- [link](#) PhD dissertation - Tomographic Reconstruction Methods for Optical and Intra-operative Functional Imaging, Tobias Roman Lasser
- [link](#) Lecture - Tomographic Image Reconstruction: An Introduction, Erika Garutti & Florian Grüner

Some Theory



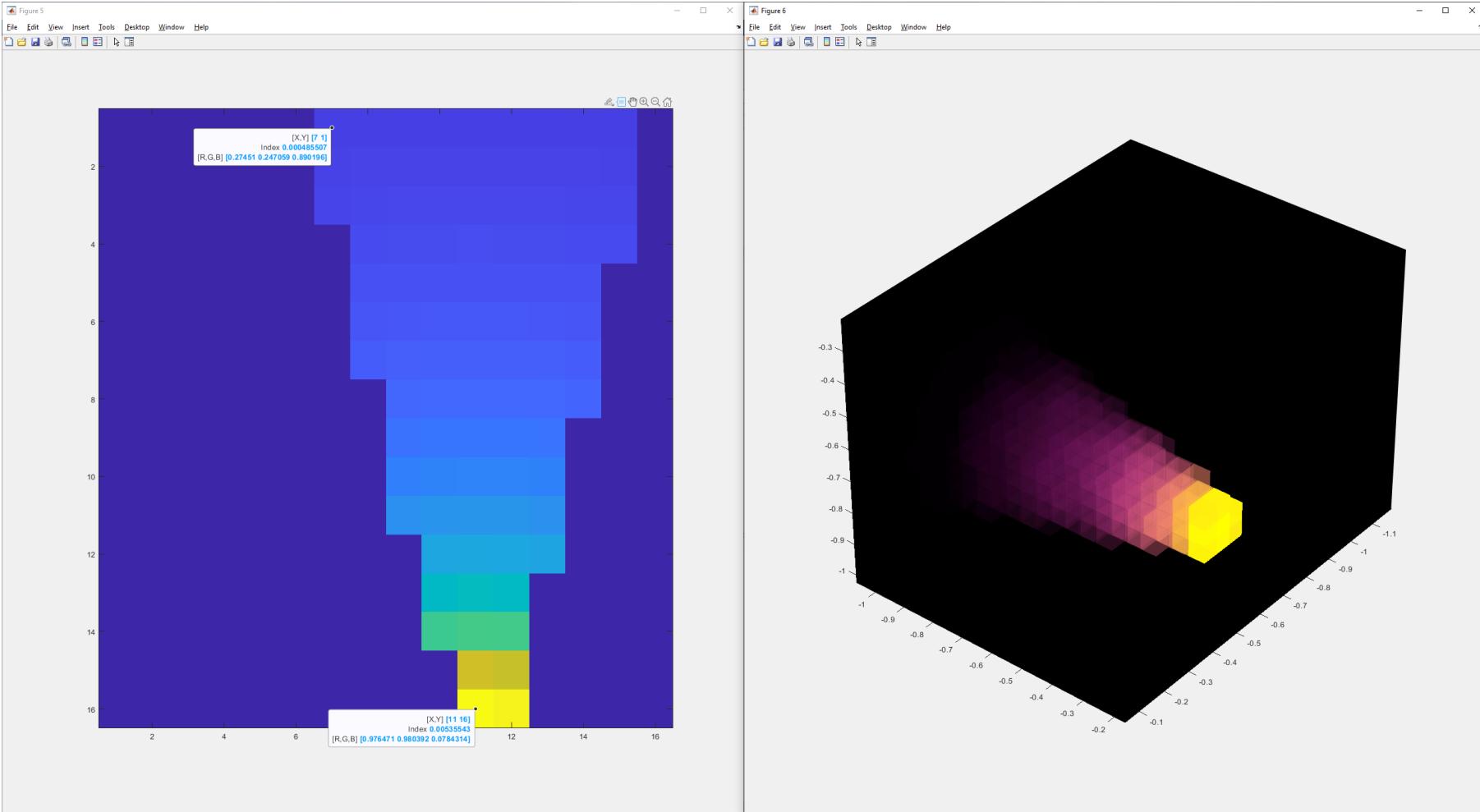
Simple Model

$$M_{ij} = \frac{\cos(\alpha_{ij})}{d_{ij}^2}$$

➤ Radioactivity contribution from voxel j to detector i

Some Theory

- Contribution field from voxels to a particular pixel;



Some Theory

- $\mathbf{y} = \mathbf{Ax}$ or $y_j = \sum_i A_{ij}x_i$
- Inverse problem: Know y_i , want x_i
- Could do $\mathbf{x} = \mathbf{A}^{-1}\mathbf{y}$
- But: \mathbf{A} is huge & cannot be inverted
- Solve inverse problem iteratively
 - Measurements y_i : independent random variables (**Poisson**)
 - Expectation value: $\mu_i = \mathbf{A}_i \cdot \mathbf{x} = \sum_j A_{ij}x_j$
 - Probability to measure k given λ : $p(k|\lambda) = \frac{e^{-\lambda}\lambda^k}{k!}$

Likelihood:

$$L(\mathbf{x}) = p(\mathbf{y}|\mathbf{x}) = \prod_i p(y_i|\mathbf{x}) = \prod_i \frac{e^{-\mathbf{A}_i \cdot \mathbf{x}} (\mathbf{A}_i \cdot \mathbf{x})^{y_i}}{y_i!}$$

- Among all possible images \mathbf{x} we choose the one that maximises the probability of producing the data (find most likely image)
- Maximise the log-likelihood, i.e. maximise $\log(p(\mathbf{y}|\mathbf{x}))$

Maximum Likelihood - Expectation Maximisation (ML-EM)

- Objective function to maximise: log-Likelihood (ML)
- Maximisation algorithm: Expectation Maximisation (EM)

- Initial guess for the image (uniform)
 $x_i^{(0)}$
- Simulate measurements from estimate (forward proj.)
 $y_j^{\text{simu}} = \sum_k A_{kj}x_k^{(0)}$
- Compare this with actual measurements
Ratio $R_j = \frac{y_j}{y_j^{\text{simu}}}$
- Improve image estimate (backward projection)
 $x_i^{(1)} = x_i^{(0)} \cdot \frac{1}{\sum_j A_{ij}} \cdot \sum_j A_{ij}R_j$
- Repeat until convergence

ML-EM

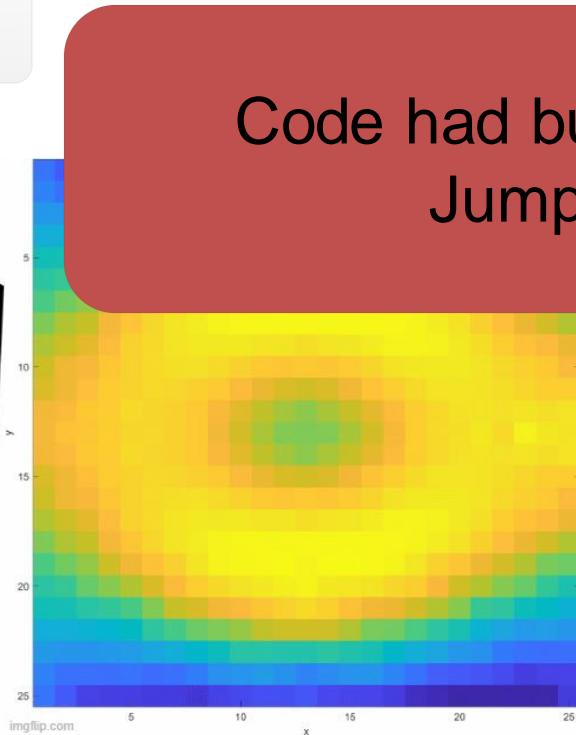
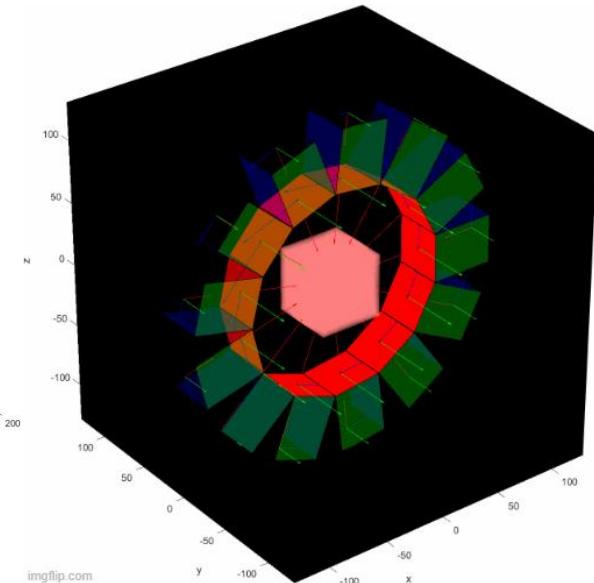
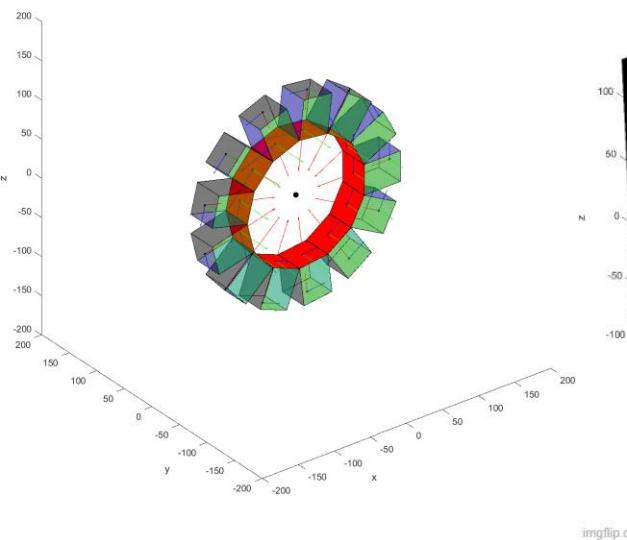
$$x_i^{(n+1)} = x_i^{(n)} \cdot \frac{1}{\sum_j A_{ij}} \cdot \sum_j A_{ij} \frac{y_j}{\sum_k A_{kj}x_k^{(n)}}$$

Simple Reconstruction Example | Point source (artificially generated with matlab)

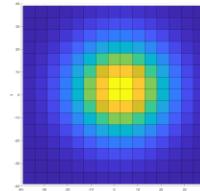
- Full-circular trajectory
- 14 acquisitions

- Grid size: 50x50x50 mm
- Voxel size: 2 mm

Code had bugs, resolved later
Jump to slide 17



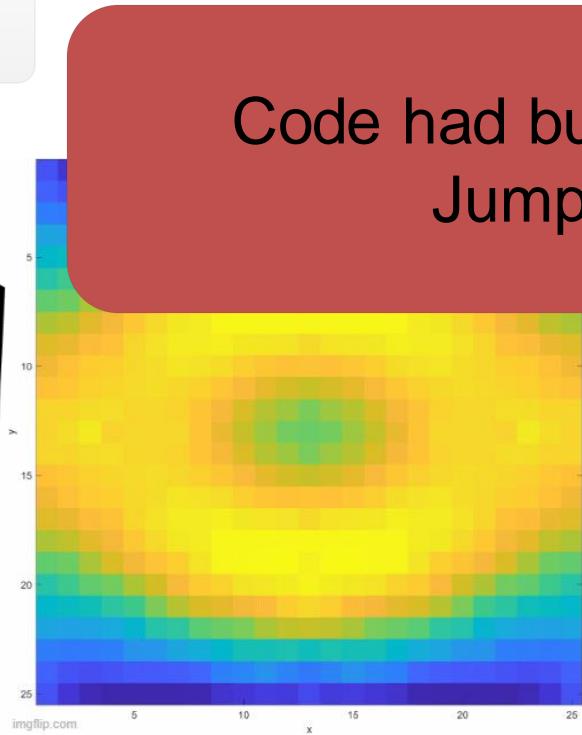
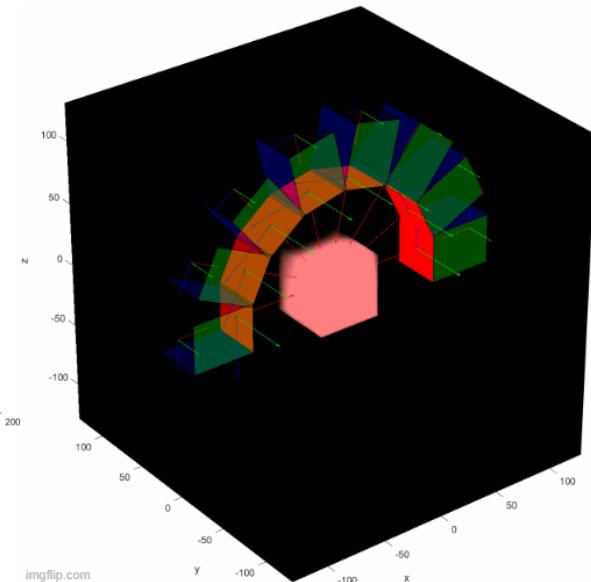
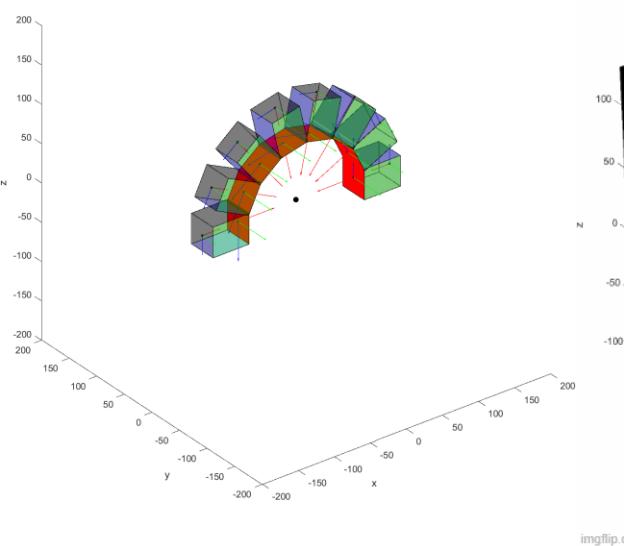
- what every camera would see at every acquisition point;



Simple Reconstruction Example | Point source (artificially generated with matlab)

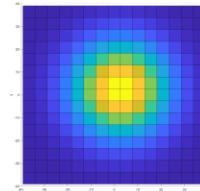
- Semi-circular trajectory
- 8 acquisitions

- Grid size: 50x50x50 mm
- Voxel size: 2 mm



Code had bugs, resolved later,
Jump to slide 17

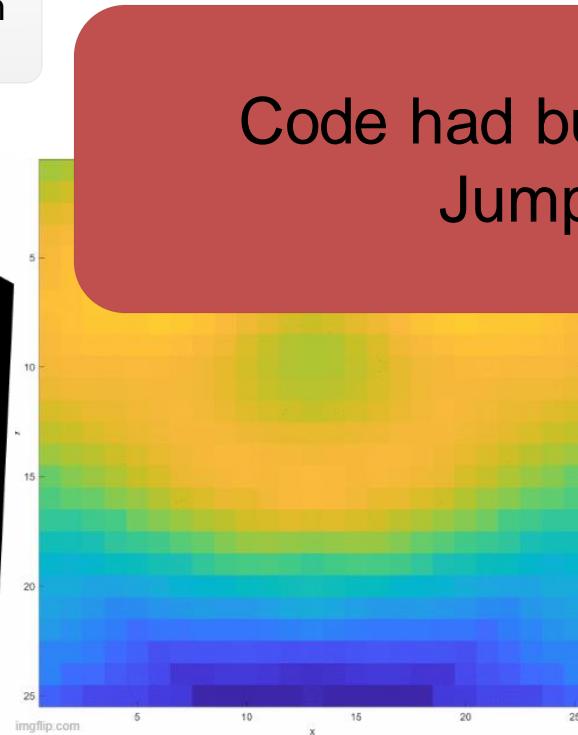
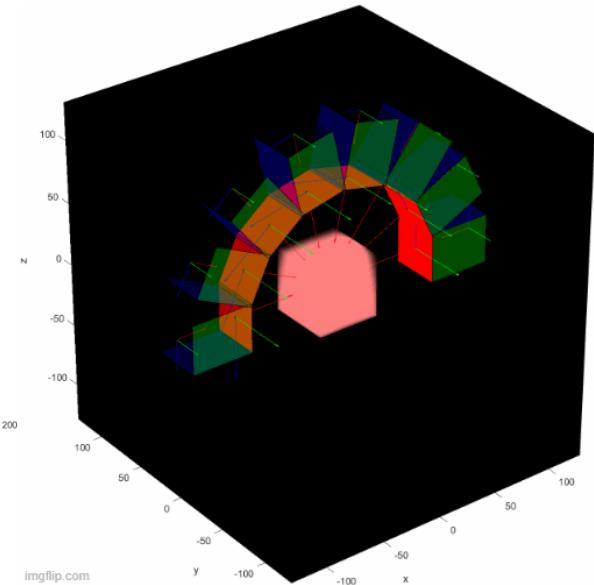
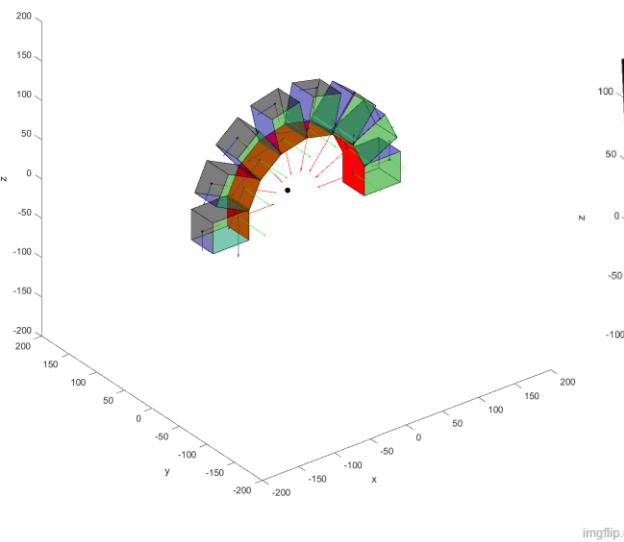
- what every camera would see at every acquisition point;



Simple Reconstruction Example | Point source - shifted (artificially generated with matlab)

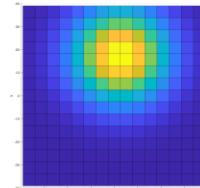
- Semi-circular trajectory
- 8 acquisitions

- Grid size: 50x50x50 mm
- Voxel size: 2 mm



Code had bugs, resolved later,
Jump to slide 17

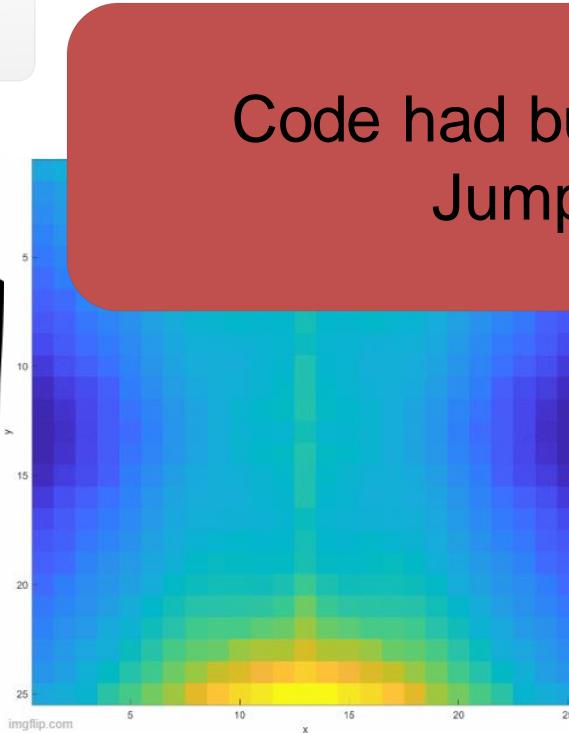
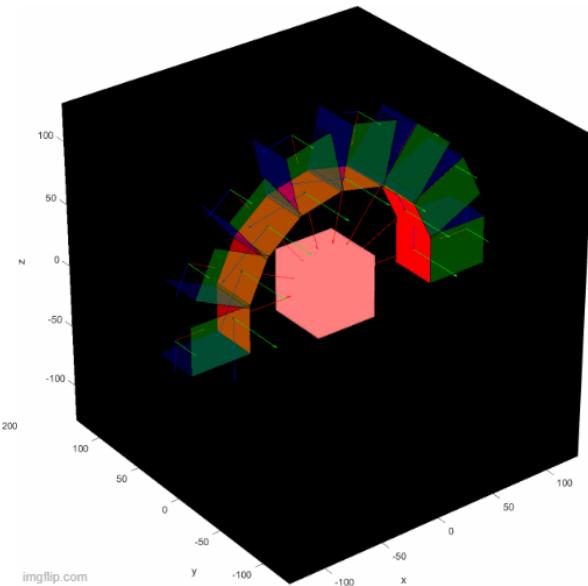
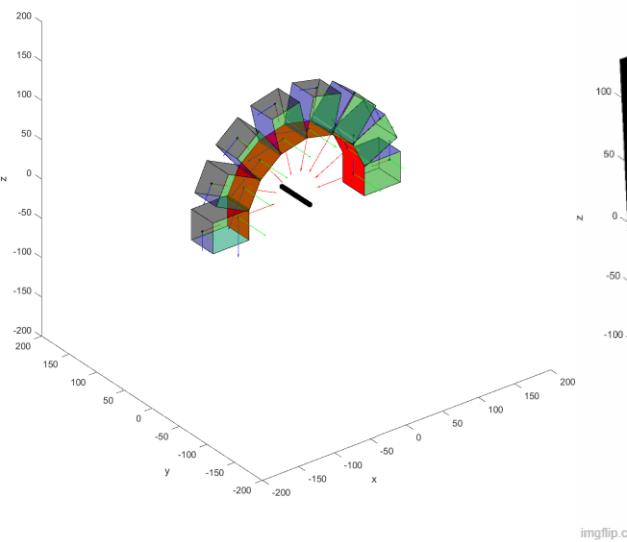
- what every camera would see at every acquisition point;



Simple Reconstruction Example | Cylinder source (artificially generated with matlab)

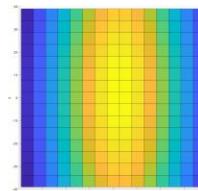
- Semi-circular trajectory
- 8 acquisitions

- Grid size: 50x50x50 mm
- Voxel size: 2 mm



Code had bugs, resolved later,
Jump to slide 17

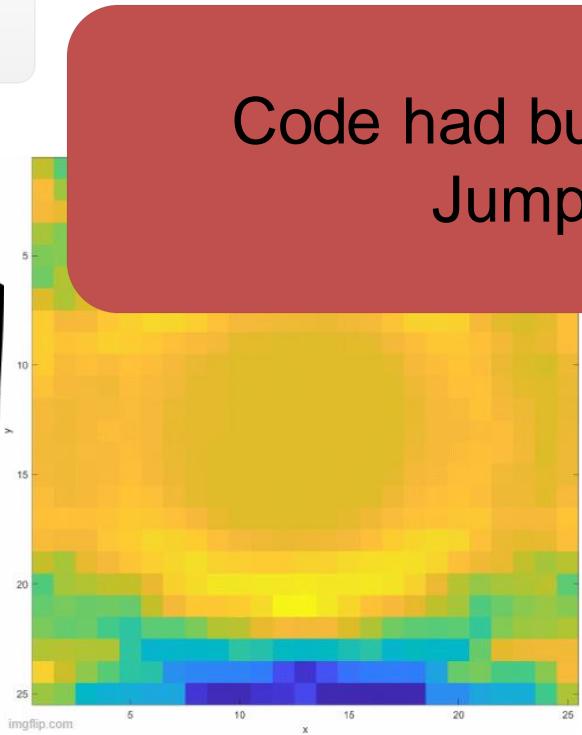
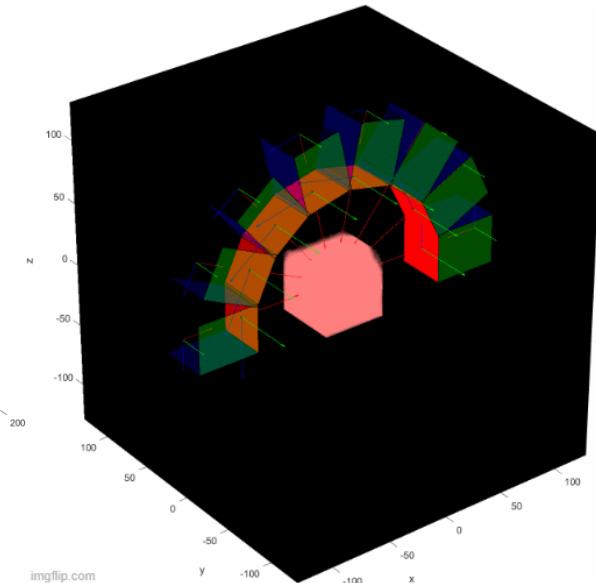
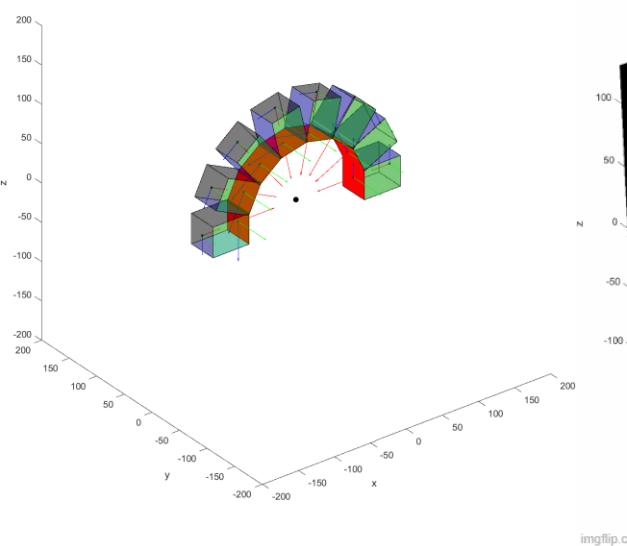
- what every camera would see at every acquisition point;



Simple Reconstruction Example | Point source (with Gate simulations)

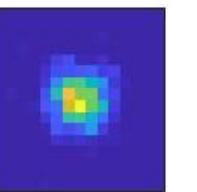
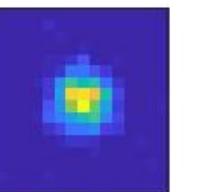
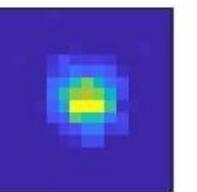
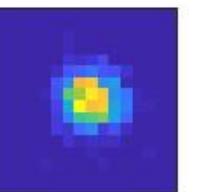
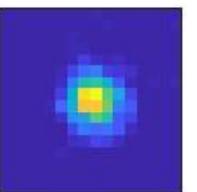
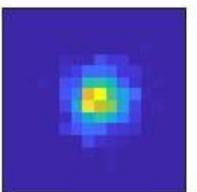
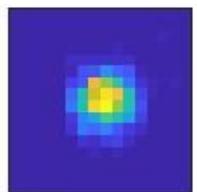
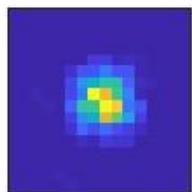
- Semi-circular trajectory
- 8 acquisitions

- Grid size: 50x50x50 mm
- Voxel size: 2 mm



Code had bugs, resolved later,
Jump to slide 17

- 8 samples from Gate simulations, corresponding to acquisition points;

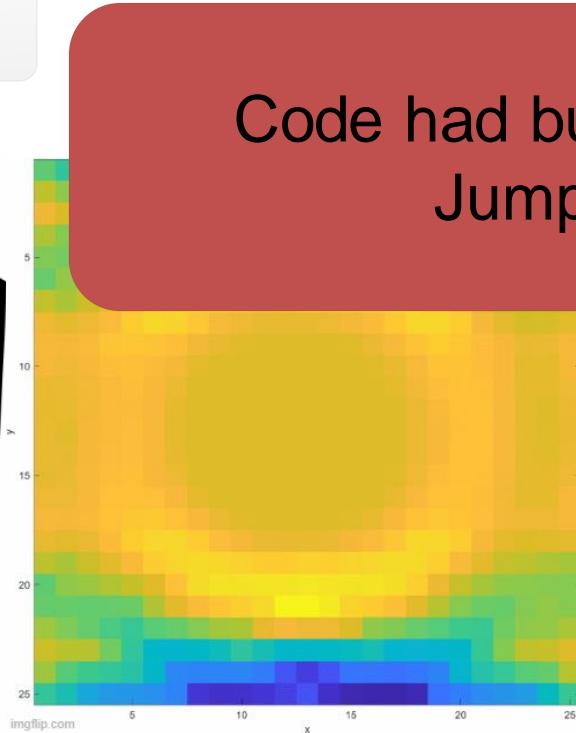
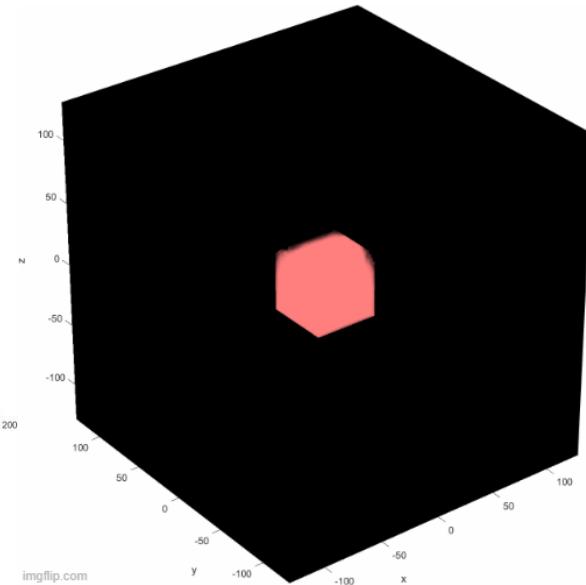
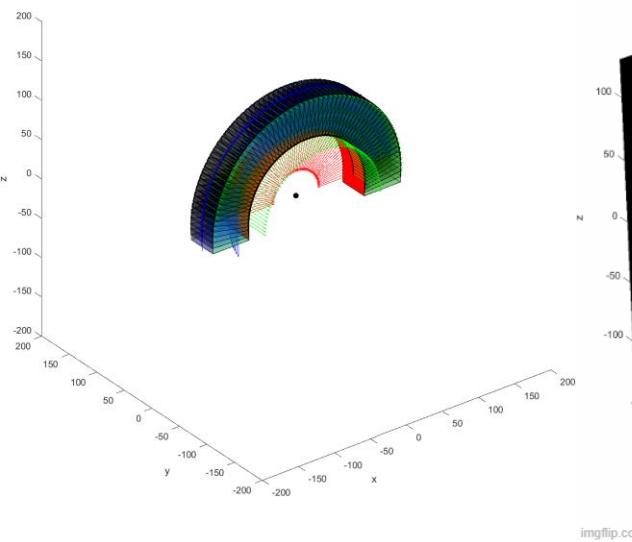


Simple Reconstruction Example | Point source (with Gate simulations)

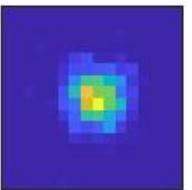
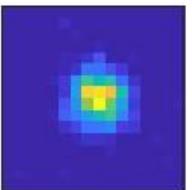
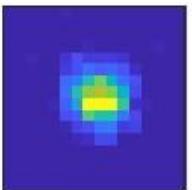
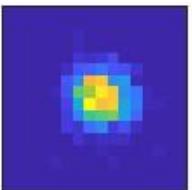
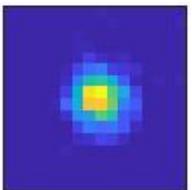
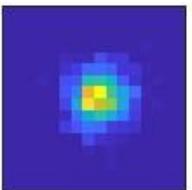
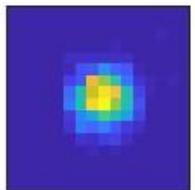
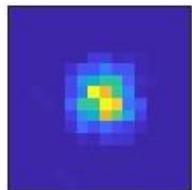
- Semi-circular trajectory
- 60 acquisitions

- Grid size: 50x50x50 mm
- Voxel size: 2 mm

Code had bugs, resolved later,
Jump to slide 17



- .. some 8 samples from Gate simulations, corresponding to acquisition points;

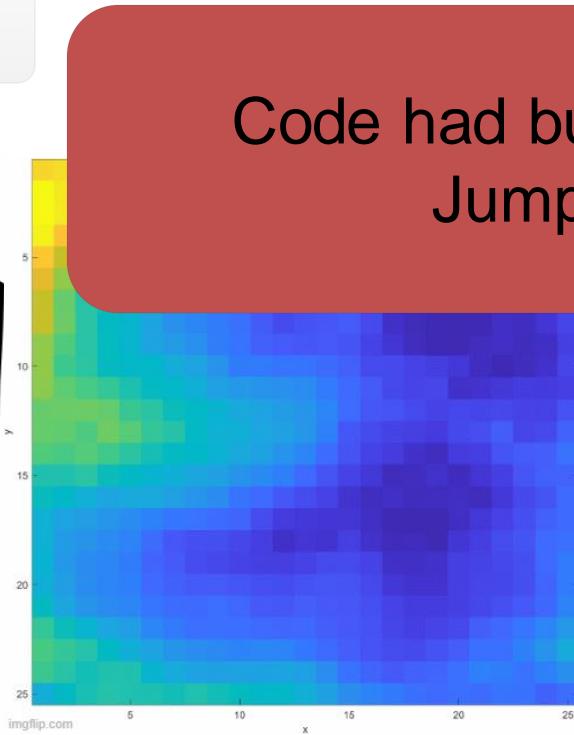
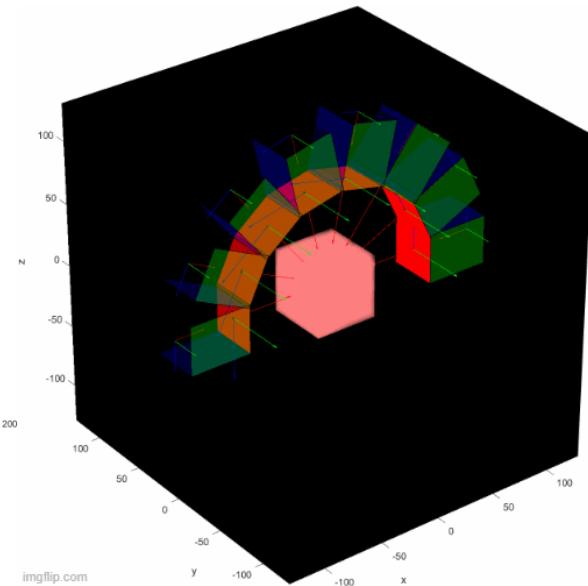
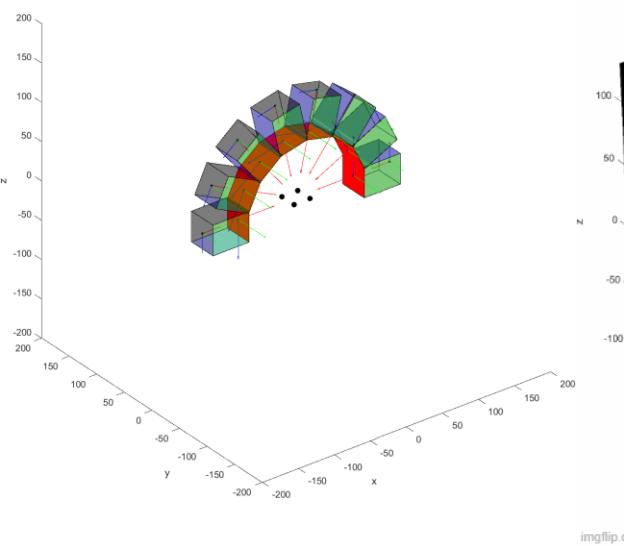


Simple Reconstruction Example | 4-Point sources (with Gate simulations)

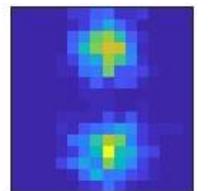
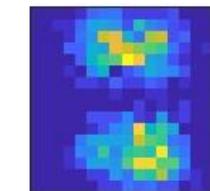
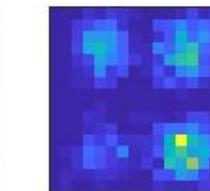
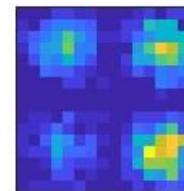
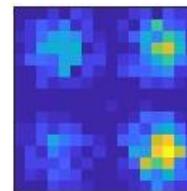
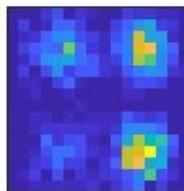
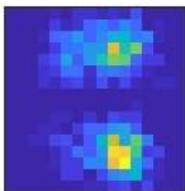
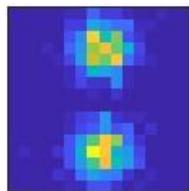
- Semi-circular trajectory
- 8 acquisitions

- Grid size: 50x50x50 mm
- Voxel size: 2 mm

Code had bugs, resolved later,
Jump to slide 17



- 8 samples from Gate simulations, corresponding to acquisition points;

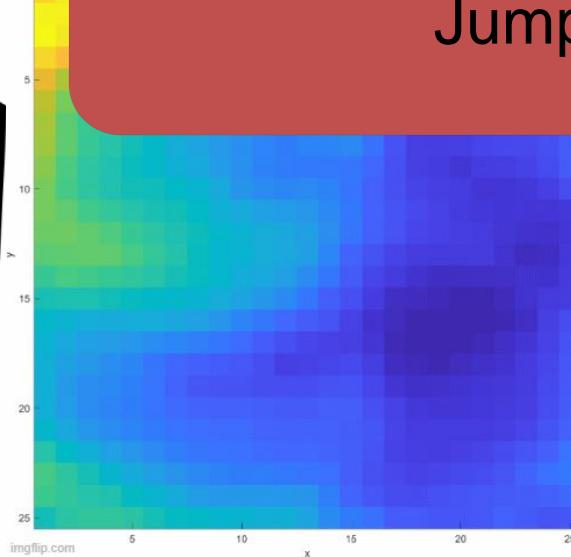
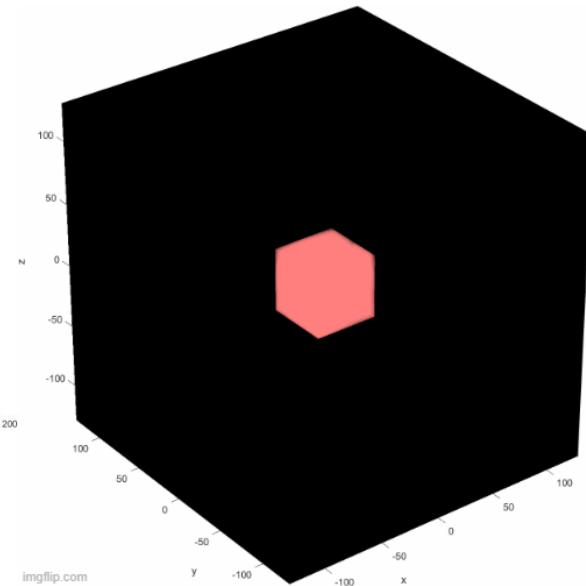
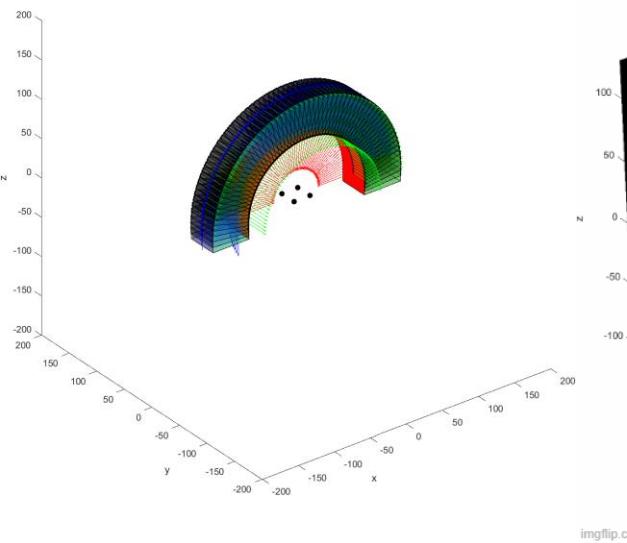


Simple Reconstruction Example | 4-Point sources (with Gate simulations)

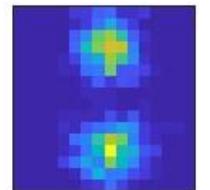
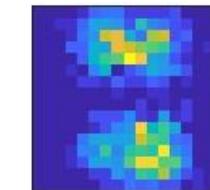
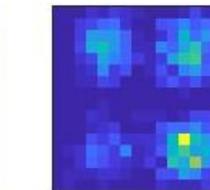
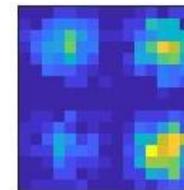
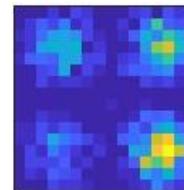
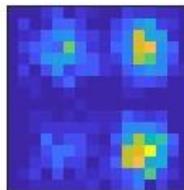
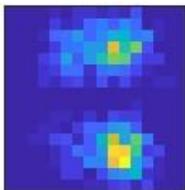
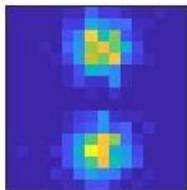
- Semi-circular trajectory
- 60 acquisitions

- Grid size: 50x50x50 mm
- Voxel size: 2 mm

Code had bugs, resolved later,
Jump to slide 17



- .. some 8 samples from Gate simulations, corresponding to acquisition points;



What's next?

- Holes that are seen in the reconstructions should not happen
- There could be a problem with incorrect traversing of arrays or incorrect camera–voxel distances

High Priority;

- [Bugfix] Consider also the 1cm of crystal depth when building the system matrix
- [Debug] Make reconstruction volume bigger, crop it so that we only have meaningful visuals for the region of interest
- [Debug] Work with less complicated scene (3x3 cam)
- [Debug] Compare forward projection with camera acquisitions

Medium Priority;

- Tabulate the system matrix, using Gate simulations

Low Priority;

- Try more complex system modellings
- Gate simulations with the trajectory obtained from NDI tracking around neck
- Export reconstruction as dicom file

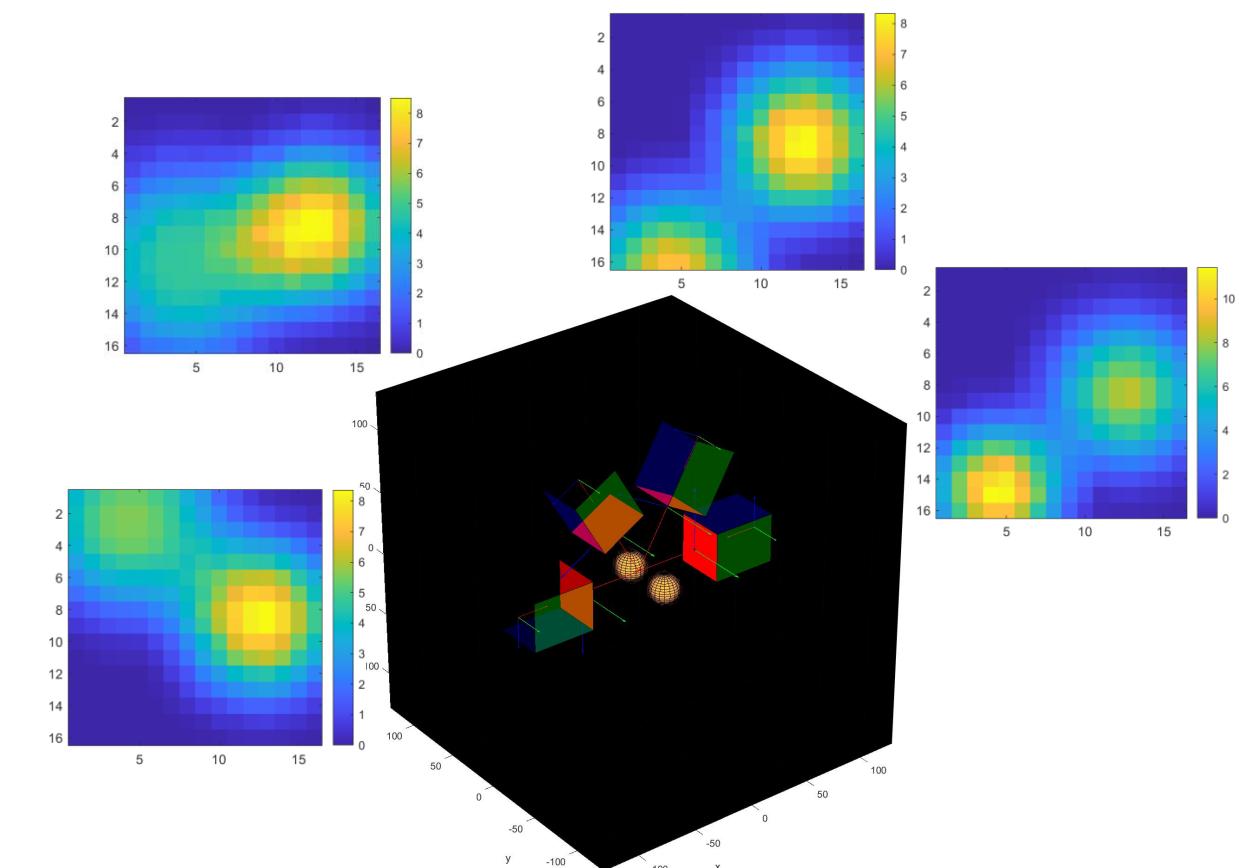
Sanity check

➤ Experiment workflow

1. Define the radioactivity field **f_ref**
(known voxel grid as reference)
2. Build the system matrix **H**
(fixed for the scene)
3. Forward projection to get camera acquisitions **g_ref = H * f_ref**
(known cam acquisitions as reference)
4. Use the reference **g_ref** and the same system matrix **H**
to do the reconstruction **f_recons**
(solve for **g_ref = H * f_recons**)

Forward projection on the reference radioactivity field **f_ref**

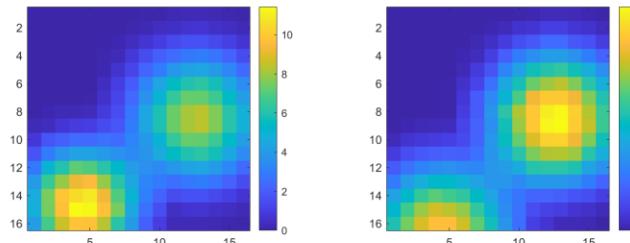
➤ Reference camera acquisitions: **g_ref**



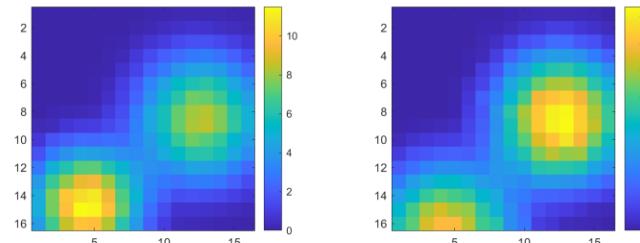
Sanity check

Forward projection comparison

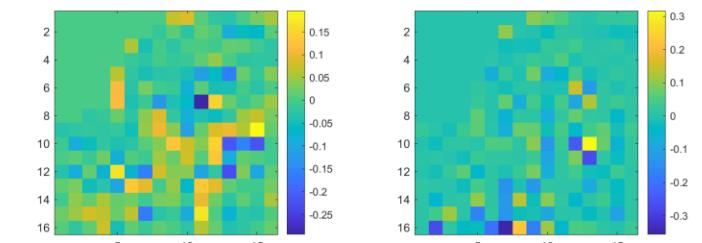
Forward Projection with True Volume



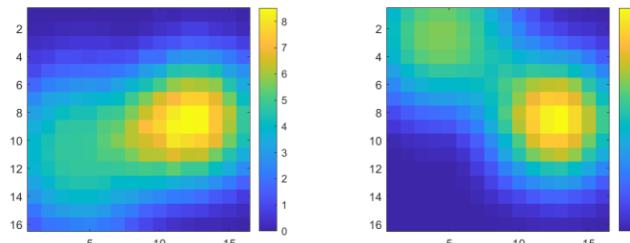
Forward Projection with Reconstructed Volume



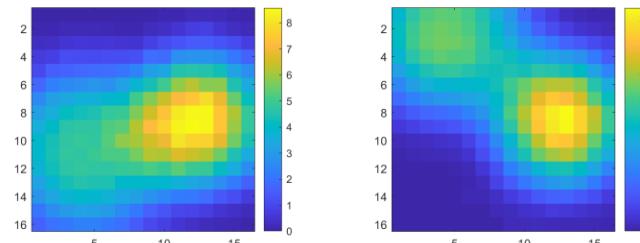
Difference between real and sim acquisitions



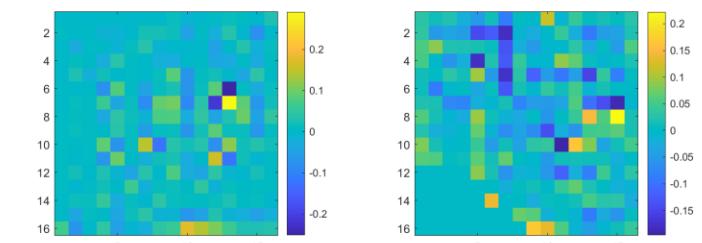
g_ref



g_sim

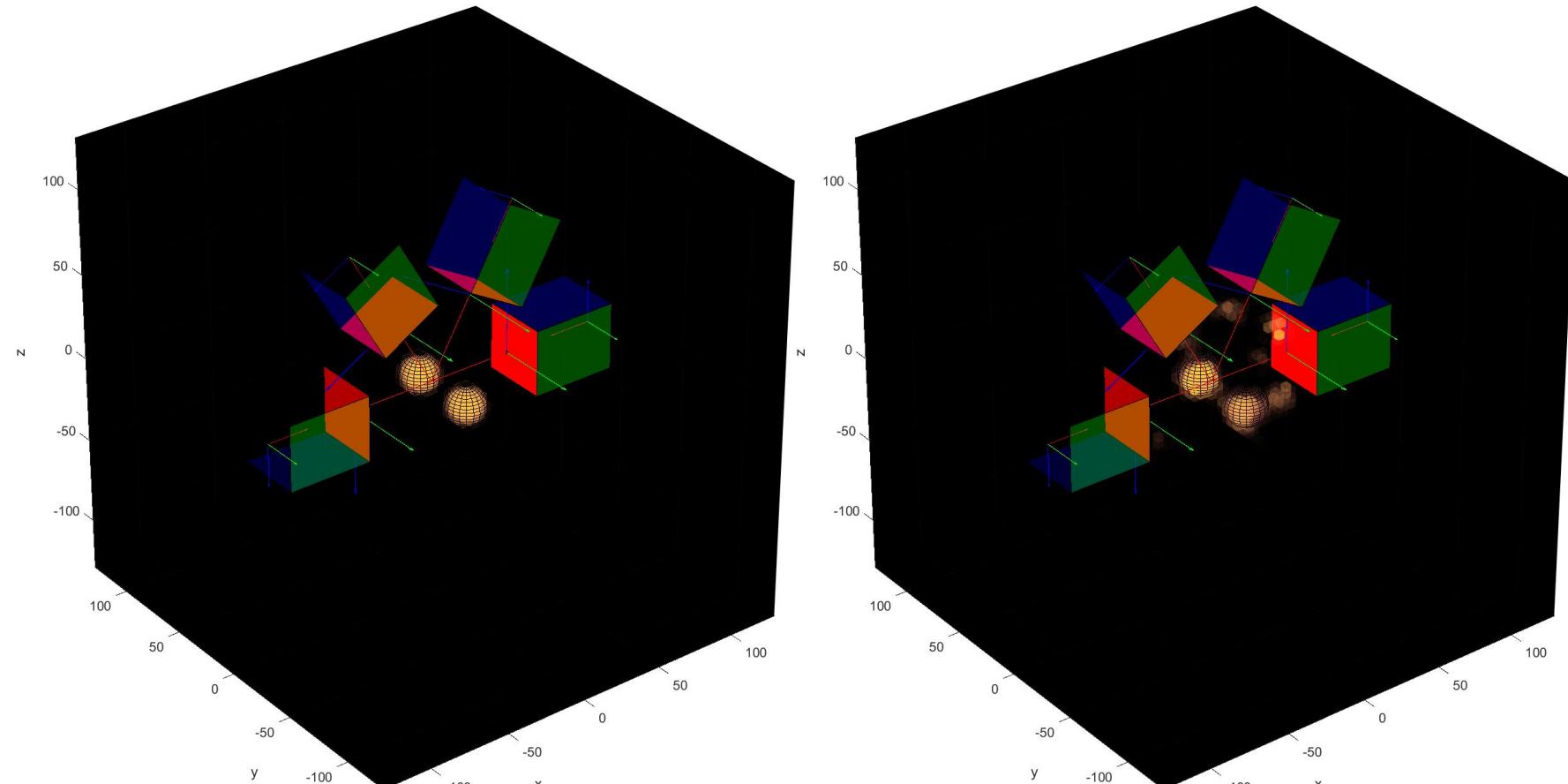


g_diff



Sanity check

Radioactivity field comparison

**f_ref****f_recons**

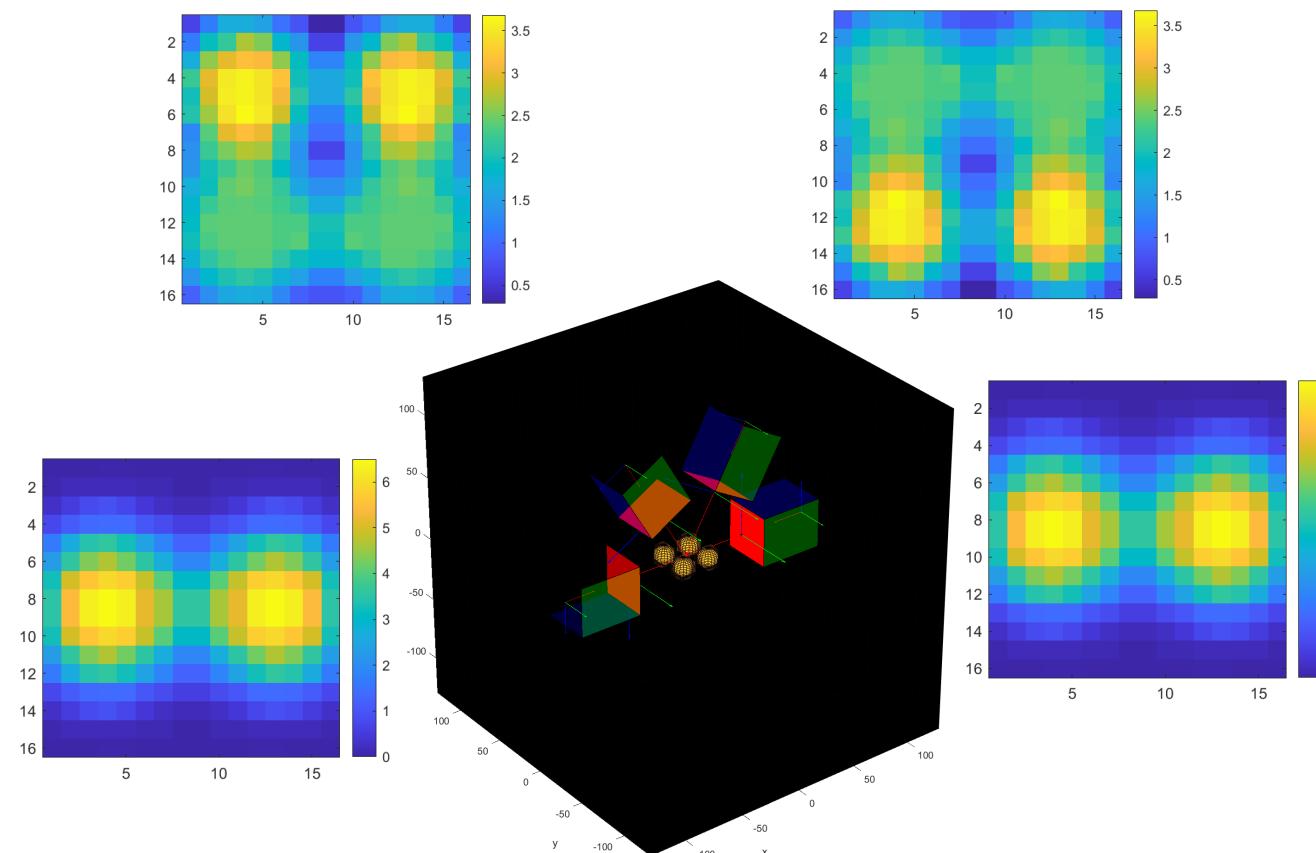
Sanity check

Experiment workflow

1. Define the radioactivity field **f_ref**
(known voxel grid as reference)
2. Build the system matrix **H**
(fixed for the scene)
3. Forward projection to get camera acquisitions $\mathbf{g}_{\text{ref}} = \mathbf{H} * \mathbf{f}_{\text{ref}}$
(known cam acquisitions as reference)
4. Use the reference **g_ref** and the same system matrix **H**
to do the reconstruction **f_recons**
(solve for $\mathbf{g}_{\text{ref}} = \mathbf{H} * \mathbf{f}_{\text{recons}}$)

Forward projection on the reference radioactivity field **f_ref**

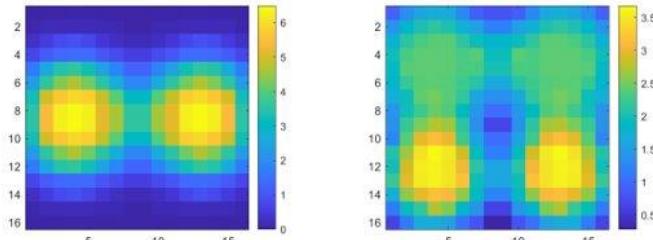
➤ Reference camera acquisitions: **g_ref**



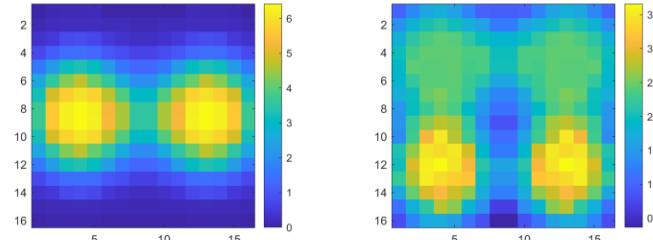
Sanity check

Forward projection comparison

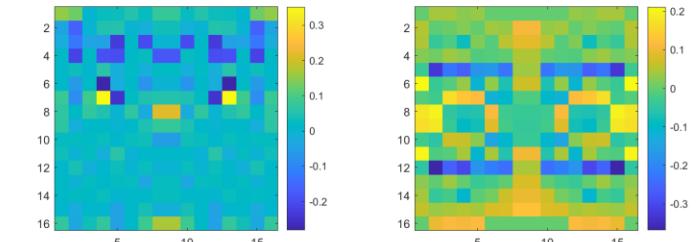
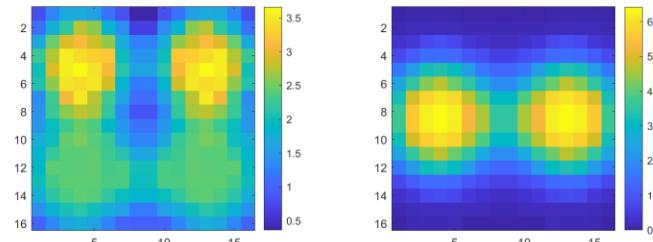
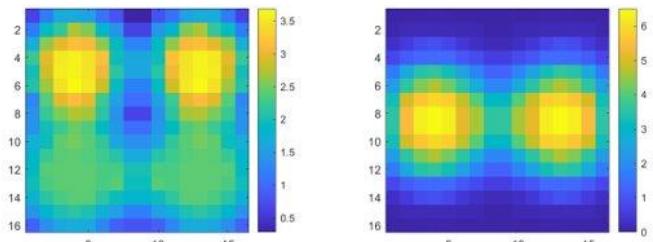
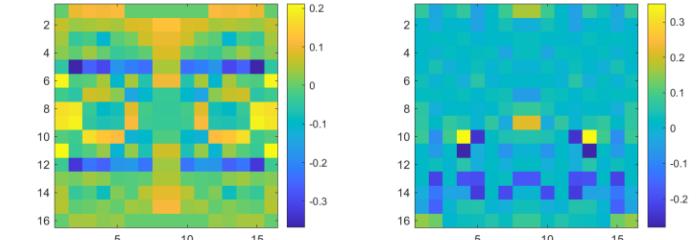
Forward Projection with True Volume



Forward Projection with Reconstructed Volume



Difference between real and sim acquisitions



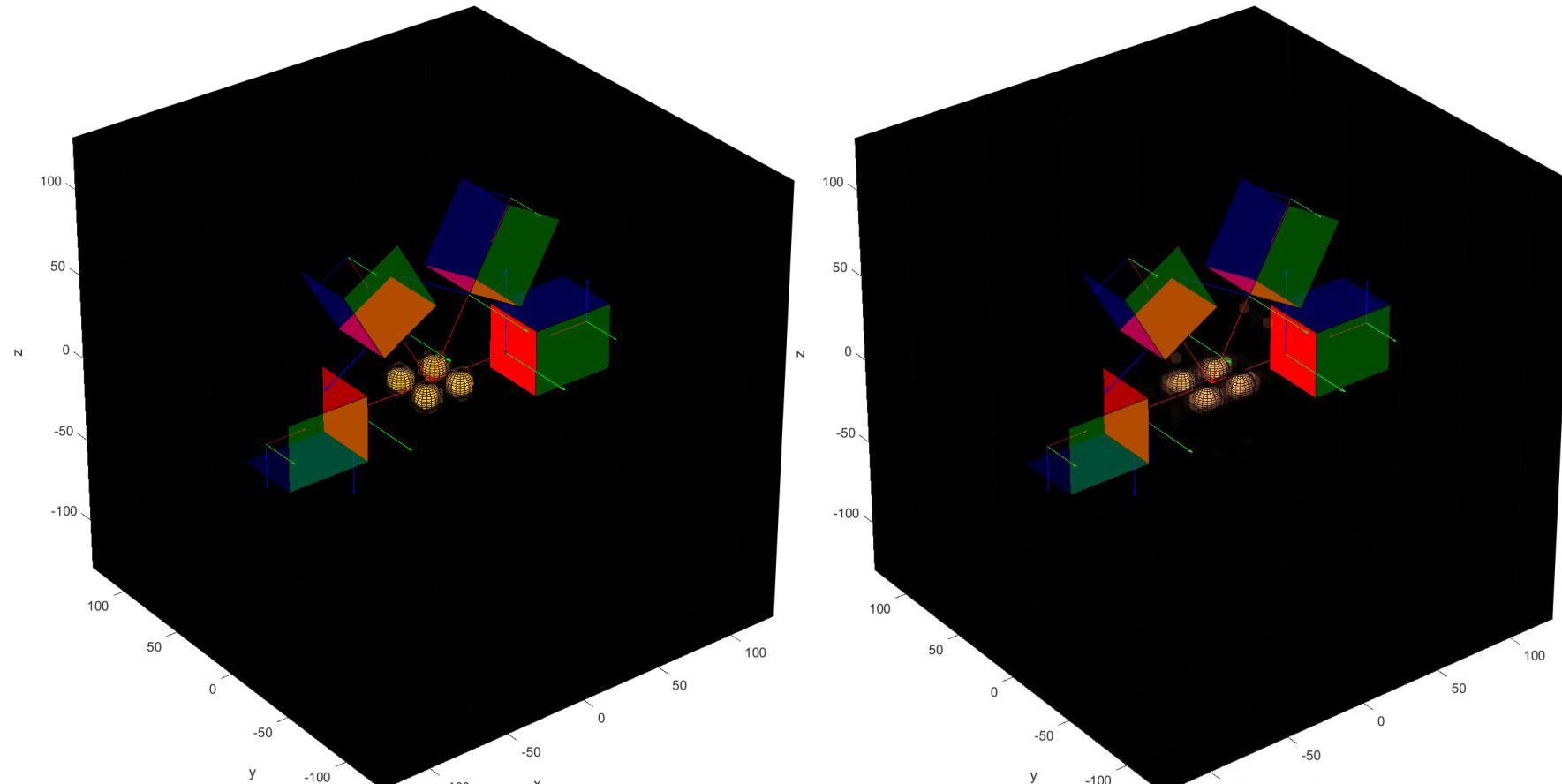
g_ref

g_sim

g_diff

Sanity check

Radioactivity field comparison

**f_ref****f_recons**

What's next?

- Sanity check works
- Reconstruction now runs slow due to larger reconstruction volume and more camera acquisitions... $\sim O(M * N^3)$

High Priority:

- Refactor Matlab code in a way that it runs on GPU
- Do reconstructions using Gate simulations; single point, 4 points ...

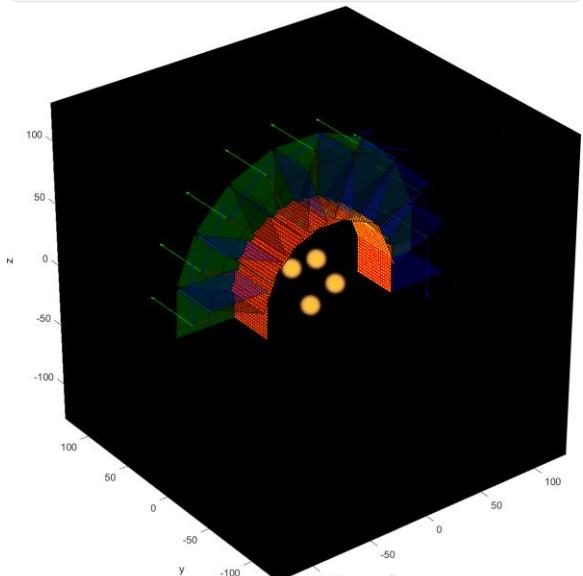
Medium Priority:

- Tabulate the system matrix, using Gate simulations
- Do reconstructions using Gate simulations of thyroid with multiple cameras
- Gate simulations with the trajectory obtained from NDI tracking around neck

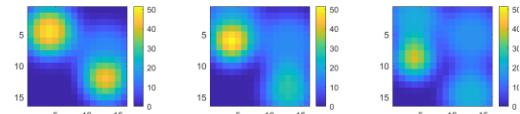
Low Priority:

- Try more complex system modellings
- Export reconstruction as .dicom file

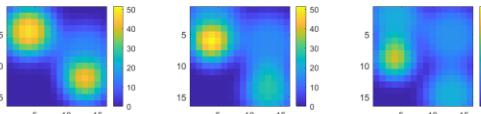
Sanity check.. but on GPU this time

f_ref

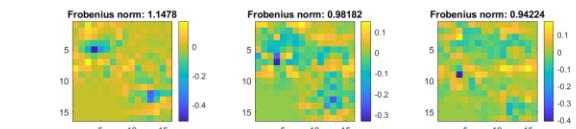
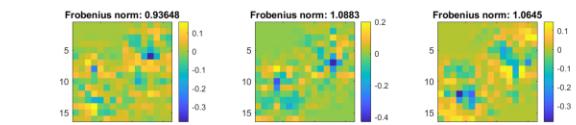
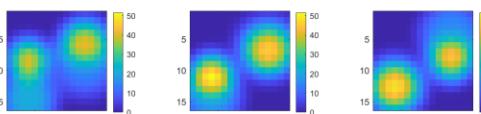
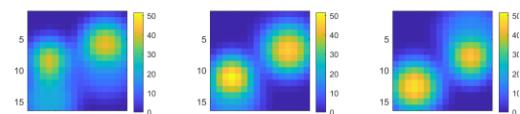
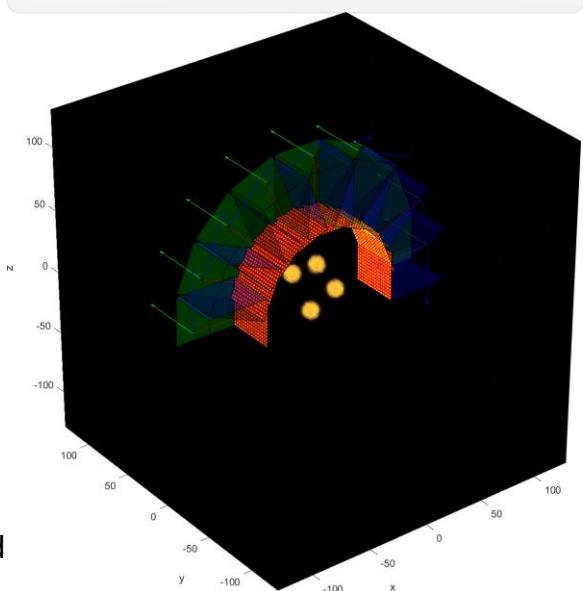
Forward Projection with True Volume



Forward Projection with Reconstructed Volume



Difference between real and sim acquisitions

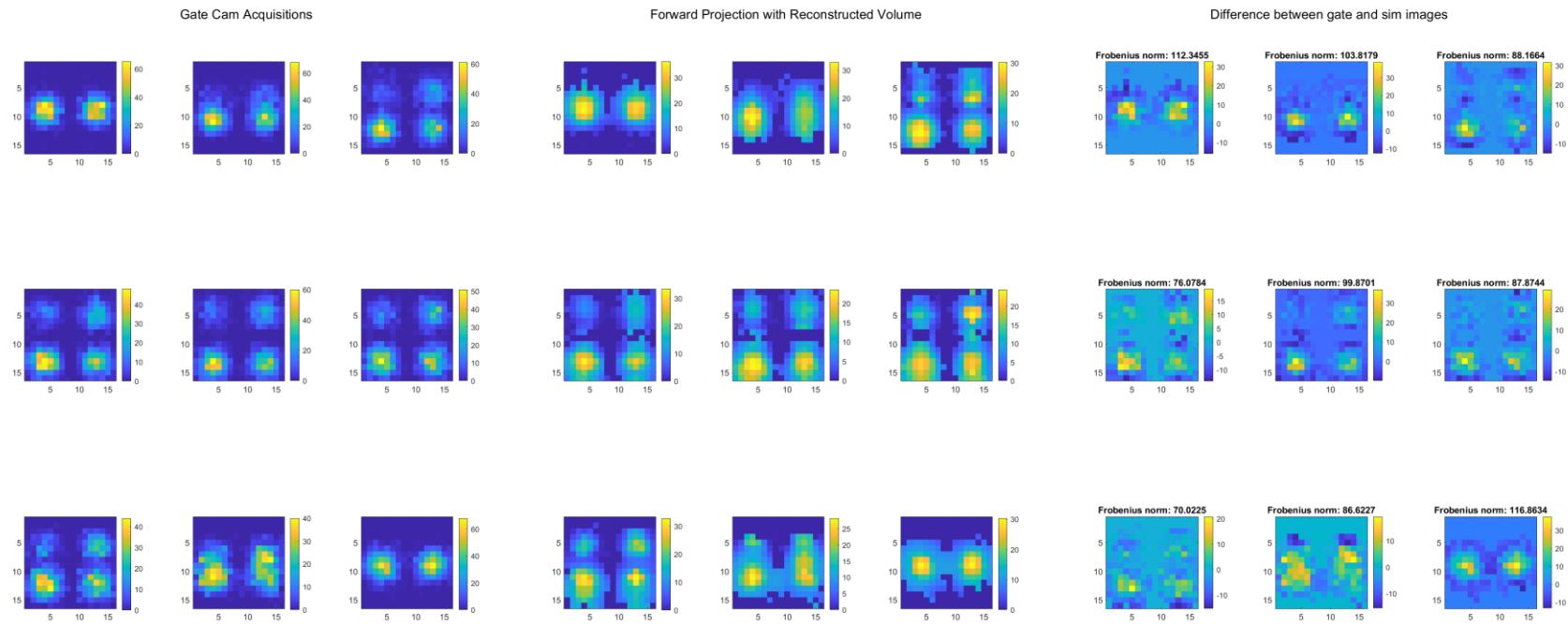
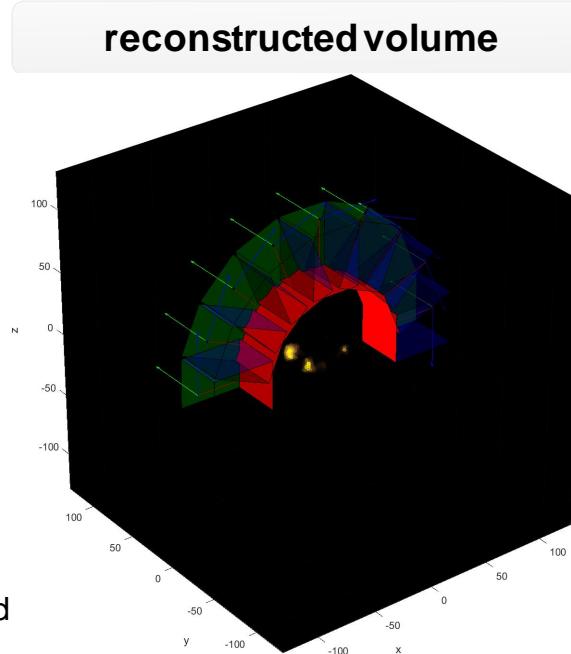
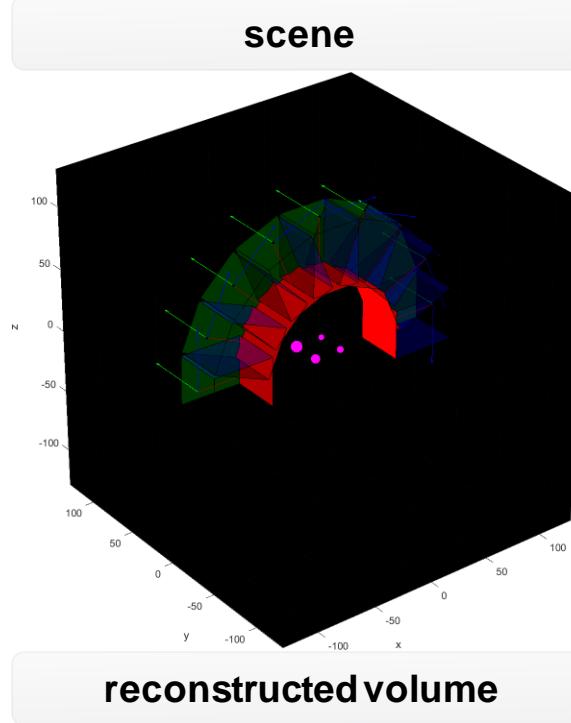
**f_recons**

- Time elapsed for (9 cam acquisition, [32, 32, 32] voxel grid with 2mm voxel size);
 - Building the system matrix: **20 secs** (~2.2 secs per cam acquisition)
 - Solving the system : **35 secs** @ 2k iteration (~0.02 secs per iteration)

- Before it was..

- Building the system matrix: **176 secs** (~19.5 secs per cam acquisition)
- Solving the system : **550 secs** @ 2k iteration (~ 0.27 secs per iteration)

3D Reconstructions with Gate Simulations | 4 point-sources



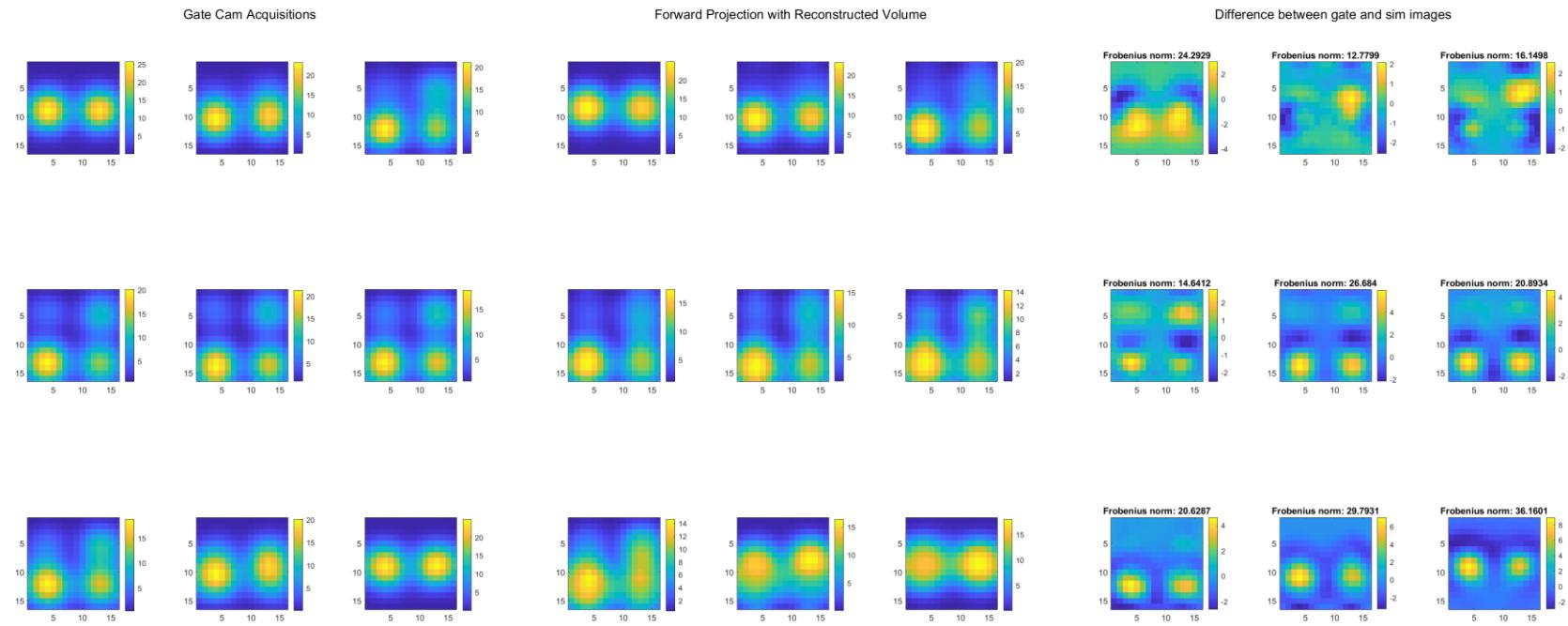
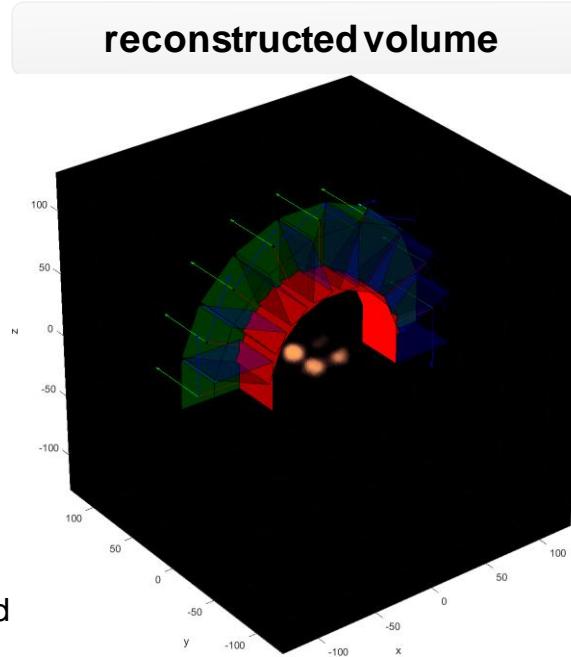
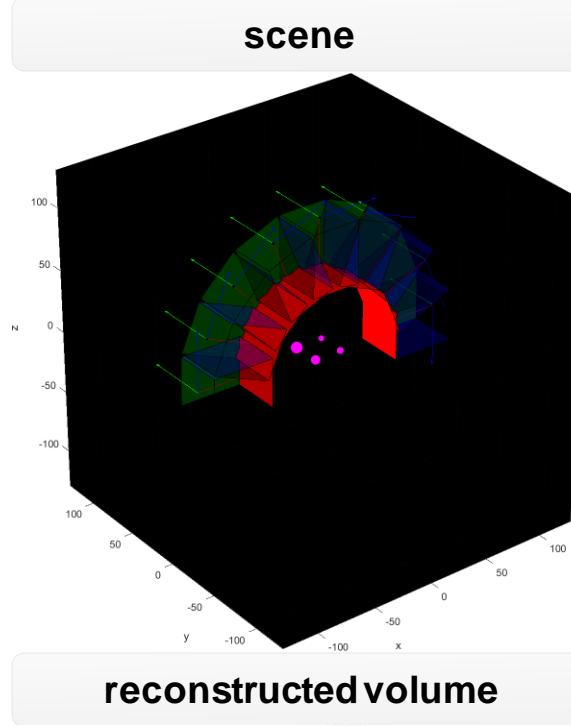
➤ **Gate dataset properties**

- 360 seconds of total acquisition
- 180 degrees of rotation (0.5 deg/s)
- Period of 0.25 secs for each slice (1440 slices in total)
- Point activities of {0.4, 0.3, 0.2, 0.1} MBq

➤ **Reconstruction scene properties**

- [32, 32, 32] voxel grid with 2mm voxel size
- 9 camera acquisition
- Each camera acquisition;
 - 4 seconds of integration
 - (16 slice, +/- 1 degree)
 - No further post-processing

3D Reconstructions with Gate Simulations | 4 point-sources, smoothed



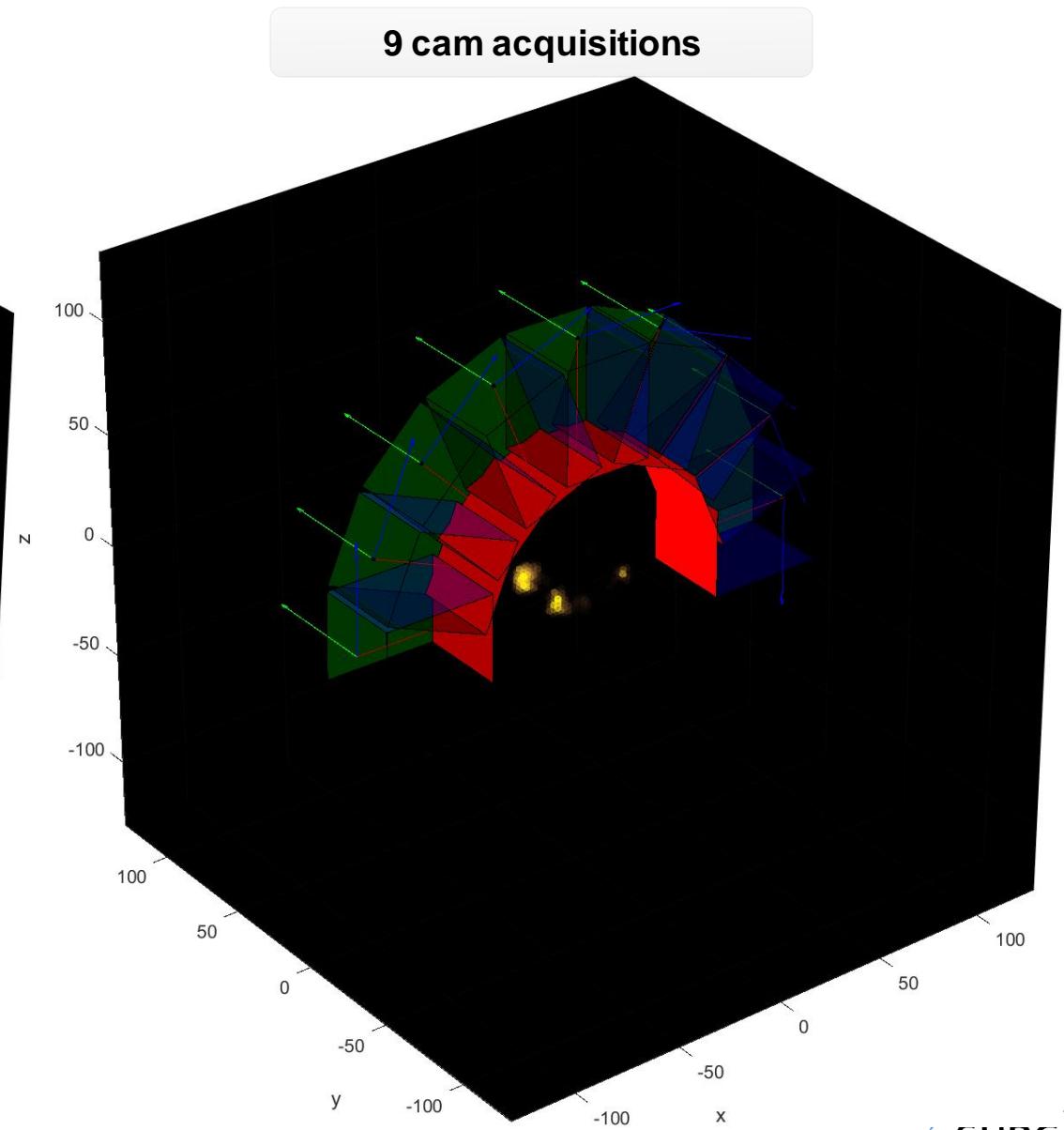
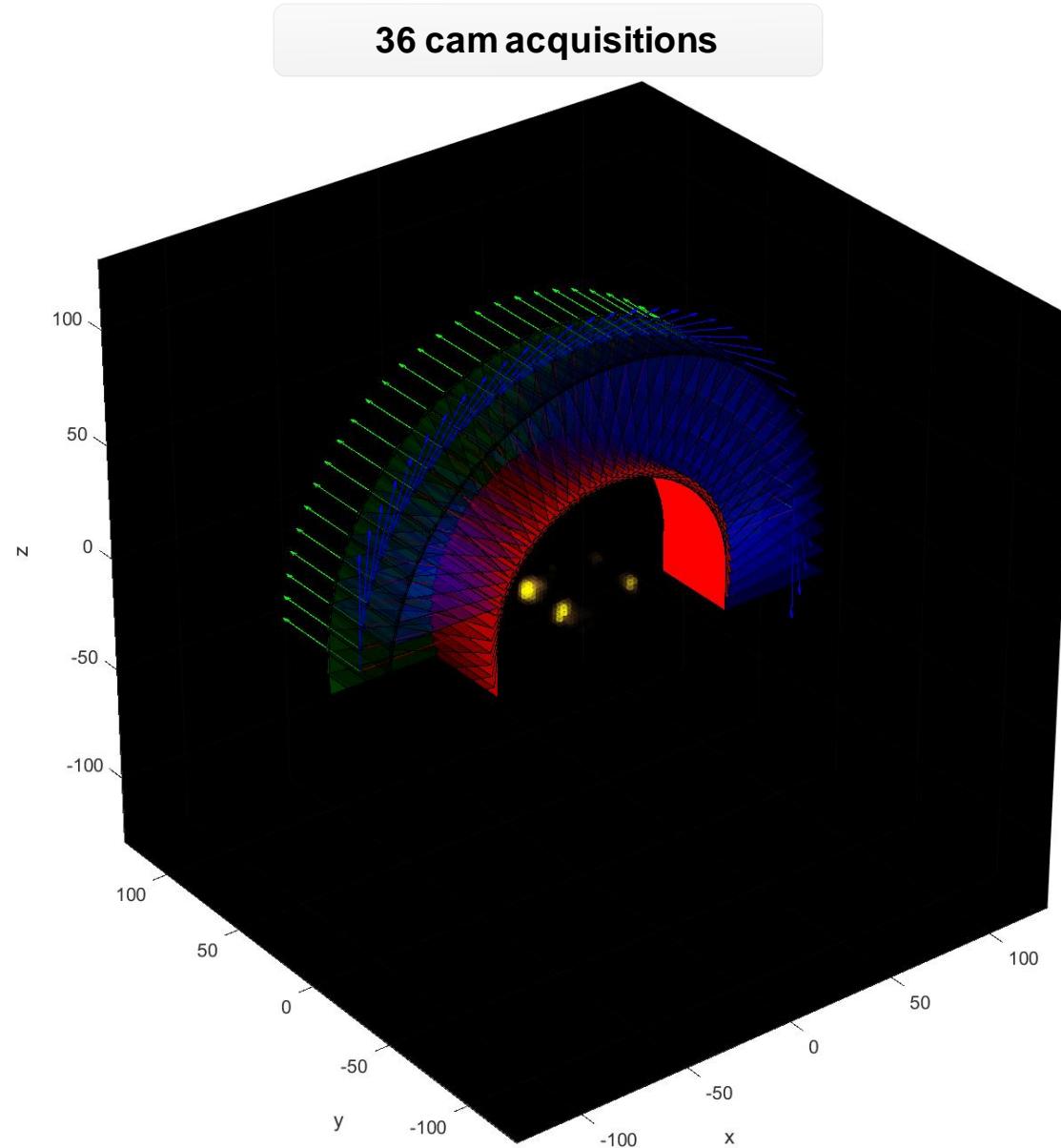
➤ Gate dataset properties

- 360 seconds of total acquisition
- 180 degrees of rotation (0.5 deg/s)
- Period of 0.25 secs for each slice (1440 slices in total)
- Point activities of {0.4, 0.3, 0.2, 0.1} MBq

➤ Reconstruction scene properties

- [32, 32, 32] voxel grid with 2mm voxel size
- 9 camera acquisition
- Each camera acquisition;
 - 4 seconds of integration
 - (16 slice, +/- 1 degree)
 - Smoothed

3D Reconstructions with Gate Simulations | 4 point-sources, more cam acquisitions

[98c833a](#)

What's next?

- Gate simulations are not smooth compared to artificial ones previously generated in Matlab
 - Do we need more acquisition time?
 - Do we need to apply filters?
 - Would multi-camera configuration with the same acquisition time help with better reconstruction?
- Code runs slow with higher number of camera acquisitions
 - The bottleneck is the data copy overhead (between RAM and GPU memory)
 - Matlab works with double precision by default... maybe use single precision (float instead of double)

High Priority;

- Do reconstructions using Gate simulations with single-/multi-camera settings
- Tabulate the system matrix, using Gate simulations

Medium Priority;

- Implement image filters (e.g., edge-preserving smoothing)
- Refactor Matlab code to change data types to float
- Try more complex system modellings; include attenuation, scattering

Low Priority;

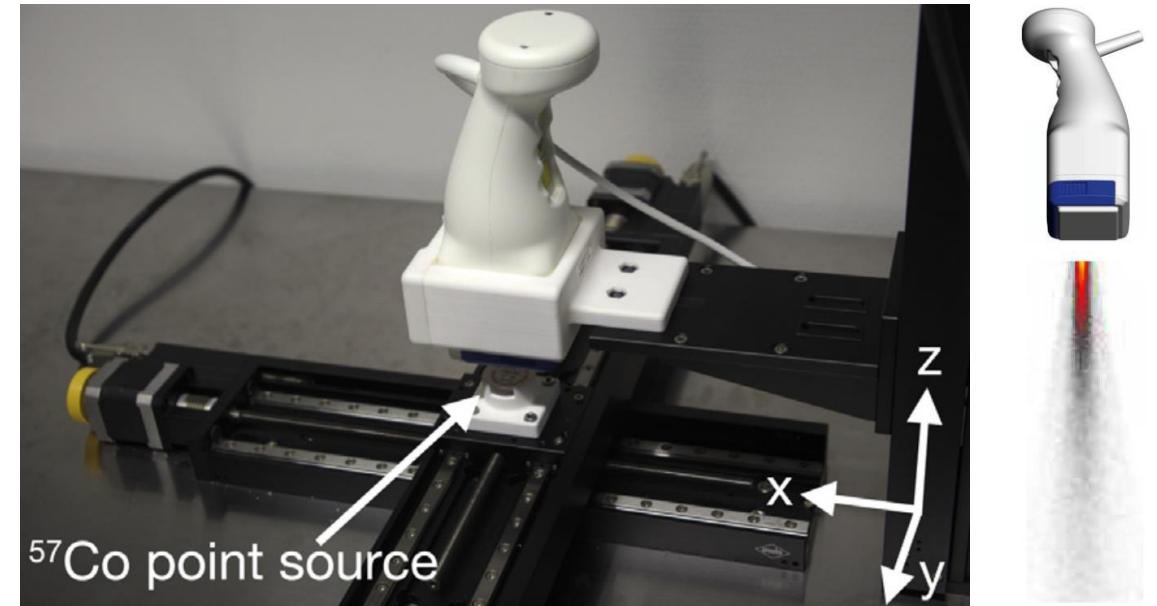
- Gate simulations with the trajectory obtained from NDI tracking around neck
- Export reconstruction as .dicom file

LUT via Gate Simulations

➤ Gate simulation dataset properties;

- 1 mm resolution
- Relative positions of point sources to detector pixel;
 $x, y = -10 : 1 : 10$ [mm]
 $z = 15 : 1 : 165$ [mm]
- Number of Gate simulations = 66150 (21x21x150)
- Point activity = 0.1 MBq
- Simulation stopping criteria = 60 seconds of acquisition
- Energy window = 130-150 keV for Tc99m
- Collimator length = 11.15 mm

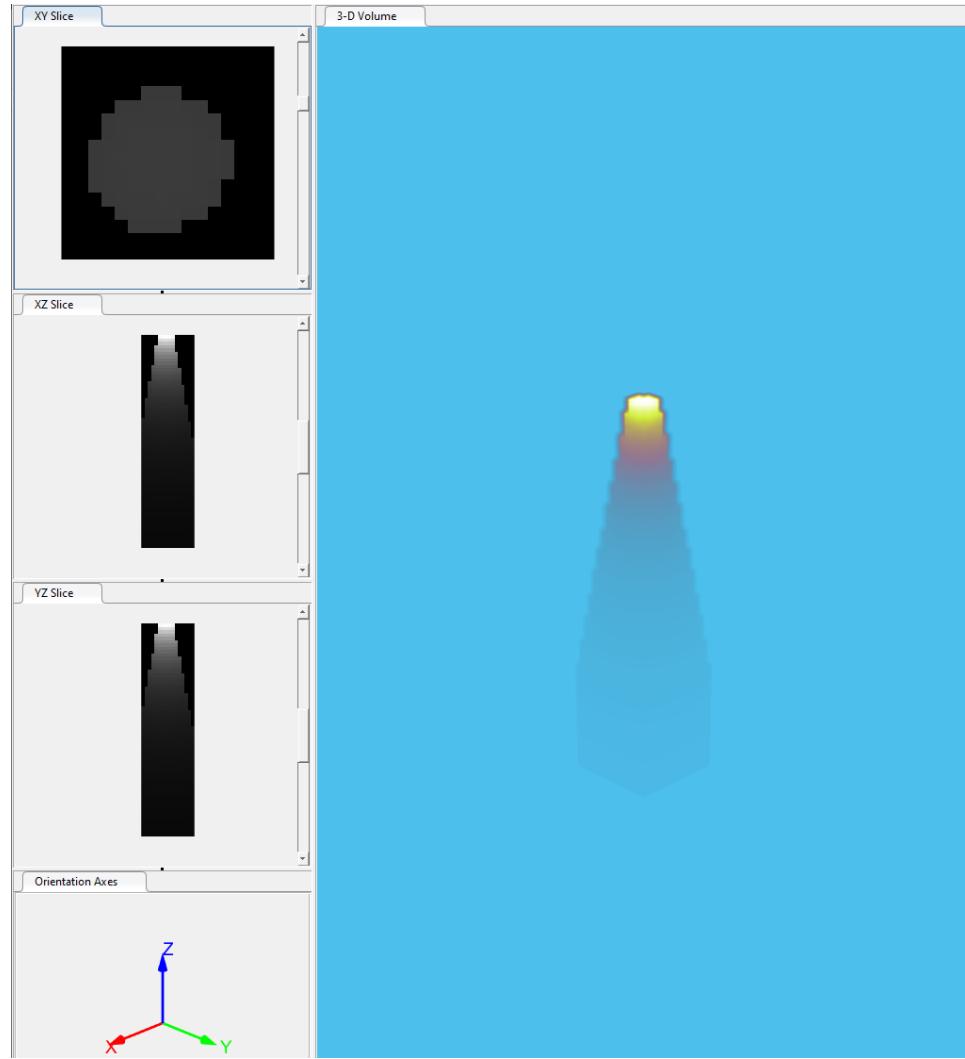
➤ Real setup previously done in [1];



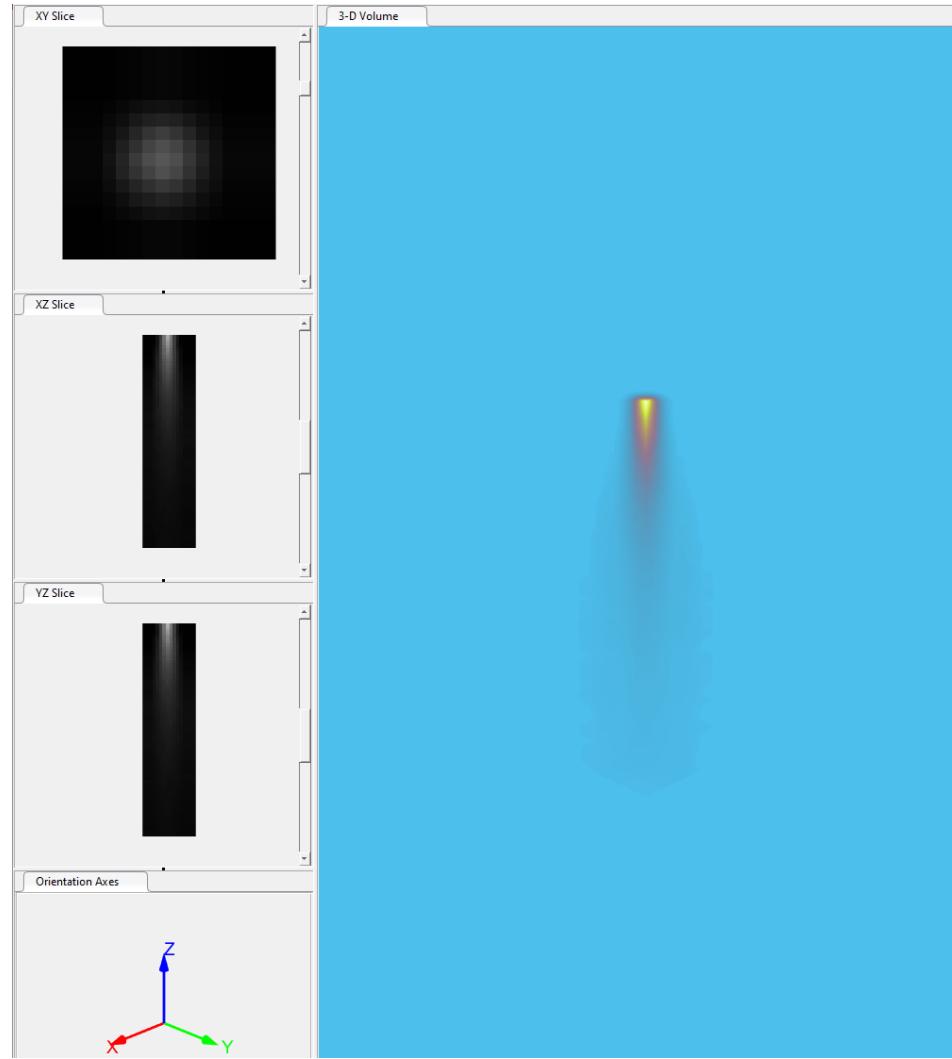
[1] Mini gamma cameras for intra-operative nuclear tomographic reconstruction. Philipp Matthies, José Gardiazabal, Aslı Okur, Jakob Vogela, Tobias Lasser, Nassir Navab. <https://doi.org/10.1016/j.media.2014.04.009>

LUT via Gate Simulations

- Simple Model in slide 5
(no attenuation/scattering correction);



- LUT via Gate Simulation;



What's next?

- Basic code refactoring is done, converted to single precision
 - Less data copy overhead (between RAM and GPU memory), faster code
- We now have a workflow for generating LUT using Gate
 - Maybe we can verify quantitatively?
 - there is already a LUT obtained in real setup
 - we just need to re-run Gate simulations with the same parameters

High Priority;

- Do reconstructions using LUT instead of Simple-Model-Computation
- Tabulate the system matrix for drop-in probe using Gate simulations (Leiden Project)

Medium Priority;

- Implement image filters (e.g., edge-preserving smoothing)
- Try more complex system modellings; include attenuation, scattering

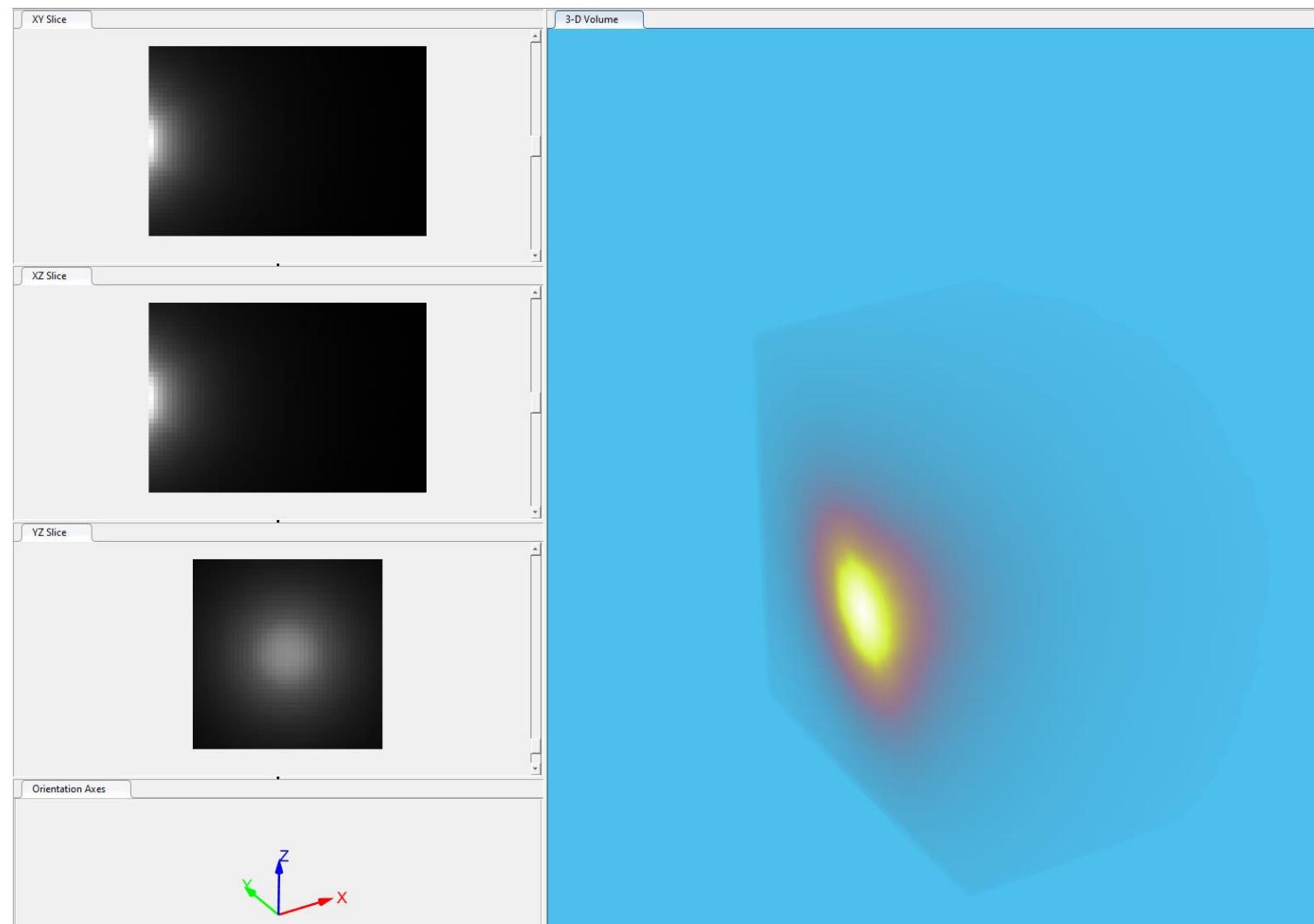
Low Priority;

- Gate simulations with the trajectory obtained from NDI tracking around neck
- Export reconstruction as .dicom file

LUT via Gate Simulations for the Drop-in Probe

➤ Gate simulation dataset properties;

- 2 mm resolution on x,y
1 mm resolution on z
- Relative positions of point sources to detector;
 $x, y = -20 : 2 : 20$ [mm]
 $z = 1 : 1 : 60$ [mm]
- Number of Gate simulations = 26460 (21x21x60)
- Point activity = 0.2 MBq
- Simulation stopping criteria = 10000 counts
- Energy window = 130-150 keV for Tc99m



3D Reconstructions with LUT

➤ How to build system matrix;

- LUT contains count values, for every detector-source position pairs
- LUT data is stored in a structured grid (with 1 mm resolution)
- During a reconstruction; detector-source position pairs are arbitrary
- Need to map detector-source position pair to the LUT

➤ First trial;

- Perform knn search on LUT
- I realized that LUT data is not ordered, so MatLab was doing exhaustive search 

➤ Second trial;

- Sort LUT, by building a kd-tree out of it
- Now knn search is $O(\log(n))$ 

➤ declipse way?;

- Floor the relative positions to integers, which would act like access indices  
- Then search simply become $O(1)$  
- But the LUT data needs to be ordered first

Multi-Cam Test Scene with 4 Point Sources

Gate Dataset Properties

➤ Single Camera

- Semi-circular motion (with a rotational speed of **0.5 deg/s**)
- **360 seconds** of acquisition (effective 360 seconds of total acquisitions)
- Period of each Gate frame is 0.25 s (**1440 frames** acquired frames)
- Point activities of {0.4, 0.3, 0.2, 0.1} MBq
- Collimator length 22.59 mm

➤ Double Camera

- Semi-circular motion (with a rotational speed of **1 deg/s**)
- **180 seconds** of acquisition **per camera** (effective 360 seconds of total acquisitions)
- Period of each Gate frame is 0.25 s (**720 frames** acquired frames **per camera**)
- Point activities of {0.4, 0.3, 0.2, 0.1} MBq
- Collimator length 22.59 mm
- Angle between cameras: 0..30 deg (every 2.5 deg)

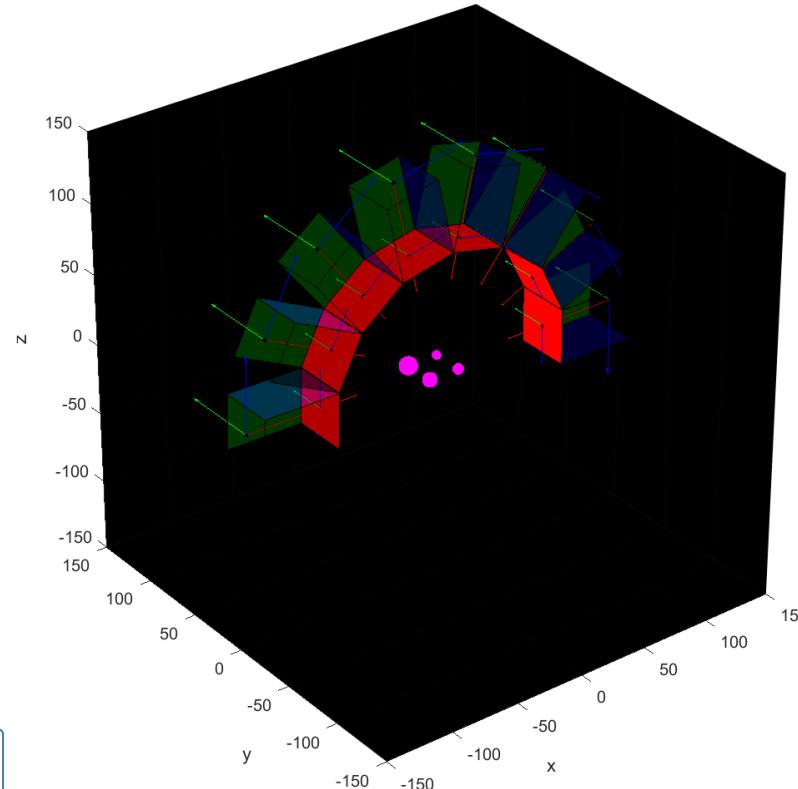
Example Evaluation Scene

➤ Single Camera

- 8 evenly distributed end effector positions
- **1 seconds of time integration** for each position (4 frames x 8 positions = **32 frames in total**)
- $32 \times 0.25 = 8$ seconds of effective acquisition time (duration that the end-user should experience)

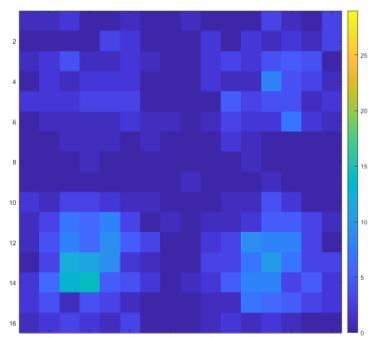
➤ Double Camera

- 8 evenly distributed acquisition positions
- **0.5 seconds of time integration** for each position (2 frames x 8 positions = **16 frames per camera**)
- $16 \times 0.25 = 4$ seconds of acquisition time per camera (duration that the end user-should experience)



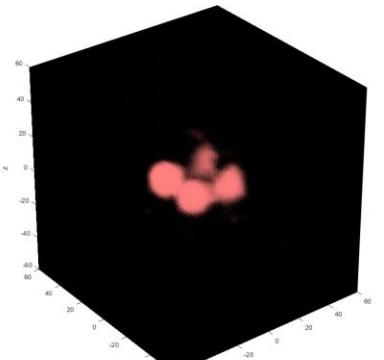
Aim is to have comparable reconstruction scenes

3D Reconstructions with LUT | Single Camera 4 point-sources

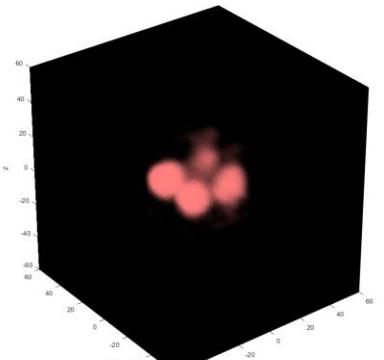


No filter

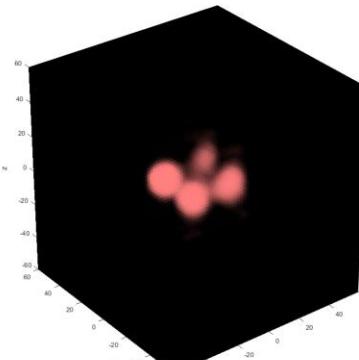
8 acq



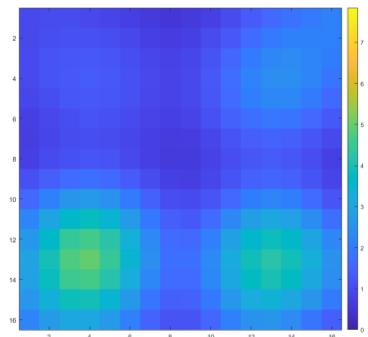
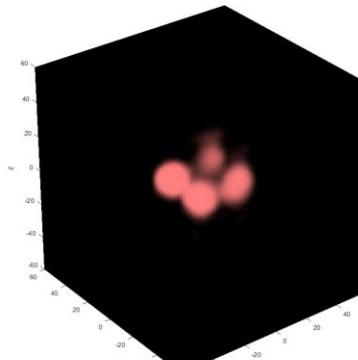
16 acq



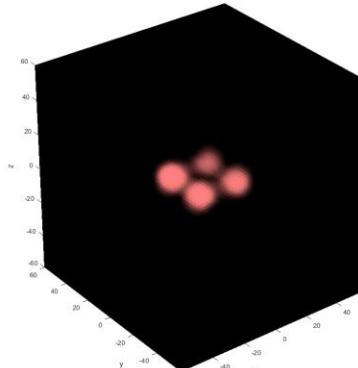
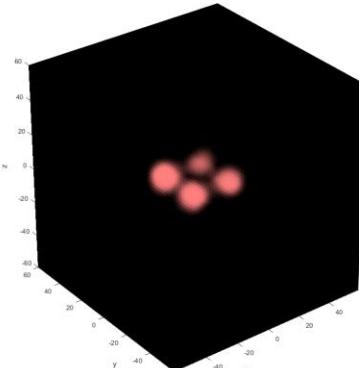
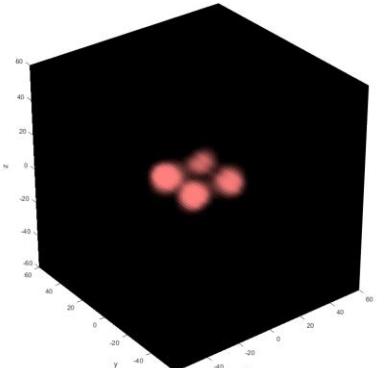
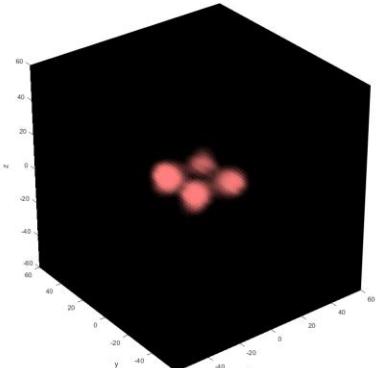
32 acq



64 acq



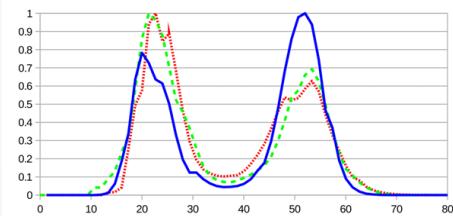
With Gaussian filter



3D Reconstructions | Quantitative Evaluations

We should decide on evaluation procedure

- Separability via intensity profiles;



J. Gardiazabal, T. Reichl, A. Okur, T. Lasser, and N. Navab, "First flexible robotic intra-operative nuclear imaging for image-guided surgery"

- Fitting 3-dim Gaussian on each volume

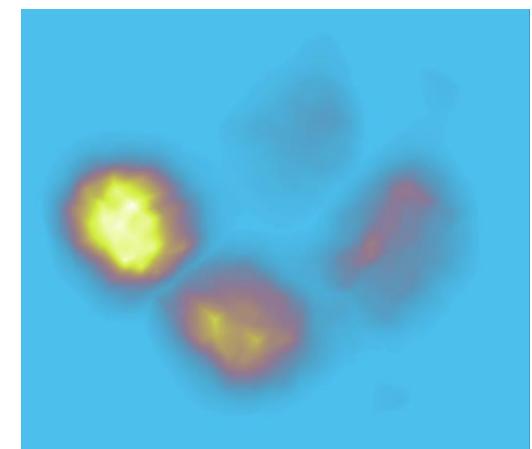
Fitting 2-dim Gaussian on slices

--> Relate mean to source positions

--> Relate std in each axis to asymmetry

Eventually to evaluate the effect of;

- angle between double camera
- filtering on the acquisitions
- time integration
- trajectory around the source



What's next?

- Single camera 3D reconstruction via LUT is done
 - Need to modify the code so that we can do reconstructions with double camera
- By mean time Gate simulations are still running
 - LUT for CrystalCam with collimator length 22.59 mm
 - Double camera with different angles

High Priority;

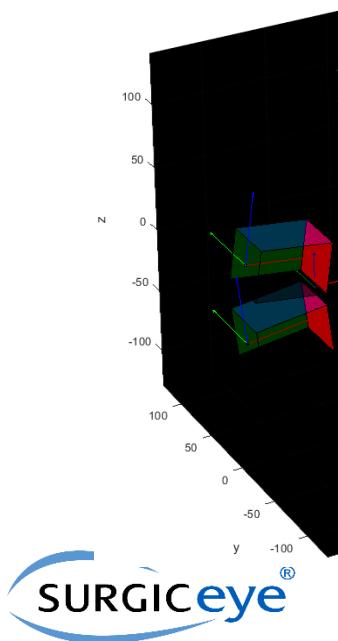
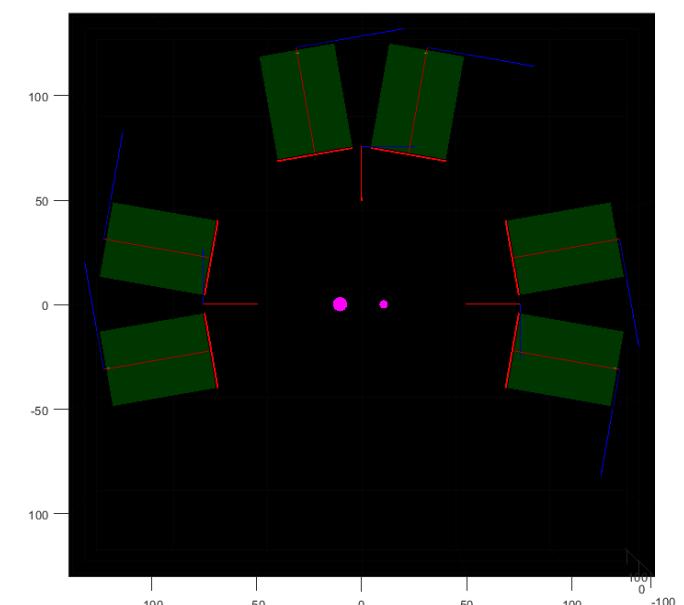
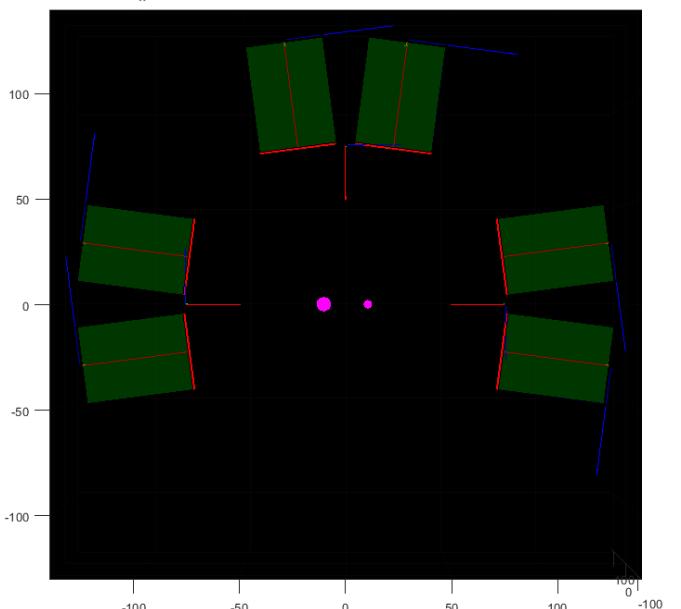
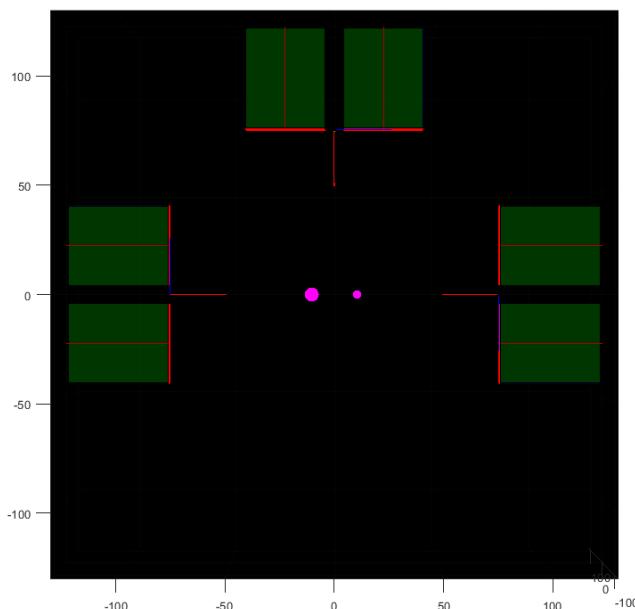
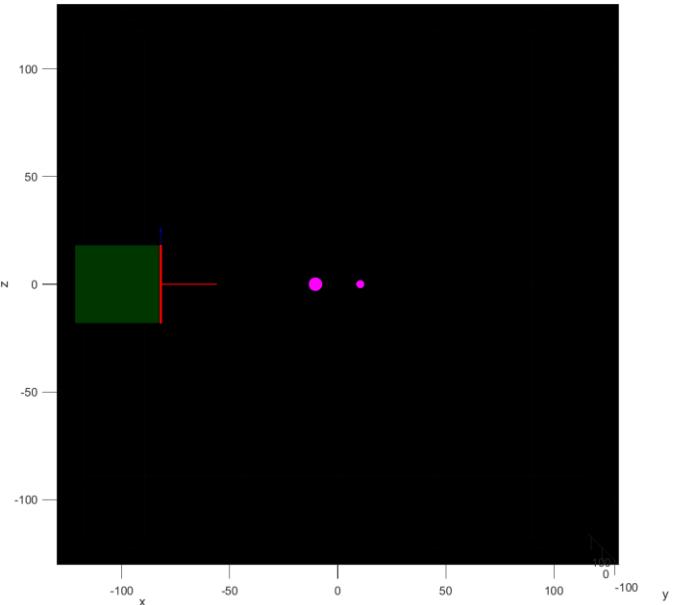
- Decision on quantitative evaluation strategy for the reconstruction quality
- Do double camera reconstructions using LUT, and make the evaluations

Medium Priority;

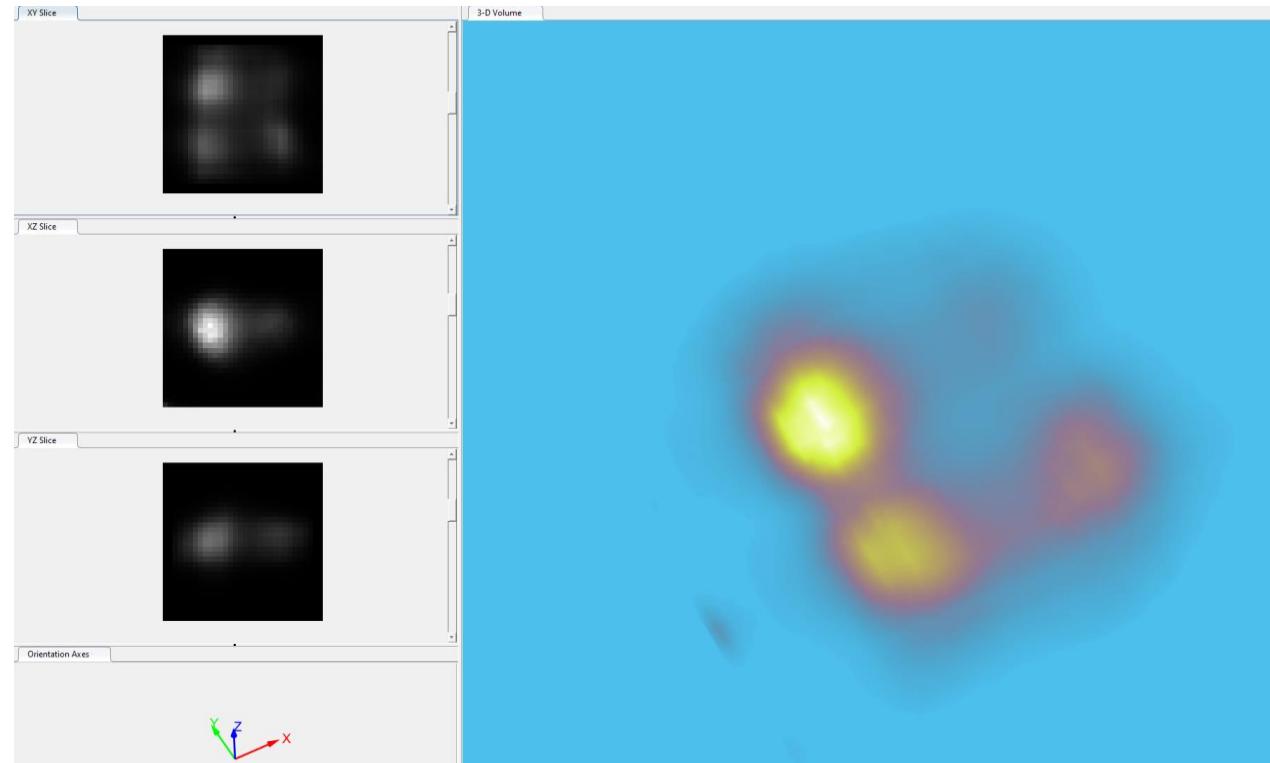
Low Priority;

- Implement image filters (e.g., edge-preserving smoothing)
- Try more complex system modellings; include attenuation, scattering
- Gate simulations with the trajectory obtained from NDI tracking around neck
- Export reconstruction as .dicom file

3D Reconstructions with LUT | Double Camera 4 point-sources

[5254fca](#)

3D Reconstructions with LUT | Single Camera 4 point-sources



Just an example reconstruction scene

- 15 deg angle between double camera
- number of acquisitions = 8
(16 CrystalCam acq.)
- Time integration = 0.5 seconds
- Simple Gaussian smoothening is applied

We should decide on evaluation strategy
then we can select best configuration

What's next?

- Double camera 3D reconstruction via LUT is done
 - Need to decide on the strategy for a quantitative evaluation
- LUT for CrystalCam with collimator length 22.59 mm is done
- By mean time Gate simulations are still running
 - Double camera with different angles (mostly done)

High Priority:

- Decision on quantitative evaluation strategy for the reconstruction quality
- Do double camera reconstructions using LUT, and make the evaluations

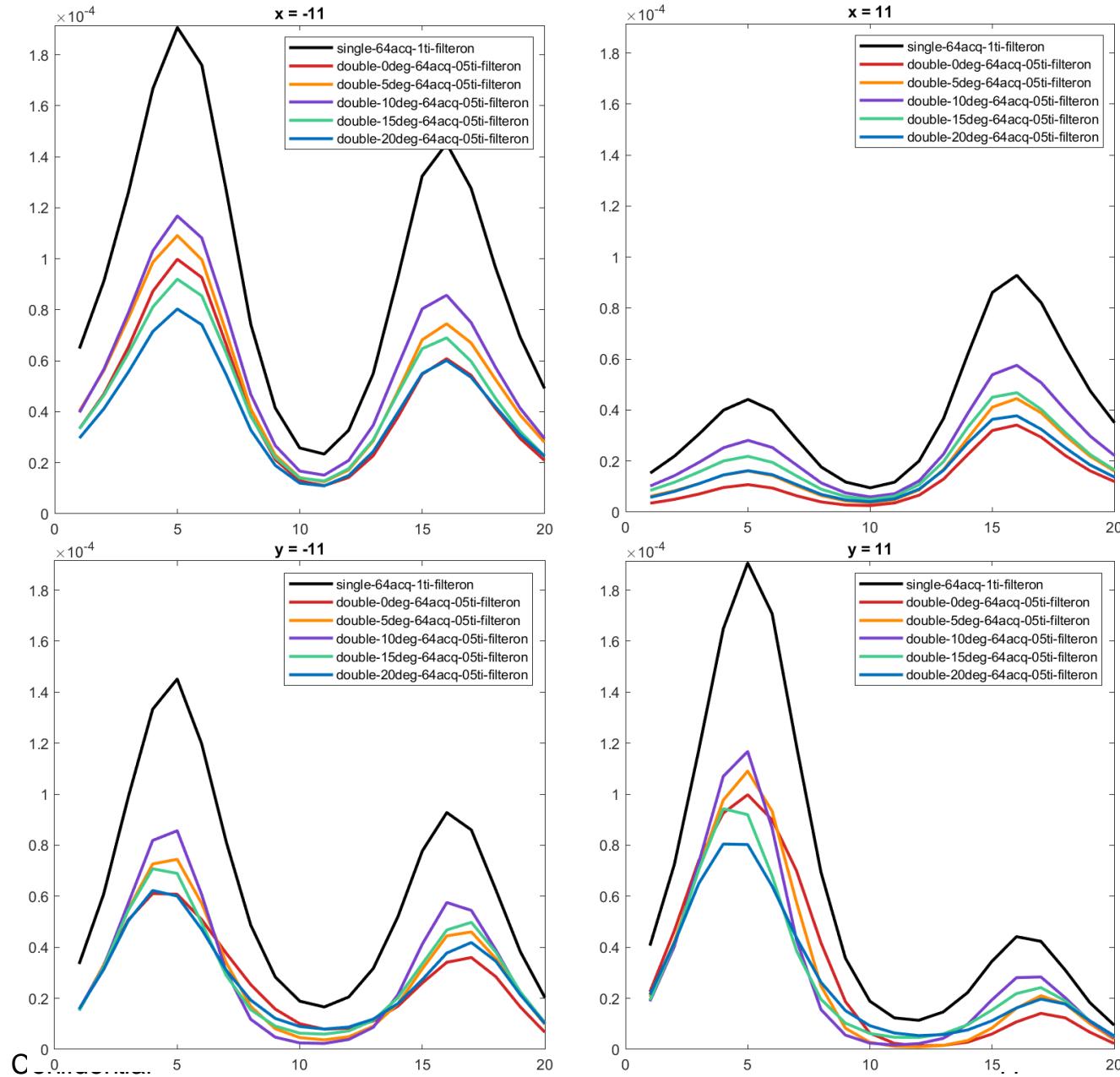
Medium Priority:

- Implement image filters (e.g., edge-preserving smoothing)

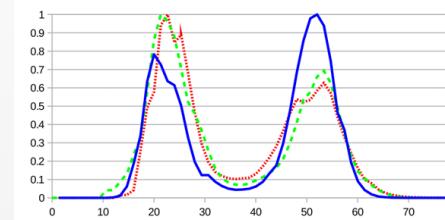
Low Priority:

- Try more complex system modellings; include attenuation, scattering
- Gate simulations with the trajectory obtained from NDI tracking around neck
- Export reconstruction as .dicom file

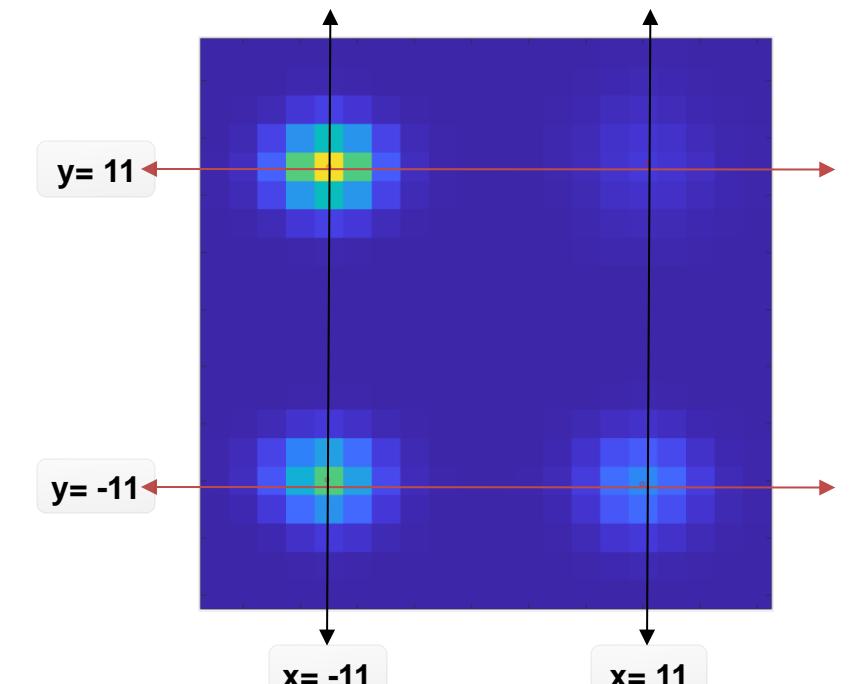
3D Reconstructions | Quantitative Evaluations



➤ Separability via intensity profiles;



J. Gardiazabal, T. Reichl, A. Okur, T. Lasser, and N. Navab, "First flexible robotic intra-operative nuclear imaging for image-guided surgery"



3D Reconstructions | Quantitative Evaluations

➤ **Volume centroids;**

- L2-norm between a centroid and its reference position
- [mm]

Detector Config

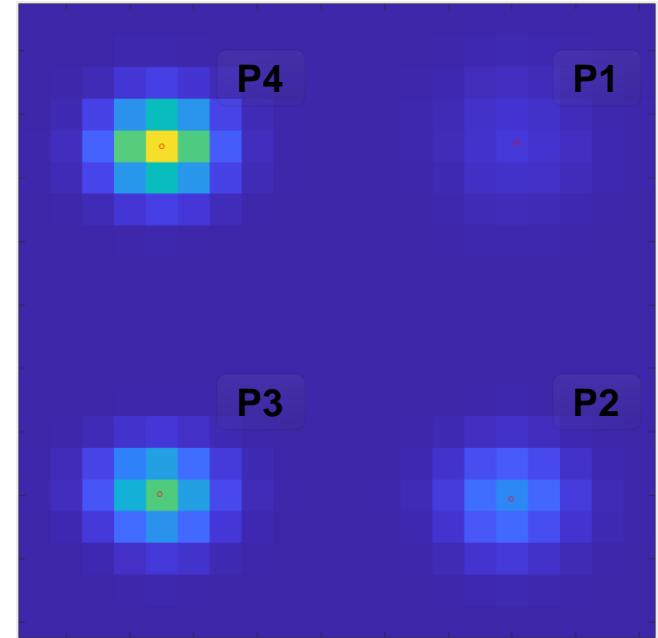
single-64acq
double-0deg-64acq
double-5deg-64acq
double-10deg-64acq
double-15deg-64acq
double-20deg-64acq

P1 P2 P3 P4

0.55	0.41	0.15	0.10
0.60	0.68	0.54	0.28
0.57	0.22	0.16	0.33
0.64	0.64	0.76	0.73
0.24	0.40	0.47	0.59
0.55	0.07	0.13	0.10

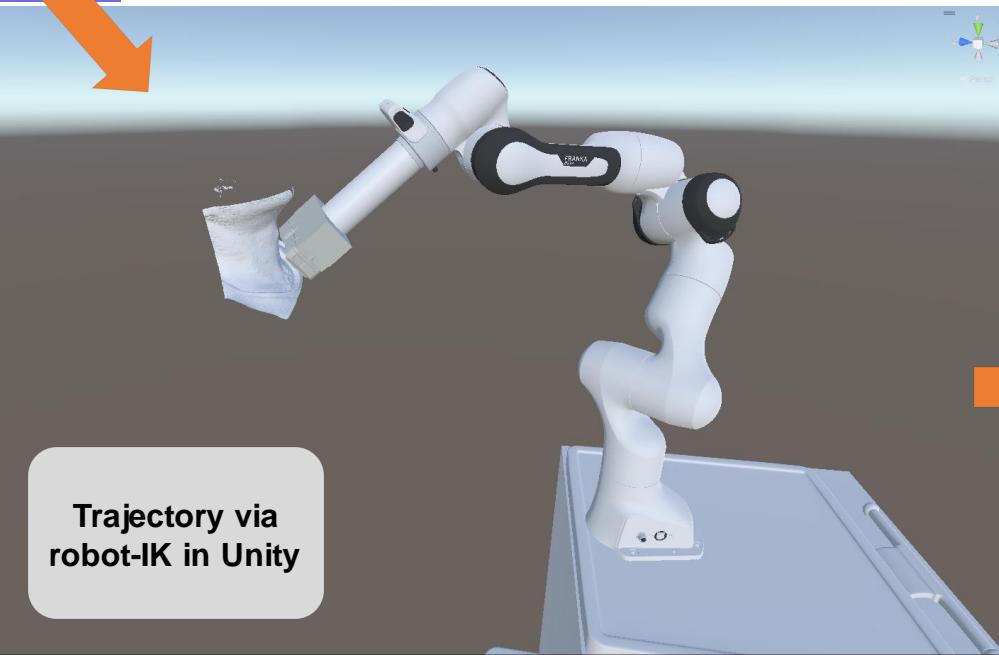
Mean L2-norm

0.30
0.52
0.32
0.69
0.43
0.21

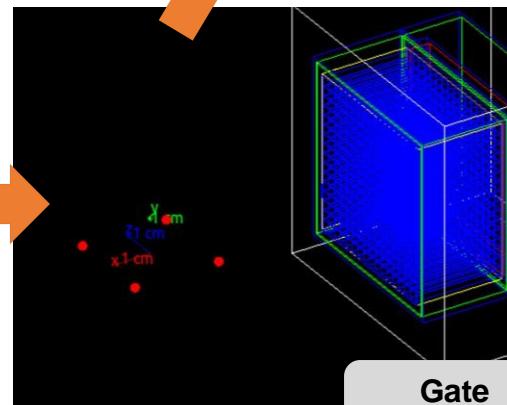
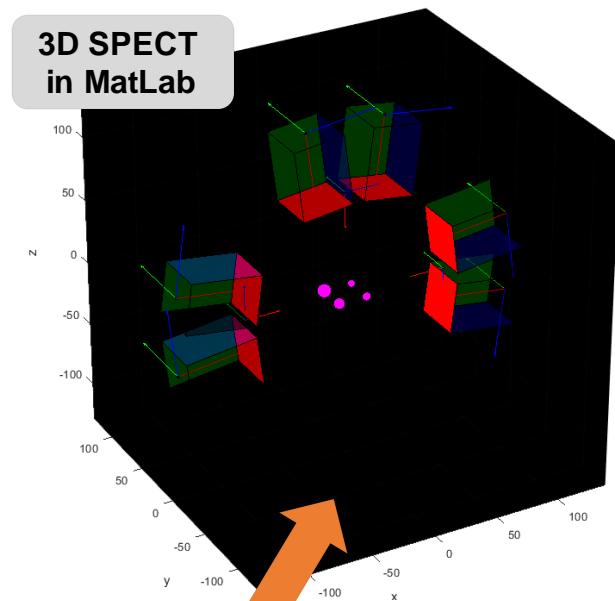


An idea for more realistic scene

Neck reconstruction
via rgbd camera



3D SPECT
in MatLab



What's next?

- An initial step towards quantitative evaluations is taken; intensity profiles and volume centroids
- Need to think about more realistic reconstruction scene
- Also need to improve code, maybe implementing List-Mode MLEM at this point is a good idea
I cannot process more than 64 CrystalCam images on my laptop with the current implementation

High Priority;

- Design of a realistic scene
 - points at off-plane
- Implement List-Mode-MLEM

Medium Priority;

- Implement image filters (e.g., edge-preserving smoothing)
- Neck trajectory via robot-IK
- Uptake evaluations

Low Priority;

- Try more complex system modellings; include attenuation, scattering
- Gate simulations with the trajectory obtained from NDI tracking around neck
- Export reconstruction as .dicom file

Multi-Cam Test Scene with 5 Point Sources

Gate Dataset Properties

➤ Single Camera

- Semi-circular motion (with a rotational speed of **0.5 deg/s**)
- **360 seconds** of acquisition (effective 360 seconds of total acquisitions)
- Period of each Gate frame is 0.25 s (**1440 frames** acquired frames)
- Point activities of {0.4, 0.3, 0.2, 0.1} MBq
- Collimator length 22.59 mm

➤ Double Camera

- Semi-circular motion (with a rotational speed of **1 deg/s**)
- **180 seconds** of acquisition **per camera** (effective 360 seconds of total acquisitions)
- Period of each Gate frame is 0.25 s (**720 frames** acquired frames **per camera**)
- Point activities of {0.4, 0.3, 0.2, 0.1} MBq
- Collimator length 22.59 mm
- Angle between cameras: 0..30 deg (every 2.5 deg)

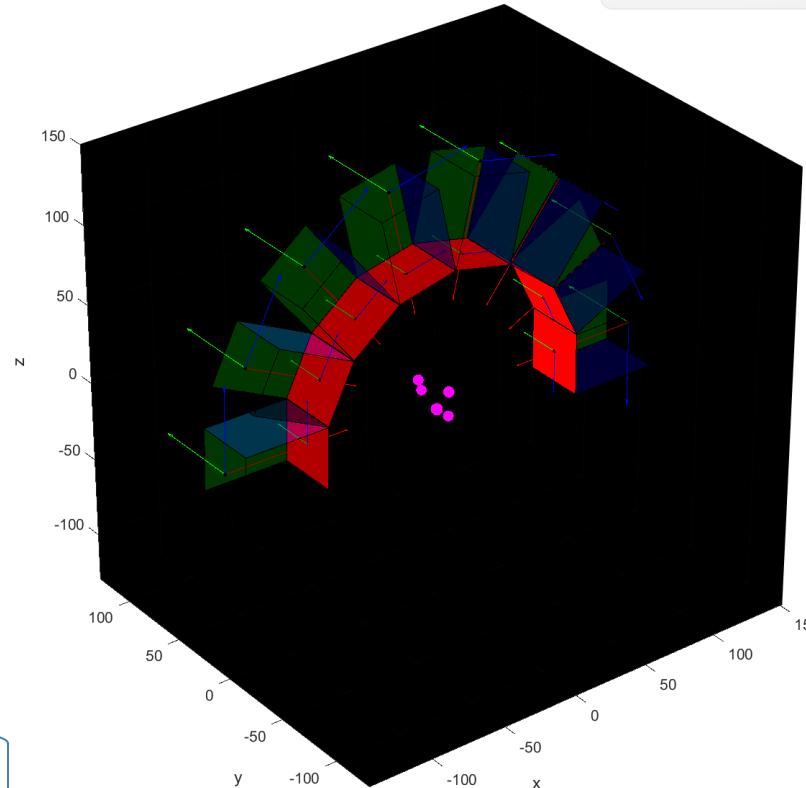
Example Evaluation Scene

➤ Single Camera

- 64 evenly distributed end effector positions
- **1 seconds of time integration** for each position (4 frames x 64 positions = **256 frames in total**)
- $256 \times 0.25 = 64$ seconds of effective acquisition time (duration that the end-user should experience)

➤ Double Camera

- 64 evenly distributed acquisition positions
- **0.5 seconds of time integration** for each position (2 frames x 64 positions = **128 frames per camera**)
- $128 \times 0.25 = 32$ seconds of acquisition time per camera (duration that the end user-should experience)



Aim is to have comparable reconstruction scenes

List-Mode ML-EM | Data Structure

➤ Projection(Binned) - Mode Data

- On a 2D image plane
- Each pixel refers to
 - Integration of detected gamma hits
 - within a certain energy-window
 - within a certain time-window
 - unit being cps

➤ List-Mode Data

- List of raw data for individual photon events
- Each event may have the following information;
 - Time of arrival
 - Energy
 - Pose
 - Detector identifier (for multi cam systems)
 - Detector timing (for multi cam systems, dead time, detector syncing)
 - Scatter / attenuation corrections (e.g. pixels with capacitive sensors)
 - Quality metrics (such as signal-to-noise ratio, event classification, confidence level)
 - Motion tracking (patient motion tracking, respiratory signals)

So that we can do;

- Event filtering based on energy range, region of interest, patient motion etc. (reduce dimensionality)
- Event clustering based on time or position (track changes in the radioactivity, Ordered-Subset-MLEM)
- Motion correction
- Statistical analysis about noise characteristics, event statistics (image quality)

List-Mode ML-EM | Data Acquisition

➤ Gate simulation output format

- https://opengate.readthedocs.io/en/latest/data_output_manager.html#hits-file-gatehits-dat-bin

➤ With this output format we can get the list of events with;

- Time of the event in [s]
- Energy in [MeV]
- Position of detected hit [XYZ, mm]
- Detector identifier

➤ We should be able to have wrapper software to include;

- Orientation
- Pixel id of each hit
- Attenuation / scattering (implicitly)

➤ CrystalCam software output format

- Each detector event with a pixel indexing is parsed
- Each event raw data is then processed into bundle of pixel-energy-time
- The unit of the energy in the pairs is arbitrary! (needs calibration per pixel to convert into keV)

➤ With the current software we should be able to store list of events with;

- Time of the event
- Detector identifier
- Detector pixel index
- Energy in arbitrary unit
- Calibration param per pixel for energy unit conversion to keV

➤ We should be able to have wrapper software to include;

- Pose
- Scatter / attenuation corrections (e.g. pixels with capacitive sensors)
- Quality metrics (such as signal-to-noise ratio, event classification, confidence level)
- Motion tracking (patient motion tracking, respiratory signals)

Plain MLEM Recap

- $\mathbf{y} = \mathbf{Ax}$ or $y_j = \sum_i A_{ij}x_i$
- Inverse problem: Know y_i , want x_i
- Could do $\mathbf{x} = \mathbf{A}^{-1}\mathbf{y}$
- But: \mathbf{A} is huge & cannot be inverted
- Solve inverse problem iteratively
 - Measurements y_i : independent random variables (**Poisson**)
 - Expectation value: $\mu_i = \mathbf{A}_i \cdot \mathbf{x} = \sum_j A_{ij}x_j$
 - Probability to measure k given λ : $p(k|\lambda) = \frac{e^{-\lambda}\lambda^k}{k!}$

Likelihood:

$$L(\mathbf{x}) = p(\mathbf{y}|\mathbf{x}) = \prod_i p(y_i|\mathbf{x}) = \prod_i \frac{e^{-\mathbf{A}_i \cdot \mathbf{x}} (\mathbf{A}_i \cdot \mathbf{x})^{y_i}}{y_i!}$$

- Among all possible images \mathbf{x} we choose the one that maximises the probability of producing the data (find most likely image)
- Maximise the log-likelihood, i.e. maximise $\log(p(\mathbf{y}|\mathbf{x}))$

Maximum Likelihood - Expectation Maximisation (ML-EM)

- Objective function to maximise: log-Likelihood (ML)
- Maximisation algorithm: Expectation Maximisation (EM)

- Initial guess for the image (uniform)
 $x_i^{(0)}$
- Simulate measurements from estimate (forward proj.)
 $y_j^{\text{simu}} = \sum_k A_{kj}x_k^{(0)}$
- Compare this with actual measurements
Ratio $R_j = \frac{y_j}{y_j^{\text{simu}}}$
- Improve image estimate (backward projection)
 $x_i^{(1)} = x_i^{(0)} \cdot \frac{1}{\sum_j A_{ij}} \cdot \sum_j A_{ij}R_j$
- Repeat until convergence

ML-EM

$$x_i^{(n+1)} = x_i^{(n)} \cdot \frac{1}{\sum_j A_{ij}} \cdot \sum_j A_{ij} \frac{y_j}{\sum_k A_{kj}x_k^{(n)}}$$

Plain MLEM vs List-Mode-MLEM

$$x_i^{(n+1)} = x_i^{(n)} \cdot \frac{1}{\sum_j A_{ij}} \cdot \left[\sum_j A_{ij} \frac{y_j}{\sum_k A_{kj} x_k^{(n)}} \right]$$

- The sum is over the projection-data
(for every binned detector pixel reading in cps)
- The y_j represents sum of the counts for each detector pixel

$$\lambda_j^{(k+1)} = \frac{\lambda_j^{(k)}}{\sum_{j \notin \text{LORs}} A_{ij}} \sum_{m \in \text{event-list}} A_{i_m j} \frac{1}{\sum_j A_{i_m j} \lambda_j^{(k)}}$$

- The sum is now only over the list of available events
(each event is a single count, not pixel-binned cps)
- Yet, the normalization term has the sum over all possible LORs
("all possible LORS" means all the detector pixels even if some pixels have no hits acquired?)
- In the ratio term, instead of (pixel binned cps) / (forw. Proj.),
now (1) / (forw. proj.)

What's next?

- Gate simulations with points sources off the plane are done
 - Need to make the evaluations of different camera configurations
- Implementation of List-Mode MLEM is started, but not finished yet
- Data acquisition from Gate in List-Mode format can be doable,
 - Static scene with a single point source is done, next step is to get a simple simulation with moving camera

High Priority;

- Evaluations of camera configurations with the 5points-scene
- Implement List-Mode-MLEM

Medium Priority;

- Neck trajectory via robot-IK
- Uptake evaluations
- List-Mode data acquisition from a simple Gate scene with a moving camera

Low Priority;

- Try more complex system modellings; include attenuation, scattering
- Implement image filters (e.g., edge-preserving smoothing)
- Gate simulations with the trajectory obtained from NDI tracking around neck
- Export reconstruction as .dicom file

we implement
interventional guidance through imaging

we define
new standards in tumor treatment

we care
about the **cure** of cancer



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