STIR and Tensorflow

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July 27, 2017

The big picture

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- iterative reconstruction algorithms
- find the optimum of a *cost function*

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$$P(\text{global LOR response}|\text{image}) = \prod_{\text{all LORs}} P(\text{LOR response}|\text{image})$$

$$P(\text{LOR response}|\text{image}) = \int_{\text{LOR}} \text{image density}$$

- Image (estimate) $\rightsquigarrow$ LOR response: *forward projection*

Ray tracing

- in the following: how to compute / approximate this integral?
- represent *image* as a discretized array of voxels

$$\int_{\text{LOR}} \text{image density} \rightsquigarrow \sum_{\text{traversed voxels}} \text{LOI} \cdot \text{voxel brightness}$$

- LOI = length of intersection of the LOR through a specific voxel

(Standard) STIR spends $> 90\%$ of the reconstruction time for *forward projection*

- is there a way to make it faster?

Table of Contents

Tensorflow

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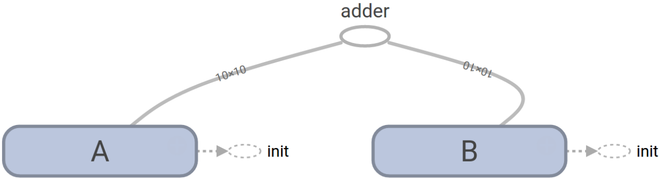

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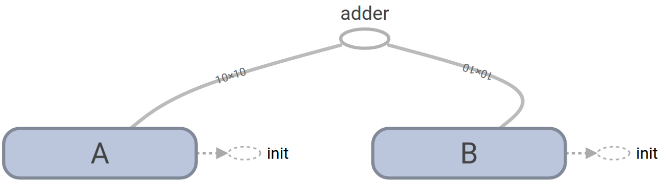


  - Design the graph *now*, save it to a file, run it *later*...
  - Can run it (almost) everywhere: CPU, GPU, a cluster, ...

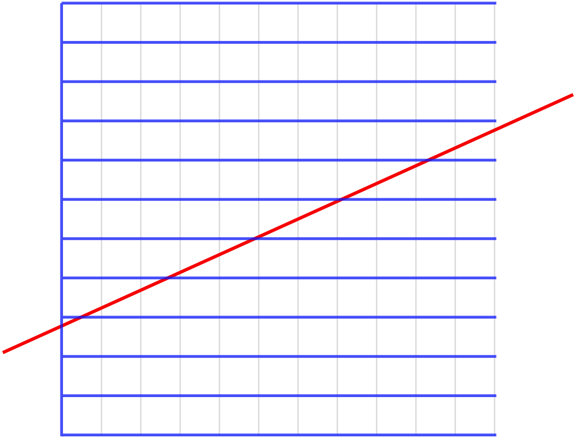
How to do ray tracing on a CPU?

Siddon's algorithm (2D)

- a (very) sequential algorithm

How to do ray tracing on a CPU?

Siddon's algorithm (2D)



- get intersections of LOI with all horizontal planes

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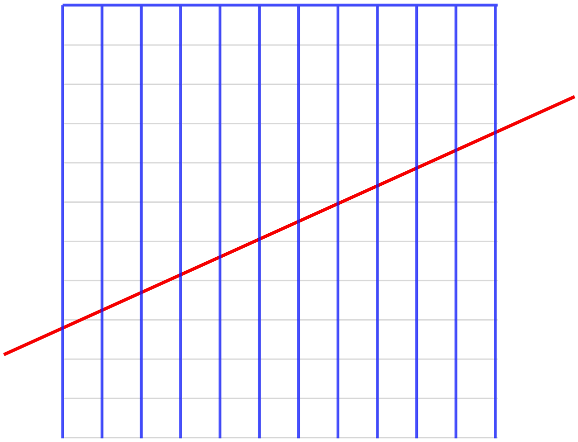

- get intersections of LOI with all vertical planes

How to do ray tracing on a CPU?

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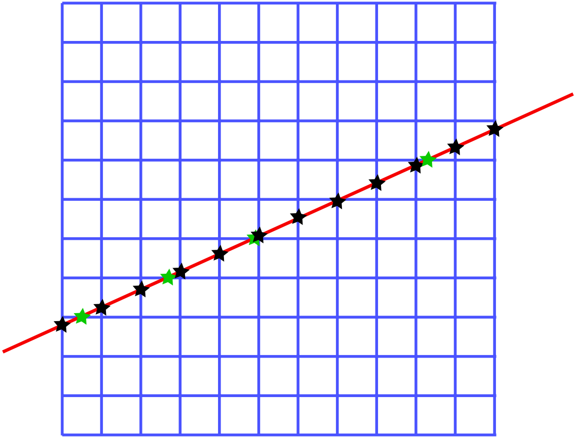

- combine them and get the individual LOIs

Siddon and Tensorflow

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- very inefficient when running with Tensorflow (GPU $\neq$ CPU architecture)
  - especially problematic when trying to trace multiple LORs "in parallel"
- for Tensorflow: need an algorithm that ...
  - uses the same algorithmic steps on *all* voxels of the LOR...
  - uses the same algorithmic steps on *all* LORs...
  - ... to efficiently use the *single-instruction-multiple-data* GPU architecture

Alternatives to Siddon

- naïve approach: for every LOR, compute the LOI through *every* voxel, then add them all up
  - works fine with Tensorflow, but scales as $\mathcal{O}(N^3)$
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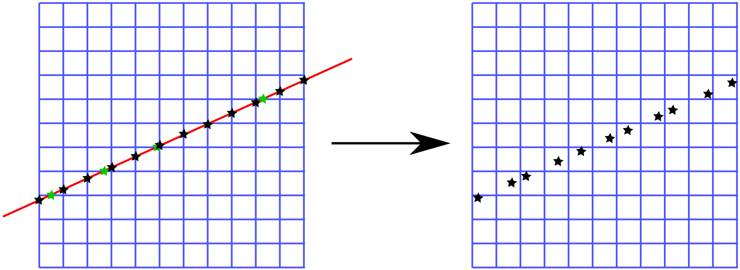

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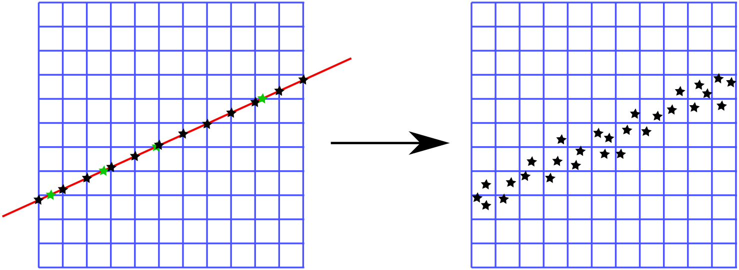

Voxel-by-voxel LOI calculation

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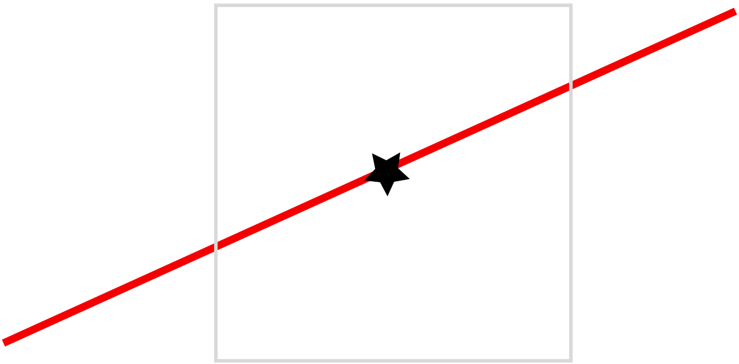

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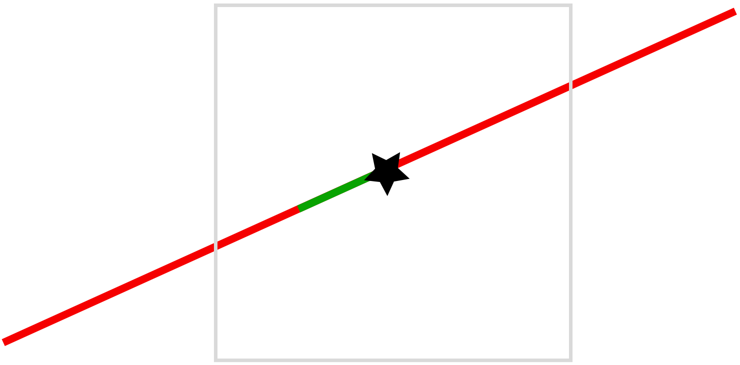

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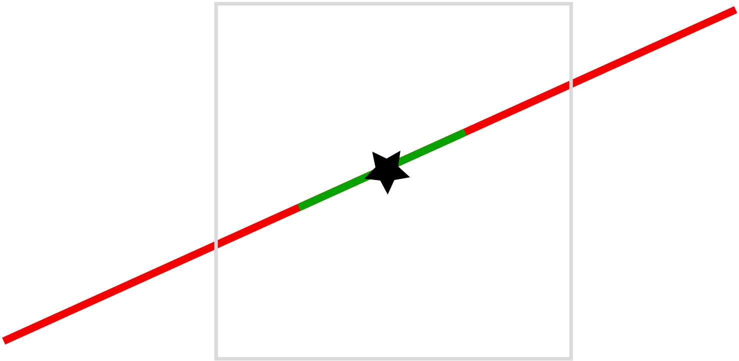

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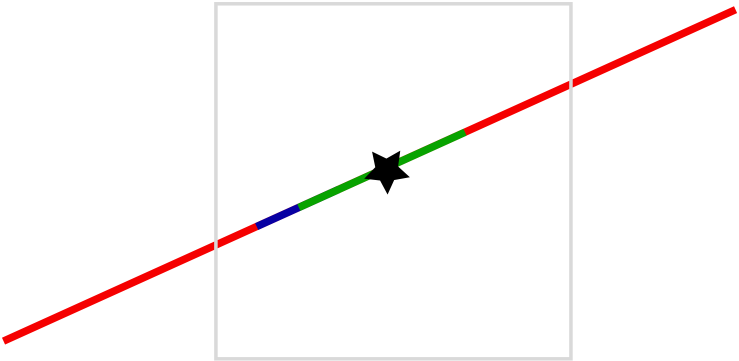

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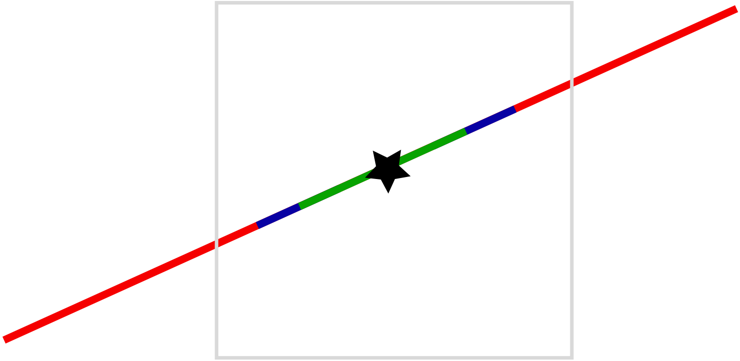

Signed Distance Functions

- a heuristic that produces an *underestimation* of the distance to the voxel boundary
  - can do the iterations more efficiently
- cheap to evaluate, much cheaper than to *actually* evaluate the true distance

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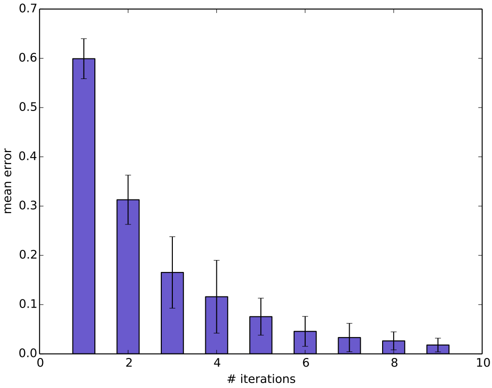
- a heuristic that produces an *underestimation* of the distance to the voxel boundary
  - can do the iterations more efficiently
- cheap to evaluate, much cheaper than to *actually* evaluate the true distance
- much more powerful than what is needed here!
  - implicitely define a *surface*
  - *union*, *intersection*, *repetition* of objects etc. translate into simple symbolic manipulations

Ray marching: an iterative algorithm

Accuracy

- assume: have "enough" points along the LOR



- with 6 iterations, are already at $\sim 5\%$ level!

Bringing together STIR and Tensorflow

The infrastructure

- Build the Tensorflow graph in a Python script
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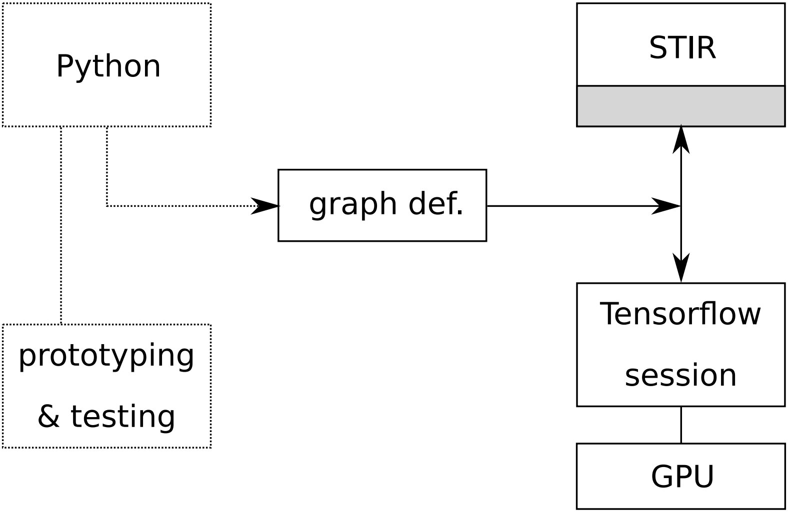
Bringing together STIR and Tensorflow

The infrastructure

- Build the Tensorflow graph in a Python script
  - much easier and faster to prototype
  - Python API much better documented and more stable
- <u>Save</u> the complete graph into a `ProtoBuf` file
- <u>Load</u> the file using the C++ API and make use of it in STIR
  - link STIR against the Tensorflow (shared) library

The workflow



Caching in STIR

- scanners have (many) symmetries
- `ProjMatrixByBin` maintains a cache
  - already computed matrix elements are stored
  - new matrix elements related by symmetries to known ones "come for free"!

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- `ProjMatrixByBin` maintains a cache
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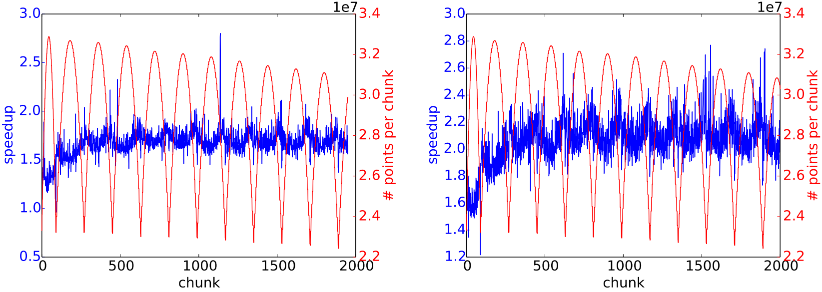
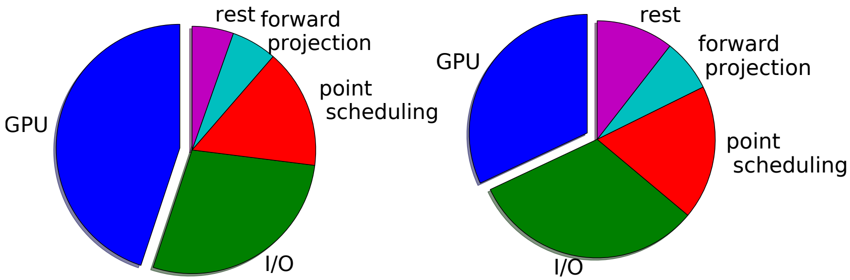
- but: caching most efficient if *every* new matrix element request is checked against cache before computing
- *batching* the matrix element requests makes caching (very) inefficient!

Speedup without caching



left: 6 ray tracing iterations, **right**: 2 ray tracing iterations

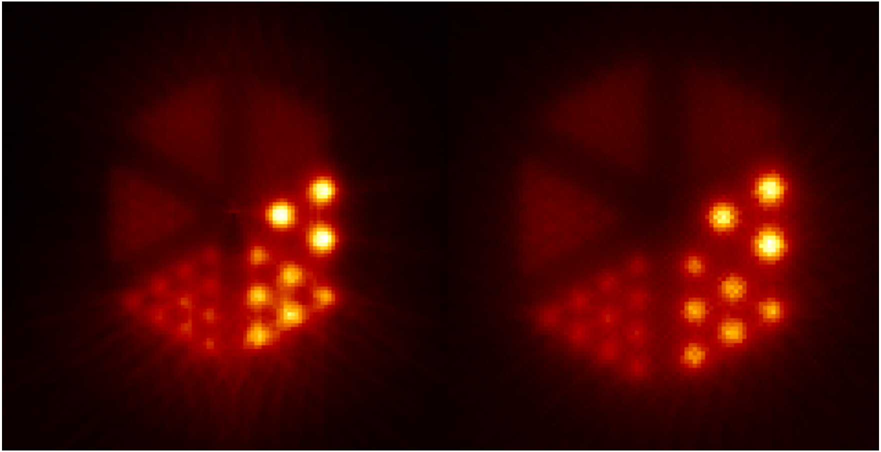
- average speedup is similar



left: 6 iterations, **right**: 2 iterations

- *I/O*: converting from `ProjMatrixElemsForOneBin` to `Tensor` and back
- *point scheduling*: choose points to sample the TOR / LOR

Images



left: 2 iterations, 20LORs per matrix element, **right**: original STIR;
both: 1 OSMAPOSL iteration

How to proceed?

- demonstrated a proof-of-concept of integrating Tensorflow into STIR
- whole toolchain is in place
  - separation of graph generation (Python) and usage (C++) works very well

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Not too bad, but still some limitations:

- how to improve utilization of GPU (conversion between Tensors and STIR objects)?

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Not too bad, but still some limitations:

- how to improve utilization of GPU (conversion between Tensors and STIR objects)?
- is there a better way to estimate the matrix elements?
- so far, use only a single thread (no `openMP` support)
  - Tensorflow sessions tend to allocate all of the available GPU memory to avoid fragmentation...

Where to find the code?

- STIR-TF: `https://github.com/philippwindischhofer/STIR/tree/stir-tf`
  - in particular: `https://github.com/philippwindischhofer/STIR/blob/stir-tf/documentation/tensorflow-documentation/doc/main.pdf`
- ray tracing scripts: `https://gitlab.phys.ethz.ch/luster/tf-raytracing` (ask Werner for access)

Any comments and contributions are welcome!

CMS Global Trigger
HEPHY Vienna
HEPHY
Institute of High Energy Physics
ÖAW
RACK STOP
AMS Lead
AMS-02
ASACUSA
ALPHA

Backup

How to do ray tracing on a CPU?

Siddon's algorithm (2D)

- parametrize the LOR

$$\mathbf{x} = (\mathbf{x}_{\mathbf{end}} - \mathbf{x}_{\mathbf{start}}) \cdot \alpha + \mathbf{x}_{\mathbf{start}}$$

$$\alpha \in [0, 1]$$

- get intersections with horizontal and vertical planes in terms of the line parameter α
- merge and sort them
- *differences* between neighbouring α values in the merged list describe the LOIs!

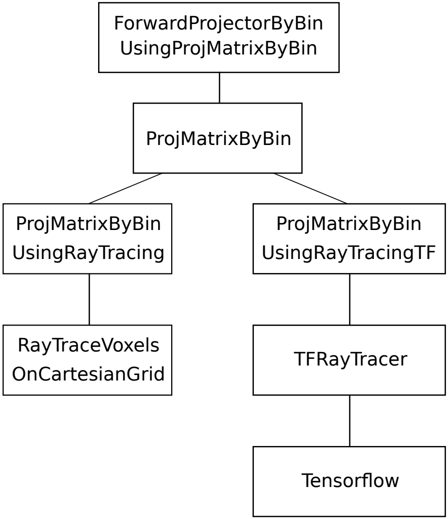
Signed Distance Functions

- a heuristic that produces an *underestimation* of the distance to the voxel boundary
  - can do the iterations more efficiently
- for a cube with side lenghts (d_x, d_y, d_z), origin in the center:

$$\mathrm{SDF}(x, y, z) = -\max\left(\left|x - \frac{d_x}{2}\right| - \frac{d_x}{2}, \left|y - \frac{d_y}{2}\right| - \frac{d_y}{2}, \left|z - \frac{d_z}{2}\right| - \frac{d_z}{2}\right)$$

- SDF is small (by design) close to the voxel boundary
  - but must march in *both* directions
  - time until convergence depends on the location of the initial point

Tensorflow in STIR



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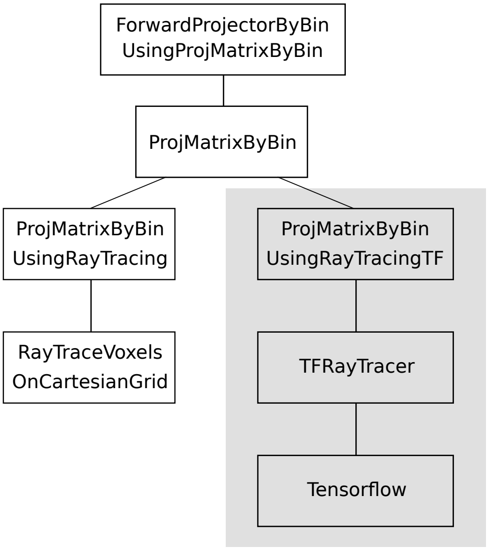
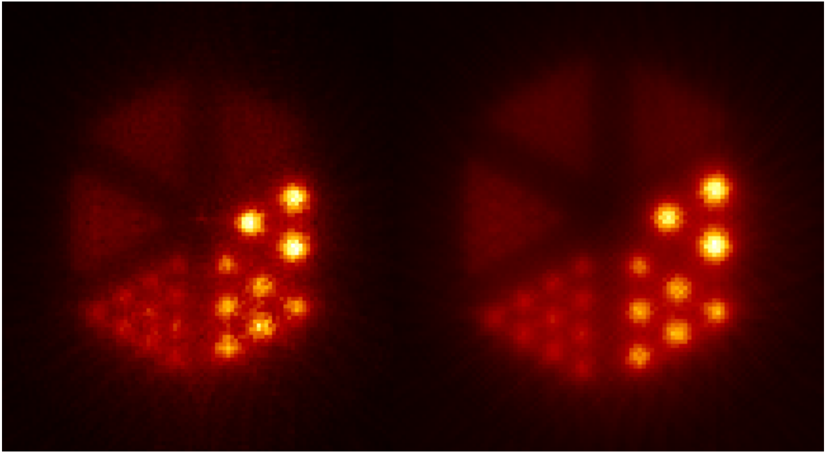
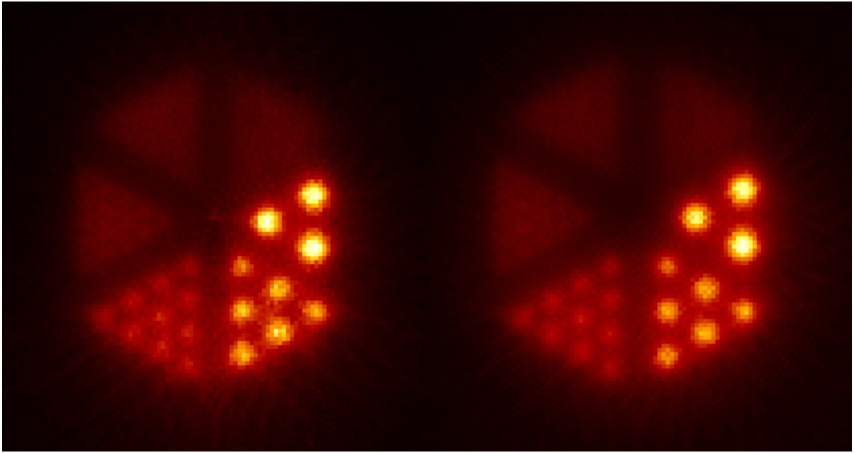




left: 3 ray tracing iterations, 2LORs per matrix element, **right**: original STIR; *both: 1 OSMAPOSL iteration*



left: 30 ray tracing iterations, 2LORs per matrix element, **right**: original STIR; *both: 1 OSMAPOSL iteration*