Parallel proton CT image reconstruction

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Motivation and role of proton imaging

- Nowadays the importance of the proton therapy is increasing
  $\Rightarrow$ more and more motivation to improve the technology
- The use of proton CT images is a promising direction
  $\Rightarrow$ lower inaccuracy in RSP measurement
  $\Rightarrow$ decreased safety zone around the tumour
- A pCT image measures the relative stopping power (RSP) distribution of the patient

Bergen pCT collaboration

- Goal: reach the clinical research with a pCT prototype
- Apply monolithic active pixel sensors (MAPS)
- Use pencil beam for imaging
- Measure 10^6 proton / second
- Reach $<$ 1 % RSP error

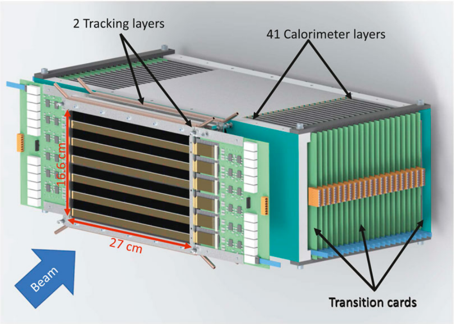


Image reconstruction – a large linear problem

The image reconstruction is a large and sparse linear problem:

$$\mathbf{y} = \mathbf{A}\,\mathbf{x}\,,$$

where:

- $\mathbf{y}$ is the measured data
- $\mathbf{x}$ is the vector of voxels
- $\mathbf{A}$ is the system matrix, contains the intaraction coefficients
    - practically the path length of protons in the voxel
    - can have 10^{12} non zero element – about 12 Tbyte
      $\Rightarrow$ on the fly calculation of the element instead of store them
    - matrix element become a function: $A_{i,j} \Rightarrow A(i,j)$

Parallelization – important parameters

Hardware:

- 4 piece of Nvidia 1080Ti
- computer capability: 6.1
- CUDA version: 11.2

Parameters:

- N: the number of protons $\sim 10^9$
- M: the number of voxels $\sim 10^7$
- L: the typical number of interaction of a proton $\sim 10^3$
- T: the number of GPU treads $\sim 10^4$
- S: the number of SMs $\sim 10^2$
- TS: tread per SM – 128 \ 256 \ 512

Main aspects

- Minimize the num. of calculations of the same matrix element
- Read only a subset of proton histories at the same time
  $\Rightarrow$ the memory use is independent of input data size
- Parallelize the problem in an efficient way
- Optimized for the given hardware
- Minimize CPU usage
- Minimize data transfer between CPU and GPU

Image reconstruction – Richardson – Lucy algorithm

- Originally introduced for astrophysics application
- It is a fixed point iteration for large and sparse linear problems
- Initialization: arbitrary positive vector
- Init: unit vector or precalculated approximate solution

The formula for the i^{th} element of the next image vector:

$$x_i^{k+1} = x_i^k \frac{1}{\sum\limits_j A_{i,j}} \sum_j \frac{y_j}{\sum\limits_l A_{l,j} x_l^k} A_{i,j} \ ,$$

where k is the number of iteration. 20-300 iteration is typical.

Parallelization & avoidance of multiply calculations

Update the i^{th} voxel in the k^{th} iteration:

$$x_i^{k+1} = x_i^k \frac{1}{\sum_j A(i,j)} \sum_j \frac{y_j}{\sum_l A(l,j) x_l^k} A(i,j)$$

$$\Downarrow$$

$$x_i^{k+1} = x_i^k N_i \sum_j \frac{y_j}{\sum_l A(l,j) x_l^k} A(i,j)$$

Pre-calculate the normalization of the i^{th} voxel:

$$N_i = \frac{1}{\sum_j A(i,j)}$$

Parallelization & avoidance of multiply calculations

Update the i^{th} voxel in the k^{th} iteration:

$$x_i^{k+1} = x_i^k N_i \sum_j \frac{y_j}{\sum_l A(l,j) x_l^k} A(i,j)$$

$$\Downarrow$$

$$x_i^{k+1} = x_i^k N_i R_i^k$$

$R_i = 0$. For i^{th} voxel and j^{th} proton history:

$$R_i^k \mathrel{+}= \frac{y_j}{\sum_l A(l,j) x_l^k} A(i,j)$$

Parallelization & avoidance of multiply calculations

Update the i^{th} voxel in the k^{th} iteration:

$$x_i^{k+1} = x_i^k N_i R_i^k$$

First: Calculate the Hadamard ratio (once per iteration):

$$H_j^k = \frac{y_j}{\sum_l A(l,j) x_l^k}$$

Second: $R_i = 0$. For i^{th} voxel and j^{th} proton history:

$$R_i^k \mathrel{+}= \; H_j^k A(i,j)$$

GPU algorithm

Algorithm 1 GPU algorithm

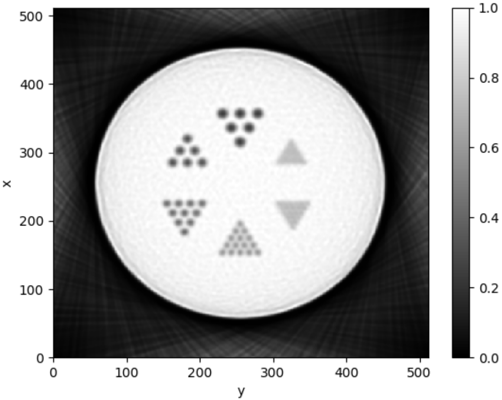
```
GPU: calculate voxel normalization
for needed number of iterations do
    while end of proton histories do
        CPU: read certain amount of proton histories
        GPU: calculate Hadamard ratio:
          • parallel calculation of proton histories
          • serial calculation of voxel interactions
        GPU: calculate voxel contribution
          • serial calculation of proton histories
          • parallel calculation of voxel interactions
        GPU: Update the image vector
    end while
end for
CPU: Save the image vector
```

Results – reconstructed Derenzo phantom

Reconstructed Derenzo phantom after 250 iterations:

Derenzo phantom:

- For measurement of spatial resolution
- Group of rods in diameter distance
- Different diameters $\Rightarrow$ test resolution



Results – reconstructed Derenzo phantom

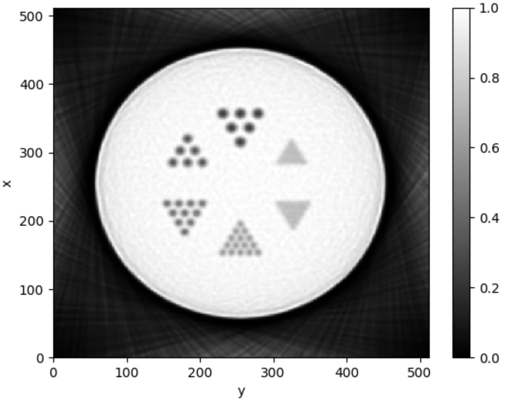
Reconstructed Derenzo phantom after 250 iterations:

Without errors:

- Exactly restored image

With errors:

- Reasonably good spatial resolution
- Point spread function FWHM = 4.3 mm
- Acceptable RSP accuracy



Summary

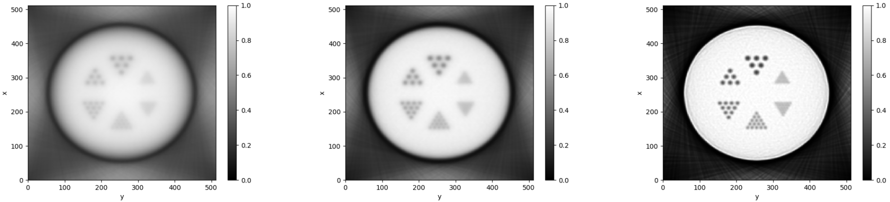
Results:

- A new development: statistically based pCT image reconstruction
- Application of Richardson – Lucy algorithm in pCT imaging
- Reasonably good resolution and acceptable RSP accuracy
  $\Rightarrow$ promising from a first implementation of the algorithm

Outlook:

- Optimize the parameters & performance of the R – L algorithm
- New algorithm is based on Maximum Likelihood method

Thank you for your attention!



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