Evaluation of A Digital Tracking Calorimeter for In-Situ Range Verification during Particle Therapy

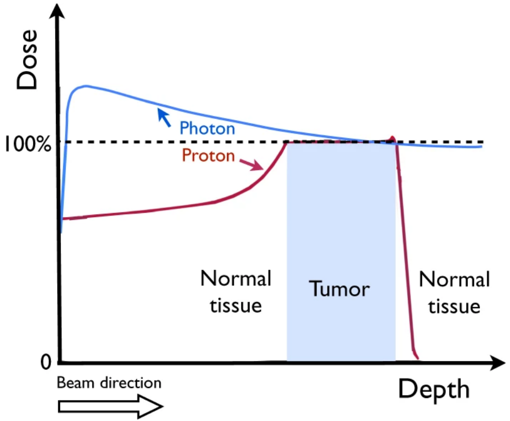
Alexander Schilling

Center for Technology and Transfer (ZTT)
University of Applied Sciences Worms

September 13, 2022

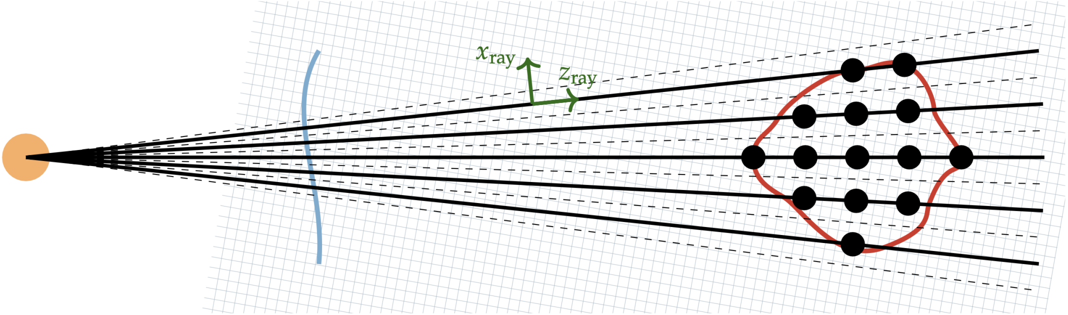
Particle Therapy

- Cancer is one of the leading causes of death
- Tumors can be treated with photons or ions (protons, carbon, ...)



[1]

Particle therapy can be done by passive scattering or **pencil beam scanning**



[2]

Range Verification

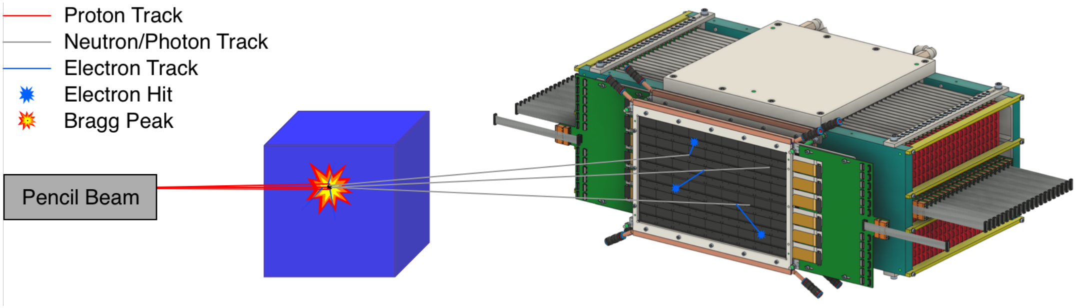
- Treatment planning provides expected locations for the Bragg peak of individual spots
- Many things can go wrong
  - Movement through breathing and other organ activity
  - Patient anatomy changes between imaging and treatment
  - Patient alignment on the treatment table

Range verification

- Goal: Predict Bragg peak location with $\leq 1\,\text{mm}$ error
- How do we know the Bragg peak is at the expected location?
  - → Positron emission tomography (PET), e.g. Parodi *et al.*, 2000 [3]
  - → Prompt gamma (PG) detection, e.g. Kurosawa *et al.*, 2012 [4]
  - → *Charged secondary particles?*

Range Verification

- Heavier ions (e.g. carbon) produce fast secondary ions
  - → Range verification with charged particles in carbon therapy: Gwosch *et al.*, 2013 [5]
- **Range verification with charged secondaries has not been done in proton therapy**
- Protons only produce neutral secondaries leaving the patient
- Neutral particles interact with matter in the detector → tertiary charged particles

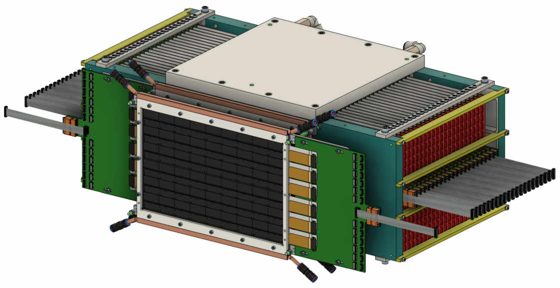


Digital Tracking Calorimeter

- Conventional CT is done with photons
  - Uncertainties when using an x-ray CT for particle treatment planning

  → Imaging with protons: proton CT (pCT)

- Bergen pCT collaboration is developing a digital tracking calorimeter (DTC) for pCT [6]
- 2 tracker layers
- 41 detector-absorber layers (calorimeter)
- Per layer: 108 ALPIDE [7] chips (monolithic active pixel sensor)



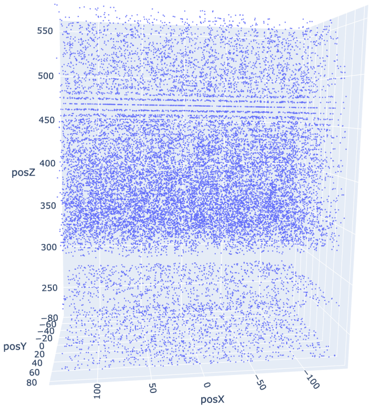
Research Questions

1. **Can the DTC be used for range verification during particle therapy?**
2. **How accurate is range verification with the DTC for carbon ions?**
3. **Is readout yield sufficient for proton range verification within 1 mm?**

Data Generation

- Simulate treatment with protons & carbon
- DTC is modeled in GATE Monte Carlo simulation
- Phantom: water cuboid, thickness: 160 – 200 mm
- $3.11 \cdot 10^7$ protons per simulation
- $3.11 \cdot 10^5$ carbon ions per simulation
- Beam energies are set to medically relevant values
  - Protons: 60.13 – 150.35 MeV in 3 mm range intervals (43 energies from matRad [8])
  - Carbon: 115.23 – 279.97 MeV/u in 2 mm range intervals (61 energies from matRad [8])

→ 213 proton samples, 305 carbon samples



Protons at 69.4 MeV, 160 mm water

Machine Learning Models

- 29 base features:
  - Water phantom thickness
  - Total number of active pixels
  - Total number of pixel clusters (hits)
  - Aggregate properties of cluster sizes
  - Different fits of aggregate properties over detector layer
- Features with ground truth range from matRad used with models:
  - Linear regression (OLS)
  - Automatic relevance determination (ARD)
  - Kernel regression
  - Gaussian process (GP)
  - Deep neural network (DNN)
- For Kernel regression, GP, and DNN, the feature set is reduced to different subsets

Results – Mean Absolute Error

	Linear	ARD	Kernel	GP	DNN
Protons	0.71 mm	0.76 mm	0.29 mm	**0.28 mm**	0.54 mm
Carbon	0.58 mm	0.61 mm	0.25 mm	**0.24 mm**	0.43 mm

- Carbon works better than protons despite 100 times fewer primaries
- GP performs best in both cases
- Sub-mm error even for protons

The MODE Perspective

- The detector has shown potential for range verification
- ... but it is optimized for pCT through Monte Carlo simulations
- Extremely low yield requires too many simulations to do the same for range verification

→ Differentiated MC simulation (GATE/Geant4)

- Then we can optimize some properties
  - Existence and thickness of converter materials
  - Replace empirical with analytical models to predict range
  - Improved uncertainty quantification

Conclusion & Outlook

The Bergen pCT collaboration's DTC is the first detector shown to be capable of in-situ range verification through charged particles in proton therapy

What's next?

- More realistic data (pediatric head simulation)
- Replace manual feature engineering with graph neural network of raw data
- As soon as differentiated physics simulation is available: detector design optimization

The Bergen pCT Collaboration and SIVERT Research Training Group

- University of Bergen, Norway
- Helse Bergen, Norway
- Western Norway University of Applied Science, Bergen, Norway
- Wigner Research Center for Physics, Budapest, Hungary
- DKFZ, Heidelberg, Germany
- Saint Petersburg State University, Saint Petersburg, Russia
- Utrecht University, Netherlands
- RPE LTU, Kharkiv, Ukraine
- Suranaree University of Technology, Nakhon Ratchasima, Thailand
- China Three Gorges University, Yichang, China
- University of Applied Sciences Worms, Germany
- University of Oslo, Norway
- Eötvös Loránd University, Budapest, Hungary
- Technical University TU Kaiserslautern, Germany

Contact: aschilling@hs-worms.de

References

[1] S. C. Kamran *et al.*, "Proton versus photon-based radiation therapy for prostate cancer: Emerging evidence and considerations in the era of value-based cancer care," *Prostate cancer and prostatic diseases*, vol. 22, no. 4, pp. 509–521, 2019.

[2] N. Wahl, "Analytical models for probabilistic inverse treatment planning in intensity-modulated proton therapy," Ph.D. dissertation, 2018.

[3] K. Parodi and W. Enghardt, "Potential application of pet in quality assurance of proton therapy," *Physics in Medicine & Biology*, vol. 45, no. 11, N151, 2000. DOI: 10.1088/0031-9155/45/11/403.

[4] S. Kurosawa *et al.*, "Prompt gamma detection for range verification in proton therapy," *Current applied physics*, vol. 12, no. 2, pp. 364–368, 2012. DOI: 10.1016/j.cap.2011.07.027.

[5] K. Gwosch *et al.*, "Non-invasive monitoring of therapeutic carbon ion beams in a homogeneous phantom by tracking of secondary ions," *Physics in Medicine & Biology*, vol. 58, no. 11, p. 3755, 2013. DOI: 10.1088/0031-9155/58/11/3755.

[6] J. Alme *et al.*, "A high-granularity digital tracking calorimeter optimized for proton CT," *Frontiers in Physics*, vol. 8, p. 460, 2020, ISSN: 2296-424X. DOI: 10.3389/fphy.2020.568243.

[7] M. Mager, "Alpide, the monolithic active pixel sensor for the alice its upgrade," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 824, pp. 434–438, 2016. DOI: 10.1016/j.nima.2015.09.057.

[8] H.-P. Wieser *et al.*, "Development of the open-source dose calculation and optimization toolkit matrad," *Medical Physics*, vol. 44, no. 6, pp. 2556–2568, 2017, ISSN: 2473-4209. DOI: 10.1002/mp.12251.

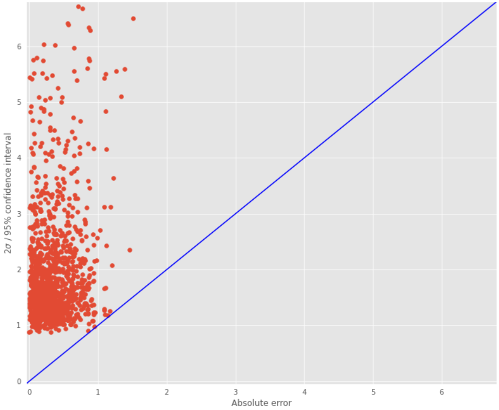
Features

29 base features:

- Water phantom thickness
- Total number of active pixels
- Total number of pixel clusters (hits)
- Number of clusters over threshold (5, 20 pixels)
- Mean and standard deviation of cluster sizes
- Linear and cubic fit for active pixels over layer
- Linear and cubic fit for hits over layer
- Linear and cubic fit for deposited energy over layer
- Exponential fit and its mean squared residuals for active pixels over layer

Gaussian Process

- Features: Phantom thickness, clusters, mean cluster size, linear fit for pixels over layer
- Kernel: const $*$ RBF $+$ const $*$ RBF
- MAE: 0.33



Deep Neural Network

- Features: Fits for clusters over layer and energy deposition over layer are removed
- Fully-connected network with 2 hidden layers (256 and 128 units, sigmoid, 5% dropout)
- MC dropout raises MAE to $> 1\,\text{mm}$