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Surrogate Model for Linear Accelerator: A fast Neural Network approximation of ThomX’s simulator

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GOAL

Design a new fast-executing, physics-aware surrogate model of ThomX, expected to:

1. Quickly estimate the behavior of the beam, depending on the setting;
2. Efficiently support the surrogate optimization
3. Accommodate the wide variability of settings and beams corresponding to the diversity observed on an in-commissioning machine

HOW TO MODELIZE

THOM’S LINAC

LINACNET

Modular Neural Network architecture base on physical description of the machine

The beam is handled with a PointNet¹-like architecture (particle-based representation)

HOW TO LEARN

• Each module $m_i$ predicts the distribution at the next diagnostic given:
  • $d_{i-1}$: previous distribution
  • $a_i$: value of the control setting
  • $\theta_i$: eight of the neural network
  • Modules can be combined to represents a sub-part of the machine:
  
  $f_i(d_i, a_i; \theta_i) = m_i\left(\left(\left(\cdots\left(\left(d_i, a_i, \theta_i; \theta_1\right)\right)\cdots\right)\right)\right)$

• The final loss is the weighted combination of these predictions:

  $L_{\alpha \delta \theta}(d, a; \theta) = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{i, j} \|f_i(d, a; \theta) - d_j\|_2$

WEIGHTING STRATEGY ($\alpha_{i, j}$)

• Equal weights : Each combination of the modules is deemed equally important
• End-to-End : Only the $\alpha_{0, j}$ are considered
• Independent : Each module $m_i$ is learnt independently
• MGDA (Multiple Gradient Descent Analysis) : Dynamic weighting of the module that moderates conflicting loss between modules

RESULTS

Simulation Prediction Simulation Prediction Simulation Prediction

The simulated point cloud is the result of the simulation up to the end of the Linac of a misaligned machine with suboptimal control parameters. The resulting beam is a bi-modal, truncated beam in the transverse phase space.

The surrogate model successfully recovers the properties of the beam. The projections of the predicted beam (red histogram) match those of the simulated beam (green histogram)

LinacNet accurately reproduces the beam distribution at the end of the Linac, despite very deteriorated conditions

PERSPECTIVES

• SURROGATE OPTIMIZATION: Validate the performance of the surrogate model with the optimization task
• MODULARITY: An evolution of the machine only need an evolution of the corresponding modules
• REALITY GAP: The large sampling domain is well-suited to handle the gap between simulation and real-world machines

REFERENCES