

Charged Particle Track Finding with MCTS

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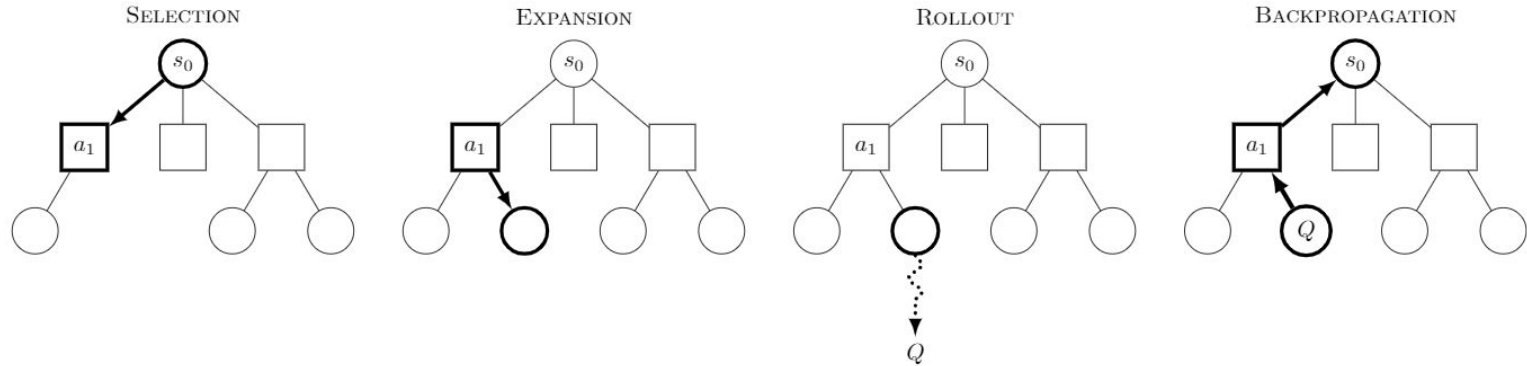


Motivation

- Original goal of the project was to investigate track reconstruction algorithms that integrate machine learning and Kalman filtering.
 - Kalman filtering for domain knowledge.
 - Machine learning for improved GPU architecture.
- Something similar in structure to the Combinatorial Kalman Filter (CKF) but with strong machine learning heuristics.

Monte Carlo Tree Search (MCTS)

Algorithm that uses random playouts for optimal action selection. Edges of a tree are iteratively updated with these playouts to bring out “promising” actions.



Structural Advantages of MCTS for tracking

- Kalman filtering can be easily integrated into prior probability calculations.
 - Provides additional information like momentum which can be fed into the Policy network.
- MCTS aggressively prunes the search space, which could improve scalability of algorithm.
- MCTS iteratively reduces uncertainty, so it can be adapted to different requirements depending on the stage of reconstruction.

Neural Networks

Policy network

- Takes in a pair of hits on adjacent layers and returns how likely they are to be part of the same track.

Evaluation network

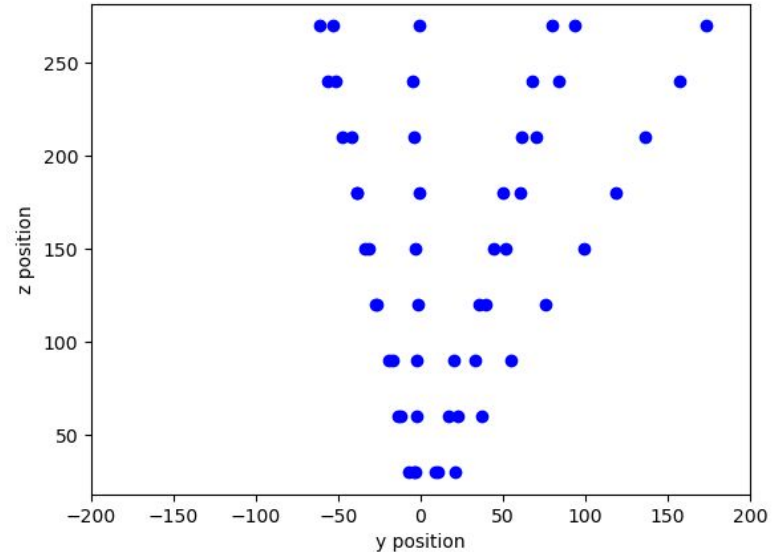
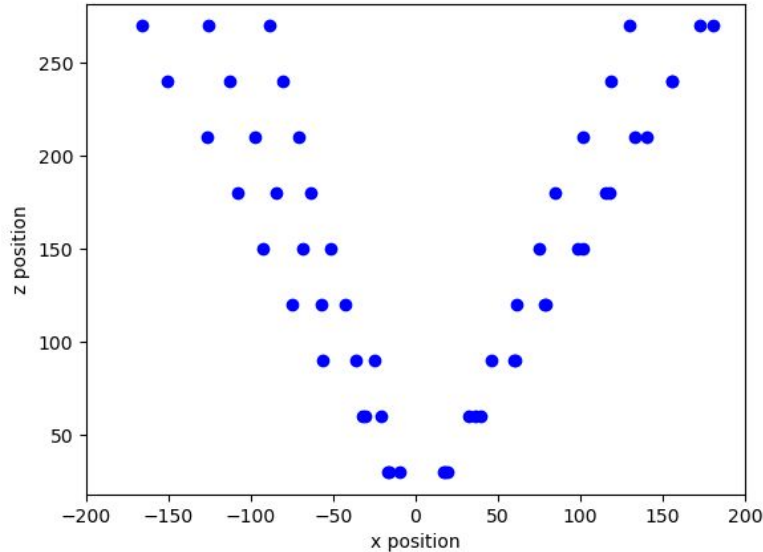
- Takes in a list of hits in sequence and returns how likely it is to be a valid track.

Algorithm Description

For each iteration:

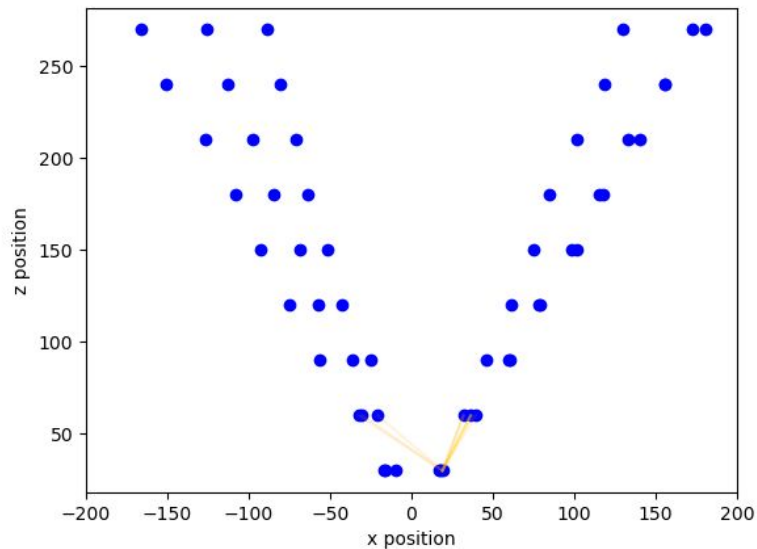
1. Traverse the tree to find an unexplored “promising” hit.
 - a. Traversal is done with prior probabilities, previous playouts, and possibly Kalman filtering
2. Expand the hit to new options, imbuing each with a prior probability from the policy network.
3. Execute a Monte Carlo playout with the policy network from that hit constructing a track candidate.
4. Evaluate the candidate with the evaluation network and update all visited edges.

Example (9 layer telescope detector, 8 muon event)

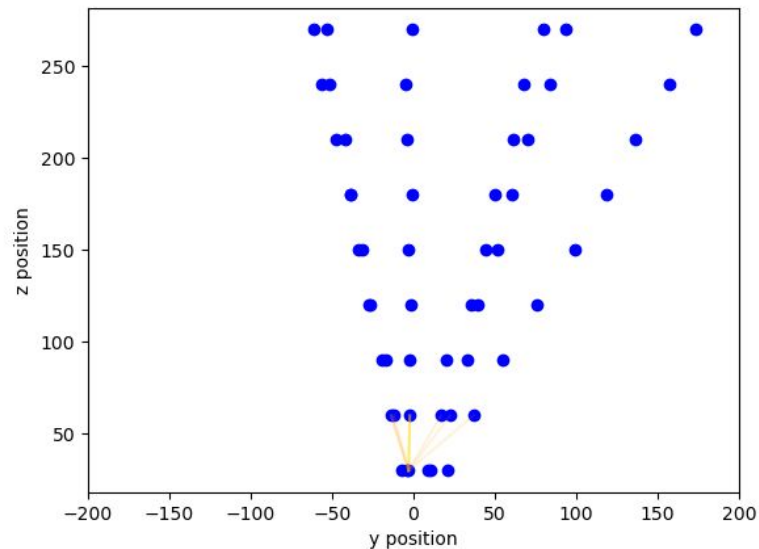


Iteration 1

Iteration 1

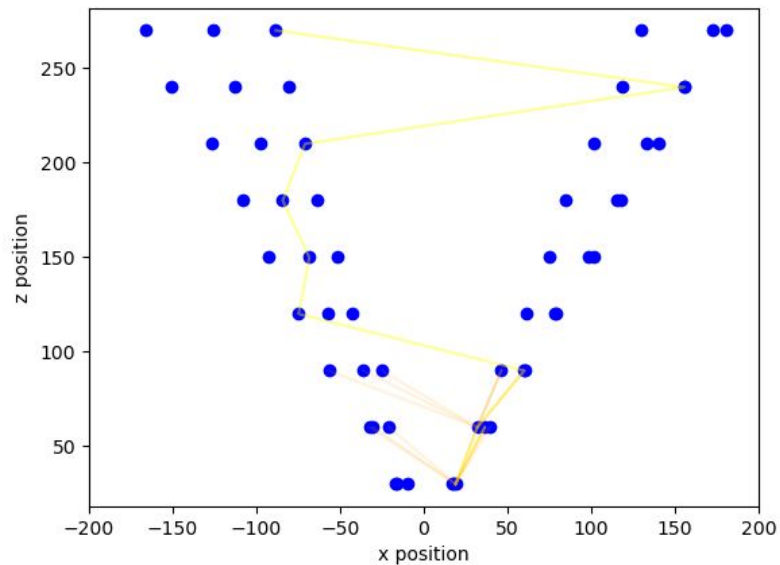


Iteration 1

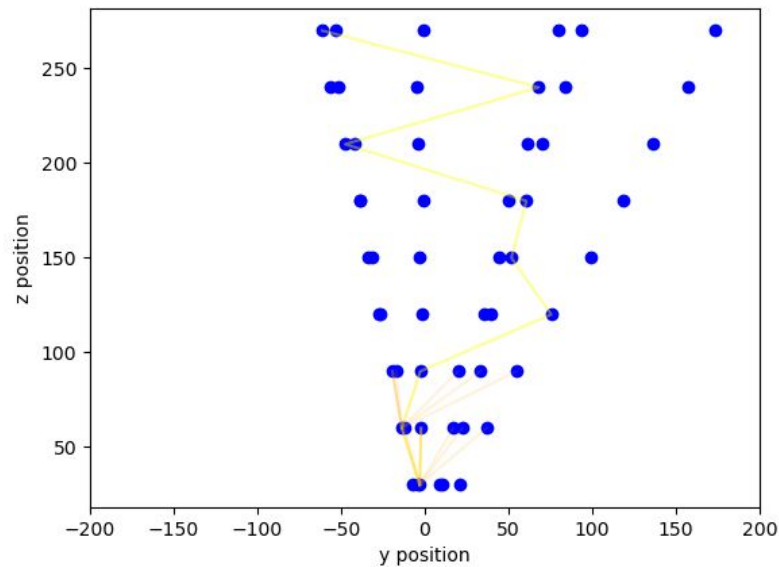


Iteration 2

Iteration 2

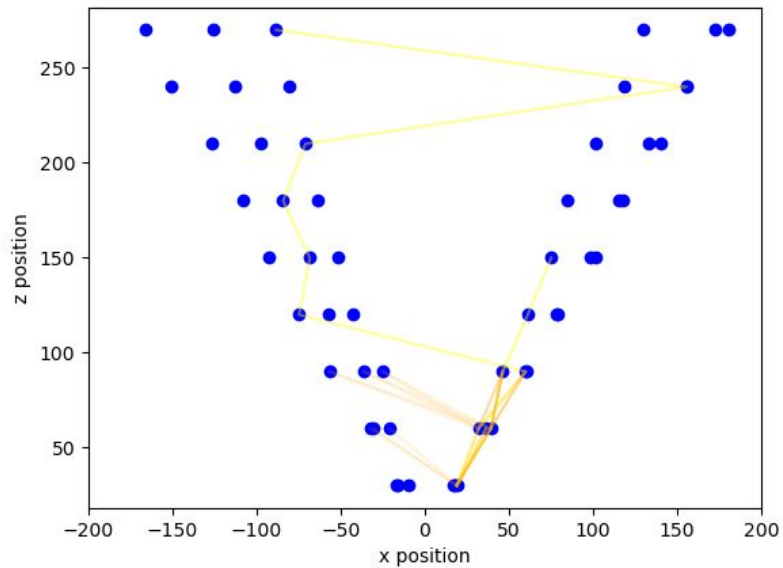


Iteration 2

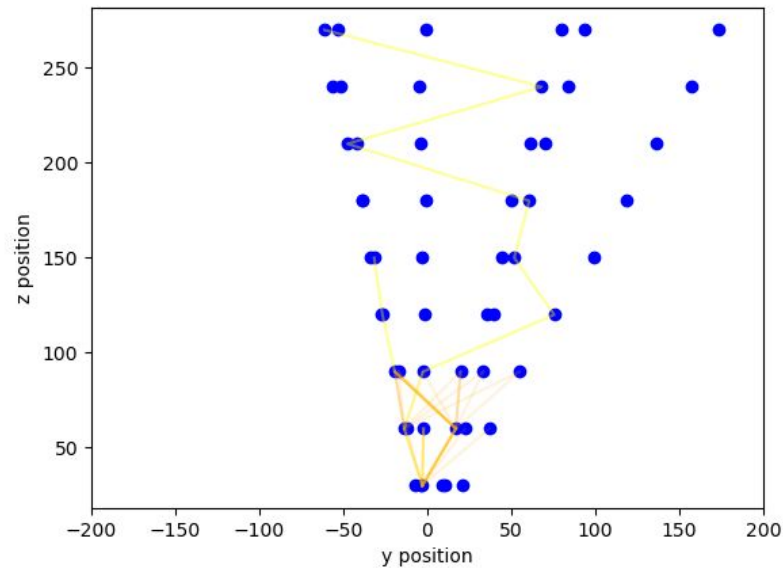


Iteration 3

Iteration 3

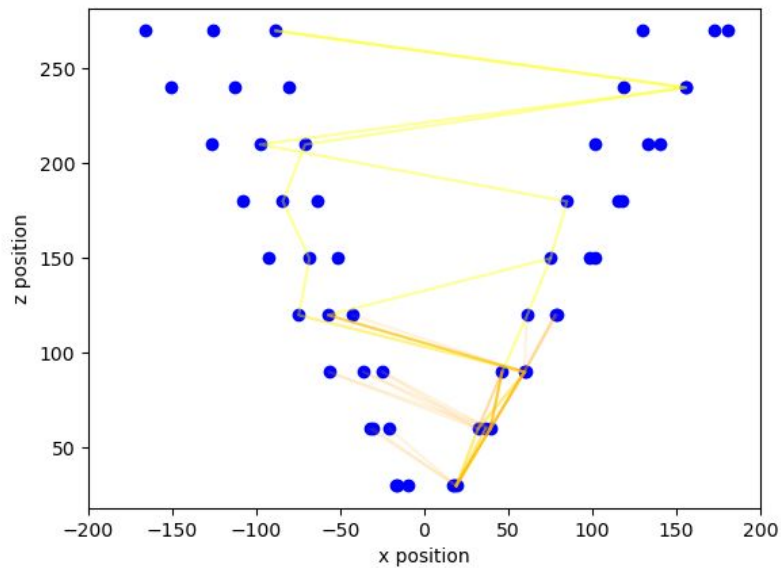


Iteration 3

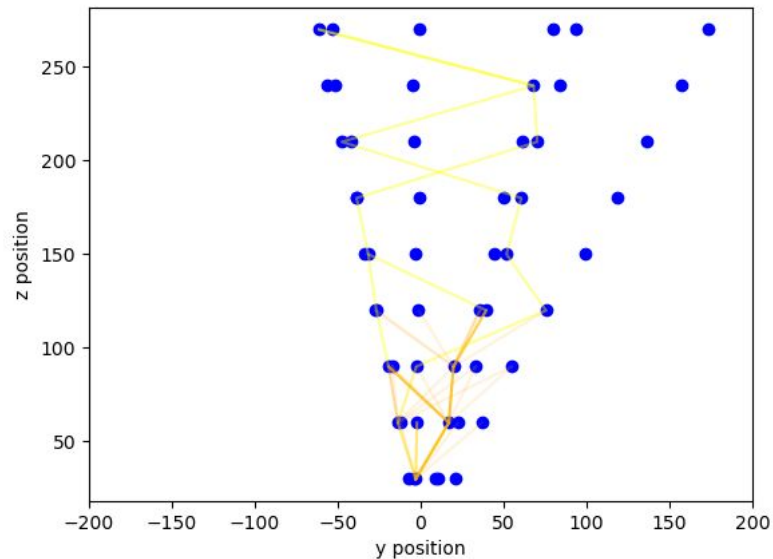


Iteration 4

Iteration 4

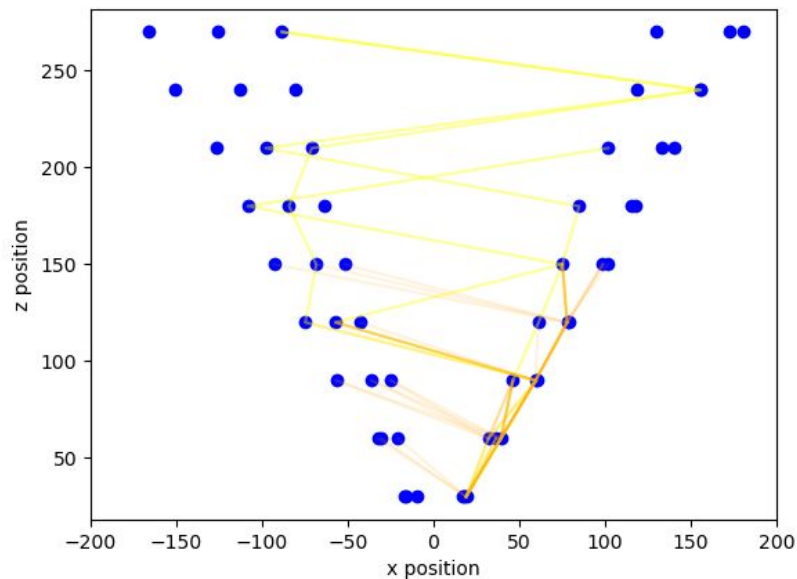


Iteration 4

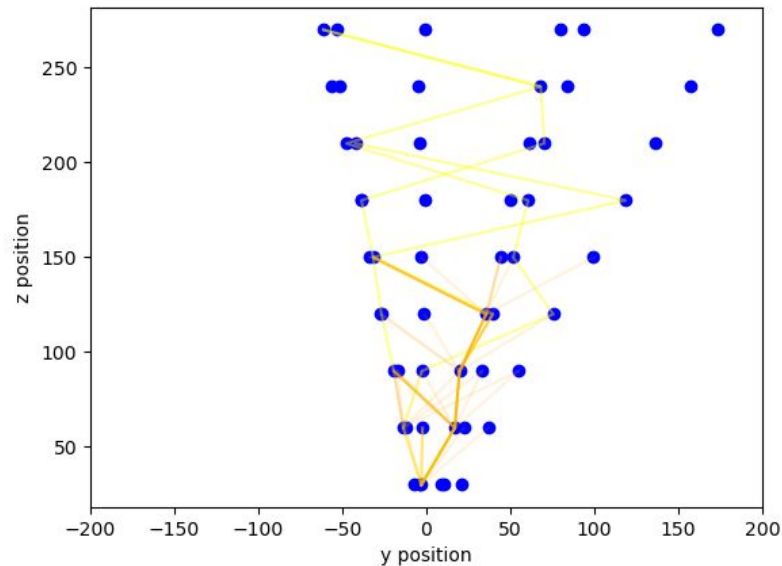


Iteration 5

Iteration 5

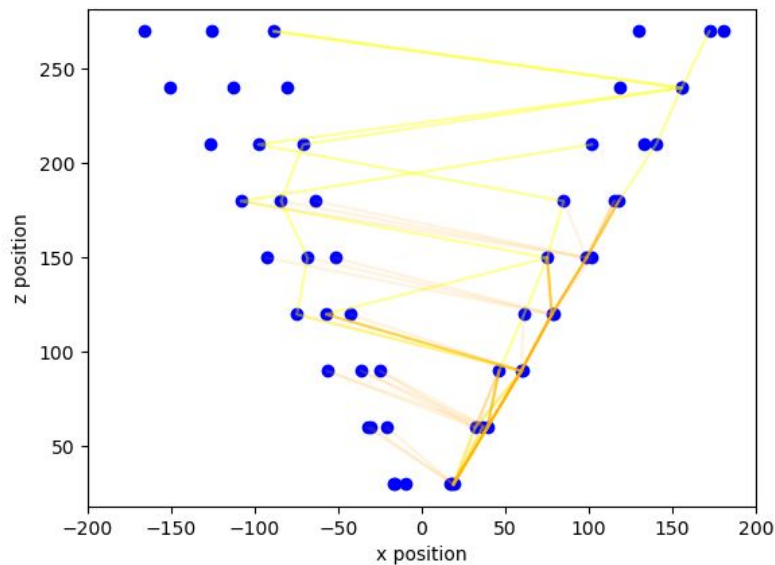


Iteration 5

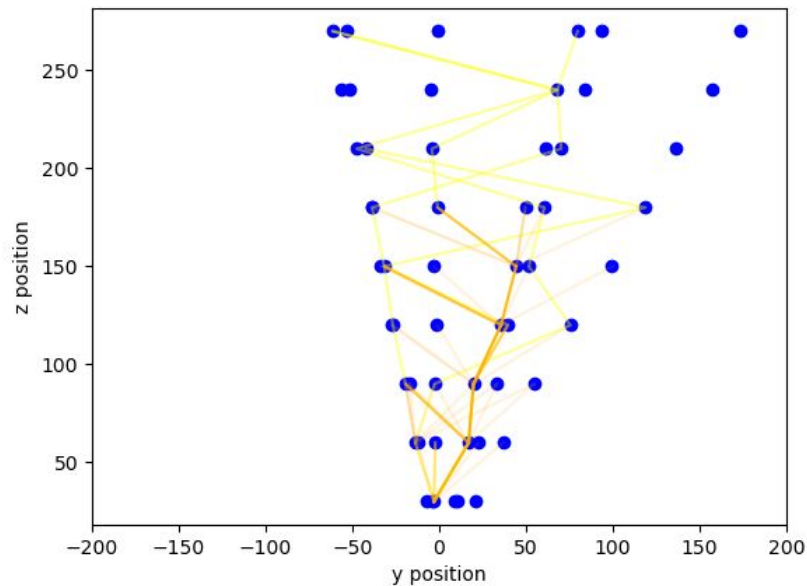


Iteration 6

Iteration 6

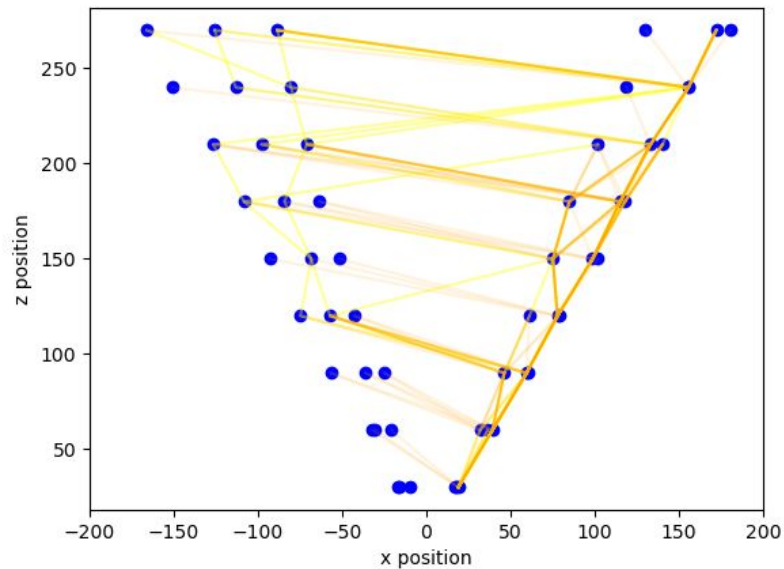


Iteration 6

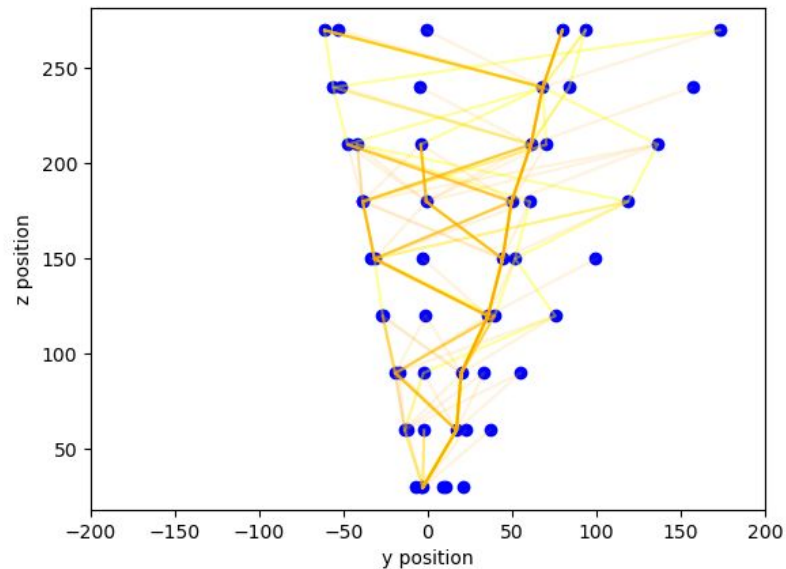


Iteration 16

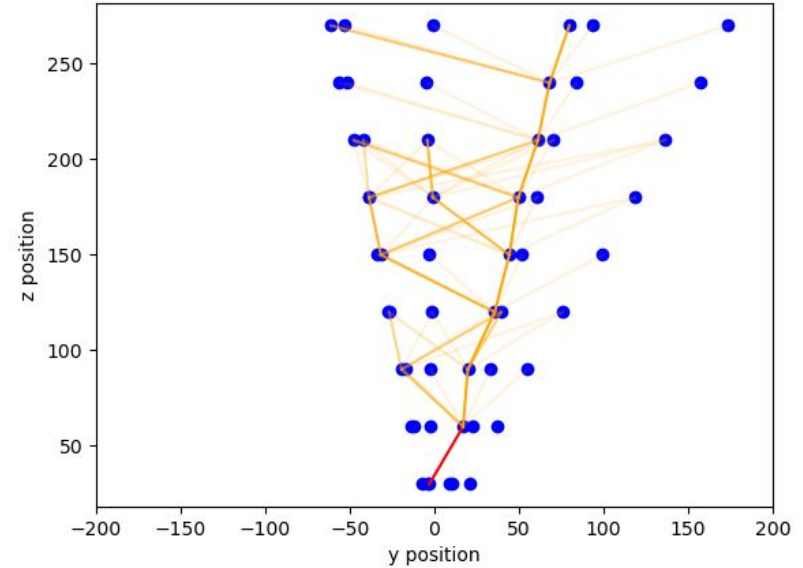
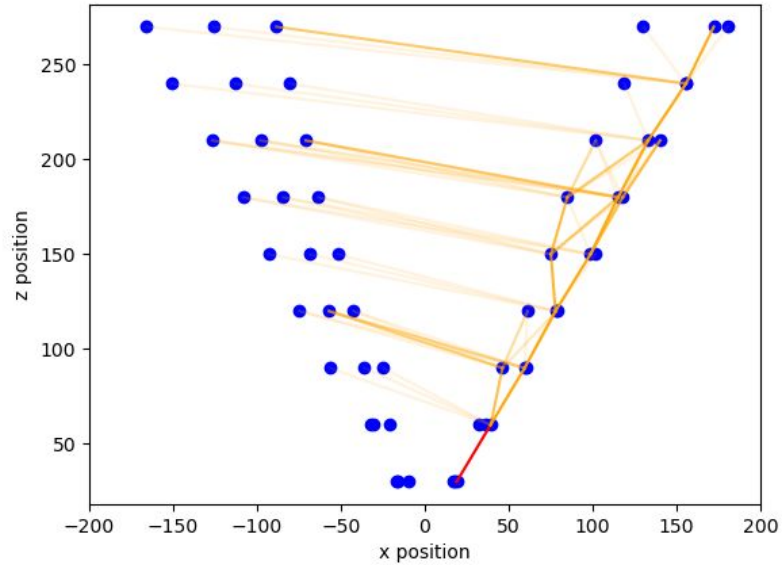
Iteration 16



Iteration 16



Locking in an edge



Preliminary Testing

- MCTS is seen to augment performance when policy is weak.
- No effect or even degradation when policy is strong.

	Random policy	Trained policy
Policy only efficiency	42.0%	99.6%
Policy only purity	69.3%	99.6%
MCTS efficiency	66.8%	98.9%
MCTS purity	77.6%	99.2%

Improvements and Future directions

- Algorithm currently does not consider tracks skipping layers. This will need to be added as another possible action.
- Policy network can be split into two networks, one fast for MC playout and one slow for assigning prior probabilities.
- Kalman filtering should be integrated into tree traversal.
- Goal is to apply algorithm to more sophisticated detector geometry and higher density events.
- Develop more precise benchmarks for comparison with other algorithms.

Questions