

ML Based Tracking Reconstruction

Andrea De Vita, Dolores Garcia, Brieuc Francois, Michele Selvaggi

Table Of Contents

1. **Geometric Graph Neural Network Based Track Finder**

- From Current Challenges to a Novel Approach
- Insights into the Neural Network Design
- Performance Analysis on CLD
- Comparison between CLD and IDEA
- Background Studies on CLD
- Background Studies on IDEA

2. **Track Fitting Using Genfit2**

- Introduction to Genfit2
- Performance on Pixel + Drift Chamber

3. **Summary and Next Steps**



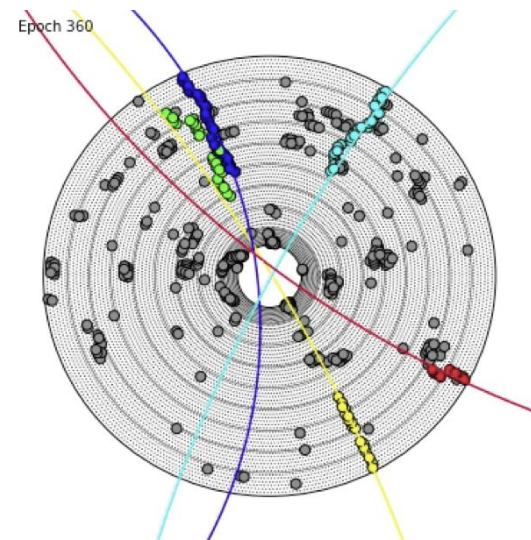
Geometric Graph Neural Network Based Track Finder

From Current Challenges to a Novel Approach

Traditional track finding methods are often complex and detector-specific, limiting their adaptability. To address this, we propose the **Geometric Graph Track Finding (GGTF)** method, an end-to-end detector-agnostic approach.

Key features include:

- **Compatibility** with multiple sub-detectors and tracking technologies.
- **Independence from detector geometry** and material specifications.
- **No reliance on analytical trajectory parameterization.**

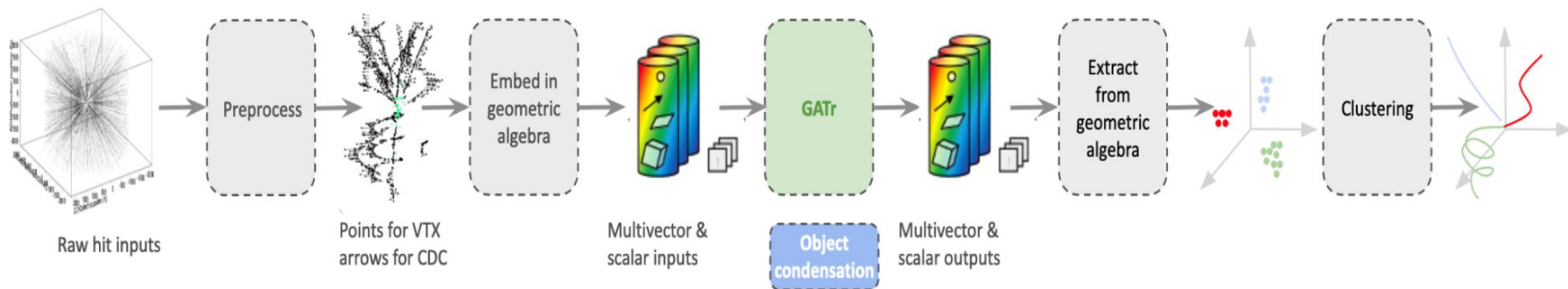


Insights into the Neural Network Design 1/2

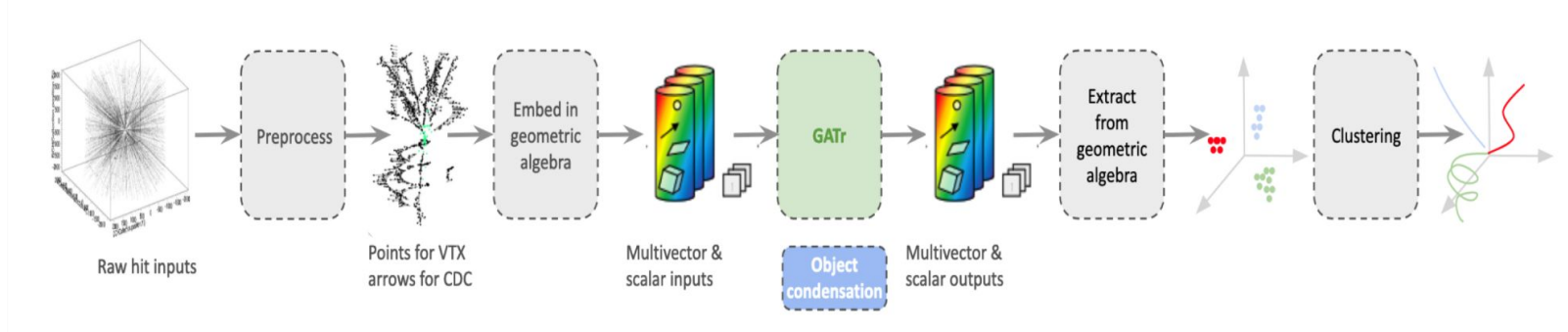
Inputs : Collection of raw hits created by aggregating hits from each subdetector $X=\{X_v, X_i, X_o, \dots\}$

Outputs : Set of track, where each track is a collection of hits from different tracking components.

Note: The model can be applied to any geometry and material configuration, at the cost of retraining it for the specific detector of interest (e.g. IDEA, CLD...).



Insights into the Neural Network Design 2/2



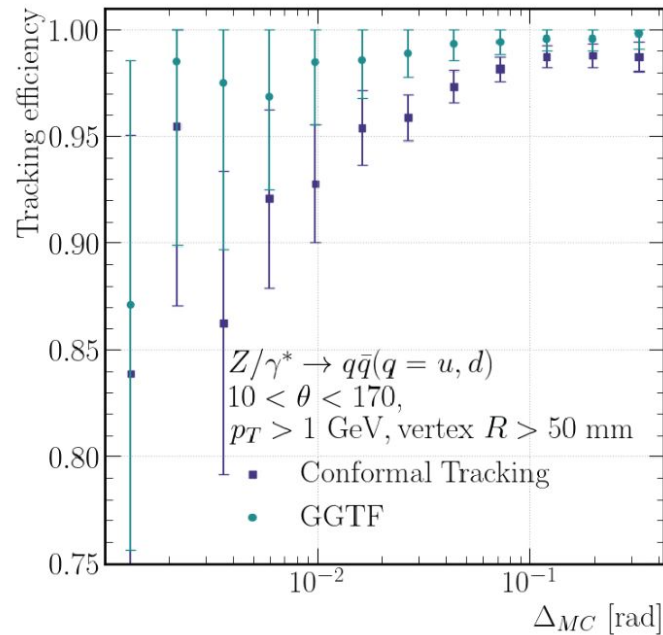
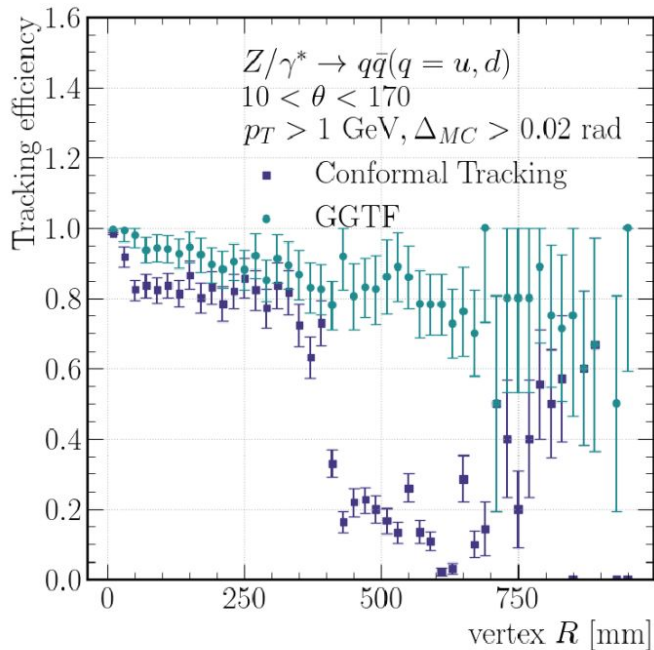
ML step: The Track-finding approach is based on a graph structure of the inputs, where geometric algebra transformations are applied. The result is a set of pairs (β , coordinates) in the embedding space.

Clustering step: Tracks can be identified in the embedding space by applying a clustering algorithm, establishing a one-to-one correspondence between clusters and tracks.

Performance Analysis on CLD

Conformal tracking assumes all tracks originate from a single common point: **GGTF is better than the baseline in reconstructing displaced tracks.**

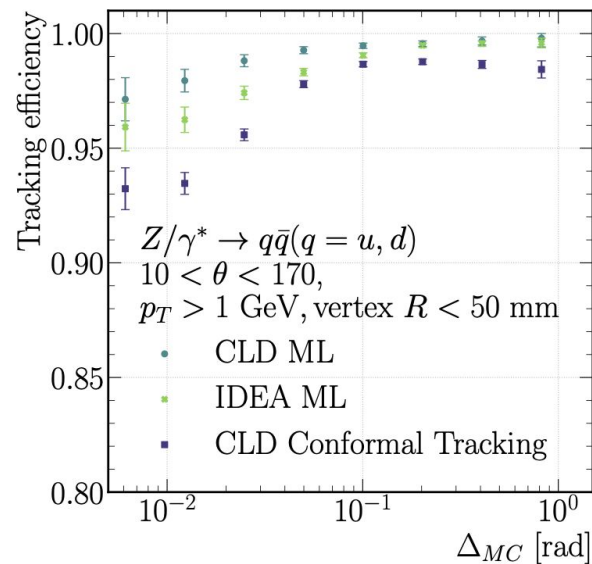
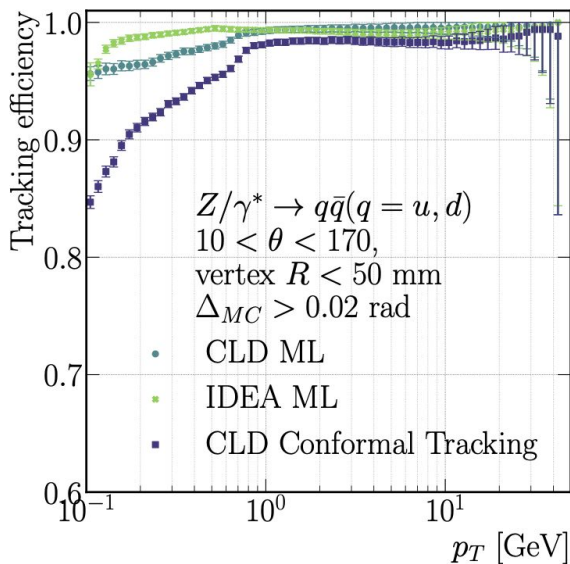
GGTF has good performance in detecting closely spaced tracks, outperforming the baseline in these cases.



Comparison between CLD and IDEAv2

Without background, a comparison of CLD and IDEA shows that IDEA achieves better tracking efficiency at low p_T . This is due to the drift chamber design, which allows particles to **traverse a larger portion of the tracker**.

CLD, on the other hand, ensures better identification in the case of **closely spaced tracks**.



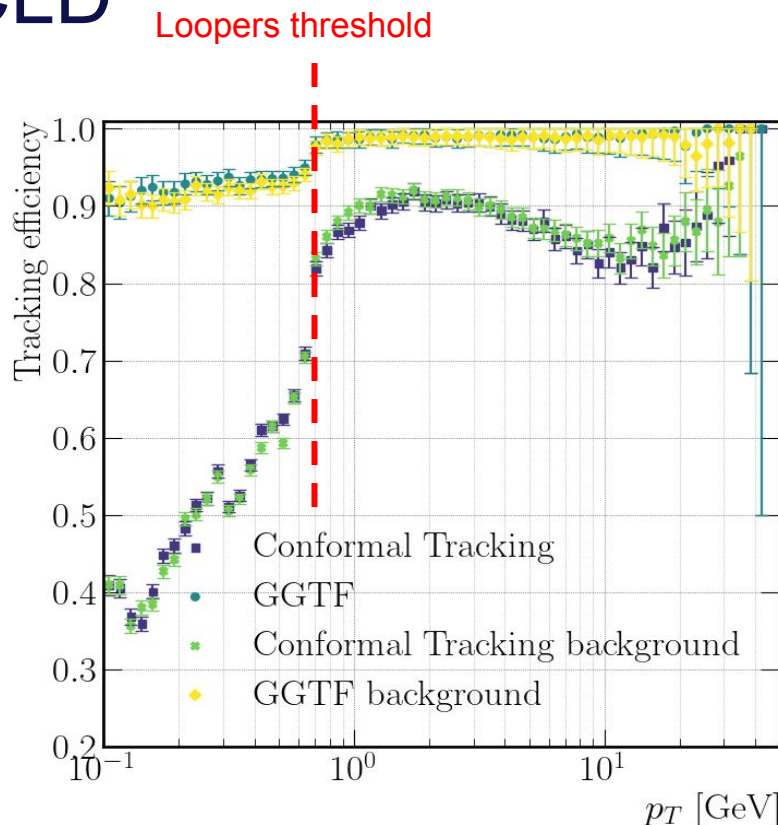
Background Studies on CLD

The results comparing the CLD with and without background show that the **same tracking performance** can be achieved.

This result is valid for both conformal tracking and GGTF and it confirms that tracking efficiency is higher with GGTF over the entire p_T range.

Tracking Efficiency : the percentage of reconstructable charged particles with both ratios, the track hit purity and the track hit efficiency, above 50%.

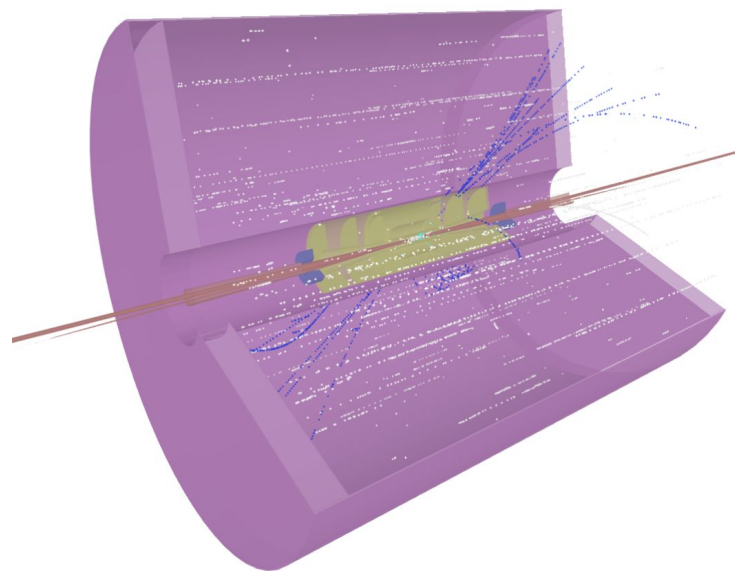
Number of fake tracks : 5.37% (ML) and 5.47% (CT)



Background Studies on IDEA

Future studies will evaluate tracking performance with background on IDEA, focusing on challenges posed by **low-energy noise particles** in the drift chamber.

These particles create horizontal lines of **loopers** with a very small radius. To prevent the identification of false tracks, they must be detected and removed before pattern recognition.

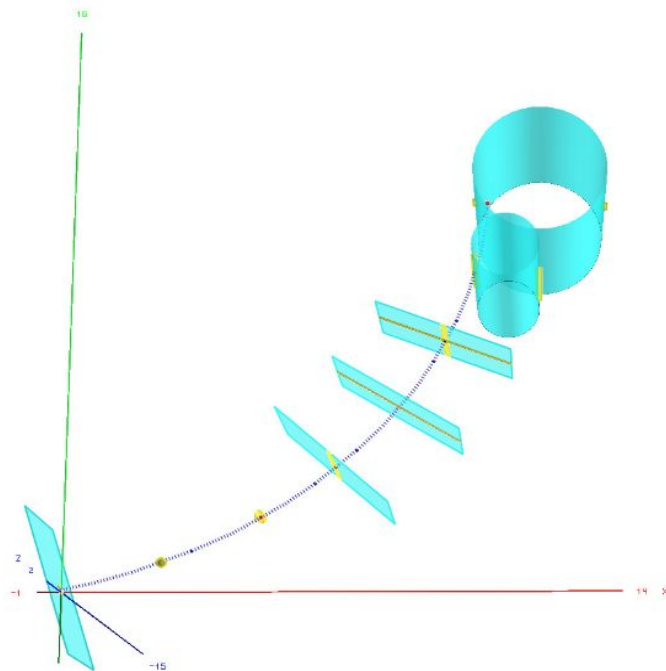




Track fitting using Genfit2

Introduction to Genfit2

The Genfit2 toolkit provides track representation, **track-fitting algorithms** and graphic visualization of tracks and detectors, and it can be used for any experiment that determines parameters of charged particle trajectories from **spatial coordinate measurements**.

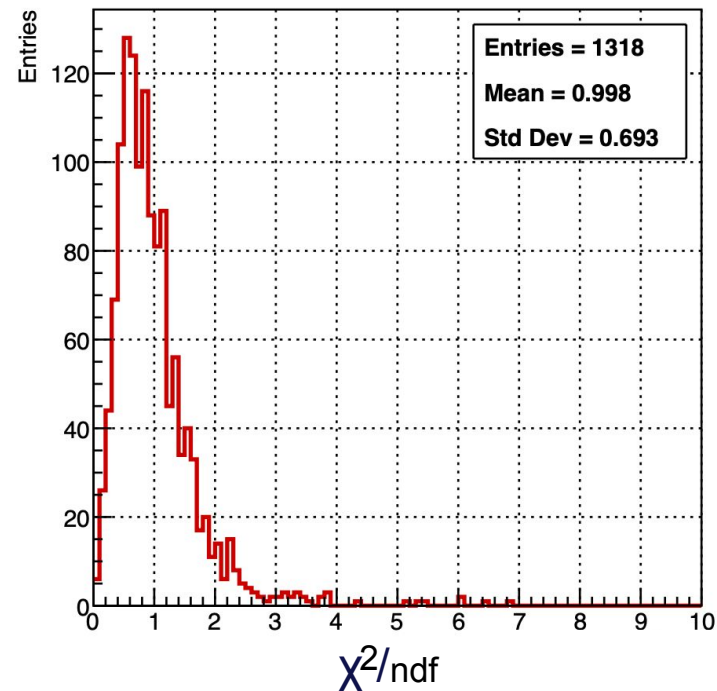
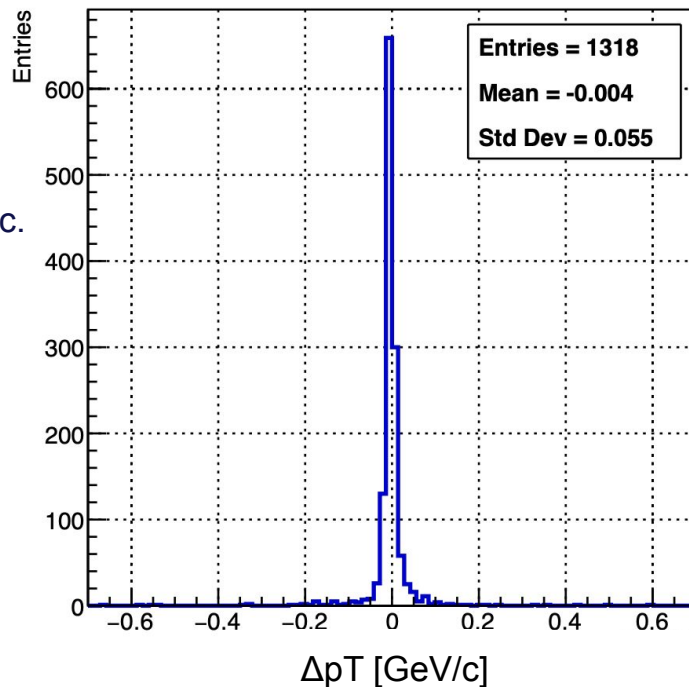


Performance on Pixel + Drift Chamber

pT and χ^2/ndf analysis on MC tracks

Results with fixed theta (60°) and momentum in the range between 0.5 GeV/c and 10 GeV/c.

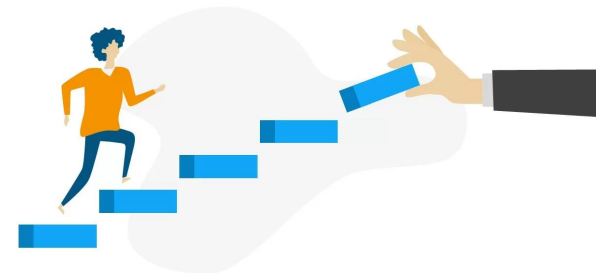
The simulation involved only pi+ generated at the IP.





Summary

Summary and Next Steps



Geometric Graph Neural Network Based Track Finder:

- **GGTF Method:** An end-to-end, detector-agnostic approach that shows encouraging results for both CLD and IDEA detector concepts.
- **Next Steps:** Background studies on IDEA to evaluate the effect of drift chamber noise on GGTF performance. Moreover Performance Studies will involve IDEAv3 with also the Silicon Wrapper.

Track Fitting using Genfit2:

- **Genfit2 framework:** The Genfit2 toolkit provides track representation, track-fitting algorithms and graphic visualization of tracks and detectors.
- **Next Steps:** Include pattern recognition in the reconstruction pipeline in order to avoid relying on ground truth.



Thank you
for your attention!

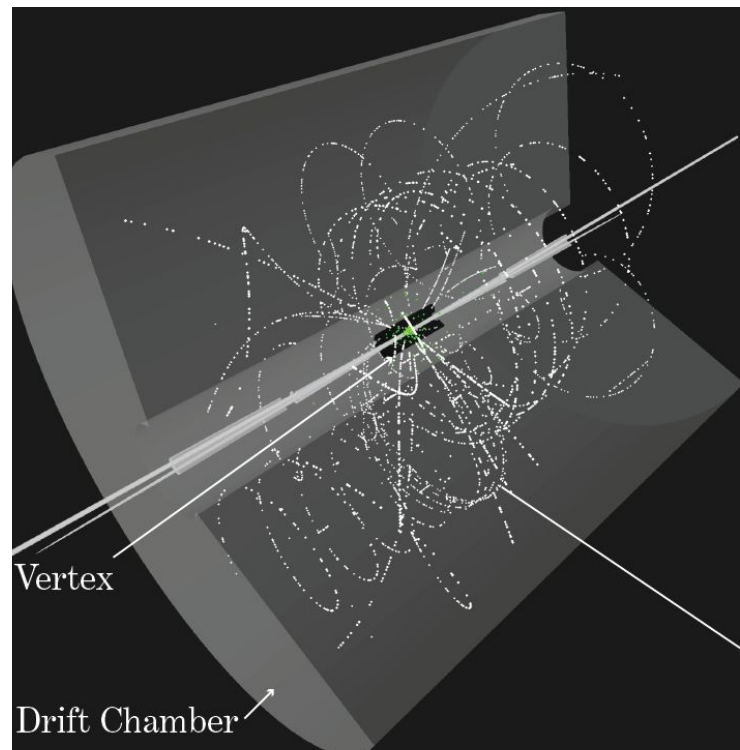


Backup

Tracking Efficiency

Each reconstructed track is matched to a ground truth particle to which it shares the largest number of hits.

Tracking Efficiency is the probability to reconstruct a track and it can be defined as the percentage of reconstructable charged particles matched to a reconstructed track with at least 4 hits.



Measurements within the Genfit2 framework

In Genfit2, a track is a collection of hits, where each hit is represented as a measurement. The abstract base class `genfit::AbsMeasurement` defines the interface for all measurement types.

- **Key4hep Hit Types in IDEA:**
 - `extension::SenseWireHit` (Drift Chamber Hits): It represents a circle around the sense wire.
 - `edm4hep::TrackerHitPlane` (Vertex Pixel Hits): A planar measurement on a silicon pixel.
- **Genfit2 Measurement Classes:**
 - Drift Chamber Hits: `genfit::WirePointMeasurement`
 - Vertex Pixel Hits: `genfit::PlanarMeasurement`

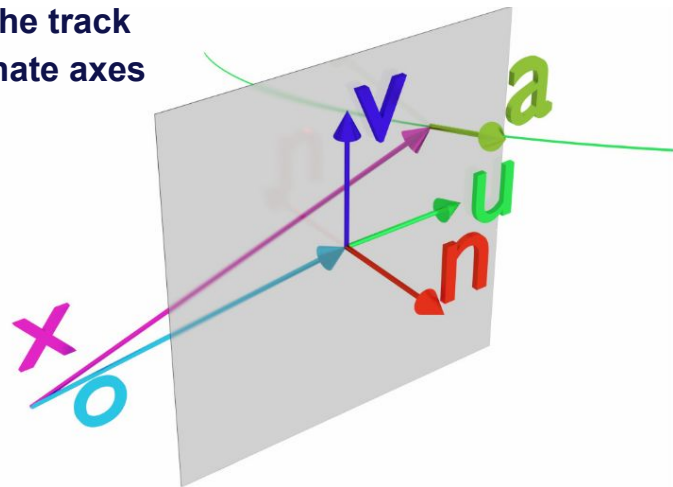
These measurement types allow for proper hit encoding within the Genfit2 tracking framework.

Tracks within the Genfit2 framework

The object processed by the fitter is a `genfit::Track`. Tracks are parameterized by 5 parameters:

- q/p : **Charge over momentum**
- u, v : **Rectangular coordinates of the plane intersecting the track**
- u', v' : **Projections of momentum direction on the coordinate axes**

All per-track data is stored within the `Track` object. It contains a set of `TrackPoint` objects, which may include `Measurements` and `FitterInfo` objects. Each `TrackPoint` holds the track status at the volume where the hit was registered. This status corresponds to the parametrized track parameters after the fit.

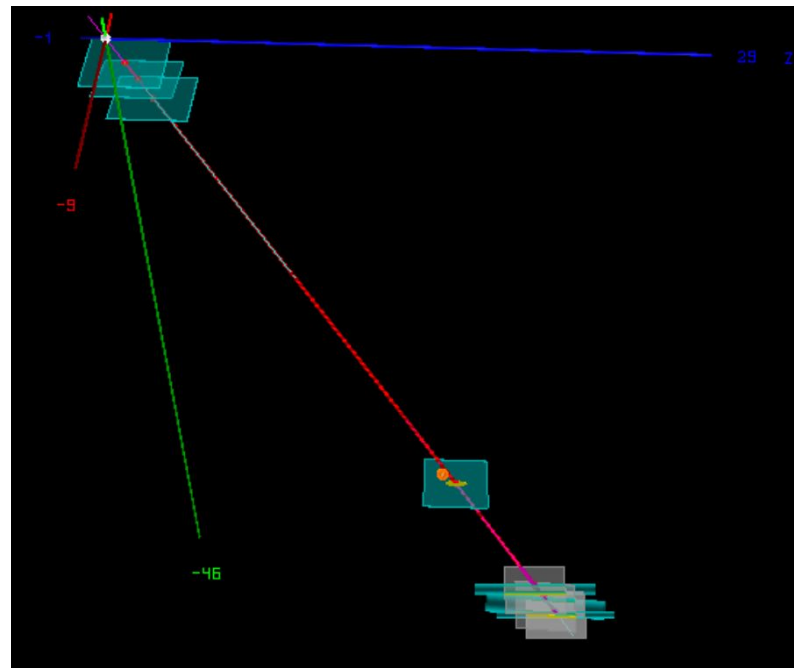


Deterministic Annealing Filter

DAF (Deterministic Annealing Filter): **Iterative Kalman Filter with reweighted observations**

Designed for track fitting in presence of outlier and background hits

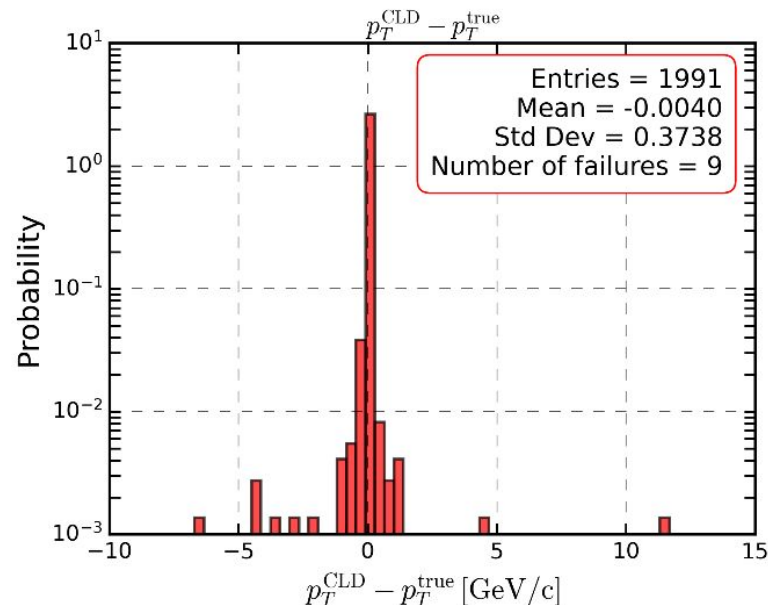
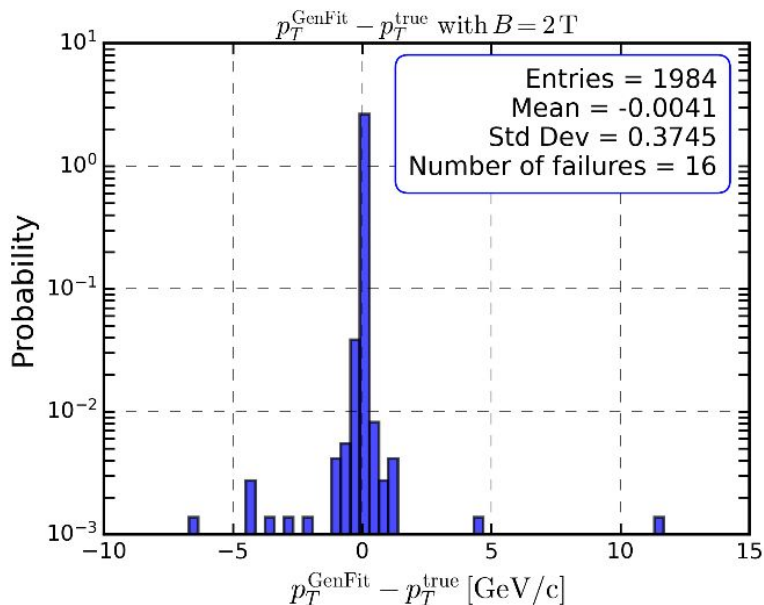
- Capable of outlier rejection, **L/R ambiguity resolution**
- Outliers: wrongly assigned hits (background hit found during track finding step)
- Hits are weighted according to their residual to the smoothed track



Performance on Silicon Hits

Validation with CLD

Both ILC-inspired results (using [MarlinWrappers](#)) and Genfit2 results were obtained from the same reconstructed tracks (from Conformal Tracking).

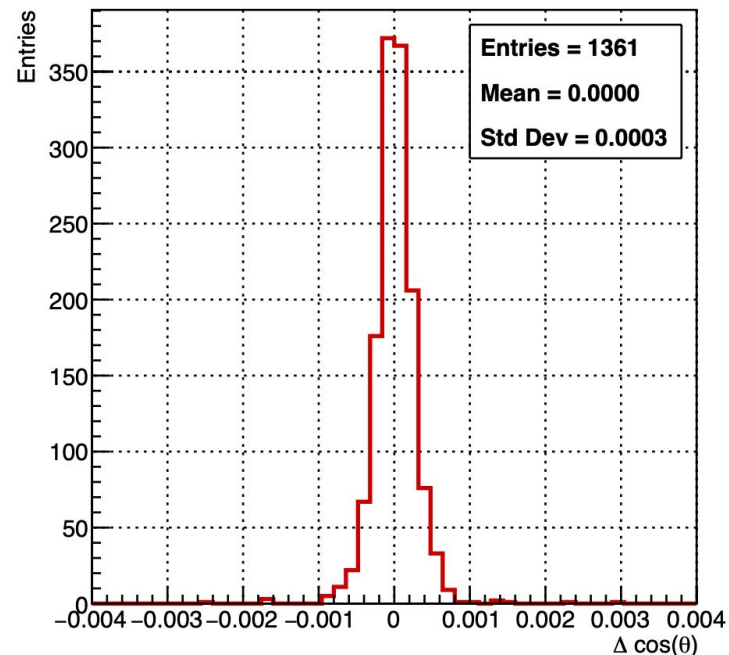
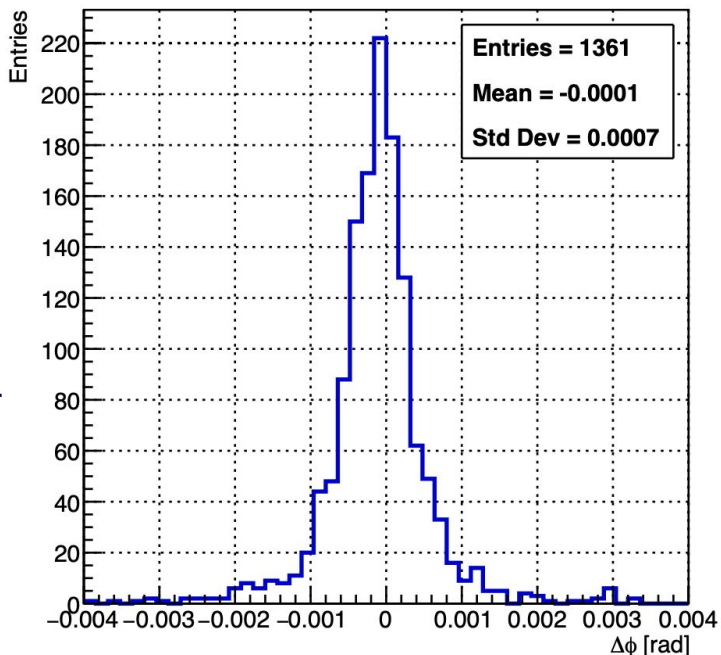


Performance on Pixel + Drift Chamber

$\cos(\theta)$ and ϕ analysis with fixed energy (5 GeV) on MC tracks

Results with $E = 5$ GeV and θ in the range between 15° and 80° .

The simulation involved only π^+ generated in the IP.



Performance on Pixel + Drift Chamber

$\cos(\theta)$ and ϕ analysis with fixed θ (60°) on MC tracks

Results with fixed θ (60°) and momentum in the range between 0.5 GeV/c and 10 GeV/c.

The simulation involved only π^+ generated in the IP.

