

Reconstrução de trajetórias em 4 dimensões para o HL-LHC

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Orientadores:

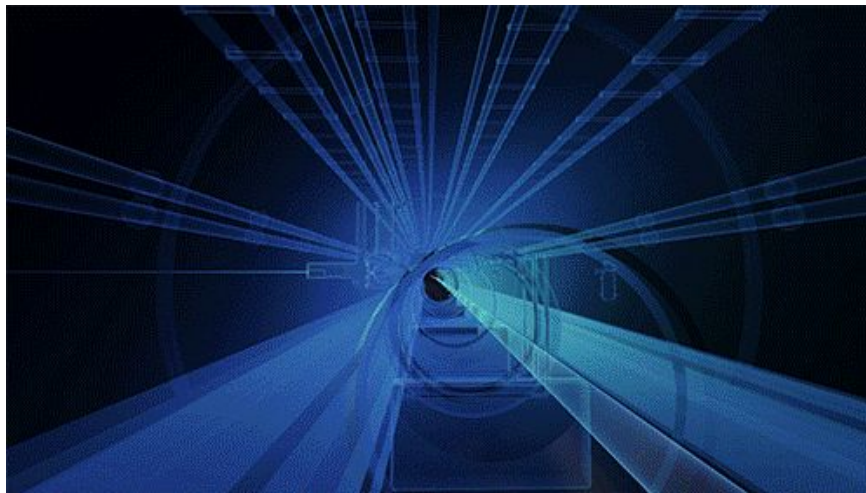
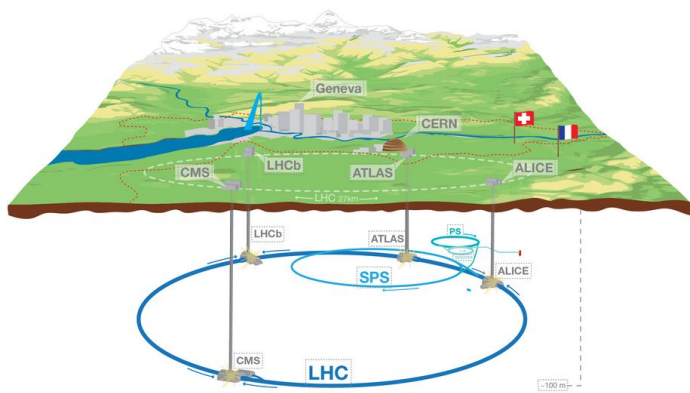
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CNPq/MCTI INCT CERN/Brazil e FAPESP (2020/04867-2)

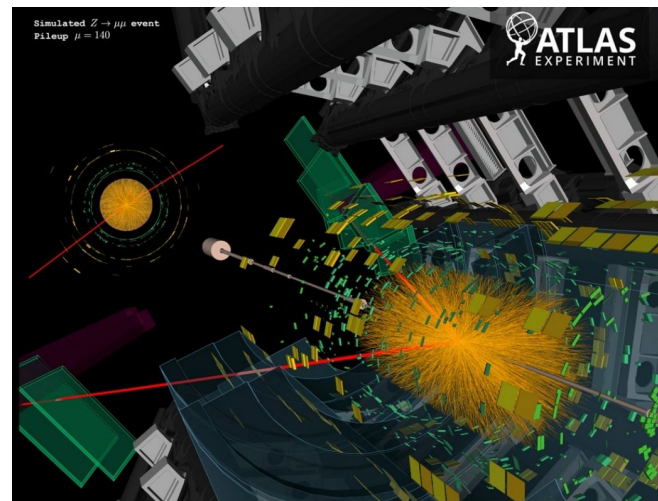
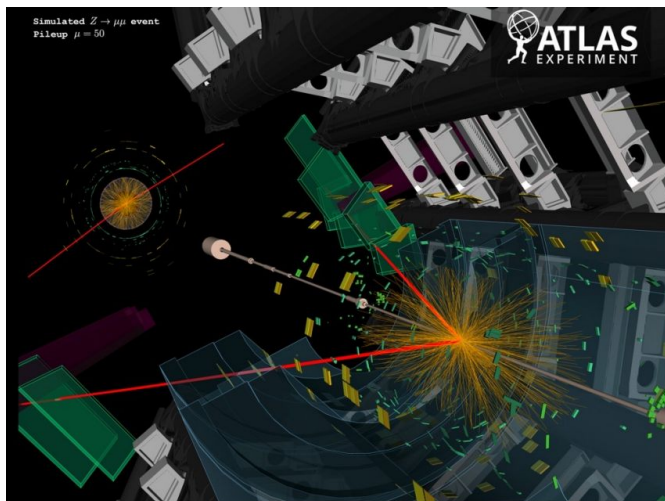
A estrutura da matéria e o LHC

- O **Large Hadron Collider (LHC)** é um acelerador e colisor de partículas construído para estudar os constituintes da matéria
 - Descoberta do Bóson de Higgs (2012) [1]
 - Atualmente estuda supersimetria, matéria escura, entre outros tópicos



Desafios na reconstrução de trajetórias no HL-LHC

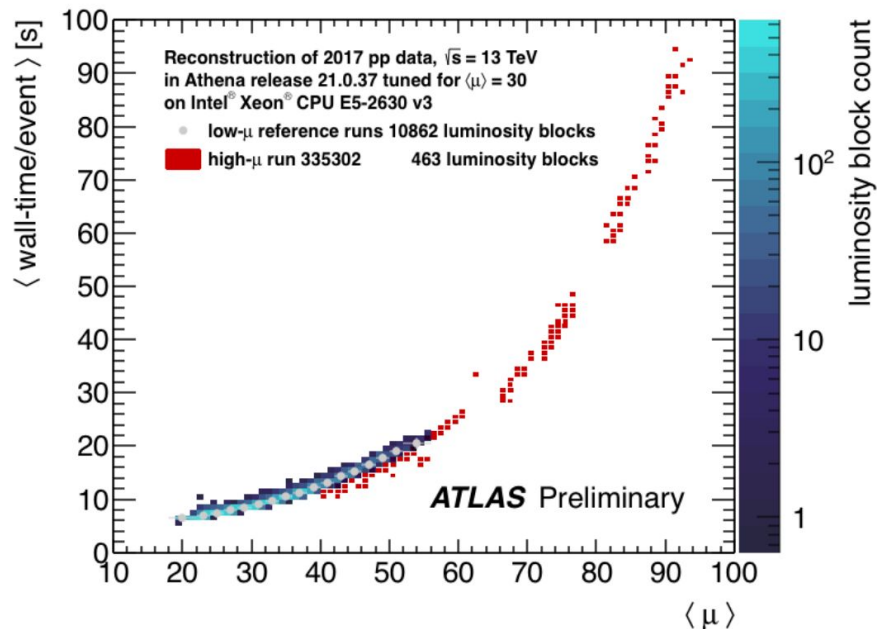
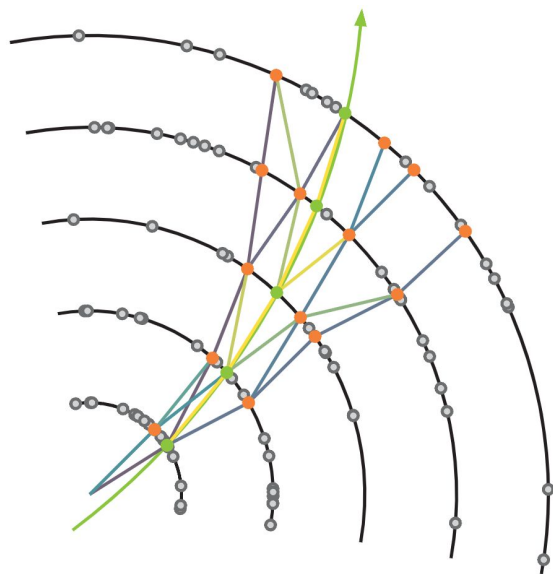
- Na HL-LHC (2029-2040) o número de colisões simultâneas ($\langle \mu \rangle$) aumentará de 65 para 200
- O processo de reconstrução de trajetórias (*tracking*) atual não terá resolução e velocidade de processamento o suficiente para esse novo cenário



Simulação de evento $Z \rightarrow \mu\mu$ no experimento ATLAS com $\langle \mu \rangle = 50$ (esquerda) e $\langle \mu \rangle = 140$ (direita)

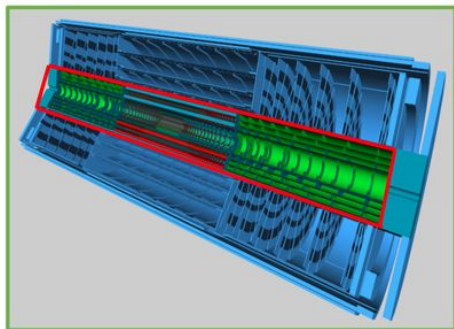
Desafios na reconstrução de trajetórias no HL-LHC

O processo de reconstrução de trajetórias (*tracking*) atual não terá resolução e velocidade de processamento o suficiente para esse novo cenário

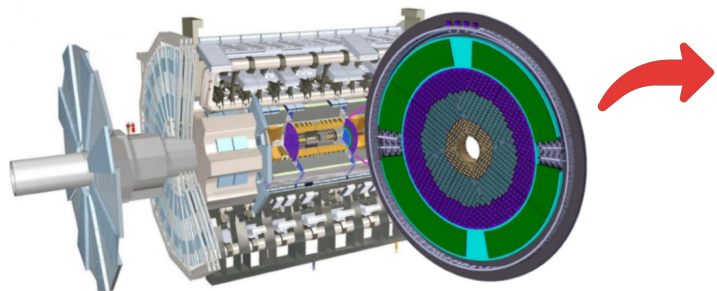


Preparação do ATLAS para o HL-LHC

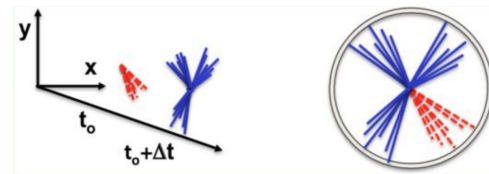
- Será instalado um novo detector de *tracking* com maior segmentação, o *Inner Tracker (ITk)*
- Um detector adicional chamado **HGTD** será instalado nas partes frontais do experimento e **proverá informação de tempo que auxiliará a reconstrução**



ITk



Posicionamento do HGTD no experimento ATLAS



Novos métodos adaptados a esses novos detectores que atendam a demanda de desempenho no HL-LHC são necessários!

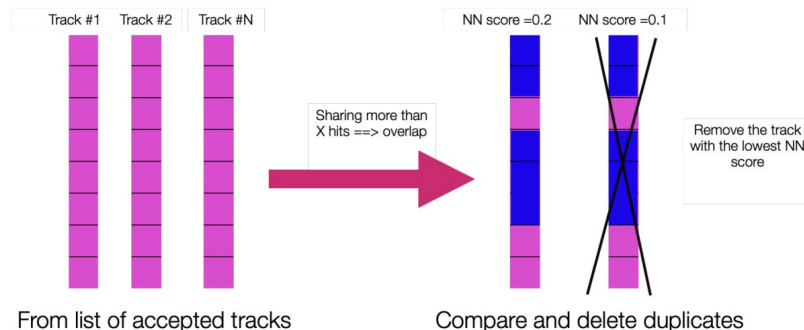
Objetivos desse projeto

Método de reconstrução de trajetória em 4 dimensões (x,y,z,t)

- Adaptado aos novos detectores
- Melhor desempenho do que os métodos atuais
 - Maior acurácia, eficiência e velocidade de processamento

Rejeição de falsos positivo (*fakes*)

- É necessário diferenciar as partículas geradas pela colisão (*Hard Scatter*) de efeitos secundários (*pileup*)

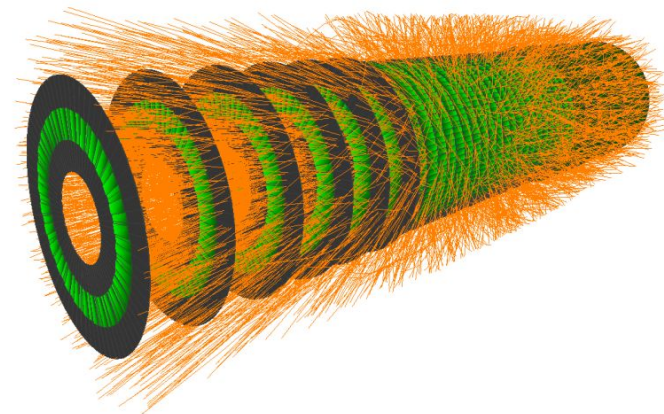


Recursos: ACTS

- O ACTS (*A Common Tracking Software*)[7] é o *framework* adotado pelo ATLAS para desenvolver/simular métodos de reconstrução de trajetória

O ACTS contém:

- Gerador de eventos Monte Carlo
- Simulação de iteração das partículas geradas com os detectores (ITk + HGTD)
- Cadeia de processamento que permite a idealização de novos métodos de reconstrução



Simulação de um evento no ACTS

- O IF-USP e a colaboração do ATLAS fornecerão toda a infraestrutura computacional necessária para o desenvolvimento

Metodologia

- Estabelecer *baseline* de desempenho utilizando o método atual no ACTS para o ITk + HGTD em eventos com $\langle u \rangle = 200$
- Será estudado o uso de *Graph Neural Networks* (GNNs) em 3D
 - Se mostraram promissoras em estudos passados [6]
 - Outras vias serão exploradas caso necessário
- Adaptação do método para 4D
- Otimização para processamento paralelo (GPU)

Cronograma

Atividade	S.1	S.2	S.3	S.4	S.5	S.6	S.7	S.8	S.9	S.10
Disciplinas do Programa da Pós Graduação	■	■	■							
Revisão da Literatura	■	■	■	■	■	■	■	■	■	■
Familiarização com os frameworks de reconstrução e análise			■	■						
Implementação dos modelos GNN em reconstrução 3D				■	■					
Preparação para o exame de qualificação					■	■				
Implementação e dos modelos GNN em reconstrução 4D					■	■	■	■		
Introdução da informação de ToT e degradação do sinal dos sensores no modelo								■		
Implementação dos métodos em arquiteturas heterogêneas CPU+GPU								■	■	
Estudo do desempenho da reconstrução (incerteza sistemática, eficiência, desempenho computacional)					■			■	■	
Estágio no CERN (atividades no HGTD e estudos de reconstrução e validação)				■			■	■		
Preparação da Defesa									■	■

Obrigado pela atenção!

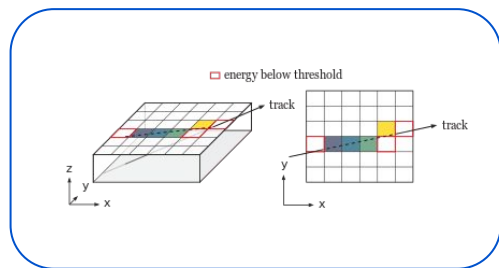
Perguntas?

Referencias

- [1] ATLAS Collaboration. *Observation of a new particle in the search for the Standard Model Higgs boson with the ATLAS detector at the LHC*. Physics Letters B, 2012. <https://doi.org/10.1016/j.physletb.2012.08.020>.
- [2] M. Gullstrand, and S. Maraš. “Using Graph Neural Networks for Track Classification and Time Determination of Primary Vertices in the ATLAS Experiment” (Dissertation). Disponível em <http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-288505>
- [3] JU, X. et al. *Performance of a geometric deep learning pipeline for HL-LHC particle tracking*. The European Physical Journal C, v. 81, n. 10, p. 876, out. 2021. ISSN 1434-6052. DOI: 10.1140/epjc/s10052-021-09675-8. Disponível em <https://doi.org/10.1140/epjc/s10052-021-09675-8> .
- [4] ATLAS Collaboration, “Technical Design Report for the ATLAS ITk Pixel Detector”, Tech. Rep. ATL-COM-ITk-2018-019, CERN, Geneva, 2018. Disponível em: <https://cds.cern.ch/record/2310230>
- [5] ATLAS Collaboration, “Technical Design Report: A High-Granularity Timing Detector for the ATLAS Phase-II Upgrade”. Technical report, CERN, Geneva, 2020. Disponível em: <https://cds.cern.ch/record/2719855/files/ATLAS-TDR-031.pdf>
- [6] Paul Gessinger-Befurt. *Development and improvement of track reconstruction software and search for disappearing tracks with the ATLAS experiment*, 2021. Presented 30 Apr 2021.
- [7] ATLAS Collaboration. *ACTS documentation*. Disponível em: <https://acts.readthedocs.io/en/latest/index.html>

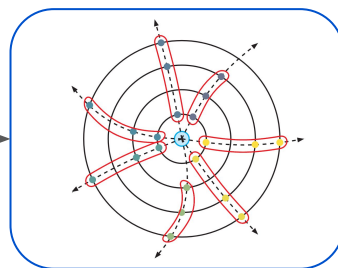
Backup

Track reconstruction processing chain



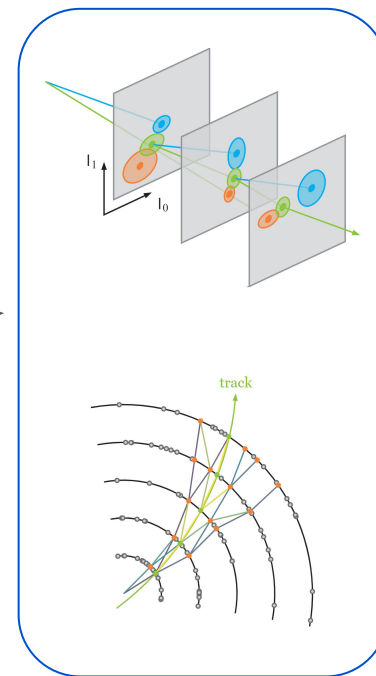
Clustering

Group together sensor activations that belong to the same deposition



Seeding

Evaluate triples of deposition in the inner layers to filter the best candidates for track seeds



Track fitting and finding

Combinational Kalman Filters

Defining a state space

- We can define the measures we observe as a function of the true position and measurement errors
- A simple **measurement equation** would be:

$$\vec{m}(n) = \mathbf{H}(n)\vec{x}(n) + \vec{\epsilon}(n)$$

n layer (surface) index

$\vec{m}(n)$ measure vector (x,y,z)

$\mathbf{H}(n)$ projection matrix (x to m)

$\vec{x}(n)$ state vector ← **Value to be estimated**

$\vec{\epsilon}(n)$ measurement error, white gaussian noise

- As we know the system dynamics, we can also define a **system equation**

$$\vec{x}(n) = \mathbf{F}(n-1)\vec{x}(n-1) + \vec{\omega}(n-1)$$

$\mathbf{F}(n-1)$ transport state vector from (n-1) to (n)

*extrapolation achievable by numeric integration

$\vec{\omega}(n)$ system error, white gaussian noise

is independent of the measurement error

- These two equations define our **state space**

Innovation process and estimative update

- If we have a **prior estimative of the state vector** (before observing the actual measurement) is possible to define a metric that measures the information gain that the new measurement offers
- The **innovation** is achievable with the following equations:

$$\vec{\alpha}(n) = \vec{m}(n) - \hat{m}(n) \qquad \hat{m}(n) = \mathbb{E}[\vec{m}(n)] = \mathbf{H}(n)\vec{x}(n)$$
$$\vec{\alpha}(n) = \vec{m}(n) - \mathbf{H}(n)\hat{x}(n|\mathbf{m}_{n-1}) \qquad \hat{x}(n|\mathbf{m}_{n-1}) \text{ estimative of state vector given prior measures}$$

- The innovation can be used to adjust the prior estimative:

$$\hat{x}(n|\mathbf{m}_n) = \hat{x}(n|\mathbf{m}_{n-1}) + \mathbf{K}(n)\vec{\alpha}(n)$$

- Where $\mathbf{K}(n)$ is the **Kalman gain**, which is chosen to minimize the mean-square value of the estimation error

$$\varepsilon(n|n) = \vec{x}(n) - \hat{x}(n|\mathbf{m}_n)$$
$$\mathbb{J} = \mathbb{E}\{\|\varepsilon(n|n)\|^2\}$$

Filtering Estimatives

- Iteration between **prediction (prior)** and **filtered estimative (posteriori)**

$$\vec{x}(n|\mathbf{m}_n) = \vec{x}(n|\mathbf{m}_{n-1}) + \mathbf{K}(n)\vec{\alpha}(n)$$

$$\vec{x}(n+1|\mathbf{m}_n) = \mathbf{F}(n)\vec{x}(n|\mathbf{m}_n)$$

- After all measures are available, it is also possible to smooth the estimates.

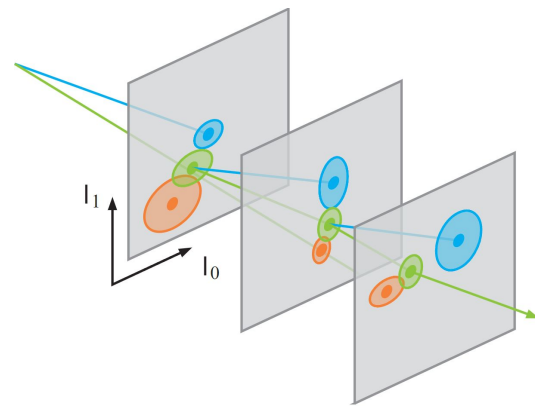


Figure 4: Illustration of KF estimative iteration. Measurement represented in orange, (prior) estimative in blue and filtered (posteriori) estimative in green [4].

Track scoring

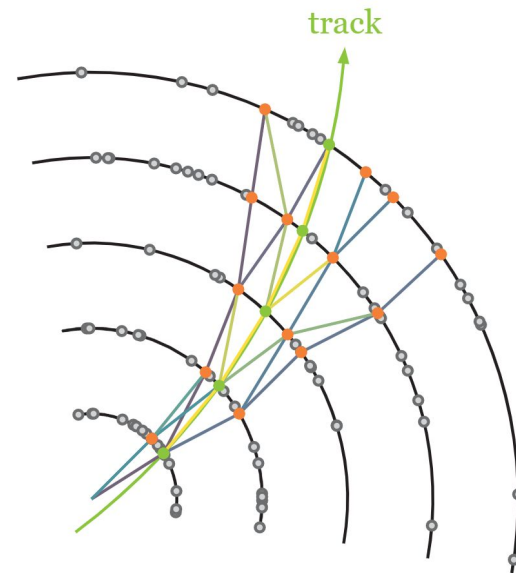
- We can define a residual between the posteriori estimate and the measure

$$\vec{r}(n) = \vec{m}(n) - \mathbf{H}(n)\hat{x}(n|\mathbf{m}_n)$$

- This value contributes to a quality factor of the reconstructed track

$$\chi_+^2 = \vec{r}^T(n)[(\mathbf{1} - \mathbf{H}(n)\mathbf{K}(n))\mathbf{V}(n)]^{-1}\vec{r}(n)$$

- The algorithm iterates over all possible tracks and uses the global quality parameter χ^2 (also depends on other track attributes*) to filter the best estimate tracks



Combinational Kalman Filter Drawbacks and Limitations

- The main drawback of the CKF is the execution time that will not be acceptable in a scenario of high luminosity
 - Execution time is $O(N^2)$, being N the number of points to be fitted
 - As it is implemented today, the iterative adjustments are optimized for CPU processing
- As the Inner Detector (ID) has no timing information, and therefore the reconstruction is done in 3 dimensions
 - With the timing information provided by the HGTD the reconstruction can be made in 4 dimensions (geometrical position + time)

ACTS first steps

ACTS - A Common Tracking Software

- “ACTS is an experiment-independent toolkit for (charged) particle track reconstruction in (high energy) physics experiments implemented in modern C++”[4]
- Originated from Athena (ATLAS simulation framework) as a standalone version of its tracking reconstruction
- Key features:
 - A tracking geometry description, which can be constructed manually or from TGeo and DD4hep input.
 - Simple event data model.
 - Implementations of common algorithms
 - for track propagation and fitting.
 - basic seed finding.
 - vertexing.
- [Documentation website](#)

Runs smoothly in the SAMPA cluster 😎

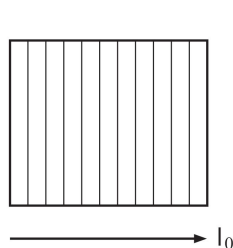
Simulating events with particle guns

- ACTS offers a series of examples of Python bindings that can be used to simulate basic scenarios
 - The use of these bindings in “production” is encouraged
- We are going to simulate the reconstruction done by the Combinational Kalman Filter
- The Setup will be
 - ODD detector structure
 - Particle gun of 100 muons distributed uniformly between η -3 and 3
 - Using “standard” seeding algorithms
 - Using CKF to reconstruct the tracks

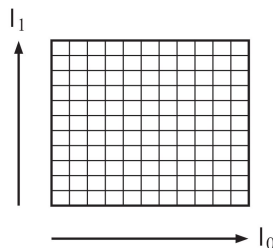
State vector and analysis

- The simulation outputs ROOT files that can be analysed for performance evaluation.
 - We will use ACTS analysis application to generate the performance plots
 - Can do our analysis in the future
- As we know the real particle paths is possible to extract residual metrics
- The state vector is defined as:

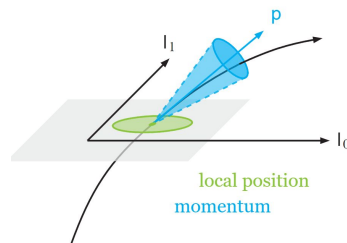
$$\vec{x} = (l_0, l_1, \phi, \theta, q/p, t)^T$$



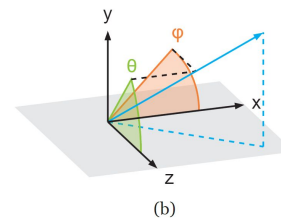
(a) strip



(b) pixel

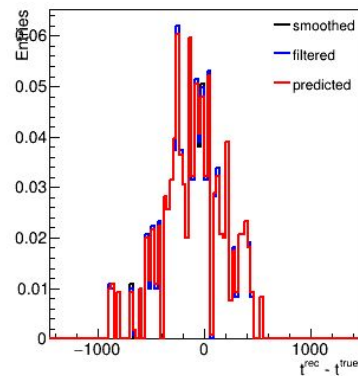
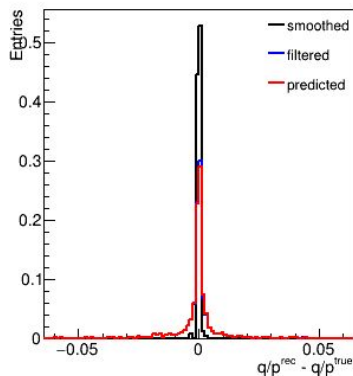
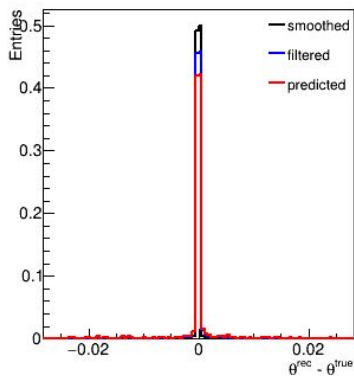
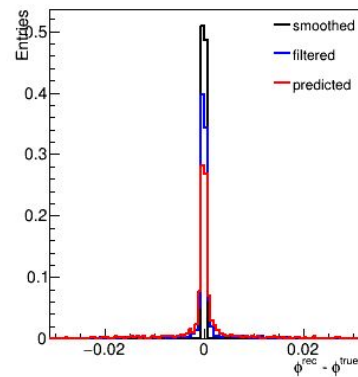
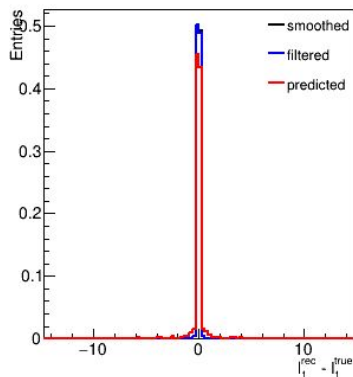
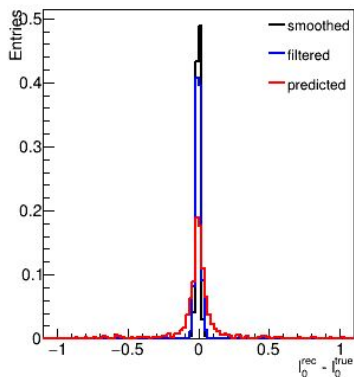


(a)



(b)

Kalman Filter performance (muons) - Residual plots



Kalman Filter performance (muons) - Regional residual plots

