Reconstruction

CBM-TRD
TDR Review Meeting
GSI Darmstadt, Germany
March 14+15, 2017

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Reconstruction routines

- Track finding and fitting
- Electron identification

Challenges

Peculiarities for CBM:

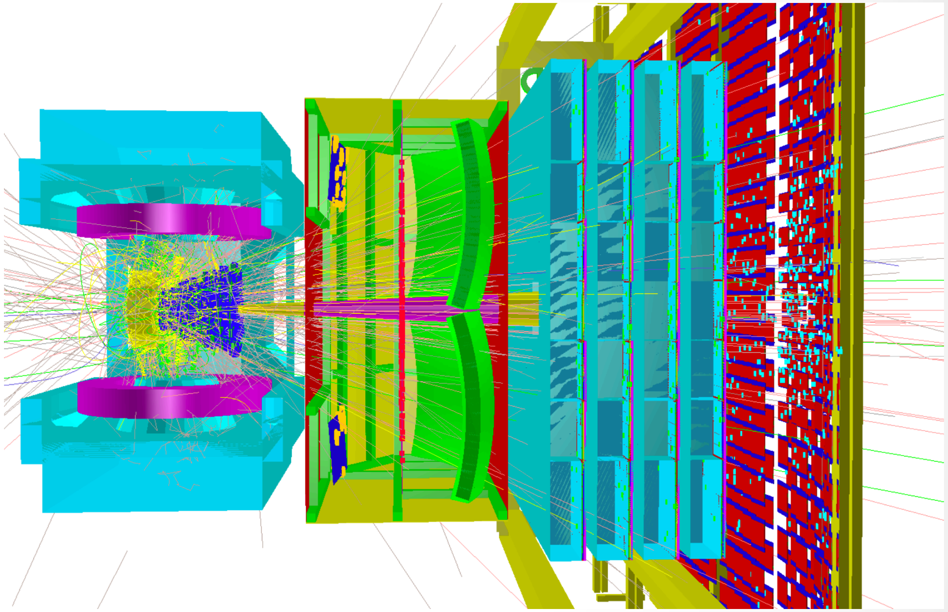
① large track multiplicities - up to **1000** charged particles per reaction in +/- 25° acceptance

② high reaction rate - up to **10 MHz**

③ measurement of rare probes → need for fast and efficient algorithms

④ high hit and track density

⑤ large material budget complex detector structure, overlapping sensors, dead zones



Central Au+Au collision at 10 *A*GeV

Track propagation

Geometrical extrapolation

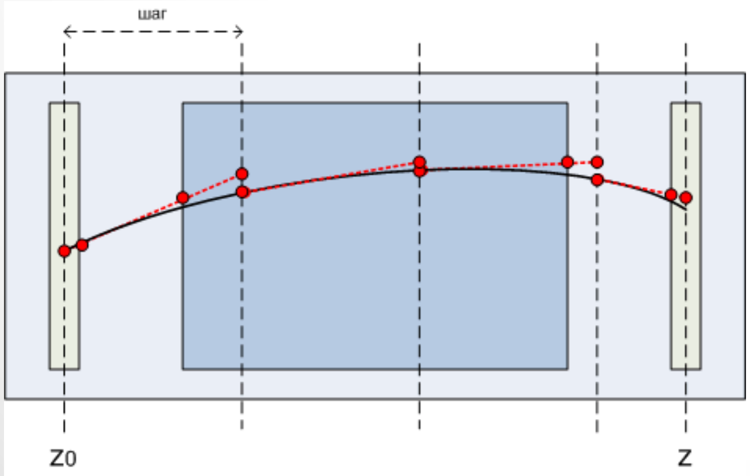
- Straight line in case of absence of magnetic field.
- Solution of the equation of motion in a magnetic field with the 4th order Runge-Kutta method, with a parallel integration of the derivatives.

Material effects

- Energy loss (ionization: Bethe-Bloch, bremstrahlung: Bethe-Heitler)
- Multiple scattering (Gaussian approximation)

Geometry navigation

Based on ROOT TGeoManager package.



The Algorithm:

Trajectory is divided into steps. For each step:

- - - Straight line approximation for finding intersections with different materials (geometry navigator)

—— Geometrical extrapolation of the trajectory

Material effects are added at each intersection point

Kalman filter (KF)

The Kalman Filter is an efficient recursive filter that estimates the state of a linear dynamic system from a series of noisy measurements.

KF advantages:

- ➢ KF is suitable for combined track finding and track fitting;
- ➢ KF is fast in comparison to global LSF fit;
- ➢ KF is optimally suits to handle many measurements in presence of multiple scattering and other energy loss effects.

KF proceeds recursively by alternating two steps:

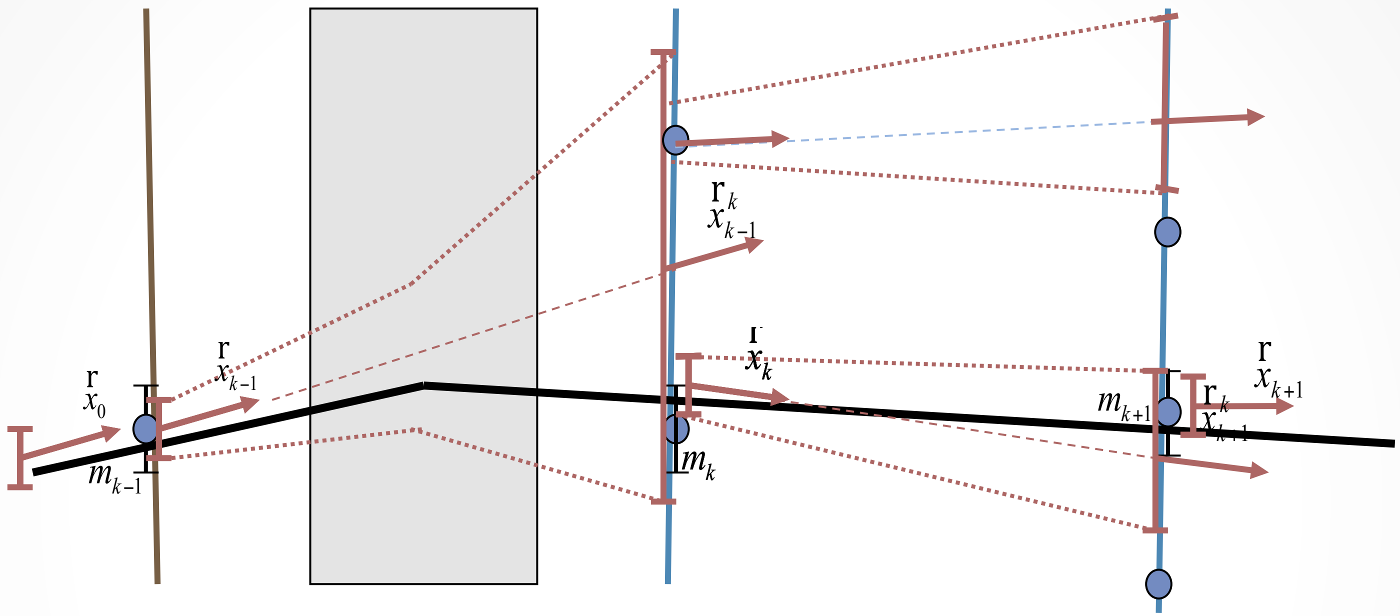
① Prediction

- ➢ Propagate state vector and covariance matrix to the next layer, increment covariance matrix by contributions from multiple scattering and energy loss.

② Update

- ➢ Compute a weighted mean of the extrapolation and the observation. The track parameters after each update step is the best estimate of the trajectory based on the measurements incorporated so far.

Track following



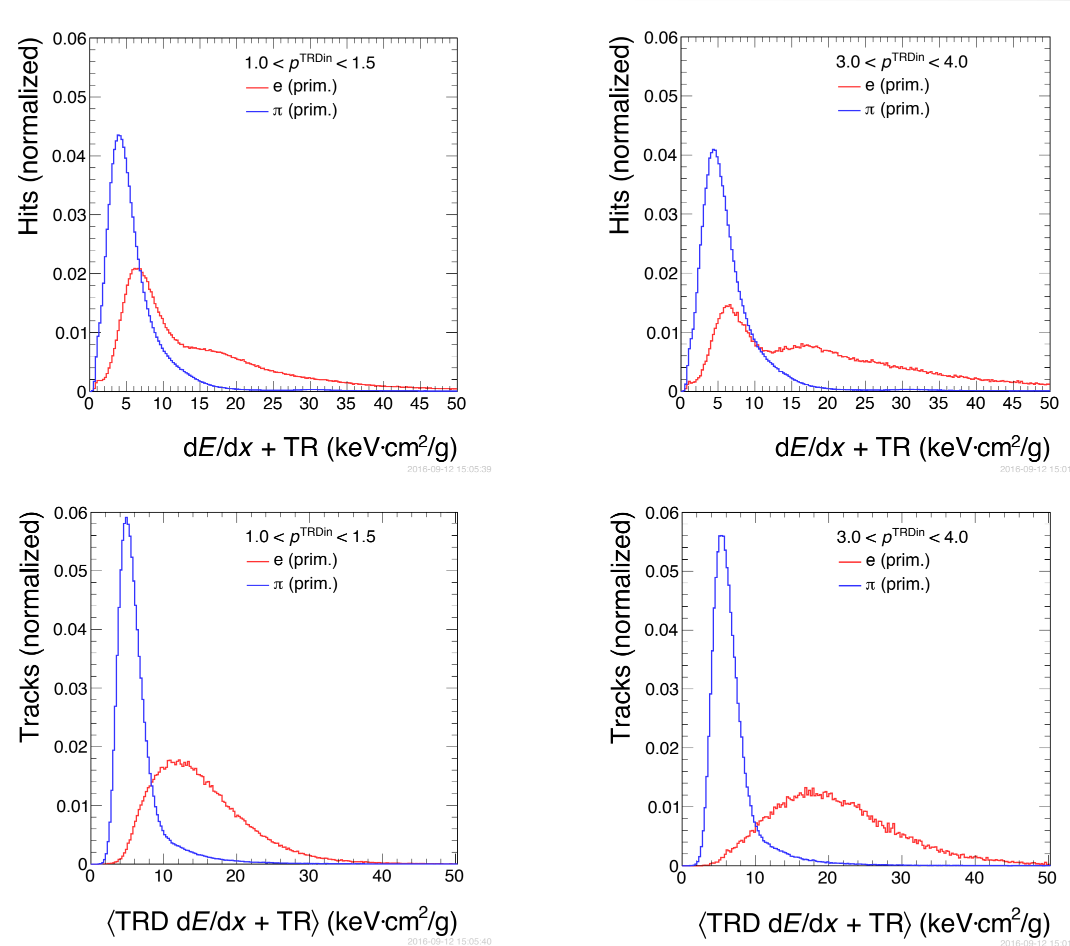
- Validation gate – searching area for hit candidates to be assigned to track
- Two hit-to-track association techniques
  ① **nearest neighbor**: attaches the closest hit from the validation gate
    - Fast and easier to implement

  ② **branching**: creates branch for each hit in the validation gate, select the best branch at the end
    - Slower due to much higher combinatorics but more efficient in some cases

Electron ID

Simulated signal distribution for a single TRD layer:

Average energy loss for tracks with $N_{\text{hits}} > 2$:



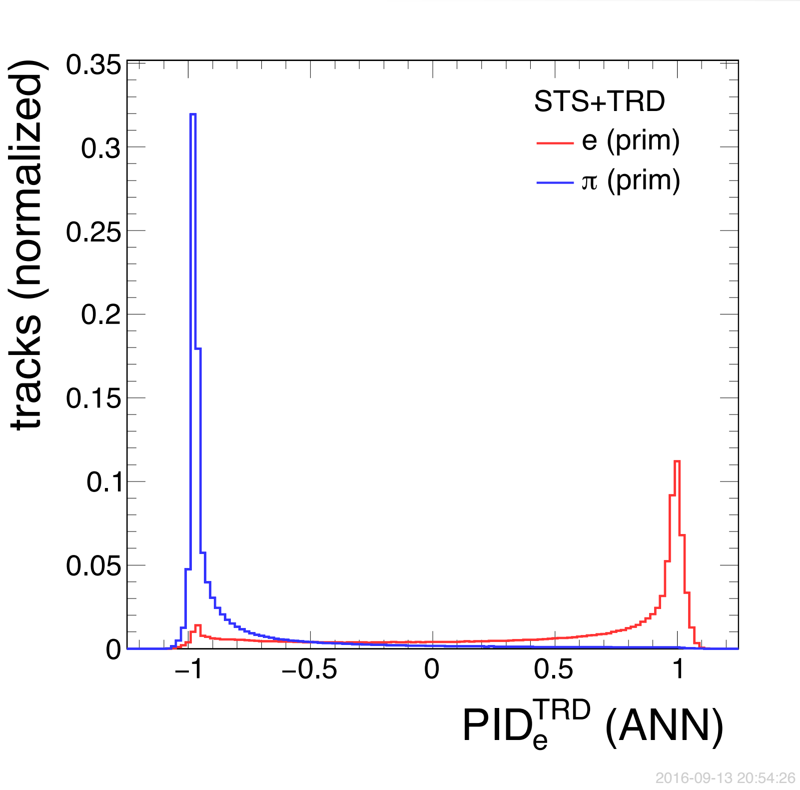
Implemented methods:

- Artificial Neural Network
- Likelihood function ratio
- Ordered statistics (median)
- Boosted Decision Tree

ANN

- ANN implementation of the multilayer perceptron type from ROOT
- ANN configuration
  - $N_{input} = N_{hits}$
  - $N_{hidden} = 2 * N_{input}$
  - 1 output neuron
- Energy loss transformation

$$\lambda_i = \frac{E_i - E_{\mathrm{mp}}}{\xi} - 0.225$$



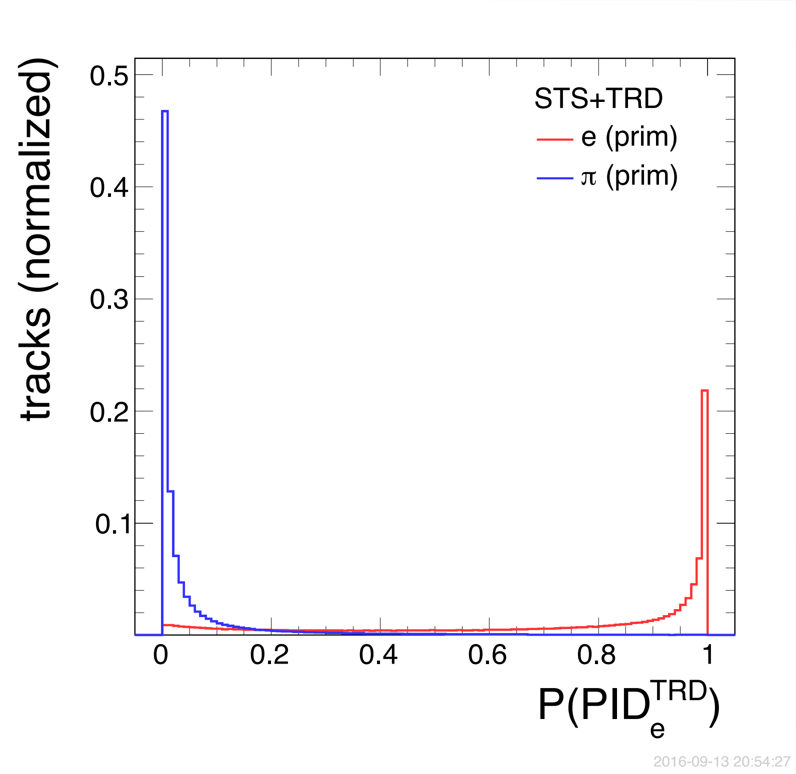
Likelihood

- The likelihood for a measured track to be an electron is defined as

$$L = \frac{P_e}{P_e + P_\pi}$$

- In case of many hits

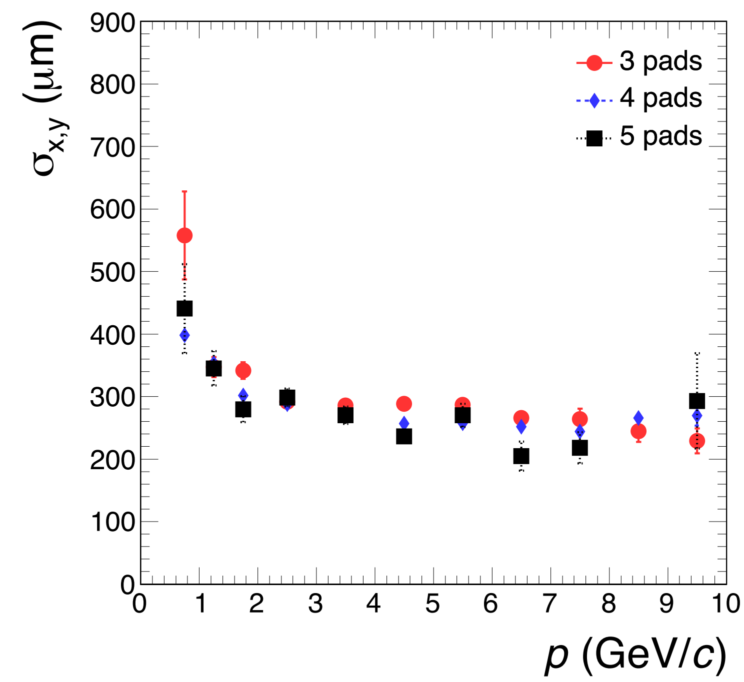
$$P_e = \prod_{i=1}^{N} P(E_i|e), \quad P_\pi = \prod_{i=1}^{N} P(E_i|\pi)$$



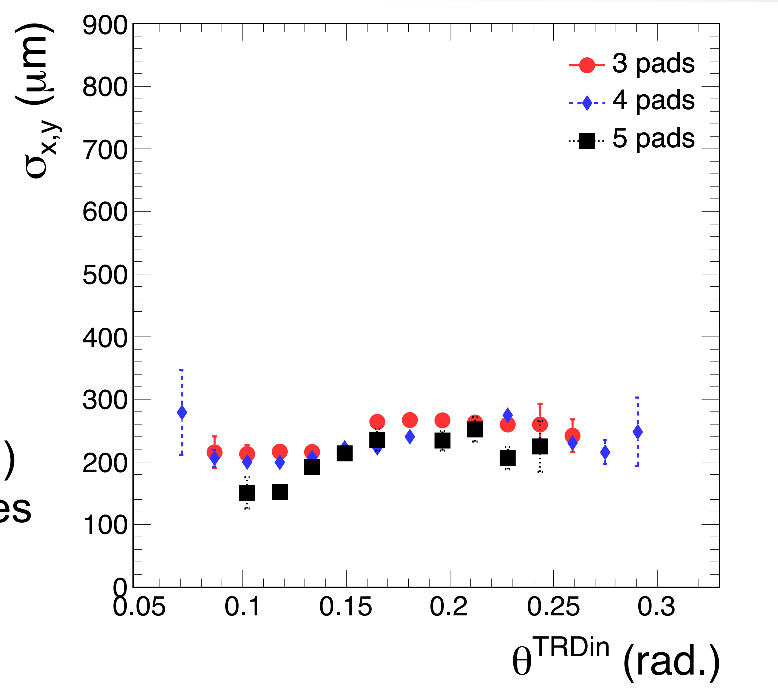
Performance

- Track finding
- Electron identification

TRD point resolution



Inner (small) module types 1, 2 and 3

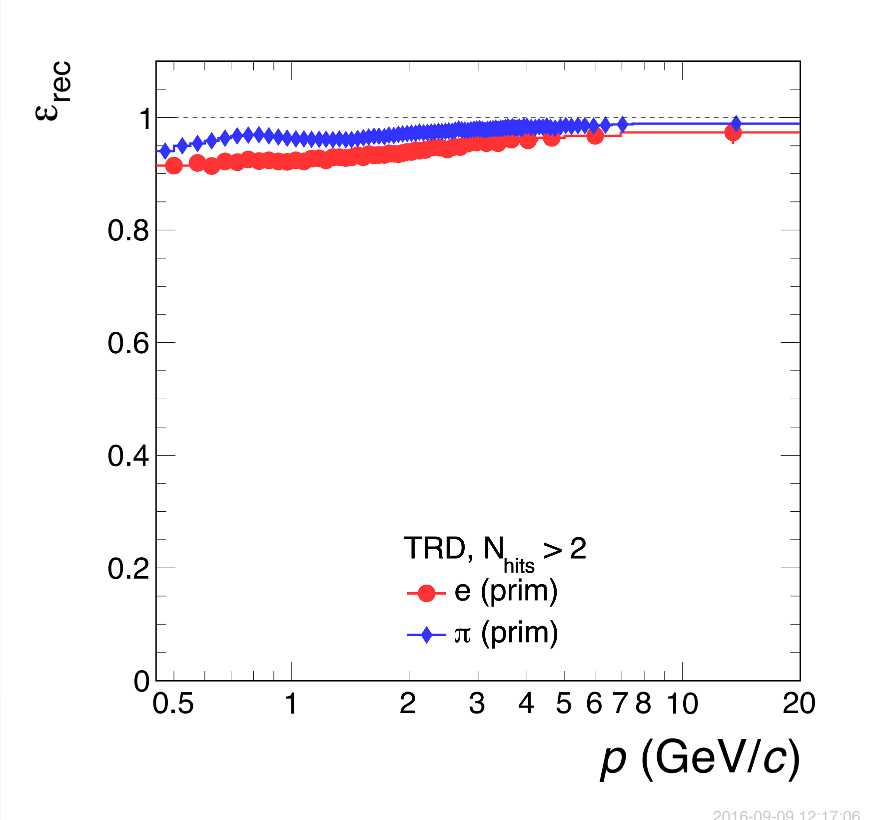


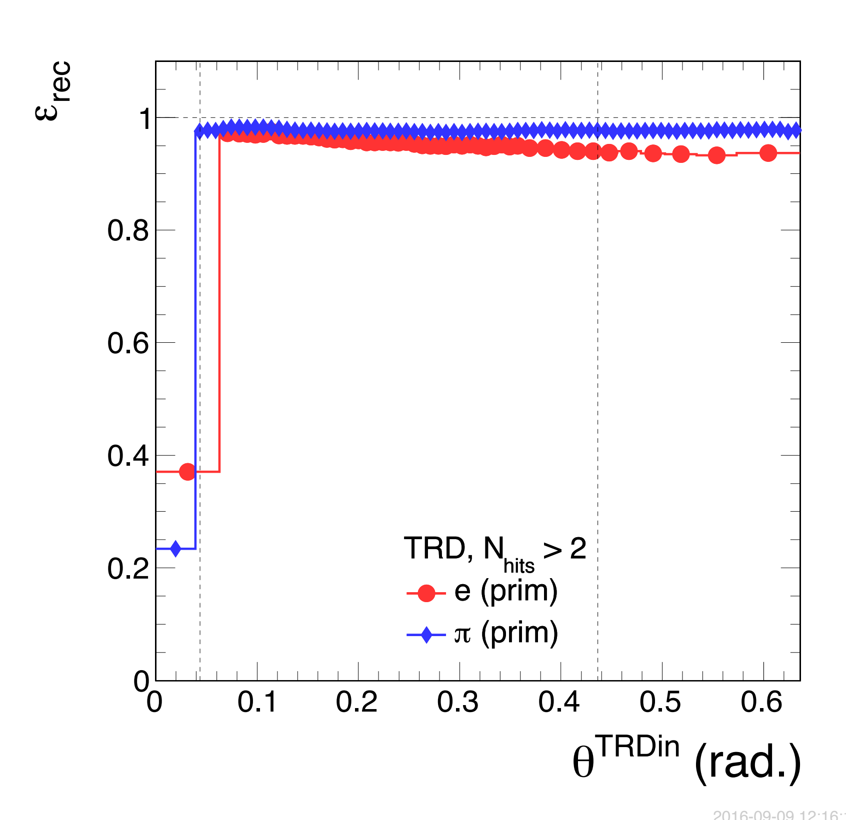
Reconstructed space points

Resolution $\sigma_{x,y}$ ~ 300 μm for p > 2 GeV/c, independent of incidence angle θ^{TRDin}

Outer module types (6, 7 and 8, not shown) $\sigma_{x,y}$ ≈ 400 μm

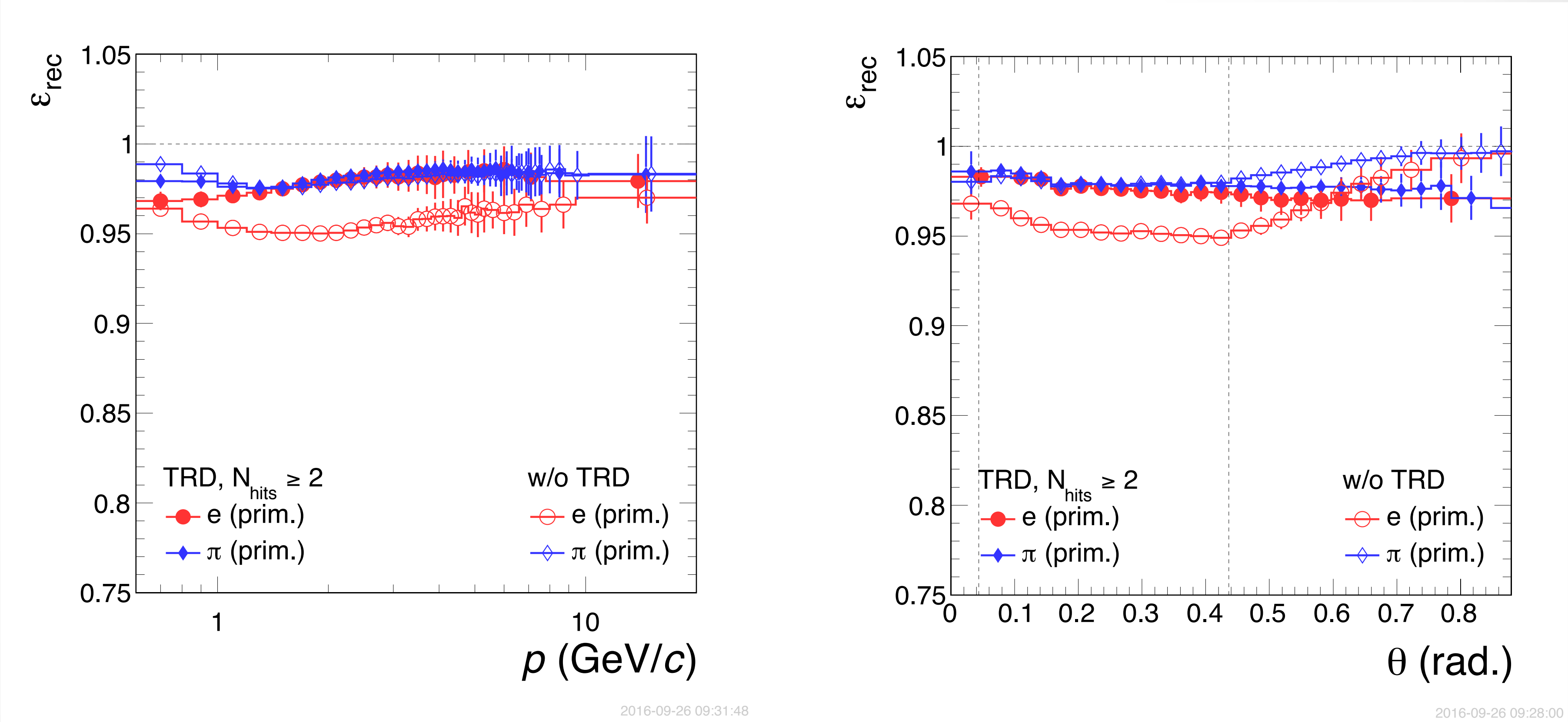
TRD tracking efficiency





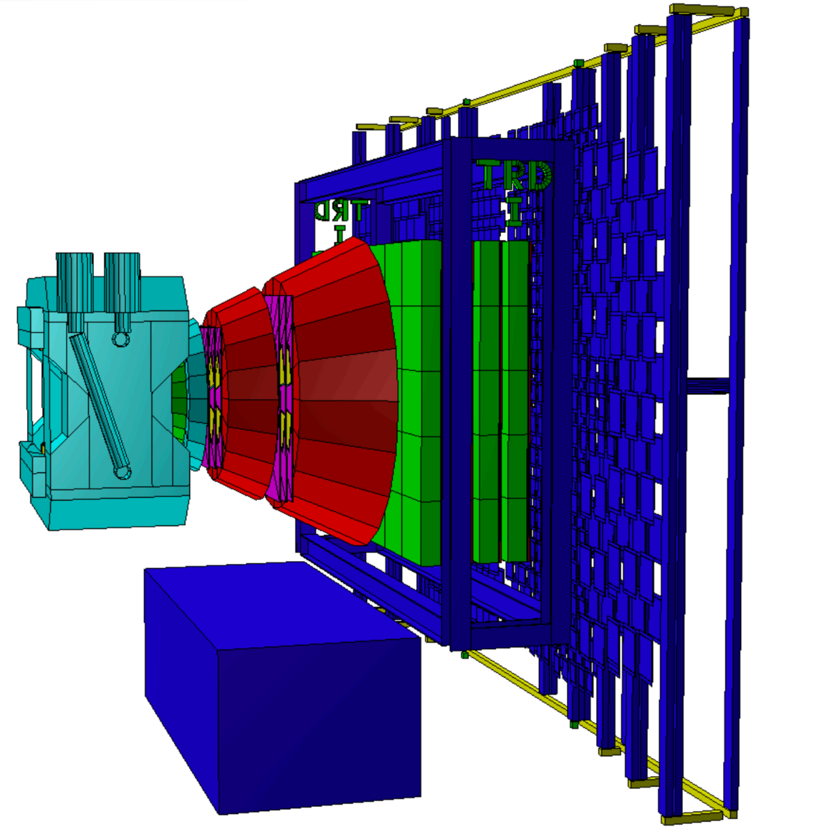
Efficiency to reconstruct tracks in TRD acceptance (N_{hit}(MC) > 2) with at least three points (N_{hit}(rec) > 2)

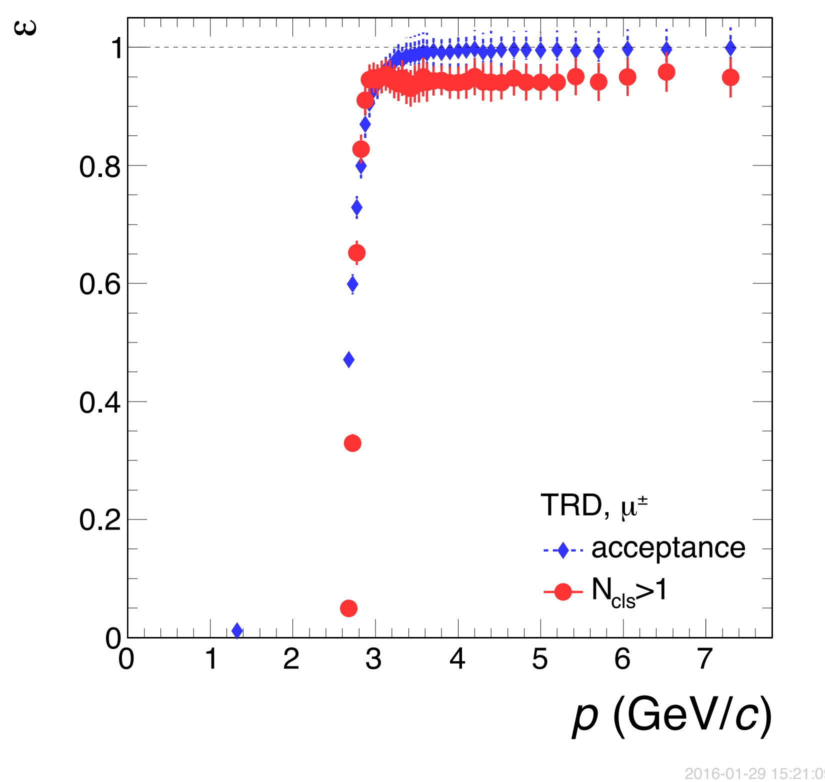
TOF matching efficiency



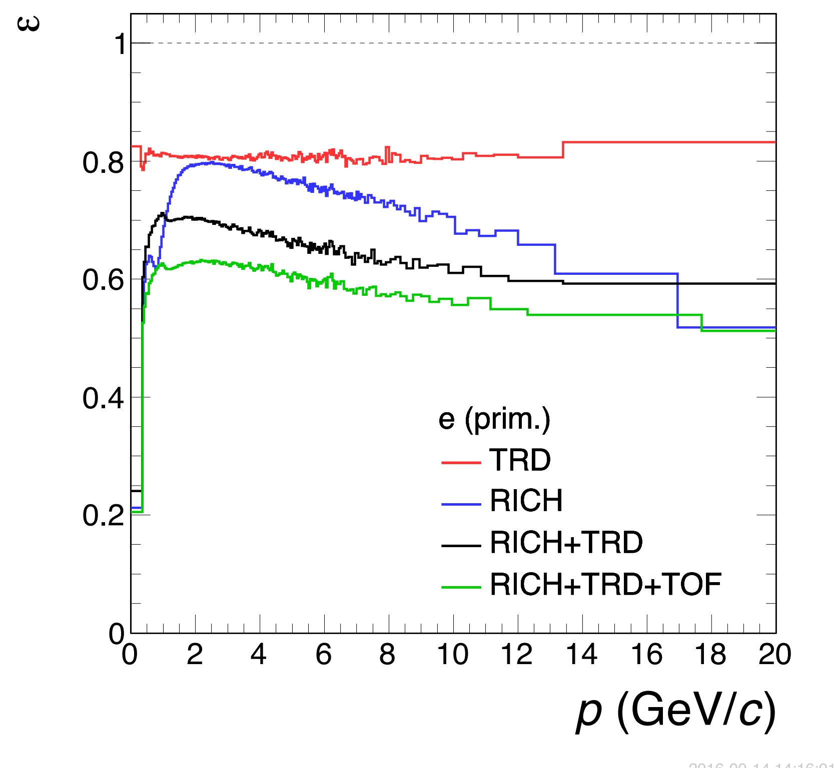
Comparison: STS+TRD and STS-alone (no TRD material)

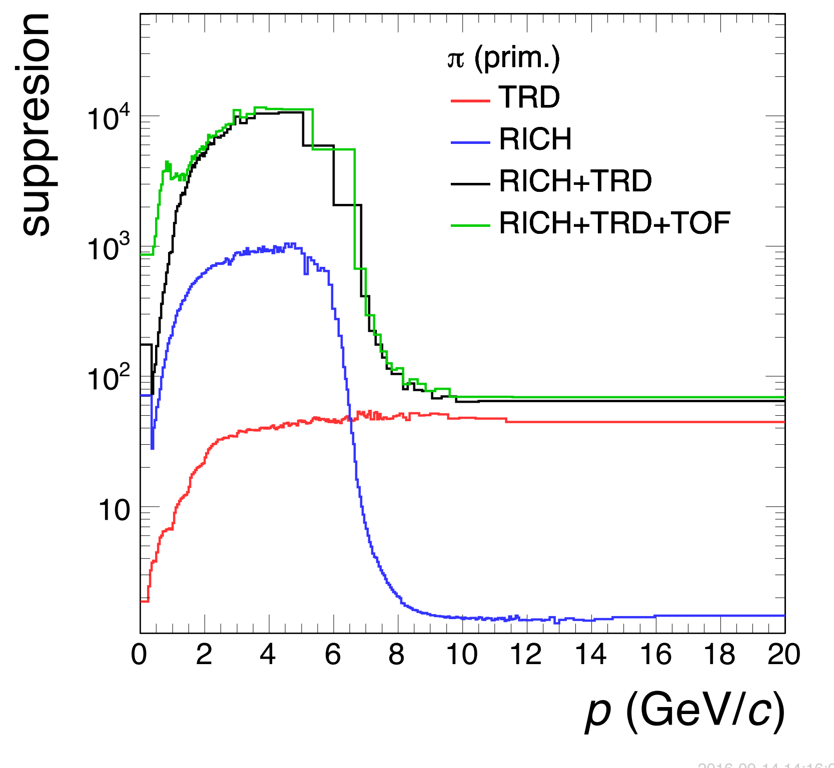
TRD in MUCH setup





Electron identification eff.



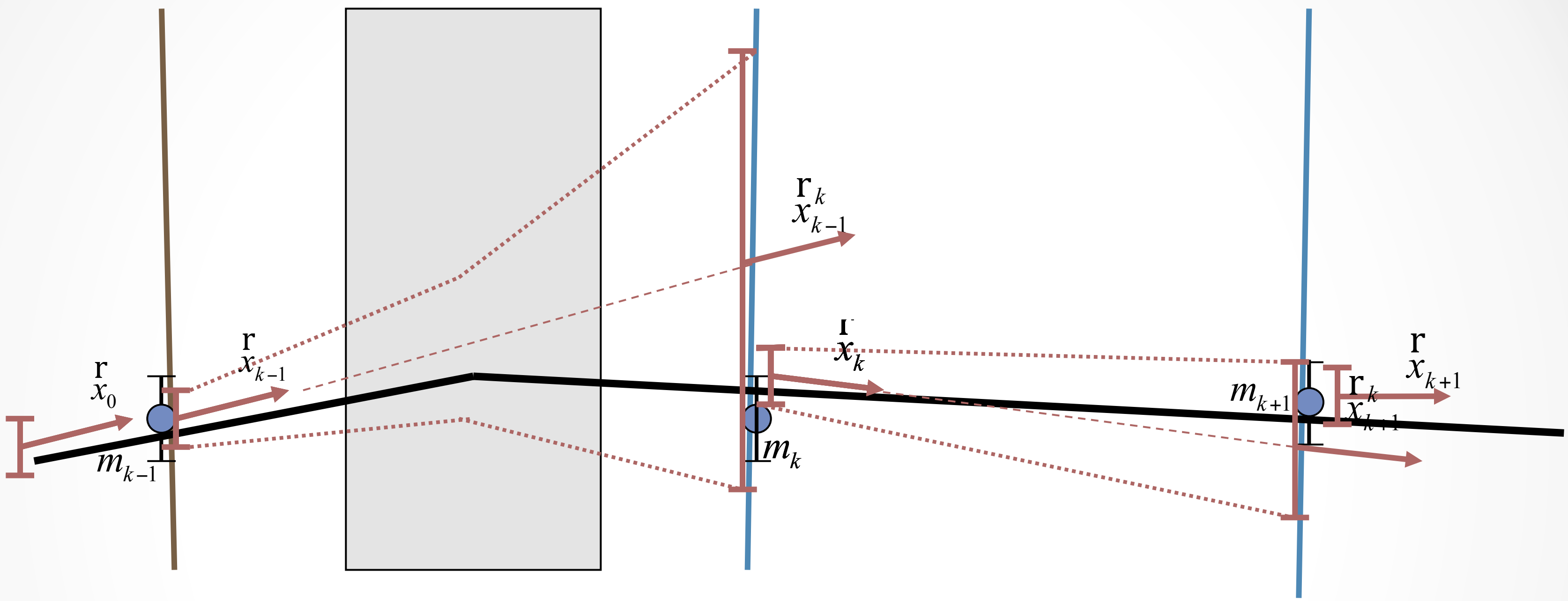


Pion suppression

Detector combination	Momentum region	Electron efficiency	Pion suppression factor
TRD	$2-8\,\mathrm{GeV}/c$	$80\,\%$	30
	$>8\,\mathrm{GeV}/c$	$80\,\%$	50
	$2-8\,\mathrm{GeV}/c$	$90\,\%$	10
	$>8\,\mathrm{GeV}/c$	$90\,\%$	15
RICH+TRD+TOF	$2-8\,\mathrm{GeV}/c$	$60\,\%$	8×10^3
	$>8\,\mathrm{GeV}/c$	$55\,\%$	80
	$2-8\,\mathrm{GeV}/c$	$70\,\%$	5×10^3
	$>8\,\mathrm{GeV}/c$	$65\,\%$	20
TRD(5L)	$2-8\,\mathrm{GeV}/c$	$80\,\%$	70
	$>8\,\mathrm{GeV}/c$	$80\,\%$	130
RICH+TRD(5L)+TOF	$2-8\,\mathrm{GeV}/c$	$60\,\%$	8×10^3
	$>8\,\mathrm{GeV}/c$	$55\,\%$	230

BACKUP

Kalman filter illustration



① Particle scatters in a material layer between layer k and k – 1.

② The track fit accounts for this effect by increasing the predicted error on the state vector x_{k-1} with $Q^k{}_k$.

③ The measurement, m_k, pulls the state back to the true trajectory, resulting in a filtered track state, x_k.