

# Tracking in Test-beam data analysis on micro-ITS3 with target (July 2021)

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INFN Bari, Italy

Previous presentations

[https://indico.cern.ch/event/1207616/contributions/5079140/attachments/2521089/4335005/Tracking\\_BeamTestData\\_Shyam.pdf](https://indico.cern.ch/event/1207616/contributions/5079140/attachments/2521089/4335005/Tracking_BeamTestData_Shyam.pdf)

[https://indico.cern.ch/event/1196877/contributions/5036272/attachments/2503083/4300248/WP3\\_meeting\\_06\\_09\\_2022.pdf](https://indico.cern.ch/event/1196877/contributions/5036272/attachments/2503083/4300248/WP3_meeting_06_09_2022.pdf)

## ➤ Status of Tracking:

- Event selection: done
- Track finding: done
- Track fitting using Global Chi2 fitting (Ignoring MS) and the Kalman filter: done
- Distance of Closest Approach between Beam and Produced Tracks: done
- Distance in the transverse plane w.r.t. to the Beam position at Z=0: done
- Event display package for both cases Chi2 fitting and Kalman filter: done

## Reference for Kalman filter:

1. R. Fruhwirth, APPLICATION OF KALMAN FILTERING TO TRACK FITTING IN THE DELPHI DETECTOR

<https://inspirehep.net/files/52ffb2cc6aed04254988586bb79e1532>

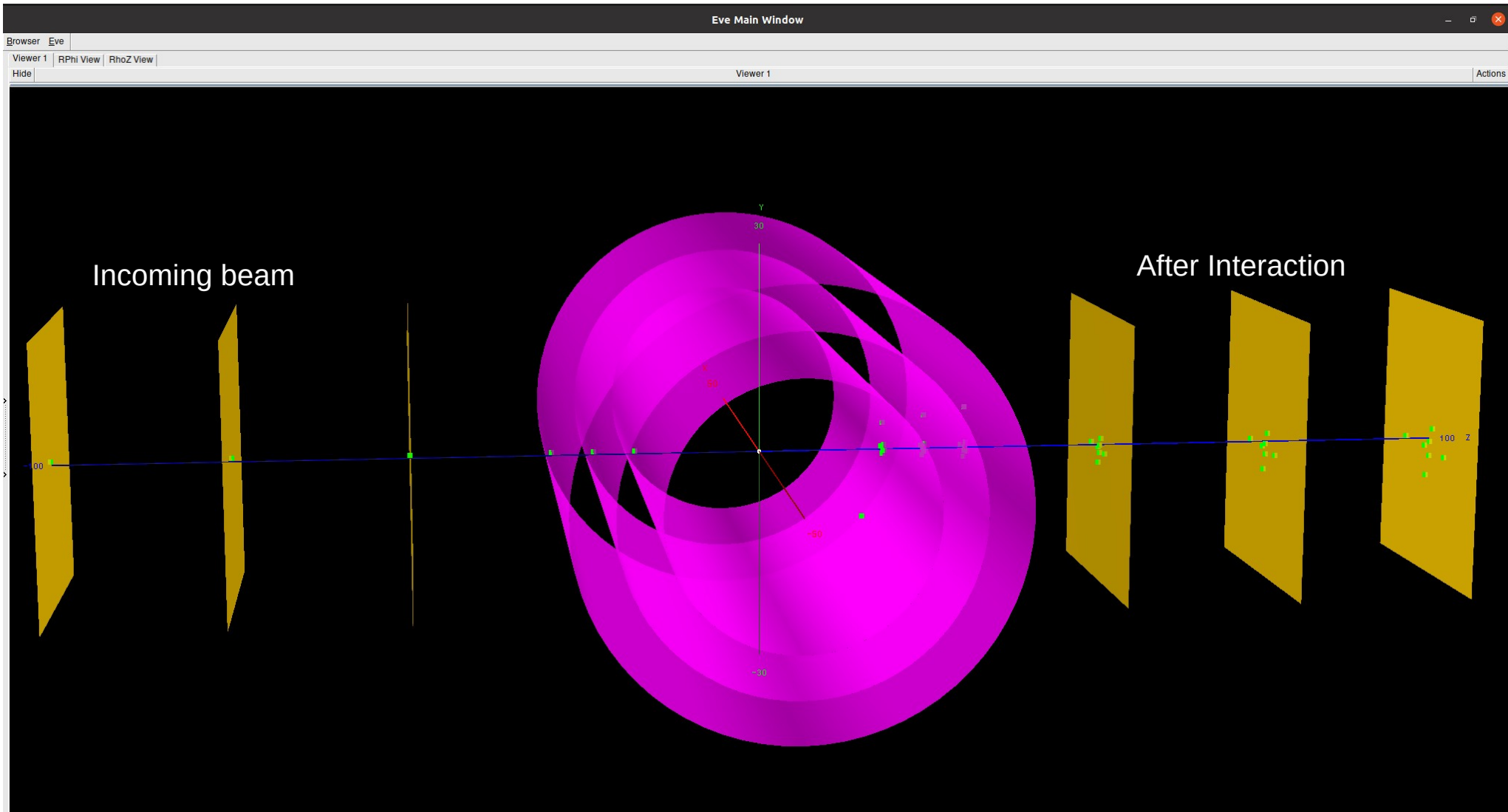
2. R. Fruhwirth, Application of Kalman filtering to track and vertex fitting

<https://www.sciencedirect.com/science/article/abs/pii/0168900287908874?via%3Dihub>

3. Belikov, Yu (Dubna, JINR ) ; Safarik, K (CERN) ; Batyunya, B (Dubna, JINR ), Kalman Filtering Application for Track Recognition and Reconstruction in ALICE Tracking System

<http://cds.cern.ch/record/689414/files/INT-1997-24.pdf>

# Event display (3D-view)

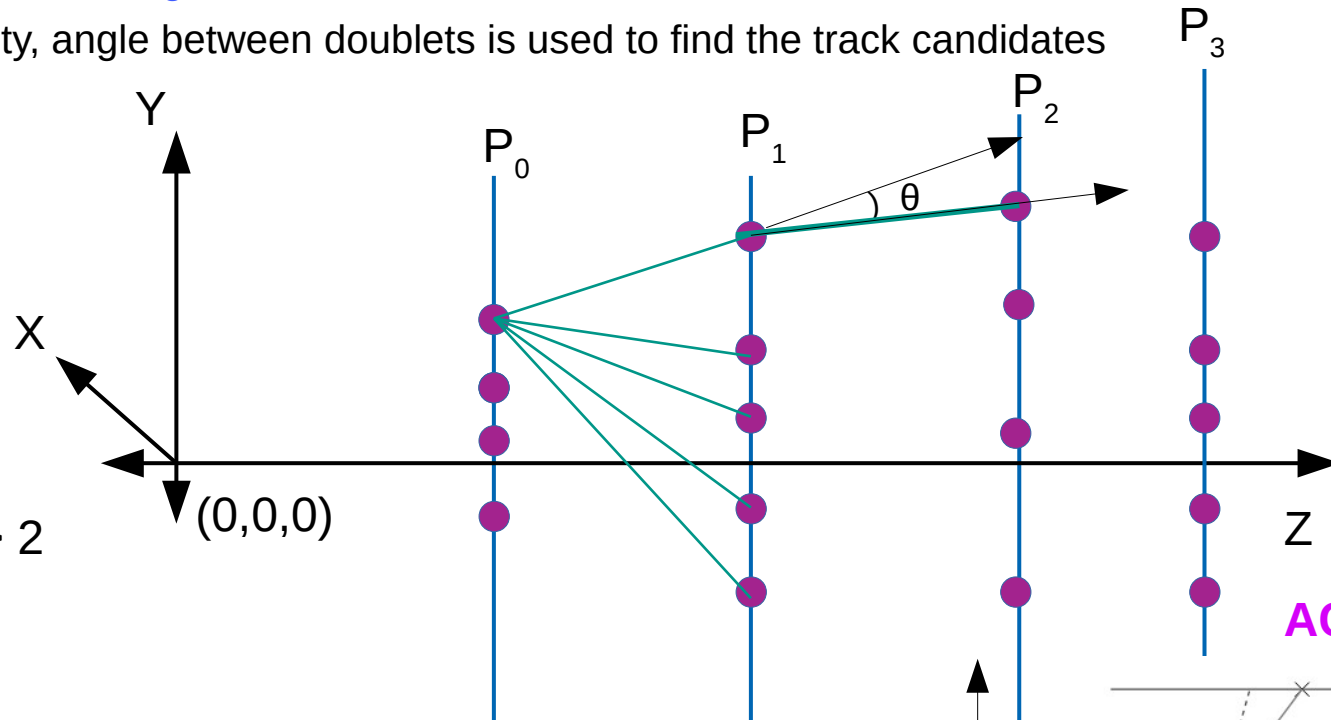


# Tracking Finding

MS: Multiple Scattering

Thanks Gianfranco for the help in implementing

- Low track density, angle between doublets is used to find the track candidates



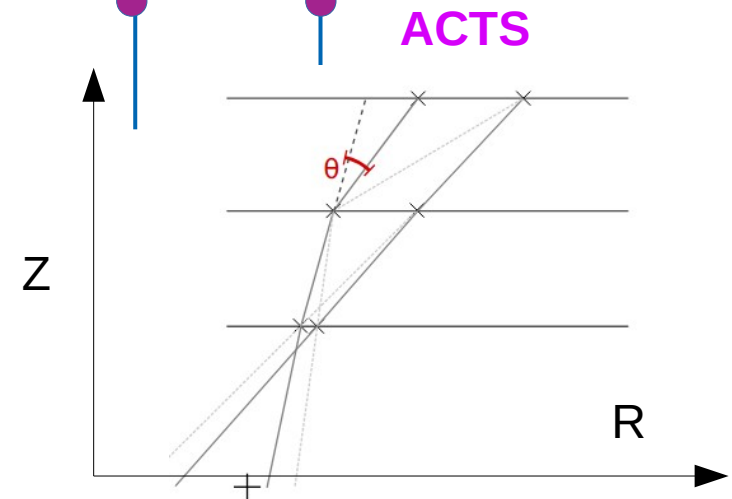
Tracking:

Number of hits  $> 2$   
Chi2/ndf

Main Idea: Hits belong to a track should be compatible with in some sigma 's of MS angle (multiple of  $\sigma_{\theta MS}$ )

[Fig2. ACTS on the link below](https://iopscience.iop.org/article/10.1088/1742-6596/898/4/042011/pdf)

<https://iopscience.iop.org/article/10.1088/1742-6596/898/4/042011/pdf>



# Track Fitting (Global Chi2 Minimization)

No Magnetic field: Track model (straight line) in three dimensions

Vector equation of a line in 3D:

$$\vec{r} = \vec{r}_0 + \vec{a}$$

If  $u$  is the unit vector along the line and  $t$  is parameter:

$$\vec{r} = \vec{r}_0 + t\vec{u}$$

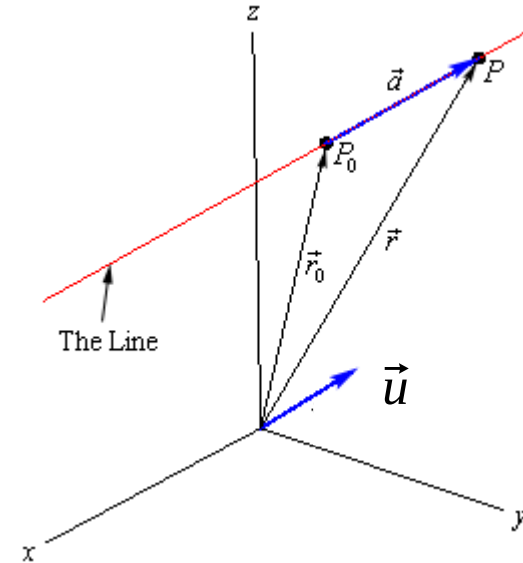
$$(x, y, z) = (x_0, y_0, z_0) + t(a, b, c)$$

$$x = x_0 + ta$$

$$y = y_0 + tb$$

$$z = z_0 + tc$$

$$t = \frac{(x - x_0)}{a} = \frac{(y - y_0)}{b} = \frac{(z - z_0)}{c}$$



To define a line in 3D, we should know a point  $(x_0, y_0, z_0)$  on the line and unit vector  $(a, b, c)$  in the direction of line  
Therefore 6 parameters to minimize!!!

<https://tutorial.math.lamar.edu/classes/calciiii/eqnsoline.aspx>

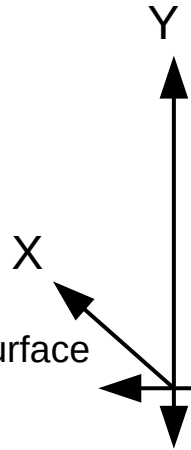
# Track Fitting (Global Chi2 Minimization)

```
x = p[0] + p[1]*t;
y = p[2] + p[3]*t;
z = p[4] + p[5]*t;
```

Our case

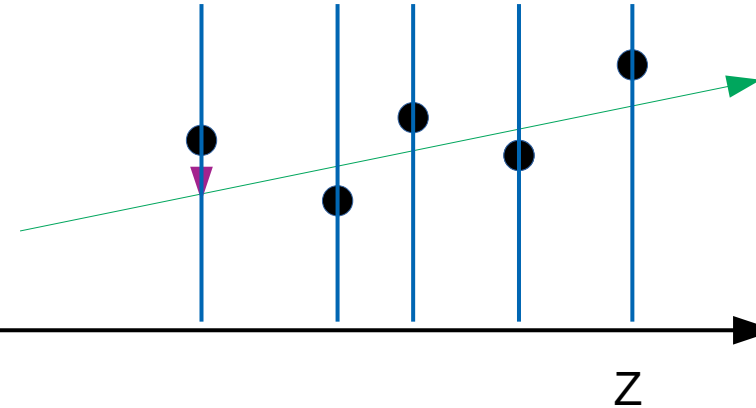
```
x = p[0] + p[1]*t;
y = p[2] + p[3]*t;
z = t;
```

P[4] = 0 and p[5] = 1; hit points on the surface



(Chi2 Minimization) Ignoring uncertainty due to MS

Z Position of sensor is known precisely



**Ndf: 2 (number of points)-4**

Each plane has 2 degrees of freedom (x,y) and lines has 4 independent parameters (constraint)

$$\sigma_x = \sigma_y = 5 \mu m \quad \chi^2 = \sum_{i=1}^n \frac{dx_i^2}{\sigma_{x_i}^2} + \frac{dy_i^2}{\sigma_{y_i}^2}$$

```
XYZVector xp(x,y,z);
double ti = z;
XYZVector u(p[0]+p[1]*ti,p[2]+p[3]*ti,z);
double d2 = ((xp-u).Mag2());
double dx = (xp-u).X(); double dy = (xp-u).Y();
double chi2 = dx*dx/(xerr*xerr)+dy*dy/(yerr*yerr);
return chi2;
```

[Corryvrecken also using the similar method as given the link of the class](#)

<https://gitlab.cern.ch/corryvreckan/corryvreckan/-/blob/master/src/objects/StraightLineTrack.cpp>

<https://github.com/Simple-Shyam/Phd-work/blob/master/HFPPT/distance.pdf>

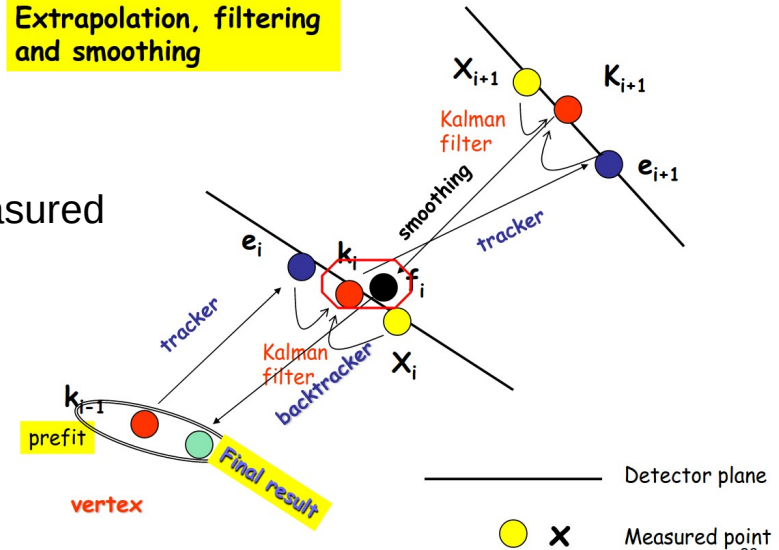
# Track Fitting (Kalman filter)

Trajectory is affected by multiple scattering

1. **Extrapolation:** Extrapolation ( $e_i$ ) on the next plane with M.S. effect
2. **Filtering:** Weighted average of extrapolated value ( $e_i$ ) and measured value ( $x_i$ ), known as Kalman filtered value ( $k_i$ )
3. **Smoothing:** Filtering in backward direction

For Multiple scattering we need to know momentum of particle  
(PYTHIA Simulation)

Extrapolation, filtering and smoothing



Kalman filter properly take care of multiple scattering

Class used is AliExternalTrackParam

[https://agenda.infn.it/event/1096/contributions/6159/attachments/4504/4980/Rotondi\\_3.pdf](https://agenda.infn.it/event/1096/contributions/6159/attachments/4504/4980/Rotondi_3.pdf)

Thanks to Ruben

More details see back up

# Track Fitting (Chi2 vs Kalman filter)

## Global Chi2 fitting

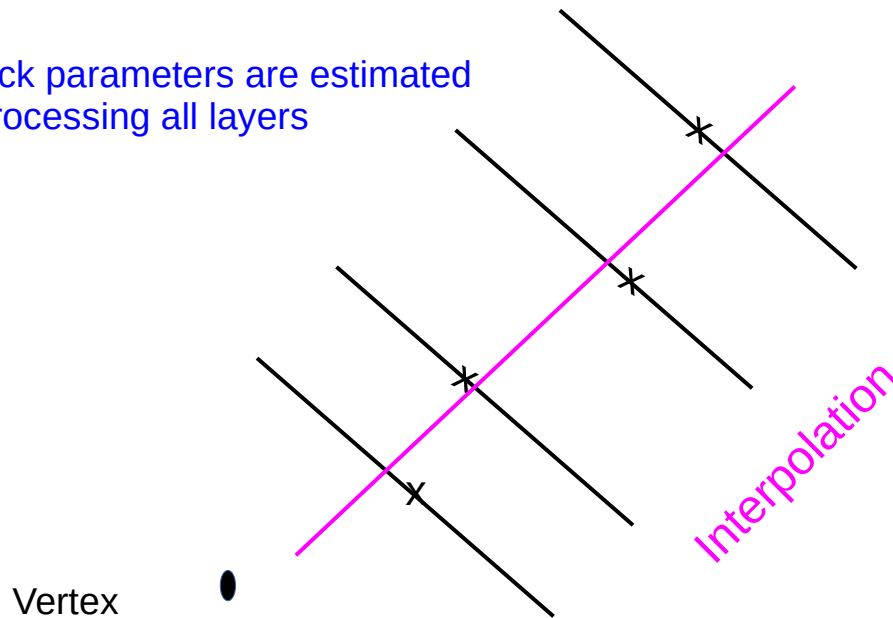
- Chi2 fitting is easier for few layers for large number of points covariance matrix is difficult to invert e.g. 200 points it should be 200x200 matrix
- It is very complicated to handle multiple scattering which is correlated among the planes: non-diagonal large matrix
- We get final parameters and errors to extrapolate to any point

## Kalman filter

- Kalman filter works as a local fitter for each step we improve information and final parameters are extracted after processing all layers. We always have 5x5 covariance matrix with 5 track parameters
- We do point by point so every step we have extra thetaMS (easier to handle as a Gaussian noise)
- We need to performed forward/backward step, extrapolation of track at long distance increase the uncertainty in extrapolation

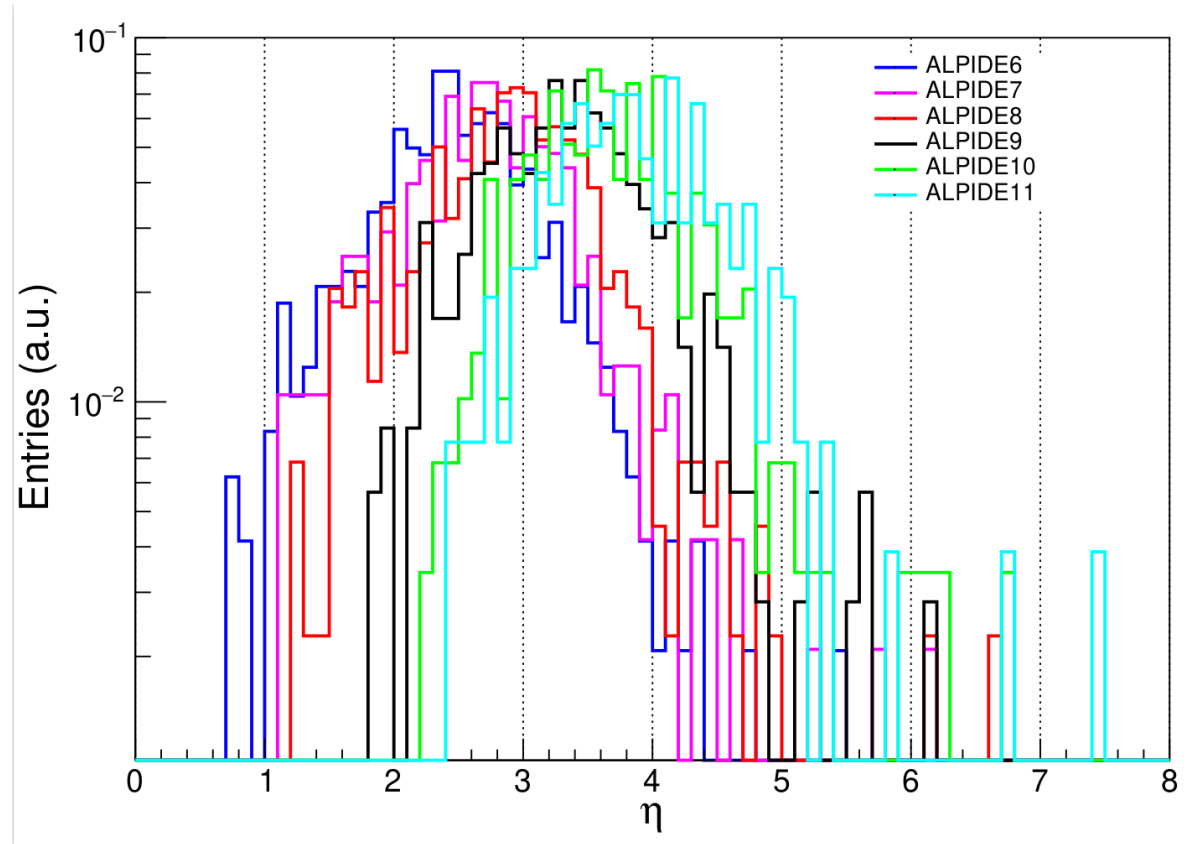
Kalman track parameters are estimated processing all layers

Global line fit (we have parameter to interpolate and extrapolate)





# Eta Maps of Hits

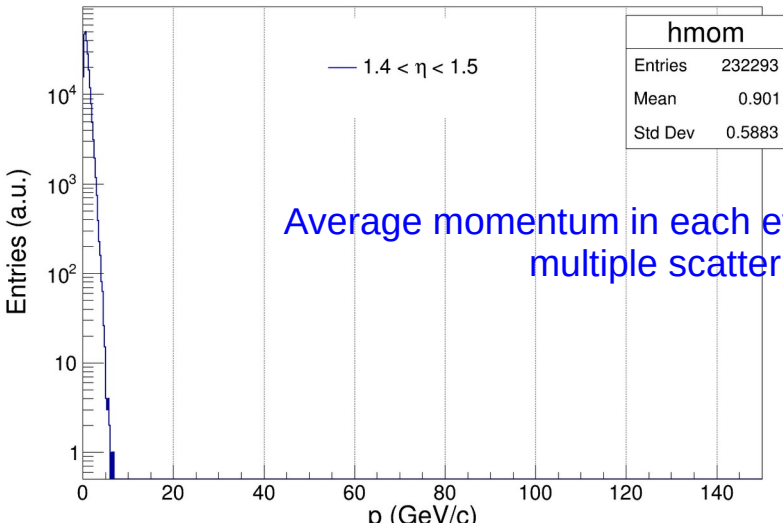


Average momentum in each eta bin is required to treat M.S. properly  
Eta maps extracted using Reconstructed Hits assuming vertex at origin

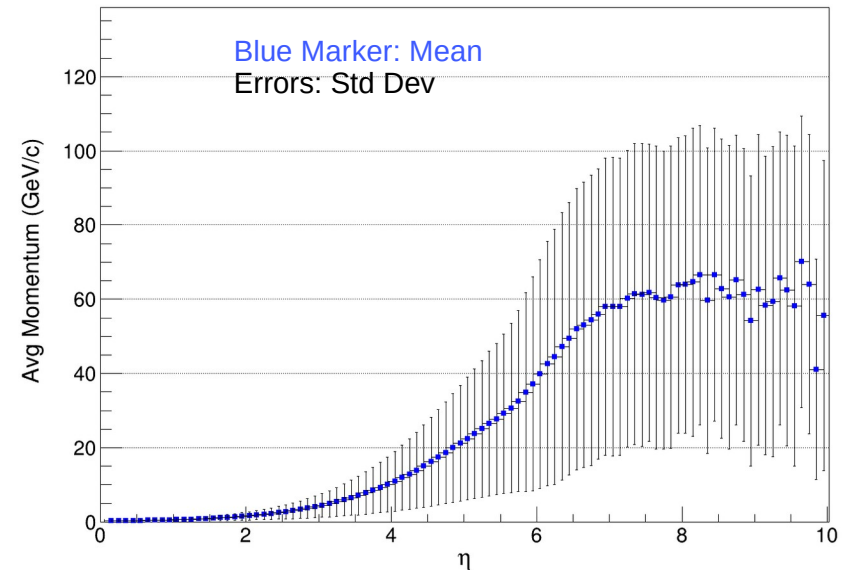
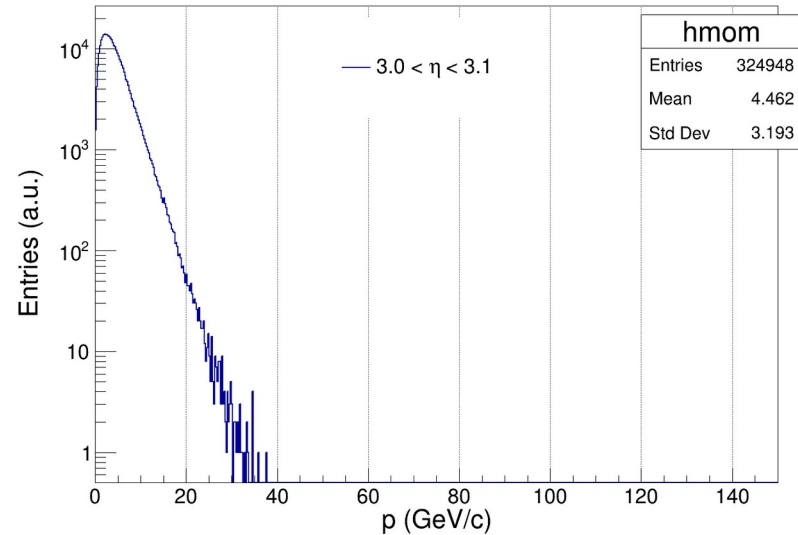
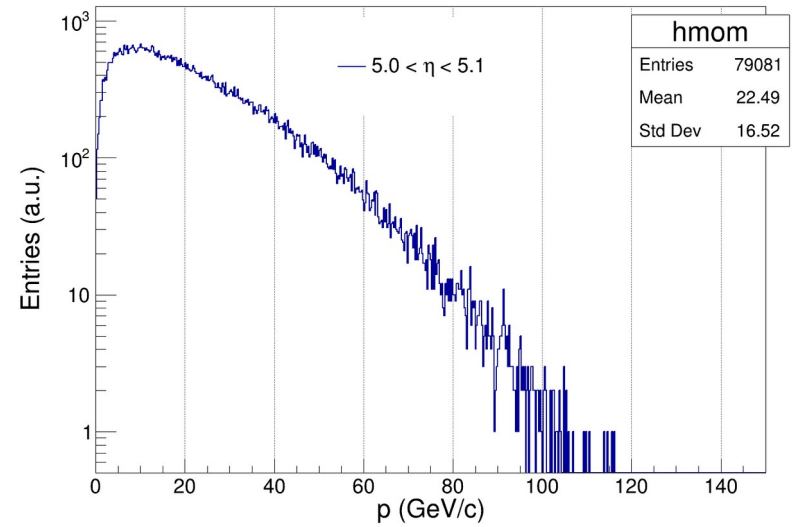
Proper treatment of M.S. requires the knowledge of average momentum in each eta bin: PYTHIA Simulation (Angantyr model)  
thanks to F. Colamaria

# PYTHIA Simulation (Angantyr model)

## 120 GeV proton on Copper Nucleus



Average momentum in each eta bin required for multiple scattering



# Track Fitting Method (ALICE)

## Tracking frame is local frame

X local is normal to the sensor

Y local is on the sensor

## Track Parameters (Local):

$$(y_l, z_l, \sin \phi, \tan \lambda, q/p_T)$$

## In this coordinate system:

- ylocal and zlocal will describes the sensor surface and uncertainties are  $\sigma(r\phi)$  and on zlocal is  $\sigma(z)$  respectively ( $x_l$  becomes radius)

```

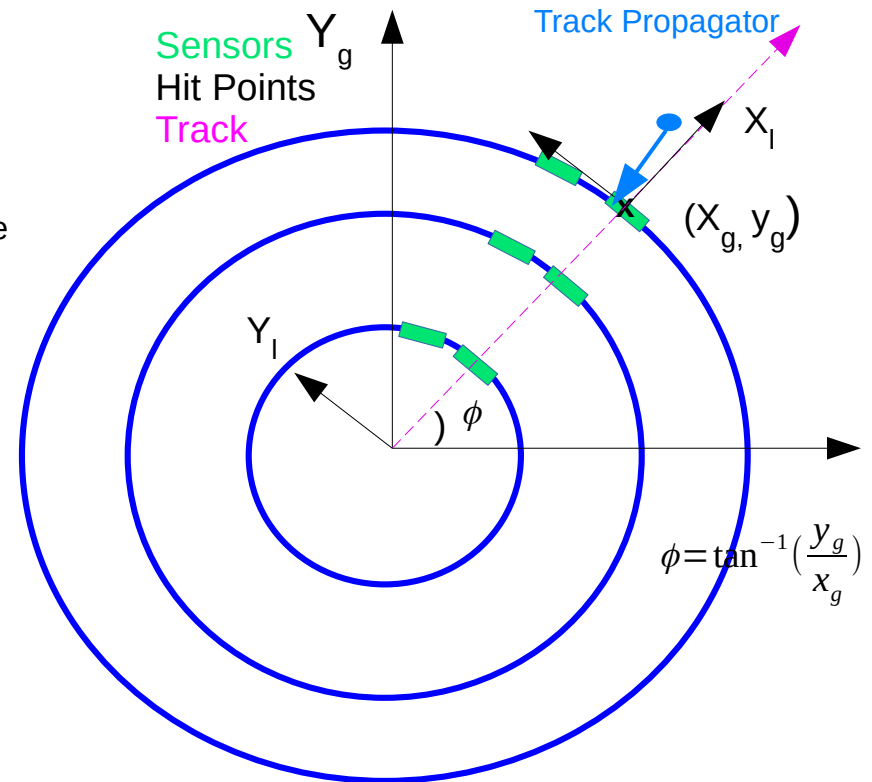
root [0] TVector2 a(2.,3.);
root [1] a.Print();
TVector2 A 2D physics vector (x,y)=(2.000000,3.000000)
(rho,phi)=(3.605551,56.309932)
root [2] TVector2 rot_a = a.Rotate(-a.Phi());
root [3] rot_a.Print()
TVector2 A 2D physics vector (x,y)=(3.605551,-0.000000)
(rho,phi)=(3.605551,360.000000)
    
```

Two things required: Extrapolation with MS and Measured Points

## Common Steps:

- ✓ Track Model initialize with the last point  $x + \text{Margin}$  (0.1)
- ✓ Convert last point to local coordinate system rotated by  $\phi$ .
- ✓ Extrapolate track to the last layer
- ✓ Rotate Track to local coordinate system
- ✓ Update extrapolation and measurement (weighted average of position and errors)
- ✓ Multiple scattering correction

Repeat above steps for each layer up to layer 0 and then extrapolate to the vertex



## Track Extrapolation

```

Bool_t PropagateTo(Double_t x, Double_t b);

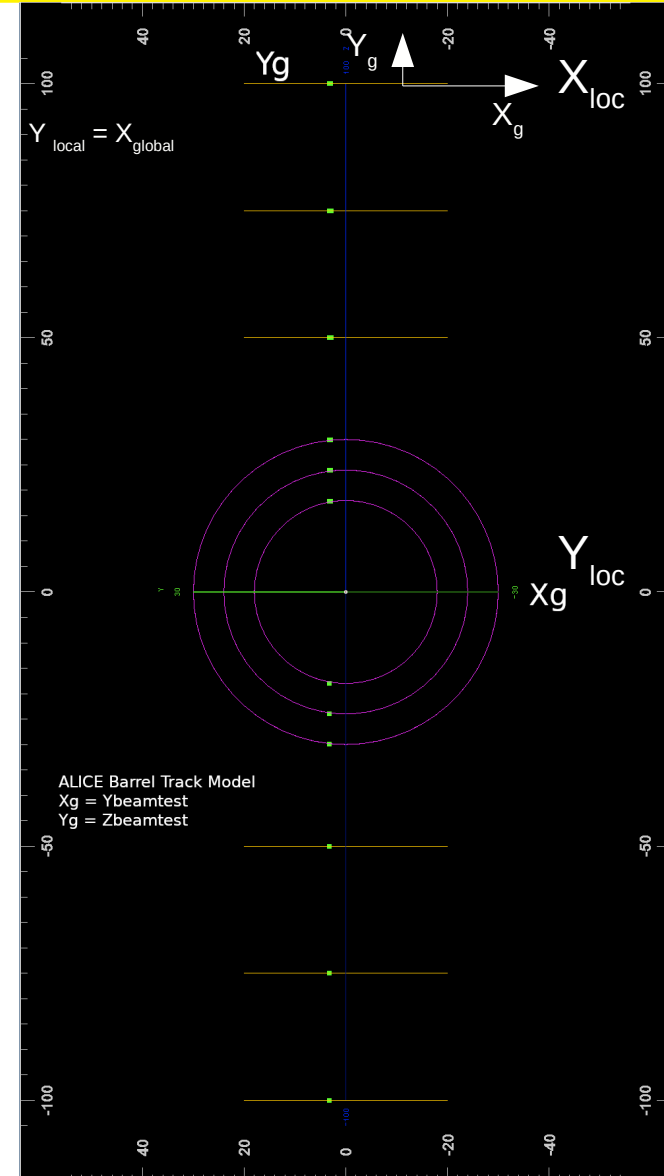
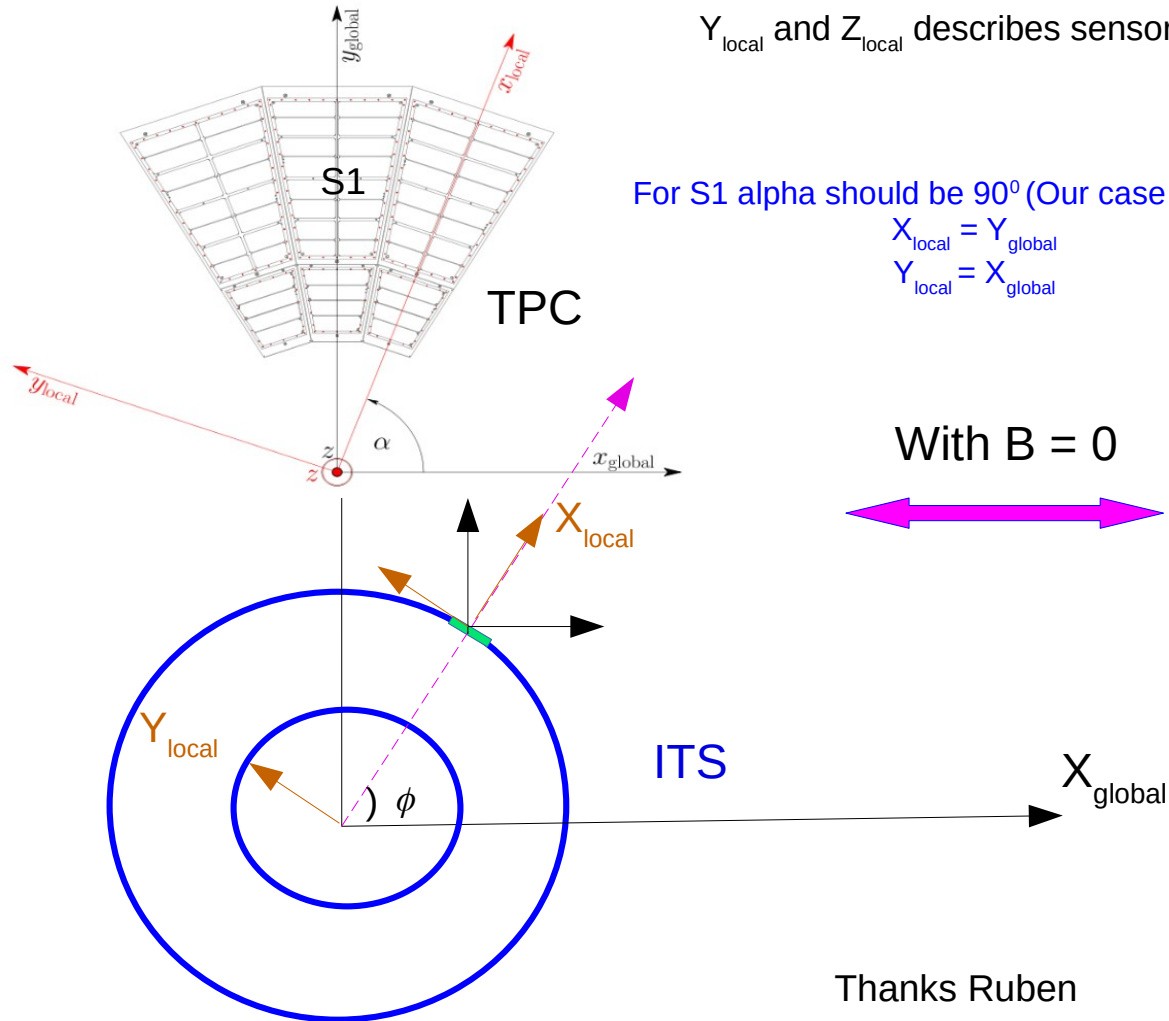
Bool_t CorrectForMeanMaterialdEdx(Double_t
xOverX0Si, Double_t 0,
Double_t mPion, Bool_t anglecorr=kTRUE);
    
```

At the vertex  $x_l = 0$  and  $y_l$  is  $DCA_{xy}$

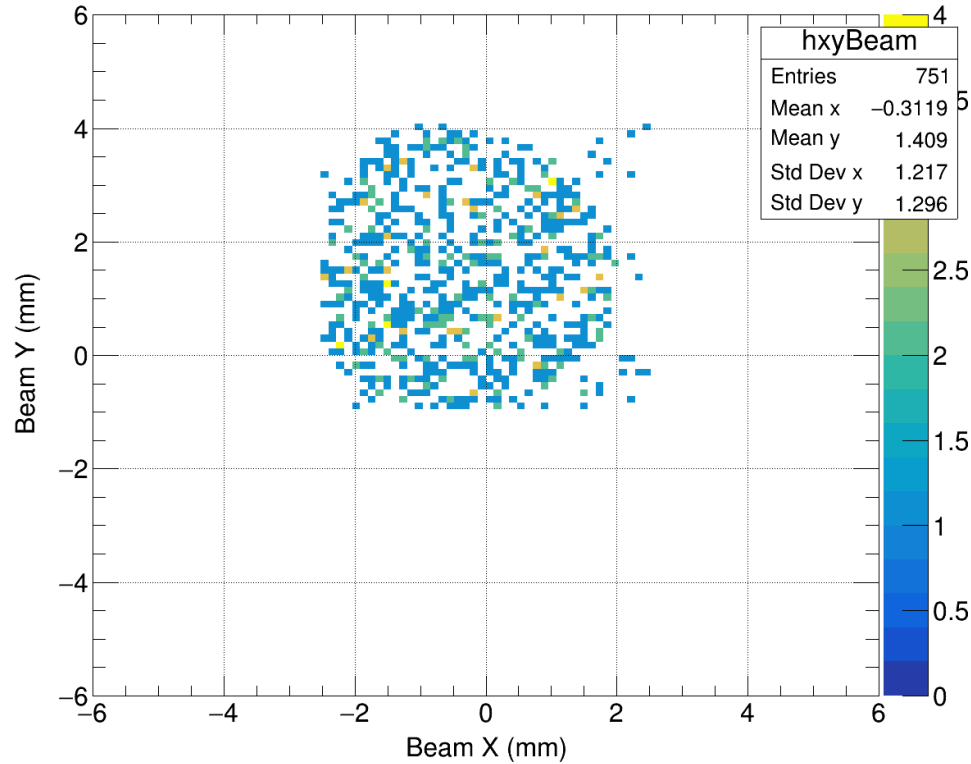
# Track Fitting (Kalman Filter)

Track Parameters (Local):  $(y_l, z_l, \sin \phi, \tan \lambda, q/p_T)$

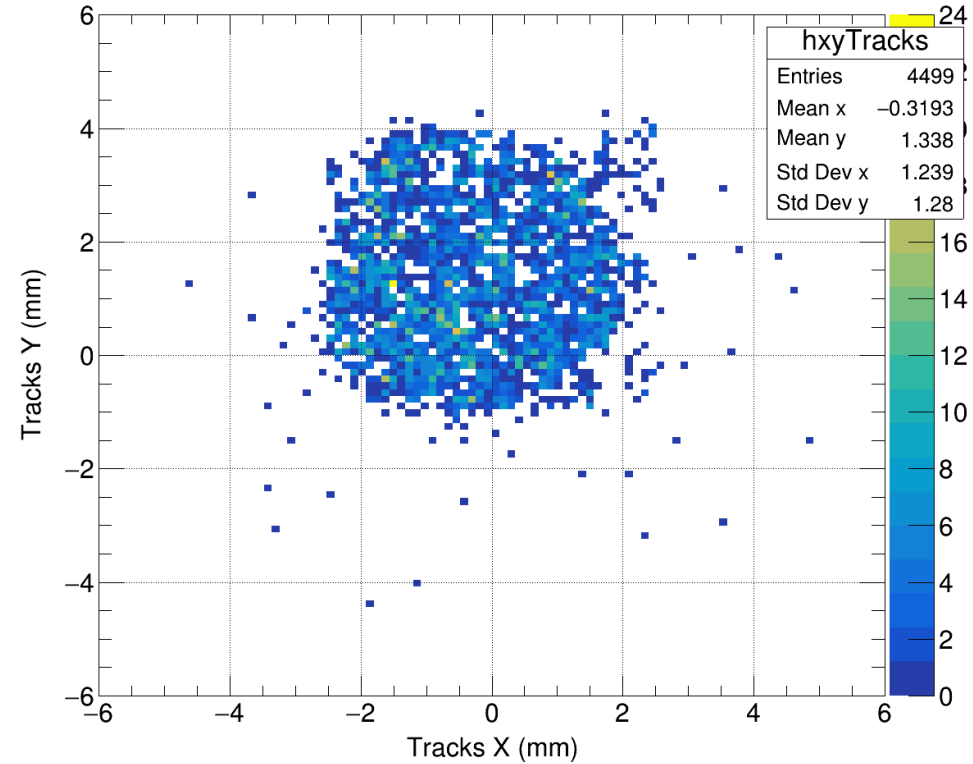
TPC single sector is a planar detector



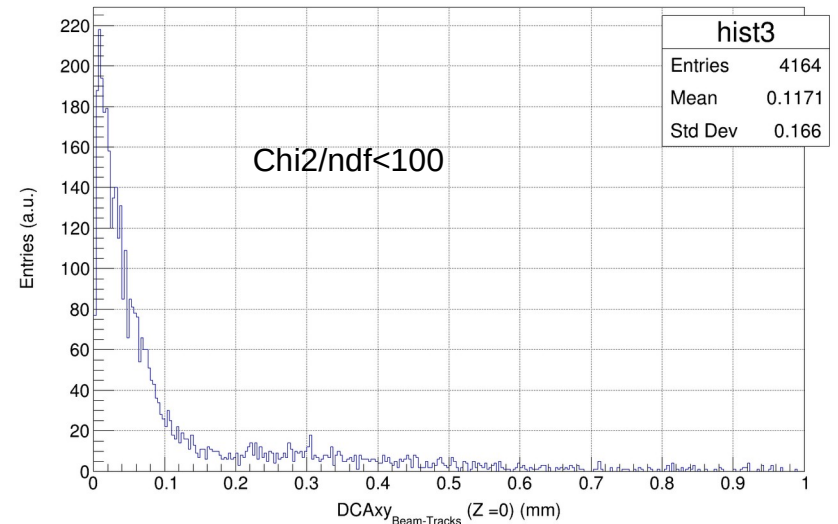
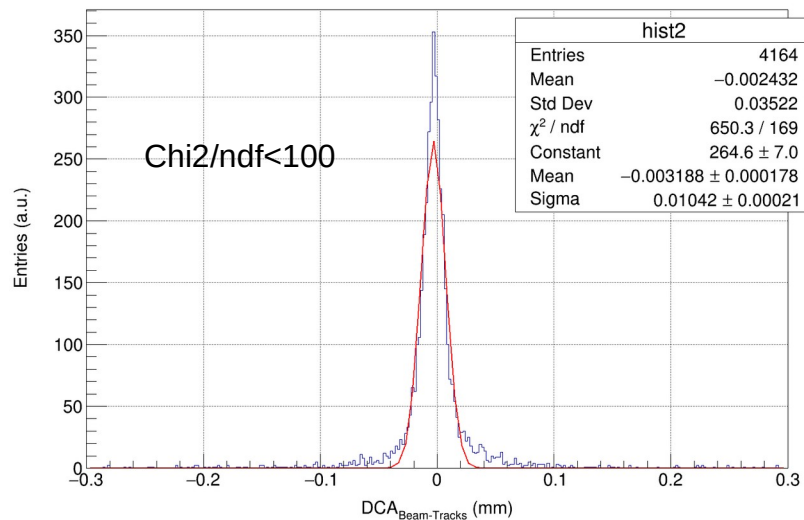
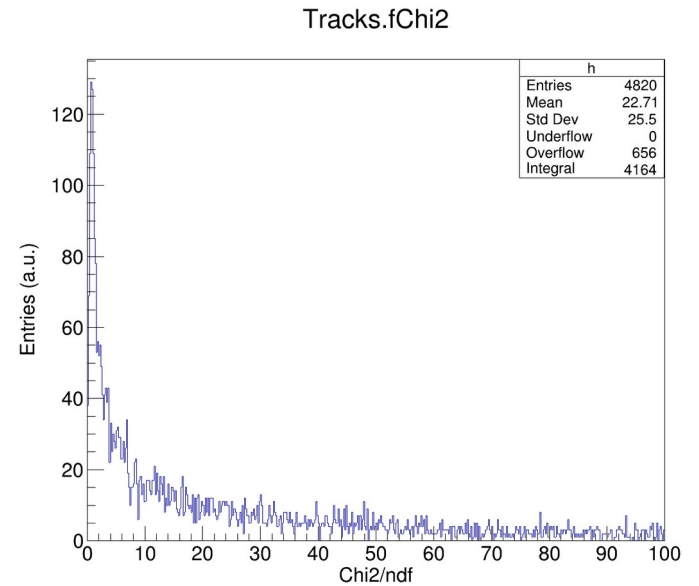
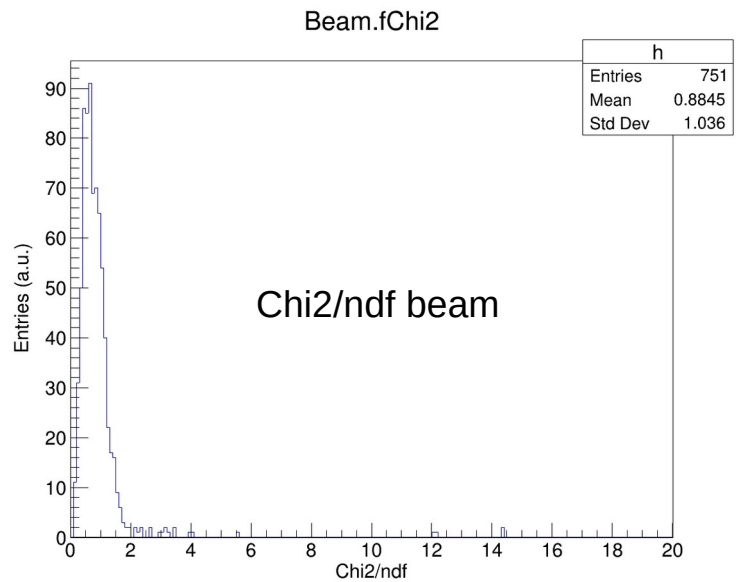
## Extrapolation of Beam at origin



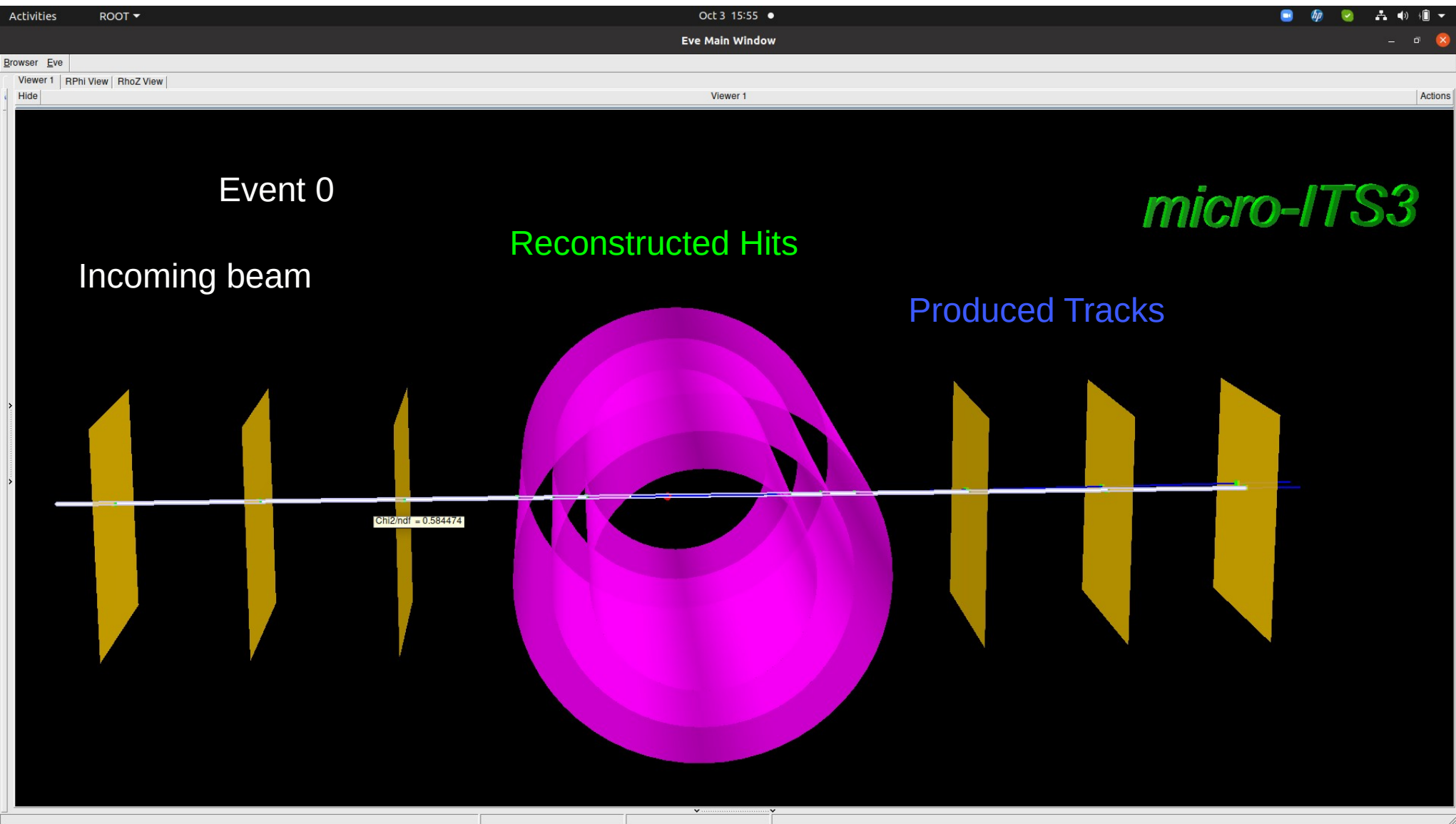
## Extrapolation of Tracks at origin



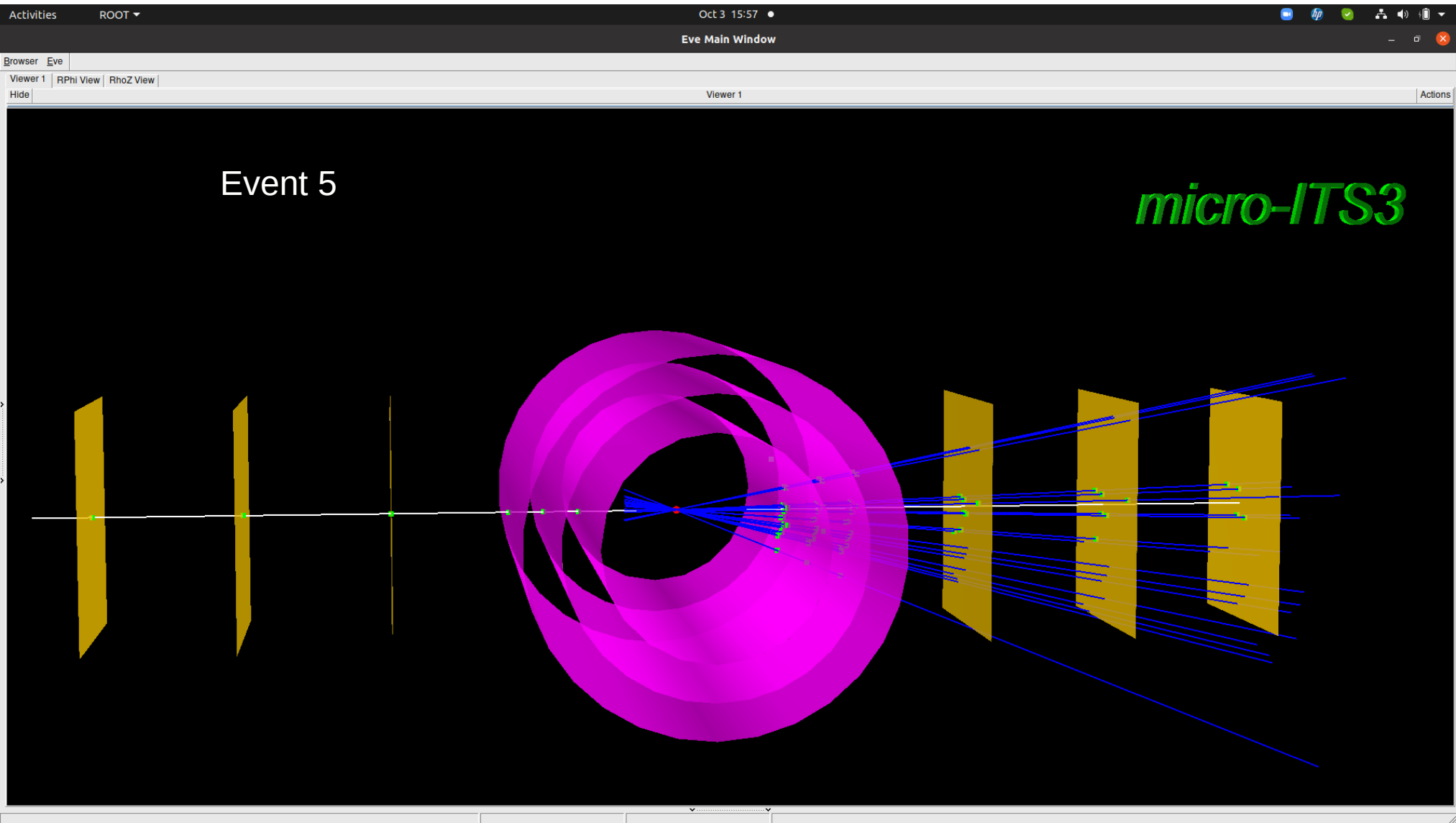
# Track Fitting Results (Global Chi2 Fitting)



# Event display



# Event display





# Definition of Chi2 (Kalman filter)

$$\chi^2 = (Y_{meas} - Y_{fit})^T W^{-1} (Y_{meas} - Y_{fit})$$

If  $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$  then

👉  $A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$

fP: filtered value of track  
p: measurement

In our case

$$\chi^2 = (fP[0] - p[0], fP[1] - p[1]) \begin{pmatrix} s_{dd} & s_{dz} \\ s_{dz} & s_{zz} \end{pmatrix}^{-1} \begin{pmatrix} fP[0] - p[0] \\ fP[1] - p[1] \end{pmatrix}$$

```
Double_t
AliExternalTrackParam::GetPredictedChi2(const Double_t p[2], const Double_t cov[3]) const {
//-----
// Estimate the chi2 of the space point "p" with the cov. matrix "cov"
//-----
Double_t sdd = fC[0] + cov[0];
Double_t sdz = fC[1] + cov[1];
Double_t szz = fC[2] + cov[2];
Double_t det = sdd*szz - sdz*sdz;

if (TMath::Abs(det) < kAlmost0) return kVeryBig;

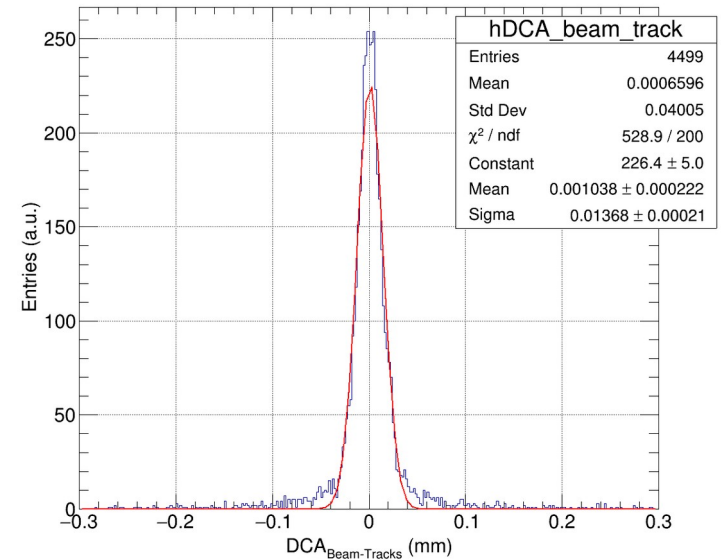
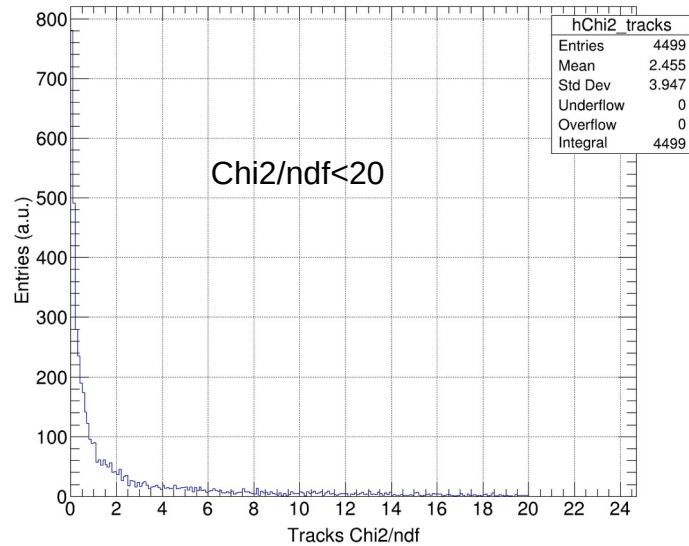
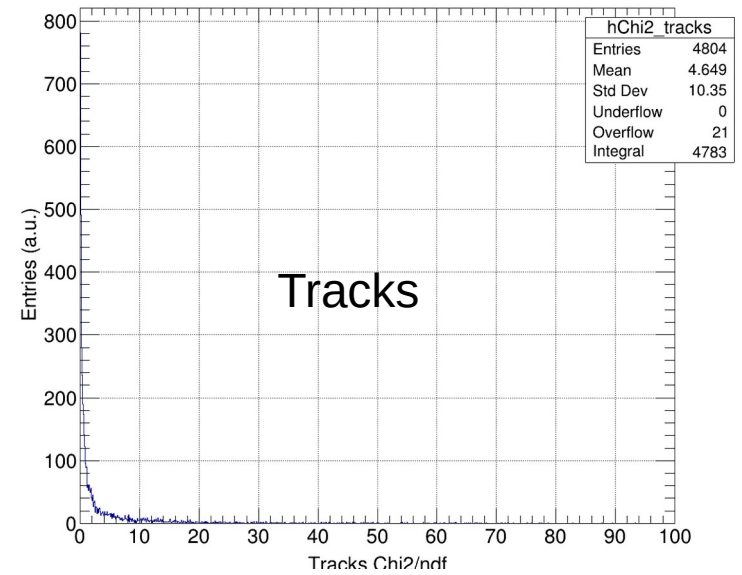
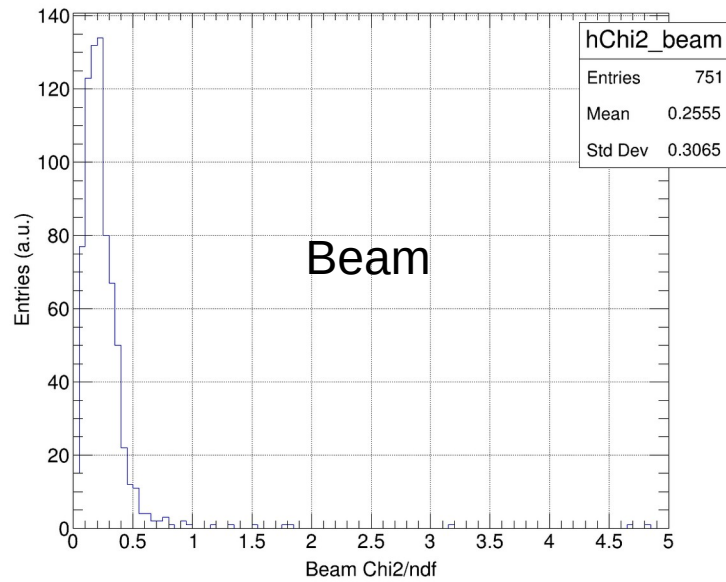
Double_t d = fP[0] - p[0];
Double_t z = fP[1] - p[1];

return (d*szz*d - 2*d*sdz*z + z*sdd*z)/det;
}
```

$$\chi^2 = (d, z) \frac{1}{s_{dd} * s_{zz} - s_{dz} * s_{dz}} \begin{pmatrix} s_{zz} & -s_{dz} \\ -s_{dz} & s_{dd} \end{pmatrix} \begin{pmatrix} d \\ z \end{pmatrix}$$

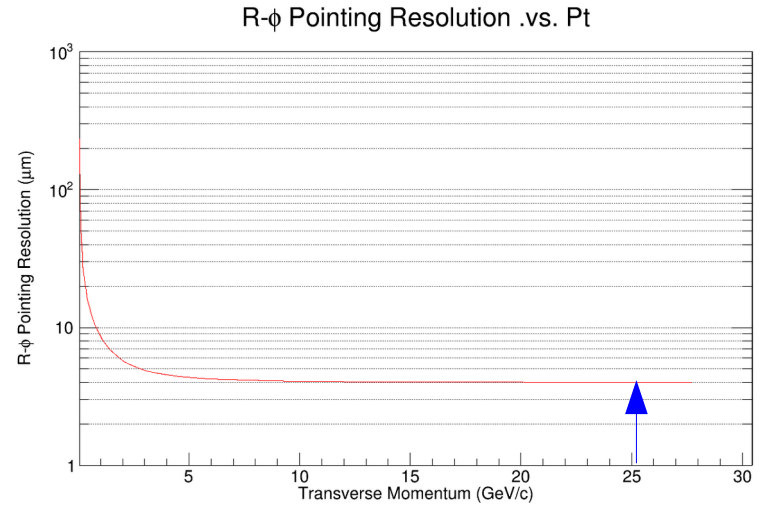
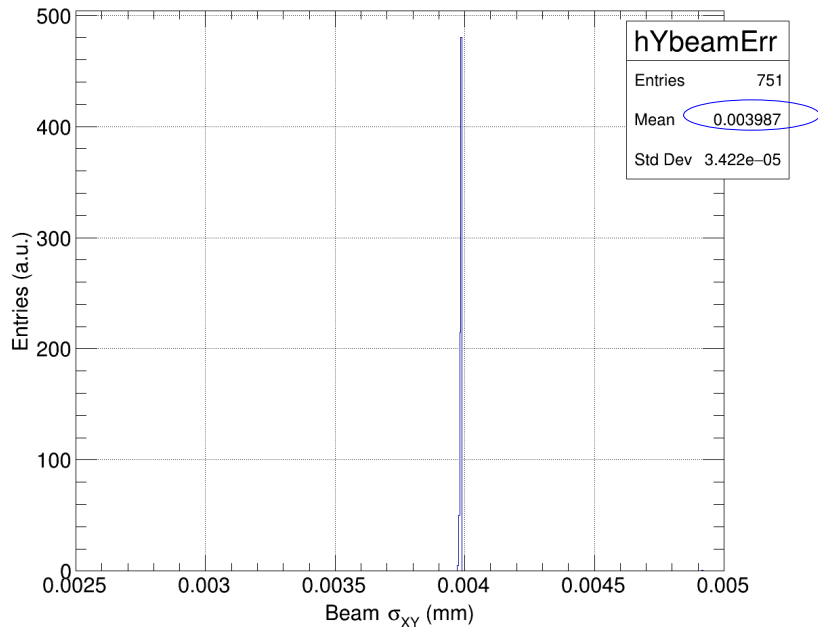
Ndf: 2 (number of points)-4

# Track Fitting Results (Kalman Filter)



# Fast Simulation (Expected DCAxy)

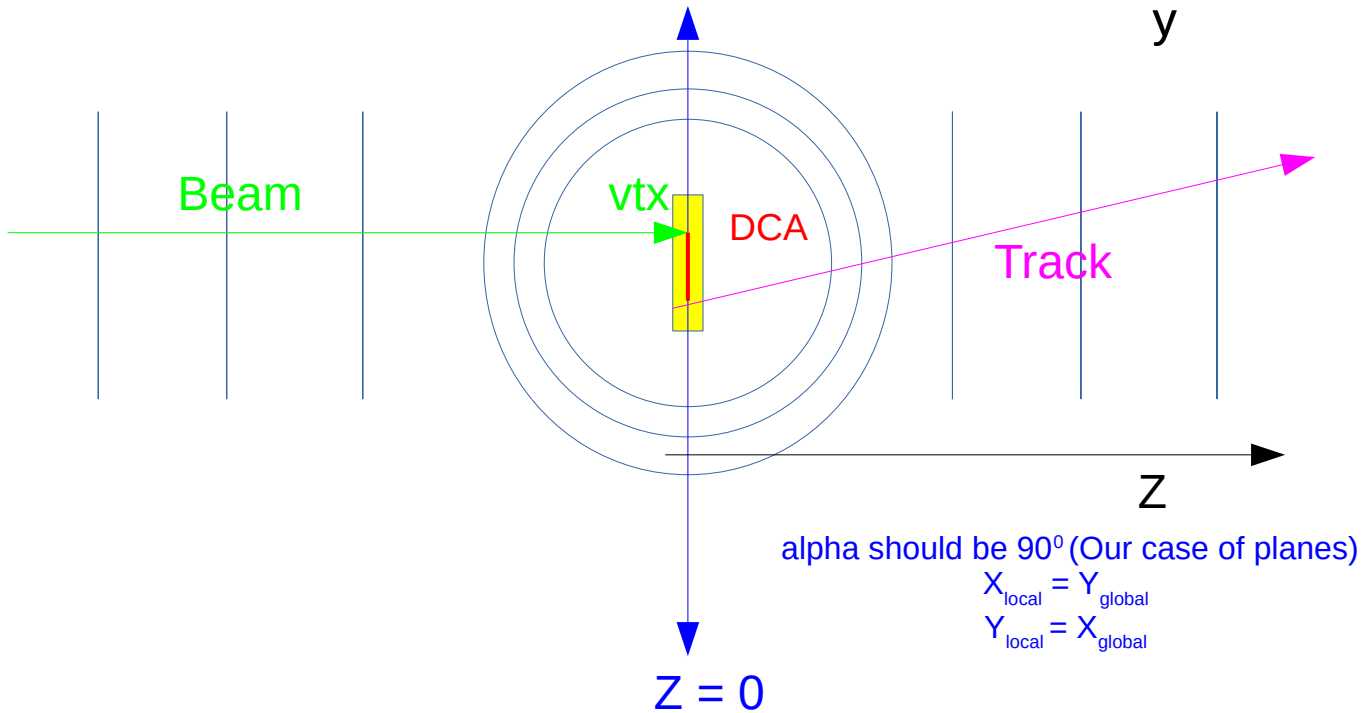
```
Detector BeamTest: "Detector"
Name      r [cm]      X0      phi & z res [um] layerEff
0. vertex  0.00      0.0000  -      -      -
1. VTX0    1.80      0.0005  5      5      1.00
2. VTX1    2.40      0.0005  5      5      1.00
3. VTX2    3.00      0.0005  5      5      1.00
4. VTX3    5.00      0.0005  5      5      1.00
5. VTX4    7.50      0.0005  5      5      1.00
6. VTX5    10.00     0.0005  5      5      1.00
```



It comes 5  $\mu\text{m}$  if we use equal distance

➤ Extrapolation of beam at the origin and error on DCAxy is compatible with fast simulation ( $\sim 4 \mu\text{m}$ )

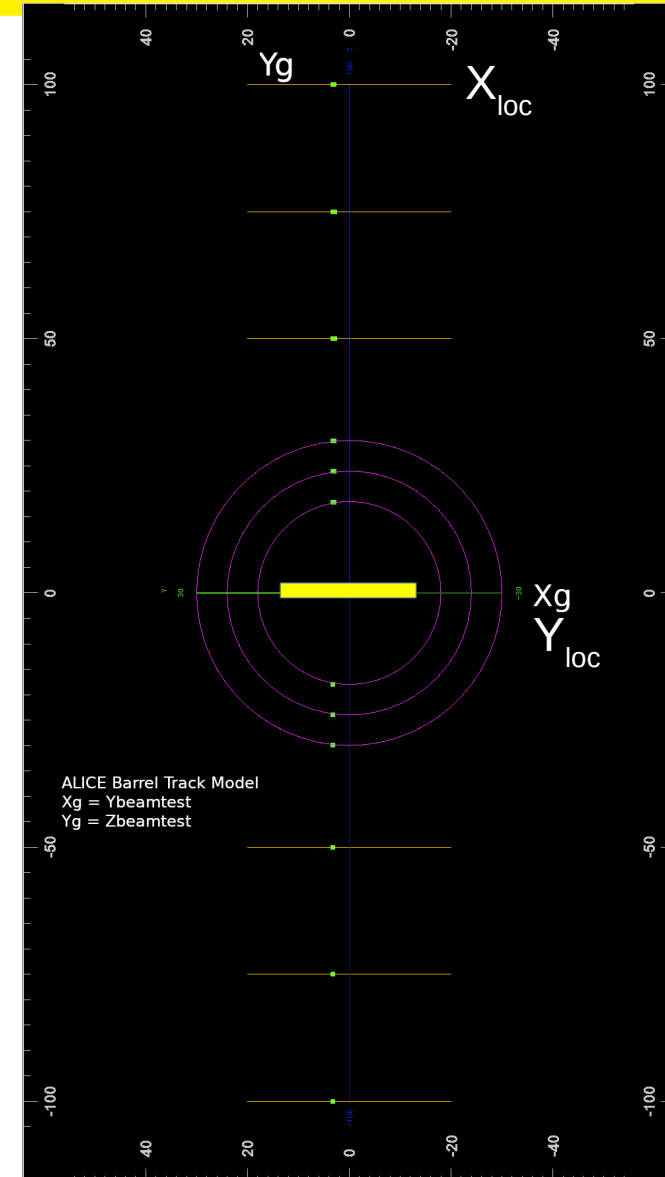
# Track Fitting Results (Kalman Filter)



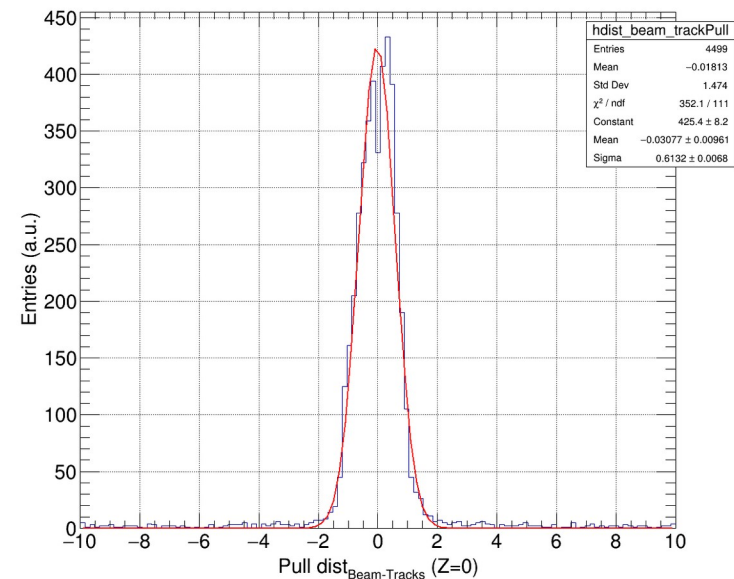
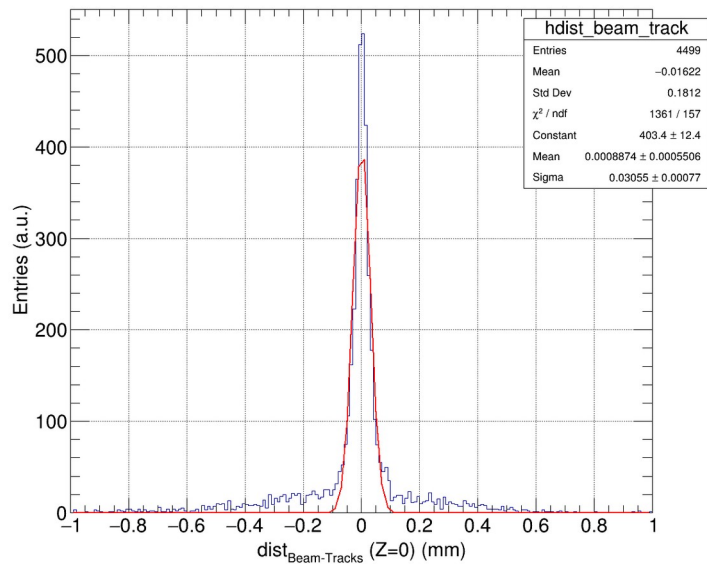
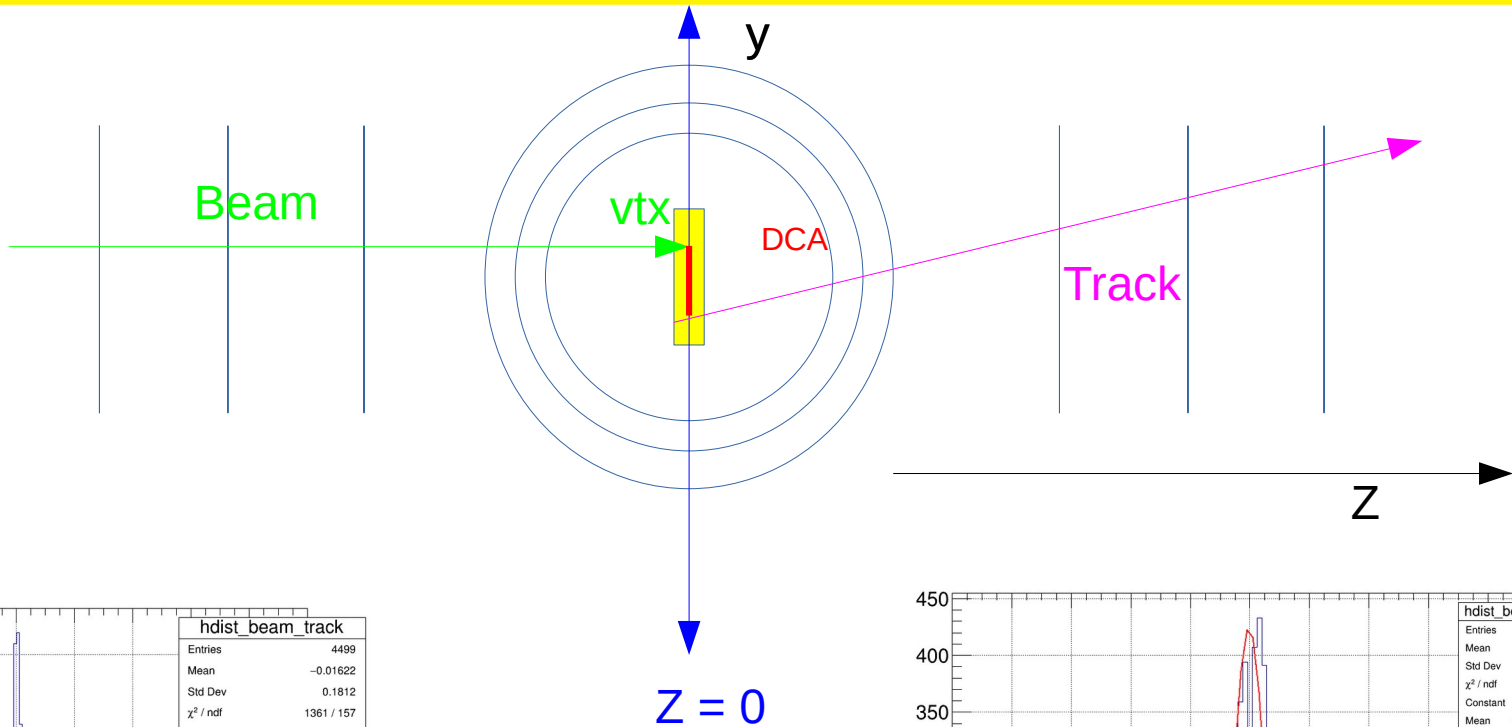
```

Bool_t AliExternalTrackParam::PropagateToDCA(const AliVVertex *vtx,
Double_t b, Double_t maxd, Double_t dz[2], Double_t covar[3]) {
//
// Propagate this track to the DCA to vertex "vtx",
// if the (rough) transverse impact parameter is not bigger then "maxd".
// Magnetic field is "b" (kG).
//
// a) The track gets extapolated to the DCA to the vertex.
// b) The impact parameters and their covariance matrix are calculated.
//
// In the case of success, the returned value is kTRUE
// (otherwise, it's kFALSE)
//

```

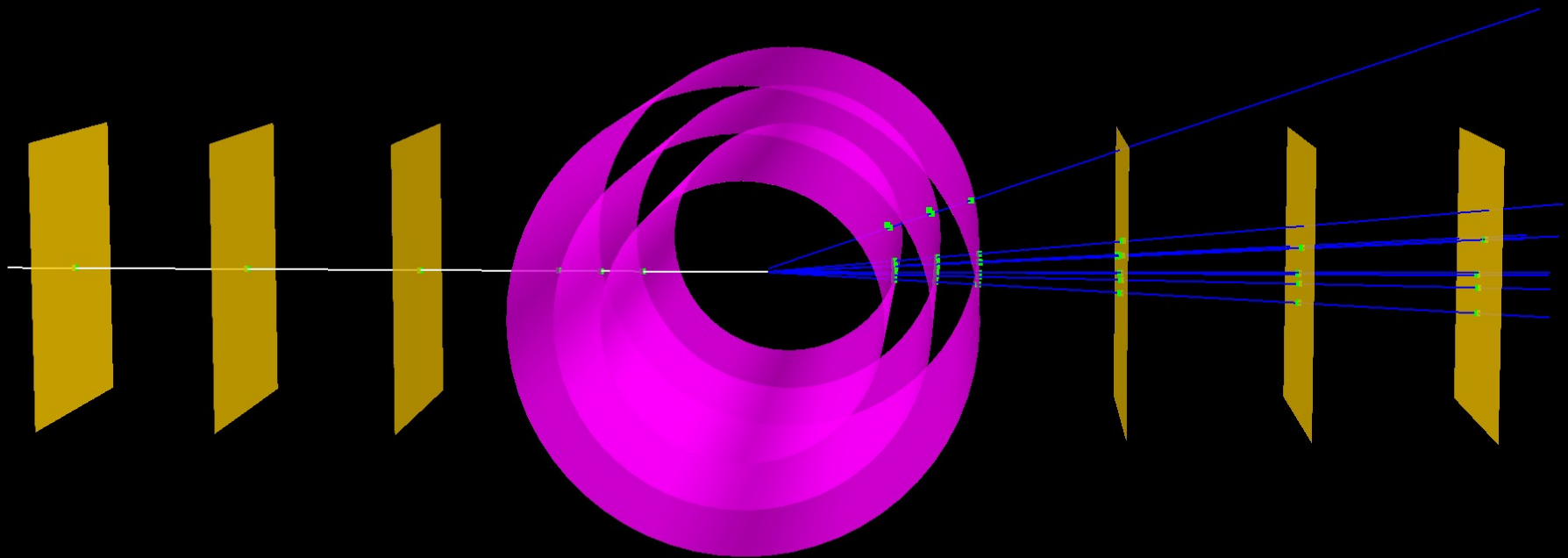


# Track Fitting Results (Kalman Filter)



Event display

*mu-ITS3*



## Summary & Future Plan

- Track finding is fixed and working fine.
- Track fitting is done using Global Chi2 fitting and Kalman filter method
- DCA between beam and tracks are evaluated using two methods
- Distance between beam and tracks and also pull distribution evaluated at  $z = 0$  and will visualize in event display

# Track Fitting (Global Chi2 Minimization)

## Detector Simulation:

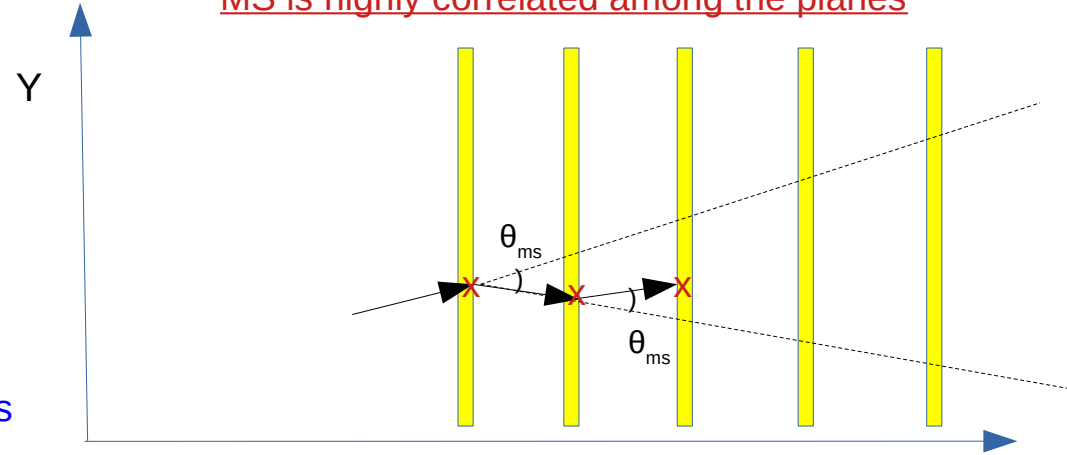
**Simulation:** Red Points we get during detector simulation considering energy loss effect and multiple scattering

**Digitization:** Smear these red point by pixel resolution (spatial resolution)

**Reconstruction:** Fit the point after digitization

In Beam test data, the points already include energy loss effect, multiple scattering, and spatial resolution

MS is highly correlated among the planes



Multiple scattering is highly correlated among the planes (Covariance matrix is non-diagonal)

Evaluate Residual (R) and Full covariance matrix for proper treatment of multiple scattering in the fit

$$\chi^2 = R^T W^{-1} R$$



# Fitting Tracks with Straight Lines (Chi2 Minimization)

Let's understand lines in 3D for fitting them

Vector equation of a line in 3D:

$$\vec{r} = \vec{r}_0 + \vec{a}$$

If  $u$  is the unit vector along the line and  $t$  is parameter:

$$\vec{r} = \vec{r}_0 + t\vec{u}$$

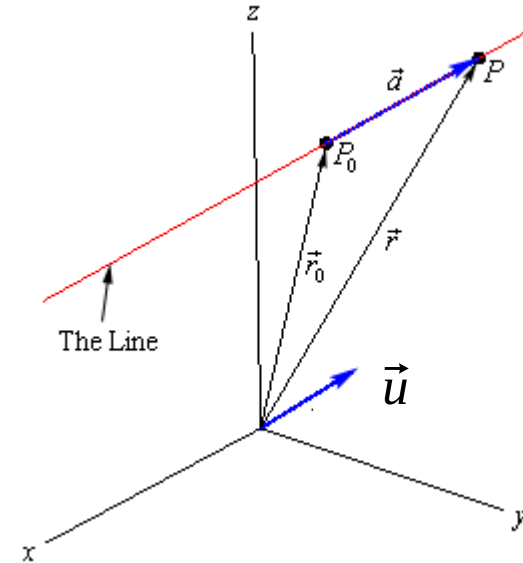
$$(x, y, z) = (x_0, y_0, z_0) + t(a, b, c)$$

$$x = x_0 + ta$$

$$y = y_0 + tb$$

$$z = z_0 + tc$$

$$t = \frac{(x - x_0)}{a} = \frac{(y - y_0)}{b} = \frac{(z - z_0)}{c}$$



To define a line in 3D, we should know a point  $(x_0, y_0, z_0)$  on the line and unit vector  $(a, b, c)$  in the direction of line  
Therefore 6 parameters to minimize!!!

<https://tutorial.math.lamar.edu/classes/calciiii/eqnsoline.aspx>

# Fitting Lines in 3D (General)

General line in 3D with 6 parameters:

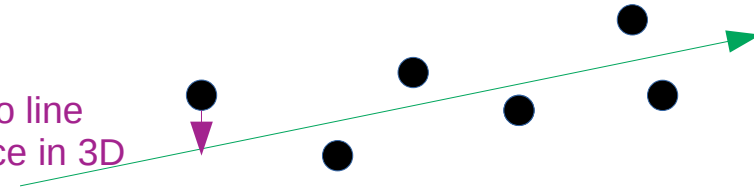
$$x = p_0 + t p_1$$

$$y = p_2 + t p_3$$

$$z = p_4 + t p_5$$

We have given hit points  $(x_0, y_0, z_0), (x_1, y_1, z_1), \dots$   
Minimize of Chi2 to best estimate the parameters

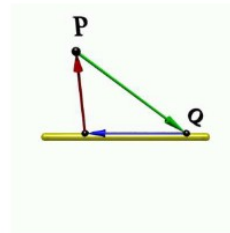
Point to line  
distance in 3D



DISTANCE POINT-LINE (3D). If  $P$  is a point in space and  $L$  is the line  $\vec{r}(t) = Q + t\vec{u}$ , then

$$d(P, L) = \frac{|(\vec{PQ}) \times \vec{u}|}{|\vec{u}|}$$

is the distance between  $P$  and the line  $L$ . Proof: the area divided by base length is height of parallelogram.



Here we are minimizing distance  
correspond to a general point

```
// define the parametric line equation
void line(double t, const double *p, double &x, double &y, double &z) {
    // a parametric line is define from 6 parameters but 4 are independent
    // x0,y0,z0,z1,y1,z1 which are the coordinates of two points on the line
    x = p[0] + p[1]*t;
    y = p[2] + p[3]*t;
    z = p[4] + p[5]*t;
}
// where ux is direction of line and x0 is a point in the line (like t = 0)
XYZVector xp(x,y,z);
XYZVector x0(p[0], p[2], p[4])
// distance line point is D= | (xp-x0) cross ux |
```

<https://github.com/Simple-Shyam/Phd-work/blob/master/HFPPT/distance.pdf>  
[https://root.cern.ch/doc/master/line3Dfit\\_8C.html](https://root.cern.ch/doc/master/line3Dfit_8C.html)

# ALPIDE Layers (See Geometry)

**ALPIDE Planes:** For Planes

$$\chi^2 = \frac{dx^2}{\sigma_x^2} + \frac{dy^2}{\sigma_y^2}$$

$$\sigma_x = \sigma_y = 5 \mu m$$

**ALPIDE Cylindrical:**

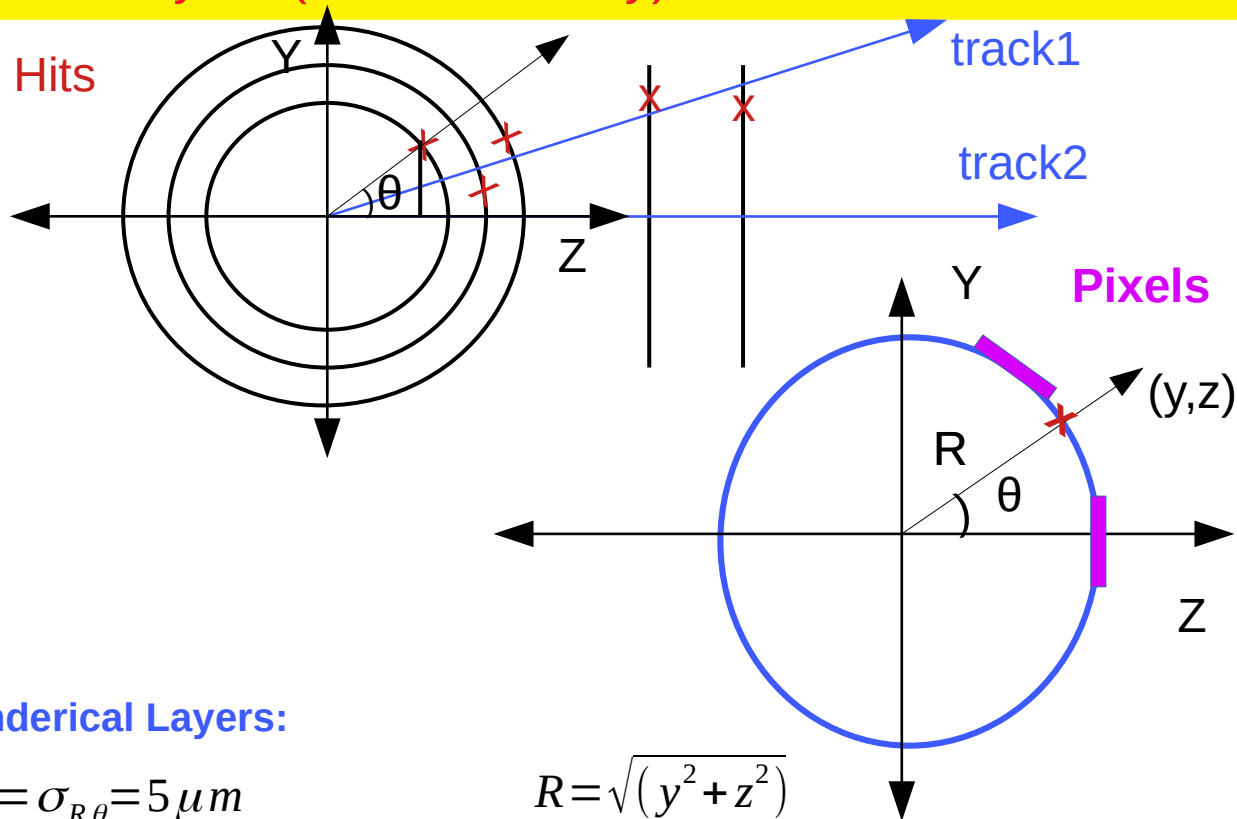
$\sigma_x$  will be the same

$$\chi^2 = \frac{dx^2}{\sigma_x^2} + \frac{dy^2}{\sigma_y^2}$$

$$\theta = \tan^{-1} \left( \frac{y}{z} \right)$$

$$\sigma_y' = \sigma_{R\theta} \cos \theta$$

Sensor frame will be helpful



**For Cylindrical Layers:**

$$\sigma_x = \sigma_{R\theta} = 5 \mu m$$

$$R = \sqrt{(y^2 + z^2)}$$

$$z = R \cos \theta$$

$$y = R \sin \theta$$

$$dy = R \cos \theta d\theta$$

$$dy = R \cos \theta d\theta = d(R\theta) \cos \theta$$

# Straight Line Fit (With Multiple Scattering)

$$y = a + bz$$

If points on planes are uncorrelated

Minimize the quantity below (works for Spatial resolutions):

$$\chi^2 = \sum_{i=0}^N \frac{(y_m - y_i)^2}{\sigma_i^2} = \sum_{i=0}^N \frac{(y_m - a - bz_i)^2}{\sigma_i^2}$$

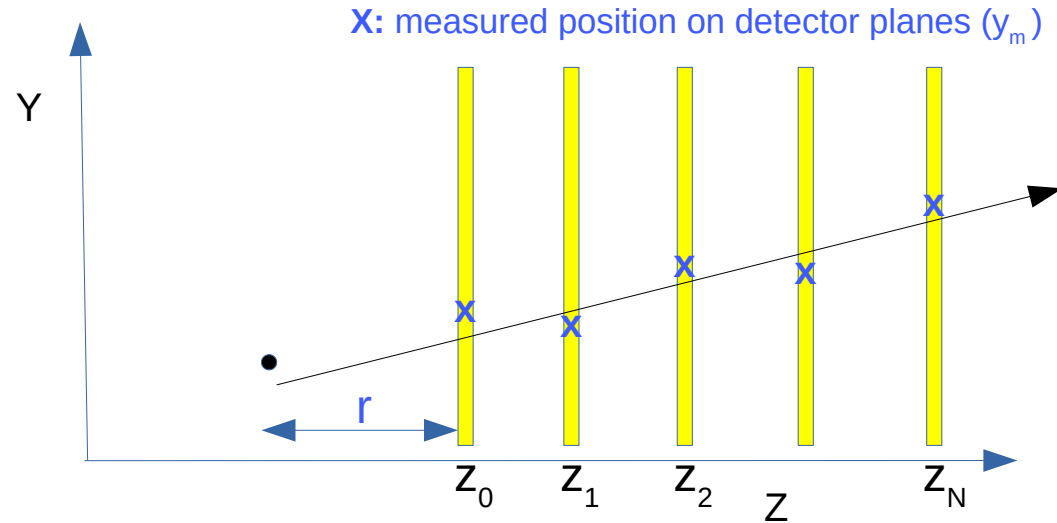
Multiple Scattering between planes are highly correlated, then quantity to be Minimized:

$$\chi^2 = \sum_{i,j=0}^N \frac{(y_{m_i} - y_i)(y_{m_j} - y_j)}{\sigma_{ij}}$$

For 100 points:

100x100 matrix difficult to Inverse (Chi2 fitting)

For Kalman filter 100 matrix of 5x5 dimensions



$$\chi^2 = (Y - Ap)^T (V_{SR} + V_{MS})^{-1} (Y - Ap)$$

$$V_{SR} = \begin{pmatrix} \sigma_0^2 & \dots & \dots & \dots & \dots \\ 0 & \sigma_1^2 & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \sigma_N^2 & \dots \end{pmatrix} \quad V_{MS} = \begin{pmatrix} 0 & \sigma_{01\dots} \\ 0 & \sigma_1^2 \dots \\ \dots & \dots \\ 0 & 0 \dots \sigma_N^2 \end{pmatrix}$$

MS matrix is non-diagonal

# Local Coordinate ALICE

Tracking frame is Sensor local frame

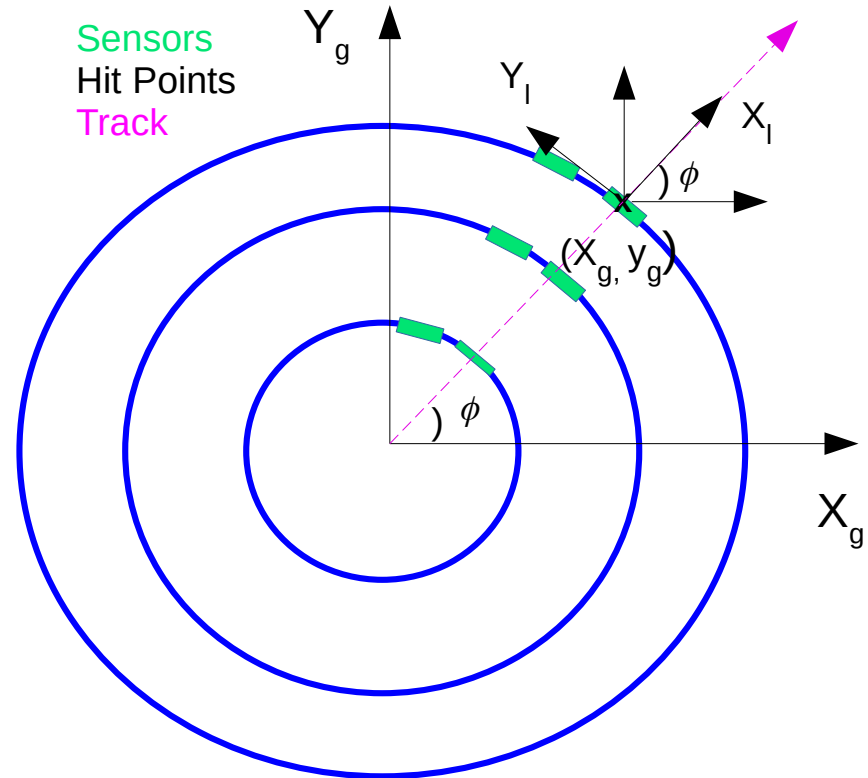
X local is normal to the sensor

Y local is on the sensor

In this coordinate system: ylocal and zlocal will describes the sensor

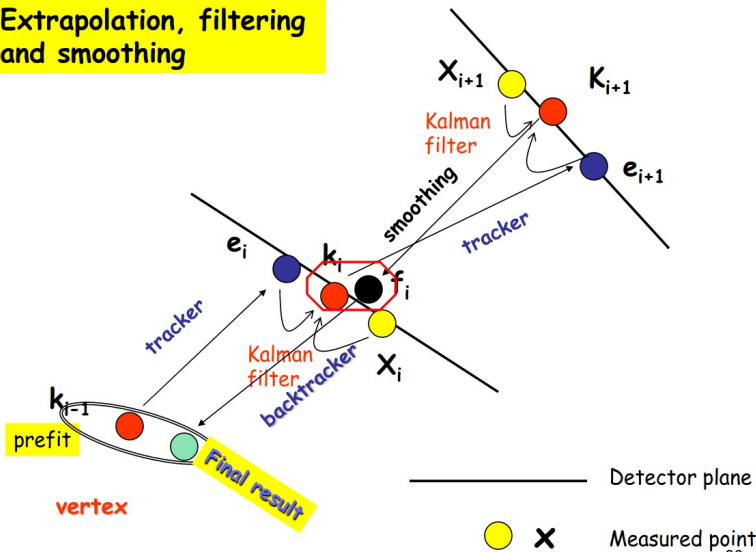
Uncertainties in ylocal is  $\sigma(r\phi)$  and on zlocal is  $\sigma(z)$   
 $x_1$  is describing the radius

$$\phi = \tan^{-1}\left(\frac{y_g}{x_g}\right)$$



Track Parameters (Local):  $(y_l, z_l, \sin \phi, \tan \lambda, q/p_T)$

Extrapolation, filtering and smoothing



Kalman Filter Method:

1. **Extrapolation:** Extrapolation ( $e_i$ ) on the next plane with M.S. effect
2. **Filtering:** Weighted average of extrapolated value ( $e_i$ ) and measured value ( $x_i$ ), known as Kalman filtered value ( $k_i$ )
3. **Smoothing:** Estimation of parameters to extrapolate

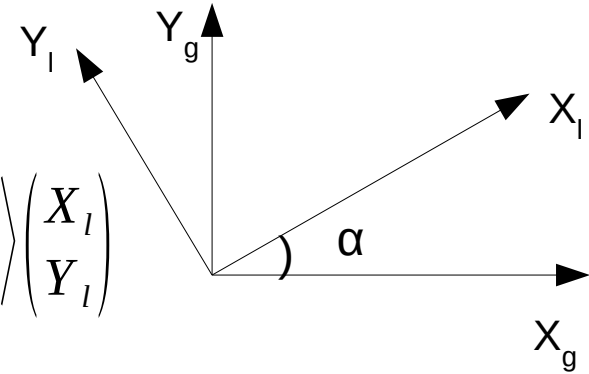
# ALICE Track Parameters

Track Parameters (Local):  $(y, z, \sin \phi, \tan \lambda, q/p_T)$

On cylindrical surface:

$$x^2 + y^2 = R^2$$

$$\begin{pmatrix} X_g \\ Y_g \end{pmatrix} = \begin{pmatrix} \cos \alpha & -\sin \alpha \\ \sin \alpha & \cos \alpha \end{pmatrix} \begin{pmatrix} X_l \\ Y_l \end{pmatrix}$$



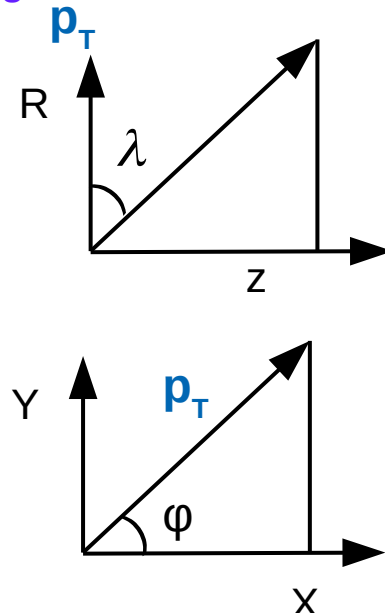
Local coordinates rotated by  $\alpha$   
w.r.t. global coordinates

$$\frac{\sigma_{1/p_t}}{(1/p_t)} = \frac{1/p_t^2 * \sigma_{p_t}}{(1/p_t)} = \frac{\sigma_{p_t}}{p_t} \quad \sigma_{DCA_{r\phi}}^2 = \sigma_y^2 \quad \sigma_{DCA_z}^2 = \sigma_z^2$$

Parameter Covariance

Track Parameters  $\begin{pmatrix} y \\ z \\ \sin \phi \\ \tan \lambda \\ 1/p_T \end{pmatrix}$

$$W = \begin{pmatrix} \sigma_y^2 & \sigma_{yz} & \sigma_{y \sin \phi} & \sigma_{y \tan \lambda} & \sigma_{y \cdot 1/p_T} \\ \sigma_{zy} & \sigma_z^2 & \sigma_{z \sin \phi} & \sigma_{z \tan \lambda} & \sigma_{z \cdot 1/p_T} \\ \sigma_{\sin \phi y} & \sigma_{\sin \phi z} & \sigma_{\sin \phi}^2 & \sigma_{\sin \phi \tan \lambda} & \sigma_{\sin \phi \cdot 1/p_T} \\ \sigma_{\tan \lambda y} & \sigma_{\tan \lambda z} & \sigma_{\tan \lambda \sin \phi} & \sigma_{\tan \lambda}^2 & \sigma_{\tan \lambda \cdot 1/p_T} \\ \sigma_{1/p_T \cdot y} & \sigma_{1/p_T \cdot z} & \sigma_{1/p_T \cdot \sin \phi} & \sigma_{1/p_T \cdot \tan \lambda} & \sigma_{1/p_T}^2 \end{pmatrix}$$



Parameter Covariance matrix = 5X5 matrix;  $5(5+1)/2 = 15$  independent entries

$$(\sigma_y^2, \sigma_{yz}, \sigma_{y \sin \phi}, \sigma_{y \tan \lambda}, \sigma_{y \cdot 1/p_T}, \sigma_z^2, \sigma_{z \sin \phi}, \sigma_{z \tan \lambda}, \sigma_{z \cdot 1/p_T}, \sigma_{\sin \phi}^2, \sigma_{\sin \phi \tan \lambda}, \sigma_{\sin \phi \cdot 1/p_T}, \sigma_{\tan \lambda}^2, \sigma_{\tan \lambda \cdot 1/p_T}, \sigma_{1/p_T}^2)$$

# Definition of Chi2

$$\chi^2 = (Y_{meas} - Y_{fit})^T W^{-1} (Y_{meas} - Y_{fit})$$

In our case

Chi2 with 5 parameters

```
Double_t
AliExternalTrackParam::GetPredictedChi2(const Double_t p[2], const Double_t cov[3]) const {
    //-----
    // Estimate the chi2 of the space point "p" with the cov. matrix "cov"
    //-----
    Double_t sdd = fC[0] + cov[0];
    Double_t sdz = fC[1] + cov[1];
    Double_t szz = fC[2] + cov[2];
    Double_t det = sdd*szz - sdz*sdz;

    if (TMath::Abs(det) < kAlmost0) return kVeryBig;

    Double_t d = fP[0] - p[0];
    Double_t z = fP[1] - p[1];

    return (d*szz*d - 2*d*sdz*z + z*sdd*z)/det;
}
```

```
TMatrixDSym c(5);
c(0,0)=GetSigmaY2();
c(1,0)=GetSigmaZY(); c(1,1)=GetSigmaZ2();
c(2,0)=GetSigmaSnPY(); c(2,1)=GetSigmaSnPZ(); c(2,2)=GetSigmaSnP2();
c(3,0)=GetSigmaTg1Y(); c(3,1)=GetSigmaTg1Z(); c(3,2)=GetSigmaTg1SnP(); c(3,3)=GetSigmaTg12();
c(4,0)=GetSigma1PtY(); c(4,1)=GetSigma1PtZ(); c(4,2)=GetSigma1PtSnP(); c(4,3)=GetSigma1PtTg1(); c(4,4)=GetSigma1Pt2();

c(0,0)+=t->GetSigmaY2();
c(1,0)+=t->GetSigmaZY(); c(1,1)+=t->GetSigmaZ2();
c(2,0)+=t->GetSigmaSnPY(); c(2,1)+=t->GetSigmaSnPZ(); c(2,2)+=t->GetSigmaSnP2();
c(3,0)+=t->GetSigmaTg1Y(); c(3,1)+=t->GetSigmaTg1Z(); c(3,2)+=t->GetSigmaTg1SnP(); c(3,3)+=t->GetSigmaTg12();
c(4,0)+=t->GetSigma1PtY(); c(4,1)+=t->GetSigma1PtZ(); c(4,2)+=t->GetSigma1PtSnP(); c(4,3)+=t->GetSigma1PtTg1(); c(4,4)+=t->GetSigma1Pt2();
c(0,1)=c(1,0);
c(0,2)=c(2,0); c(1,2)=c(2,1);
c(0,3)=c(3,0); c(1,3)=c(3,1); c(2,3)=c(3,2);
c(0,4)=c(4,0); c(1,4)=c(4,1); c(2,4)=c(4,2); c(3,4)=c(4,3);

c.Invert();
if (!c.IsValid()) return kVeryBig;

Double_t res[5] = {
    GetY() - t->GetY(),
    GetZ() - t->GetZ(),
    GetSnP() - t->GetSnP(),
    GetTg1() - t->GetTg1(),
    GetSigned1Pt() - t->GetSigned1Pt()
};

Double_t chi2=0.;
for (Int_t i = 0; i < 5; i++)
    for (Int_t j = 0; j < 5; j++) chi2 += res[i]*res[j]*c(1,j);

return chi2;
```

# Kalman Filter

$$\chi^2 = \frac{(x_p - \mu)^2}{\sigma_p^2} + \frac{(x_m - \mu)^2}{\sigma_m^2}$$

$$\frac{\partial \chi^2}{\partial \mu} = 0 \quad \text{Chi2 minimization}$$

$$\mu = \frac{\frac{x_p}{\sigma_p^2} + \frac{x_m}{\sigma_m^2}}{\frac{1}{\sigma_p^2} + \frac{1}{\sigma_m^2}} = x_p \frac{\sigma_m^2}{\sigma_p^2 + \sigma_m^2} + x_m \frac{\sigma_p^2}{\sigma_p^2 + \sigma_m^2} \quad \sigma(\mu)^2 = \frac{1}{\frac{1}{\sigma_p^2} + \frac{1}{\sigma_m^2}} = \frac{\sigma_p^2 \sigma_m^2}{\sigma_p^2 + \sigma_m^2}$$

$$\text{If } (\sigma_m \gg \sigma_p) \quad \mu \approx x_p$$

$$\text{If } (\sigma_p \gg \sigma_m) \quad \mu \approx x_m$$

$$\mu = x_m + \frac{\sigma_m^2}{\sigma_p^2 + \sigma_m^2} (x_p - x_m)$$

$$\mu = x_m + K (x_p - x_m)$$

$$\sigma(\mu)^2 = \frac{\sigma_p^2 \sigma_m^2 + \sigma_m^4 - \sigma_m^4}{\sigma_p^2 + \sigma_m^2} = \sigma_m^2 - \frac{\sigma_m^4}{\sigma_p^2 + \sigma_m^2} = \sigma_m^2 (1 - K)$$

In ALICE

$$\mu_y = \frac{y_p \sigma_m^2 + y_m \sigma_p^2}{\sigma_p^2 + \sigma_m^2}$$

$$\mu_z = \frac{z_p \sigma_m^2 + z_m \sigma_p^2}{\sigma_p^2 + \sigma_m^2}$$

$y_p, z_p$  from the track model  
 $y_m, z_m$  from the measurement

K- Kalman gain factor

Measurement is corrected by K Factor



# Track Fitting Method

Two things required: Extrapolation with MS and Measured Points

## Common Steps:

- ✓ Track Model initialize with the last point  $x + \text{Margin}$  (0.1)
- ✓ Convert last point to local coordinate system rotated by  $\phi$ .
- ✓ Extrapolate track to the last layer
- ✓ Rotate Track to local coordinate system
- ✓ Update extrapolation and measurement (weight average of position and errors)
- ✓ Multiple scattering correction

Repeat above steps for each layer up to layer 1 and then extrapolate to the vertex

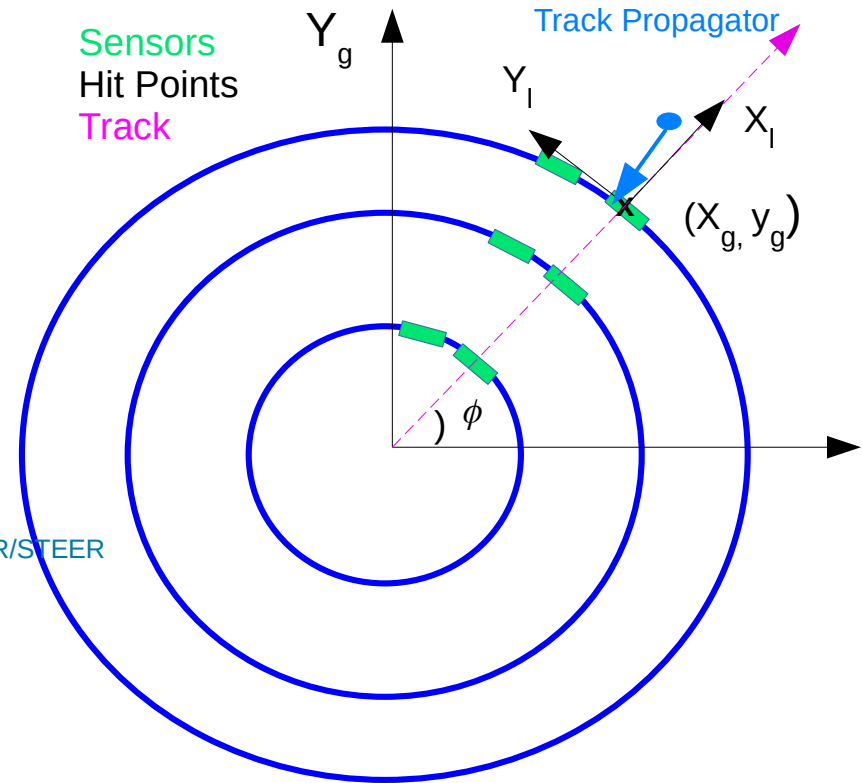
<https://github.com/alisw/AliRoot/blob/master/STEER/STEERBase/AliExternalTrackParam.h>

## Track Extrapolation

```
Bool_t PropagateTo(Double_t x, Double_t b);
```

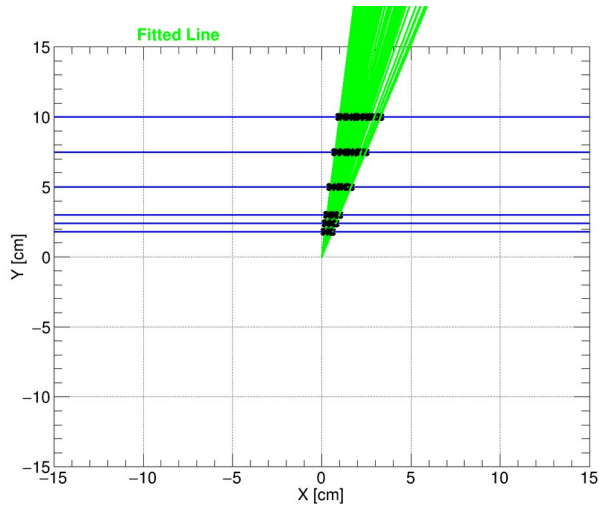
```
Bool_t CorrectForMeanMaterialdEdx(Double_t xOverX0Si, Double_t 0,  
Double_t mPion, Bool_t anglecorr=kTRUE);
```

At the vertex  $x_1 = 0$  and  $y_1$  is  $DCA_{xy}$

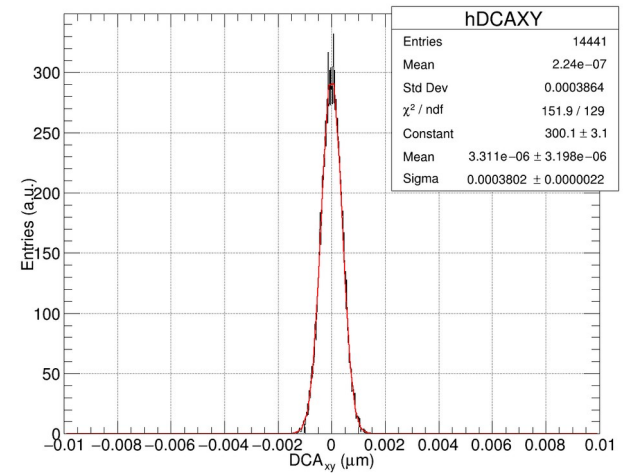
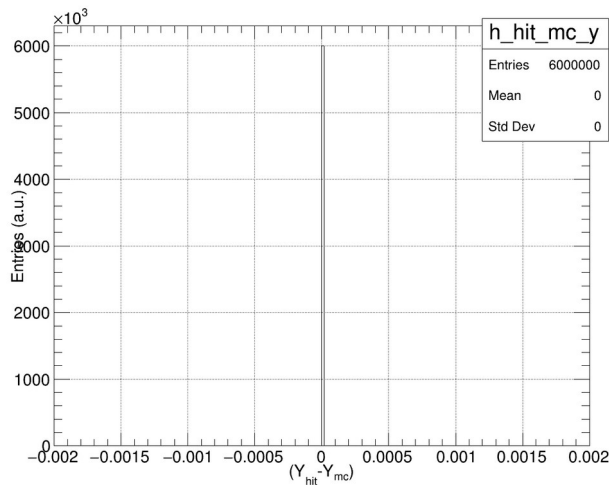
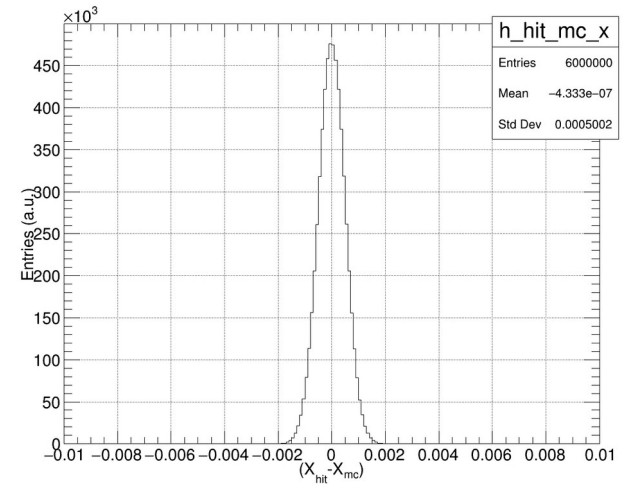


# Fast Simulation (Expected DCAxy)

## Chi2 Minimization (Ignoring Multiple Scattering)



$$y = a_0 + a_1 x$$
$$d = \frac{a_0}{\sqrt{1 + a_1^2}}$$



# Detector Simulation

**Simulation:** Red Points we get during detector simulation with energy loss and Multiple scattering

**Digitization:** Smear these red point by pixel resolution (spatial resolution)

**Reconstruction:** Fit the point after digitization

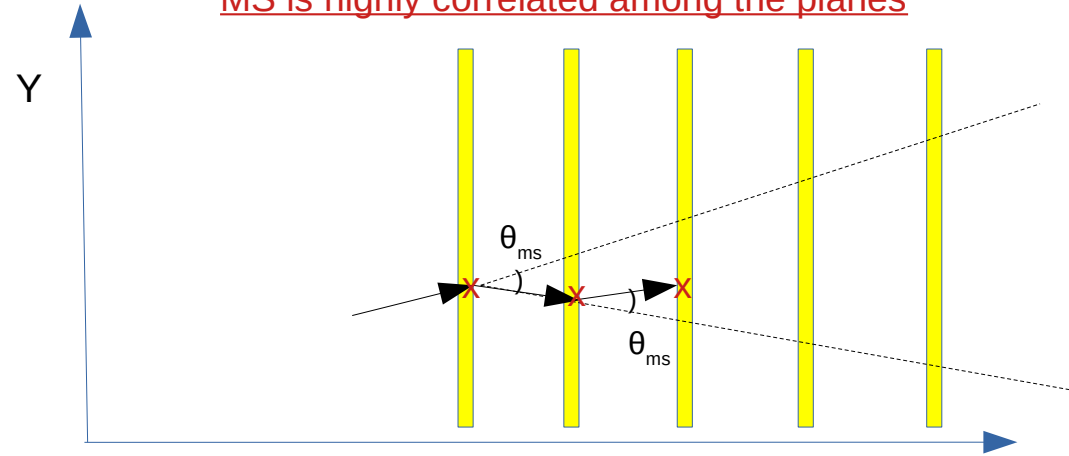
In the Beam test data, the point are already include above effects so we can directly fit the points

arXiv:1805.12014 [physics.ins-det]

Matrix by Werner Reigler (equal spacing)

$$C_y = M = \frac{\sigma_\alpha^2 L^2}{N^2} \begin{pmatrix} \frac{N^2 \sigma_0^2}{\sigma_\alpha^2 L^2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & \dots \\ 0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & \dots & \dots \\ 0 & 2 & 5 & 8 & 11 & 14 & 17 & 20 & \dots & \dots \\ 0 & 3 & 8 & 14 & 20 & 26 & 32 & 38 & \dots & \dots \\ 0 & 4 & 11 & 20 & 30 & 40 & 50 & 60 & \dots & \dots \\ 0 & 5 & 14 & 26 & 40 & 55 & 70 & 85 & \dots & \dots \\ 0 & 6 & 17 & 32 & 50 & 70 & 91 & 112 & \dots & \dots \\ 0 & 7 & 20 & 38 & 60 & 85 & 112 & 140 & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \ddots \end{pmatrix}$$

MS is highly correlated among the planes



$$C_{ij} = \langle (y_{hit} - y_{true})_i * (y_{hit} - y_{true})_j \rangle$$

Matrix by me statistically (equal spacing): Multiple scattering

6x6 matrix is as follows

	0	1	2	3	4
0	0	0	0	0	0
1	0	1	2.001	3	3.999
2	0	2.001	5.003	8.001	11
3	0	3	8.001	14	19.99
4	0	3.999	11	19.99	29.98
5	0	4.997	13.99	25.98	39.97

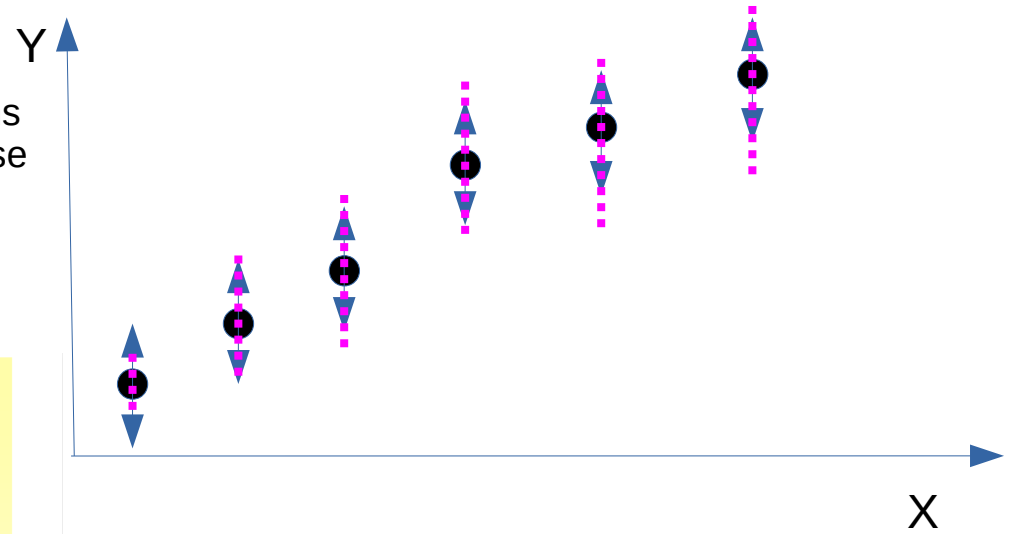
  

	5
0	0
1	4.997
2	13.99
3	25.98
4	39.97
5	54.95

# Global Chi2 fitting with MS (Line Fit)

The previous case if we use only spatial resolution means we are giving the equal weights to each points in this case

In reality points have different errors: Chi2 is overestimated



True Errors

Equal Weights

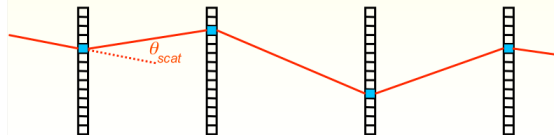
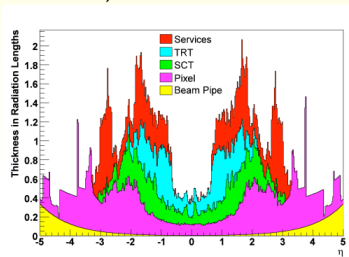
Minimize Full covariance matrix for proper treatment of multiple scattering in the fit

## Scattering Angle Formulation

- The scattering angles and the energy losses become additional fit parameters, along with the track parameters at the vertex (i.e. impact parameter, direction and momentum).
- The  $\chi^2$  function to be minimized w.r.t. the fit parameters is:

$$\chi^2 = \sum_{hits} \frac{\Delta y^2}{\sigma_{hit}^2} + \sum_{scatters} \frac{\theta_{scat}^2}{\sigma_{scat}^2} + \sum_{Eloss} \frac{(\Delta E - \overline{\Delta E})^2}{\sigma_{Eloss}^2}$$

where  $\Delta y$  are the residuals, and  $\sigma_{scat}$  and  $\overline{\Delta E}$  can be estimated from the material properties (done by the [MultipleScatteringUpdater](#) and [EnergyLossUpdater](#) tools)



CHEP07 conference 5 September 2007, T. Cornelissen

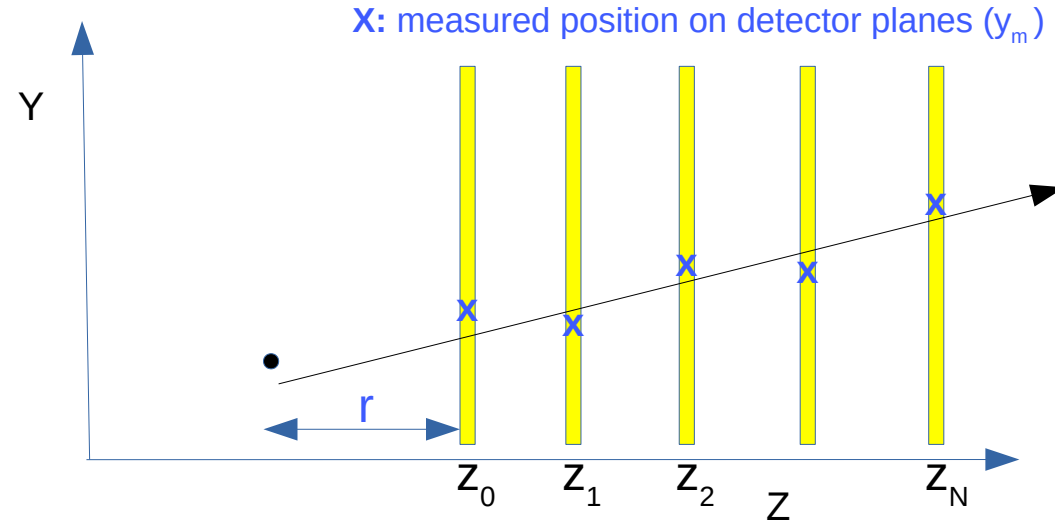
# Straight Line Fit

General line

$$y = a + bz$$

$$\chi^2 = \sum_{i=0}^N \frac{(y_m - y_i)^2}{\sigma_i^2} = \sum_{i=0}^N \frac{(y_m - a - bz_i)^2}{\sigma_i^2}$$

$$\partial \chi^2 / \delta a = 0 \quad \partial \chi^2 / \delta b = 0$$



Chi2 minimization: returns best  $a, b$  and  $\sigma_a, \sigma_b, \sigma_{ab}, \sigma_{ba}$

$$S_1 = \sum_{i=0}^N \frac{1}{\sigma_i^2}$$

$$S_y = \sum_{i=0}^N \frac{y_i}{\sigma_i^2}$$

$$S_z = \sum_{i=0}^N \frac{z_i}{\sigma_i^2}$$

$$S_{yz} = \sum_{i=0}^N \frac{y_i z_i}{\sigma_i^2}$$

$$S_{zz} = \sum_{i=0}^N \frac{z_i^2}{\sigma_i^2}$$

$$\Delta = S_1 S_{zz} - S_z^2$$

$$\sigma_a^2 = S_{zz} / \Delta$$

$$a = (S_y S_{zz} - S_z S_{zy}) / \Delta$$

$$\sigma_b^2 = S_1 / \Delta$$

$$b = (S_1 S_{zy} - S_z S_y) / \Delta$$

$$\sigma_{ab} = \sigma_{ba} = -S_z / \Delta$$

Covariance Matrix of Parameters

Rewrite



$$\begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ba} & \sigma_b^2 \end{pmatrix} = \frac{1}{\Delta} \begin{pmatrix} S_{zz} & -S_z \\ -S_z & S_1 \end{pmatrix}$$

<http://www.le.infn.it/lhcschool/talks/Ragusa.pdf>  
[http://www.foo.be/docs-free/Numerical\\_Recipe\\_In\\_C/c15-2.pdf](http://www.foo.be/docs-free/Numerical_Recipe_In_C/c15-2.pdf)

# Multiple Scattering

Covariance matrix entries affected by multiple scattering

	$1/p$	$\lambda$	$\phi$	$\gamma_{\perp}$	$z_{\perp}$
$1/p$	0	0	0	0	0
$\lambda$	0	$\langle \theta_p^2 \rangle$	0	0	$-\frac{\langle \theta_p^2 \rangle dl}{2}$
$\phi$	0	0	$\frac{\langle \theta_p^2 \rangle}{\cos^2 \lambda}$	$\frac{\langle \theta_p^2 \rangle dl}{(2 \cos \lambda)}$	0
$\gamma_{\perp}$	0	0	$\frac{\langle \theta_p^2 \rangle dl}{(2 \cos \lambda)}$	$\frac{\langle \theta_p^2 \rangle (dl)^2}{3}$	0
$z_{\perp}$	0	$-\frac{\langle \theta_p^2 \rangle dl}{2}$	0	0	$\frac{\langle \theta_p^2 \rangle (dl)^2}{3}$

[https://agenda.infn.it/event/1096/contributions/6159/attachments/4504/4980/Rotondi\\_3.pdf](https://agenda.infn.it/event/1096/contributions/6159/attachments/4504/4980/Rotondi_3.pdf)