

Tracking using Kalman filter in ALICE Framework

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https://agenda.infn.it/event/1096/contributions/6159/attachments/4504/4980/Rotondi_3.pdf

<http://www.le.infn.it/lhc-school/talks/Ragusa.pdf>

Local Coordinate ALICE

X local is normal to the sensor
Y local is on the sensor

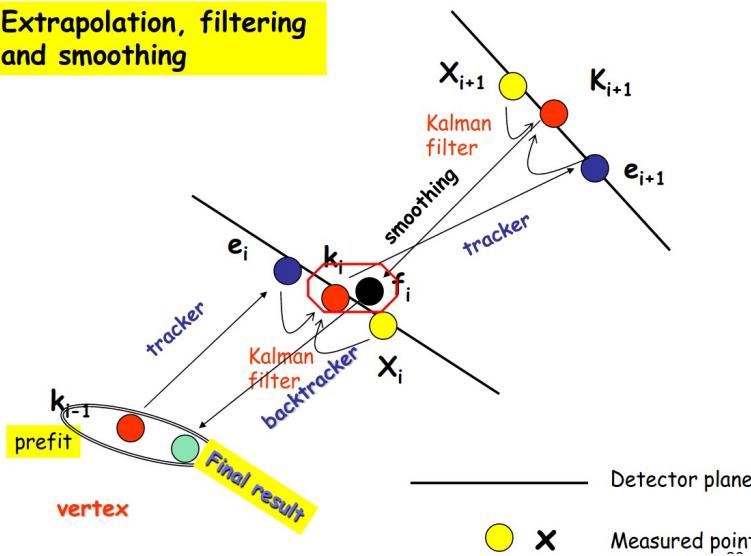
$$\phi = \tan^{-1}\left(\frac{y_g}{x_g}\right)$$

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_i is describing the radius

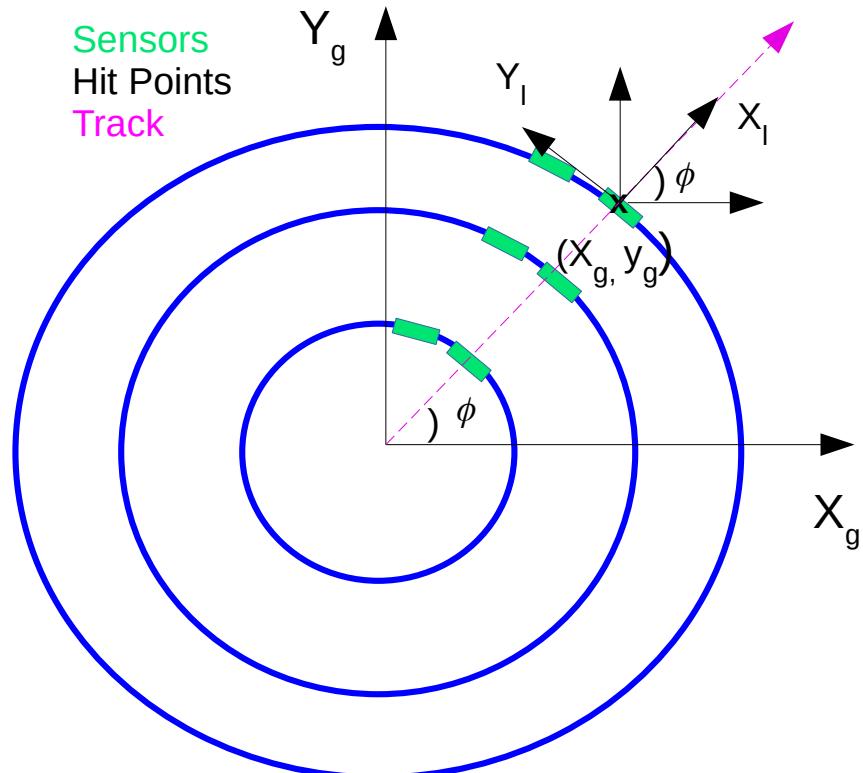
Track Parameters (Local): $(y_l, z_l, \sin \phi, \tan \lambda, q/p_T)$

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



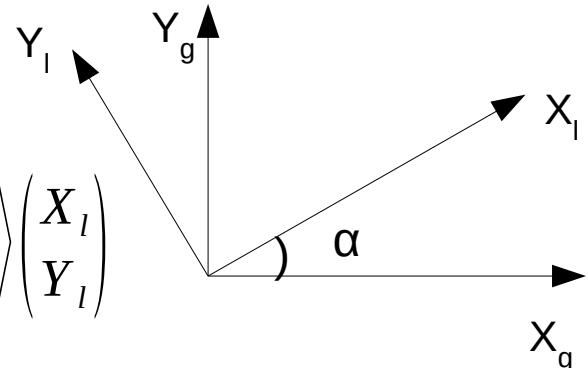
ALICE Track Parameters

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

On cylindrical surface:

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

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

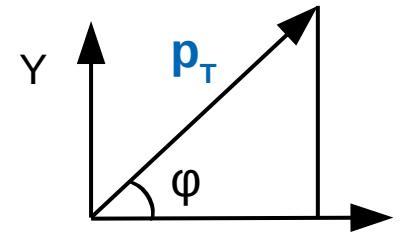
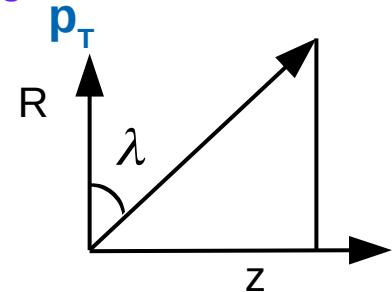


$$\frac{\sigma_{1/p_t}}{(1/p_t)} = \frac{1/p_t^2 * \sigma_{pt}}{(1/p_t)} = \frac{\sigma_{pt}}{p_t} \quad \sigma_{DCA_{r_\phi}}^2 = \sigma_y^2 \quad \sigma_{DCA_z}^2 = \sigma_z^2$$

Local coordinates rotated by α
w.r.t. global coordinates

Parameter Covariance

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



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

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

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 ϕ .
- ✓ 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

The filtering is nothing but a weighted average of the

new measurement y_n

the prediction y_p

$$y_f = \frac{\frac{1}{\sigma_p^2} y_p + \frac{1}{\sigma_n^2} y_n}{\frac{1}{\sigma_p^2} + \frac{1}{\sigma_n^2}}$$

$$y_f = \frac{\sigma_n^2}{\sigma_p^2 + \sigma_n^2} y_p + \frac{\sigma_p^2}{\sigma_p^2 + \sigma_n^2} y_n$$

Clearly if the new measurement has a very large error

$$\sigma_n \rightarrow \infty \quad y_f \rightarrow y_p$$

measurement ignored

If the prediction has a large error (for example large multiple scattering)

$$\sigma_p \rightarrow \infty \quad y_f \rightarrow y_n$$

prediction ignored

hub.com/alisw/AliRoot/blob/master/STE/RootBase/AliExternalTrackParam.h

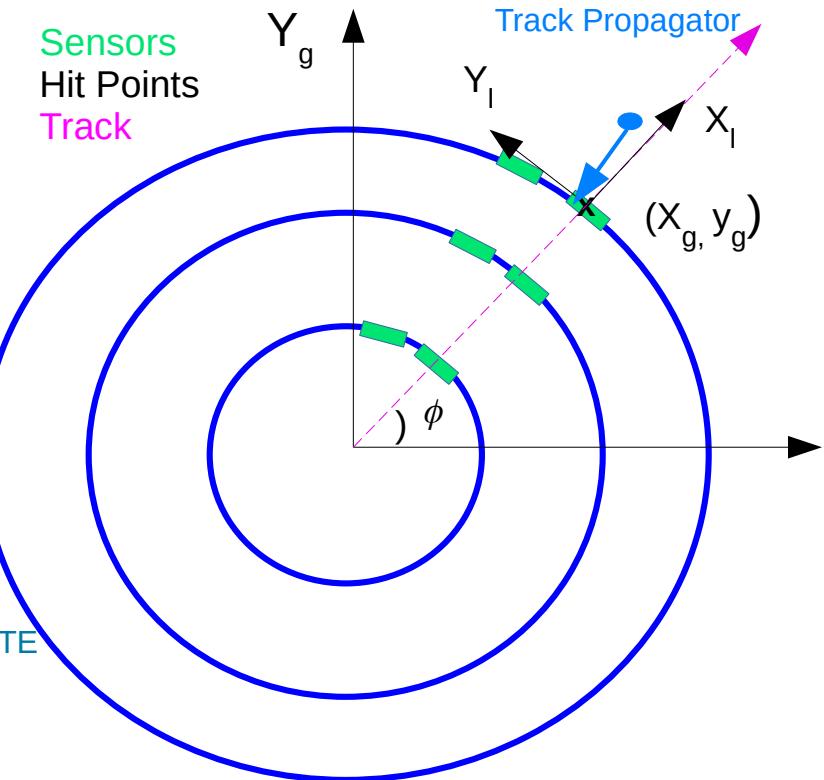
Track Extrapolation

Bool_t PropagateTo(Double_t x, Double_t b);

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

At the vertex $x_i = 0$ and y_i is DCA_{xy}

Checking code for three layers as an exercise then will apply for beam test data



Multiple Scattering

Covariance matrix entries affected by multiple scattering

	$1/p$	λ	ϕ	γ_\perp	z^\perp
$1/p$	0	0	0	0	0
λ	0	$<\theta_p^2>$	0	0	$-\frac{<\theta_p^2> dl}{2}$
ϕ	0	0	$\frac{<\theta_p^2>}{\cos^2 \lambda}$	$\frac{<\theta_p^2> dl}{(2 \cos \lambda)}$	0
γ_\perp	0	0	$\frac{<\theta_p^2> dl}{(2 \cos \lambda)}$	$\frac{<\theta_p^2> (dl)^2}{3}$	
z^\perp	0	$-\frac{<\theta_p^2> dl}{2}$	0	0	$\frac{<\theta_p^2> (dl)^2}{3}$

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