

# Master seminar: Particle tracking and identification at high rates

## Report: An introduction to track reconstruction in collider experiments

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December 1, 2017

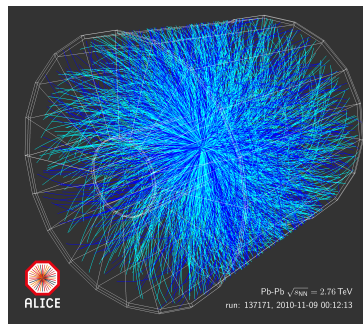


# Introduction: particle tracks in collider experiments



Big European Bubble Chamber (CERN)

From this...



to this!

In large collider experiments: particles leave hits on detector layers → huge amount! Goal: **proper linking** of hits.  
Big difficulties: high multiplicity of tracks, hit uncertainties, physical effects (multiple Coulomb scattering, measurement errors...), hit ambiguities (geometry of the detector...).

## Introduction

- Particle tracks in collider experiments
- Particles in a magnetic field
- Parametrization

## Fitting

- The Karimaki fit
- Physical effects
- The Kalman filter
  - The Kalman filter: case of no present magnetic field
  - The extended Kalman filter

## Pattern recognition

- Seed finding
- Track extension

## Conclusion

- New tracking techniques
- Summary

# Introduction: particles in a magnetic field

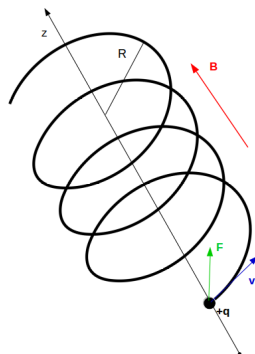
- ▶ Particle in field  $B \rightarrow$  Lorentz force:  $F_L = q(E + v \times B)$ .  $q :=$  charge,  $E :=$  electric field,  $v :=$  velocity.
- ▶ Case of most collider experiments:  $E = 0$ ,  $B = (0, 0, B_z)$ :

$$\Rightarrow F = qvB_z$$

$$\leftrightarrow \frac{mv^2}{R} = qvB_z \text{ (in circular motions)}$$

$$\leftrightarrow \frac{p}{q} = \frac{1}{k} B_z.$$

With  $R = \frac{1}{k}$ ,  $k :=$ curvature.



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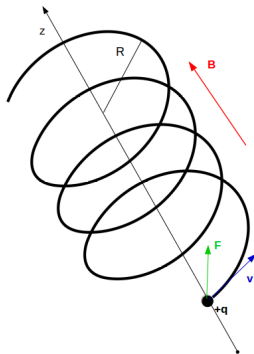
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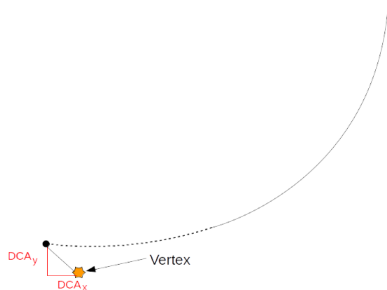
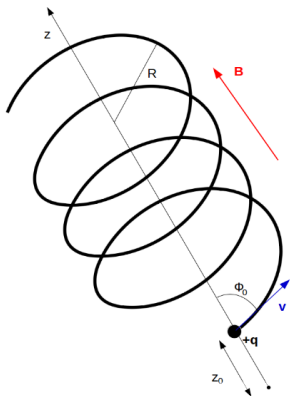
## Conclusion

One can deduce *rigidity* (momentum over charge) of particle with known magnetic field, and unknown curvature.

# Introduction: Parametrization

Trajectory of a primary particle: helix parametrized by  $(k, \eta, \phi_0, z_0, d_0)$  with:

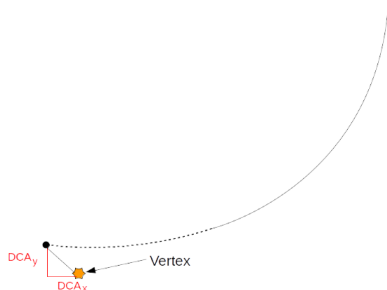
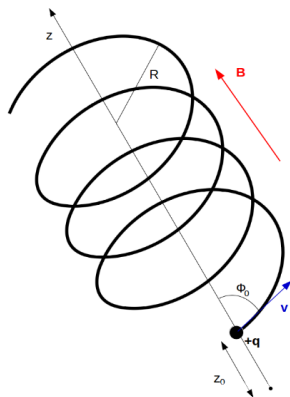
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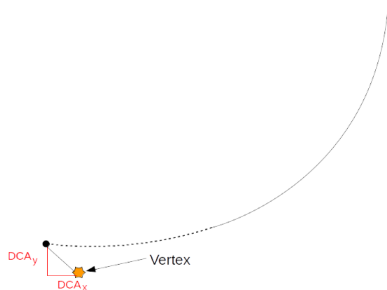
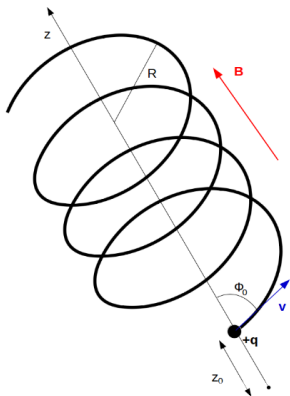
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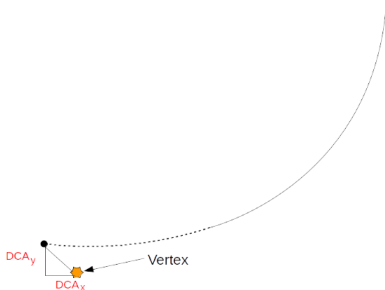
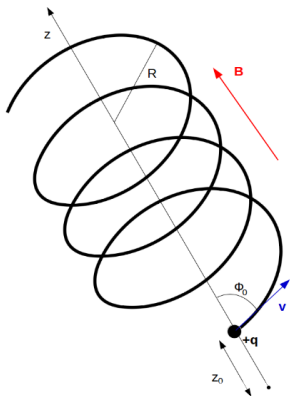




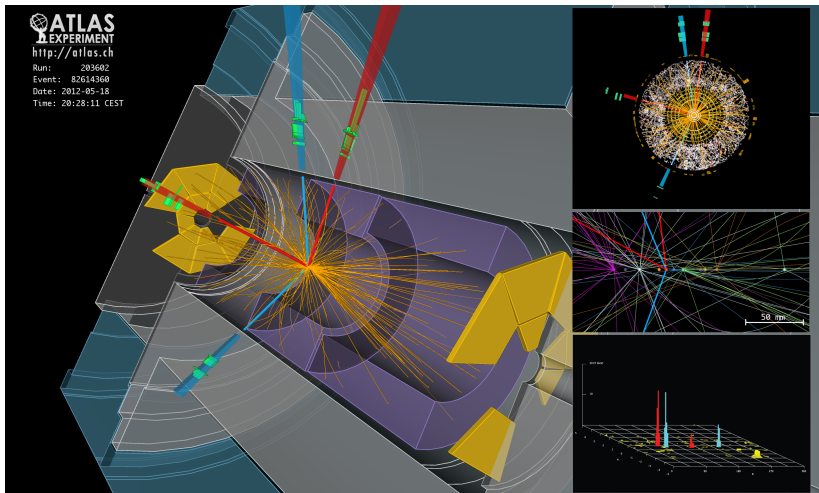
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- ▶ Distance of closest approach  $d_0 = \sqrt{\text{DCA}_x^2 + \text{DCA}_y^2}$  (often called  $\text{DCA}_{xy}$ ).



# FITTING



# The Karimaki fit

Finds circle curvature, direction and position parameters of a track with least square method. Assumptions are:

- ▶ Only spatial hit uncertainties (no multiple scattering, no inhomogeneous magnetic field),
- ▶ All hits are part of the track.

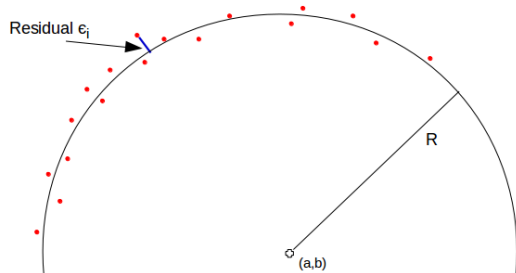
Least square method is the minimization of:

$$\chi^2 = \sum_i w_i \epsilon_i^2$$

where  $w_j :=$  weights and  $\epsilon_j :=$  measurement residuals:

$$\epsilon_i = \pm \left[ \sqrt{(x_i - a)^2 + (y_i - b)^2} - R \right].$$

$x_j$  and  $y_j :=$  measured coordinates.



Minimizing problem solved with approximation:

$$\epsilon_i \approx \pm \frac{1}{2} R^{-1} \left[ (x_i - a)^2 + (y_i - b)^2 - R^2 \right]$$

under the condition that  $|\epsilon_i \ll R|$ .

⚠ Many drawbacks: non-Gaussian...

Solution:

- ▶ Use curvature  $k$  instead of  $R$  (⚠ most important change!),
- ▶ Distance of closest approach  $d_0$  and direction of propagation  $\Phi_0$ ,
  - ▶ Used because not correlated and good straight track limit behavior (when  $R \rightarrow \infty$ ).

Equation becomes:

$$\epsilon_i = \frac{1}{2} k r_i^2 - (1 + k d_0) r_i \sin(\Phi_0 - \phi_i) + \frac{1}{2} k d_0^2 + d_0$$

with  $r_i$  and  $\phi_i$  polar coordinates of  $i$ .

# The Karimaki fit

Parameters are Gaussian and behave well at the straight track limit.

Rewrite now  $\epsilon_i$  as:

$$\epsilon_i = (1 + kd_0)\eta_i,$$

with  $\eta_i = kr_i^2 - r_i \sin(\Phi_0 - \phi_i) + \delta$ ,  $\kappa = \frac{1}{2} \frac{k}{1+kd_0}$  and  $\delta = \frac{1+\frac{1}{2}kd_0}{1+kd_0} d_0$ .

$$\Rightarrow \chi^2 = (1 + kd_0)^2 \widehat{\chi^2},$$

$$\widehat{\chi^2} = \sum_i w_i \eta_i^2.$$

In practice, minimizing  $\widehat{\chi^2}$  with  $k, d_0, \Phi_0 \rightarrow$  minimizes the true  $\chi^2$  !

Procedure:

1. minimize the  $\widehat{\chi^2}$  with respect to  $\kappa$ ,  $\Phi_0$  and  $\delta$ ,

Result:

State vector  $(k, d_0, \Phi_0)$ .

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Procedure:

1. minimize the  $\widehat{\chi^2}$  with respect to  $\kappa$ ,  $\Phi_0$  and  $\delta$ ,
2. solve the curvature and distance parameters  $k$  and  $d_0$  by inverting their expressions.

Result:

State vector  $(k, d_0, \Phi_0)$ .

Parameters are Gaussian distributed, error estimation done in respect to that.  
Error matrix  $V$ :

$$(V^{-1})_{jk} = \sum_i w_i \frac{\partial \epsilon_i}{\partial p_j} \frac{\partial \epsilon_i}{\partial p_k},$$

with  $p_{j,k} :=$  parameter.

- ▶ Corrections on error on the fitting of  $k$ ,  $\Phi_0$  and  $d_0$ , due to the minimization of  $\widehat{\chi^2}$  and not  $\chi^2$ , are added.
  - ▶ Can be implemented simply and computed quickly.

# The Karimaki fit: event reconstruction

In event reconstruction: fit first particle trajectories, then determine vertex from it → **iterative procedure**.

## Need:

- ▶ algorithm which calculates parameters and errors
  - ▶ according to a new vertex  $(x'_0, y'_0)$ .



# The Karimaki fit: event reconstruction

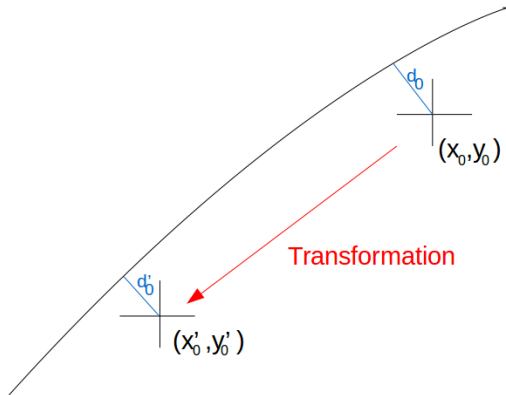
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## Solution → transformation:

- ▶  $d_0 \rightarrow d'_0$ ,
- ▶  $\Phi_0 \rightarrow \Phi'_0$ ,
- ▶  $k$  is invariant.



$\Phi_0$  is also transformed, not shown here since not on the same plane.

Mathematically (not very important for us):

$$\Phi'_0 = \arctan \frac{B}{C}, \quad d'_0 = \frac{A}{1+U}$$

$k$  is invariant.

$$A = 2\Delta_{\perp} + k(\Delta_{\perp}^2 + \Delta_{\parallel}^2),$$

$$B = k(x_0 - x'_0) + (1 + kd_0) \sin \Phi_0,$$

$$C = -k(y_0 - y'_0) + (1 + kd_0) \cos \Phi_0,$$

$$U = \sqrt{1 + kA},$$

$$\Delta_{\perp} = (x_0 - x'_0) \sin \Phi_0 - (y_0 - y'_0) \cos \Phi_0 + d_0,$$

$$\Delta_{\parallel} = (x_0 - x'_0) \cos \Phi_0 + (y_0 - y'_0) \sin \Phi_0.$$

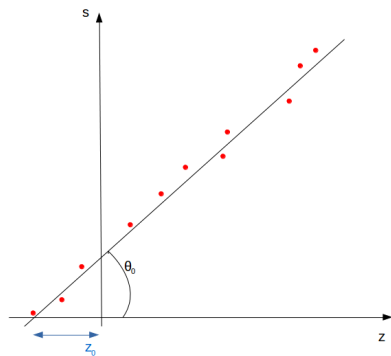
The new error matrix is then:

$$V' = J V J^T$$

where  $J$  is simply the Jacobian derivative matrix.

# The Karimaki fit: from circle fitting to helix fitting

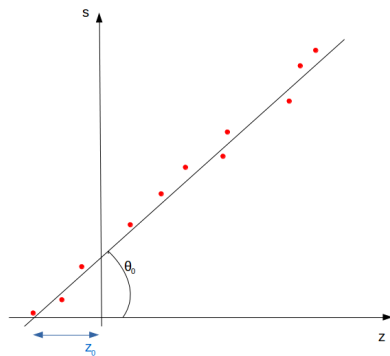
- ▶  $\triangle$  Karimaki: fits a circle, not a helix!
- ▶ To get a helix, need  $\theta_0$ :



$$\tan\theta_0 = \frac{\Delta s}{\Delta z}$$

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$$\tan\theta_0 = \frac{\Delta s}{\Delta z}$$

## Conclusion

The Karimaki fit solves a nonlinear least squares problem with an elegant solution:

- ▶ Gaussian behaved fitted parameters,
- ▶ Computes value of the  $\chi^2$  quickly (one of the quickest fits!),
- ▶ Calculates the covariance matrix of the fitted parameters.

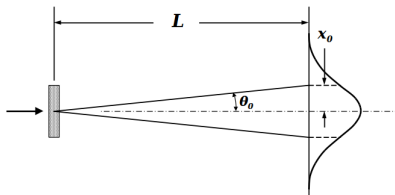
Most dominant effect that will modify particle path:

- ▶ Multiple Coulomb scattering,
- ▶ Described roughly by a Gaussian distribution.

Standard deviation of the planar scattering angle (Highland equation):

$$\theta_{\text{estimated}} := \theta_0 = \frac{13.6 \text{ MeV}}{\beta c p} Z \sqrt{L/X_0} [1 + 0.038 \ln(L/X_0)]$$

Where  $p$  := momentum,  $\beta c$  := velocity,  $Z$  := charge in electron charge units and  $L/X_0$  := thickness of the scattering material in radiation length.



Hit uncertainties → also affects proper track reconstruction.

- ▶ Drift chamber resolution: about  $100 \mu\text{m}$
- ▶ Silicon detector resolution: about  $10 \mu\text{m}$

## The Kalman filter: case of no present magnetic field

The Kalman filter and the Karimaki fit: same basic principles, but Kalman filter has more advantages.

Random process noise  $w$  (e.g Coulomb scattering) is added to the transformation:

$$x_i = F_{i-1}x_{i-1} + w_{i-1}.$$

$x_i$  := state vector,  $F_{i-1}$  := transformation.

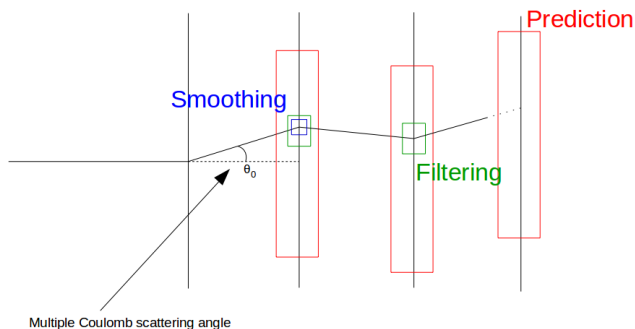
State vector not measured directly. Quantities  $m_k$  are measured by the detector  $k$ , related to the state vector with linear function  $h_k$ :

$$m_k = h_k(x_k) + \epsilon_k.$$

- ▶  $\epsilon_k$  is a measurement noise,
  - ▶ Implementation of discrepancy between a measured and true value of the detector.
- ▶ ⚠ This part extremely dependent on the experiment!

# The Kalman filter: the three operation steps

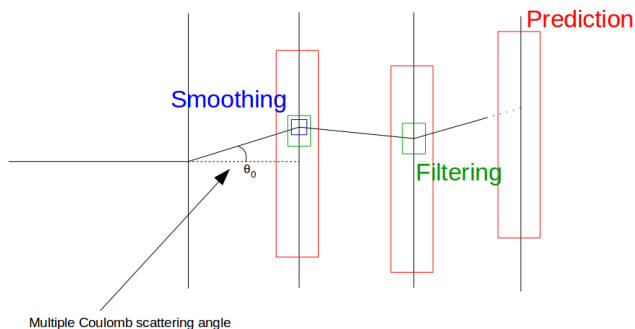
1. **Filtering:**  $x_k = x_k^{k-1} + K_k \cdot (\text{residual of prediction}),$ 
  - ▶  $K_k :=$  Kalman gain matrix.



Operations also applied on the covariance matrix! Also update of  $\chi^2$  after each iteration.

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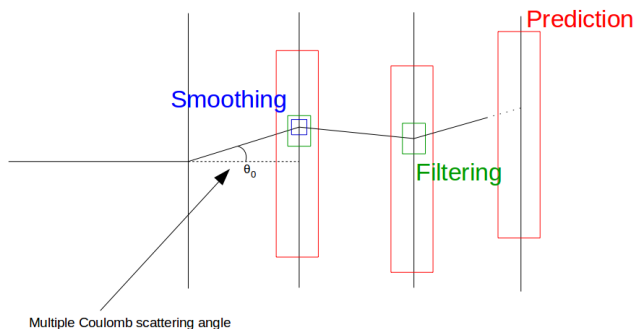


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3. **Smoothing:**  $x_k^n = x_k + A_k \cdot (x_{k+1}^n - x_{k+1}^k)$ ,
  - ▶  $A_k :=$  Smoother gain matrix.



Operations also applied on the covariance matrix! Also update of  $\chi^2$  after each iteration.

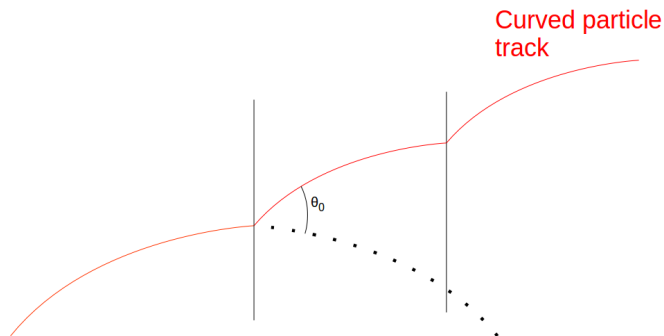
# The extended Kalman filter

In magnetic field, track propagator is nonlinear:

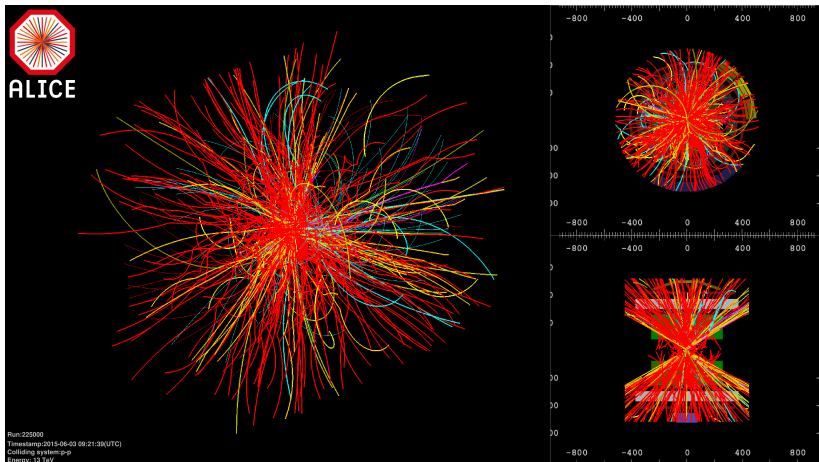
- ▶ Has to be approximated by a linear function,
- ▶ Done in the usual way by replacing it by first two terms of Taylor expansion.

→  $x_{k+1}^k = F_k x_k$  (extrapolation of state vector) becomes:

$$x_{k+1}^k = f_k(x_k)$$

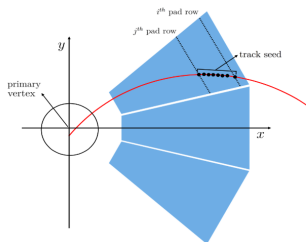


# PATTERN RECOGNITION

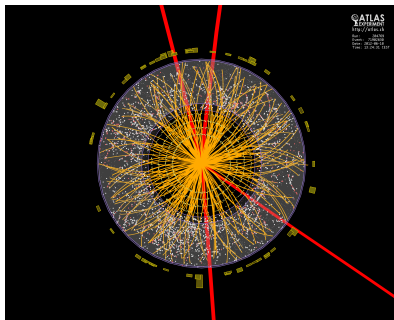


First step: *Seed finding*, in regions of low track density (outer detector regions).

Schematic view of the seeding algorithm.



Track seed: neighbor clusters roughly compatible with a track shaped as a helix pointing to the interaction.

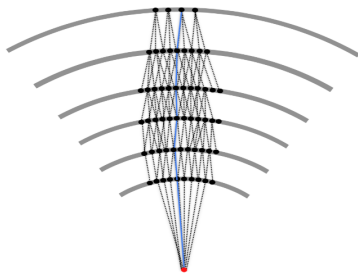


## Pattern recognition: track extension

Next step: track extension.

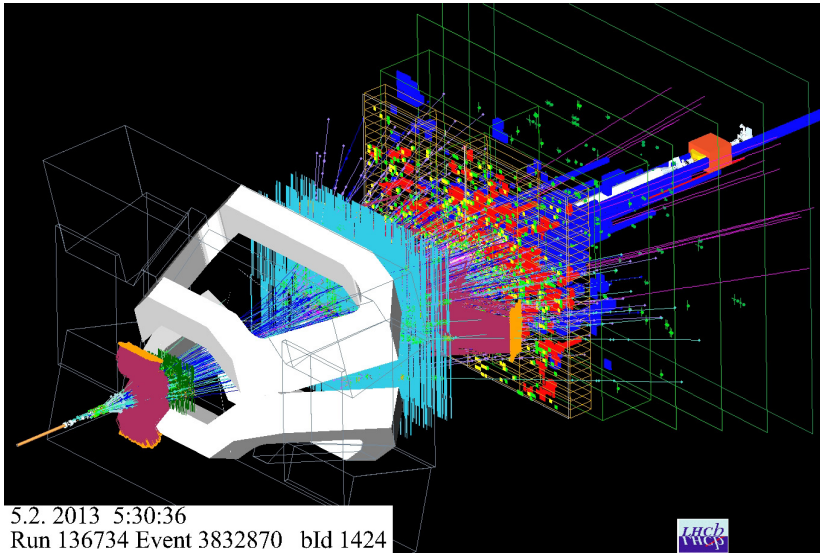
- ▶ When another layer is reached, a "tree" of possible extensions calculated, most probable candidate eventually selected with Kalman filter,
- ▶ When a cluster is associated with existing track, track parameters and covariance matrix are updated,
- ▶ Tracks usually refitted by the Kalman filter in the outward direction,
- ▶ Sometimes a final step of second inward propagation done.

Tree of possible extensions to a track.



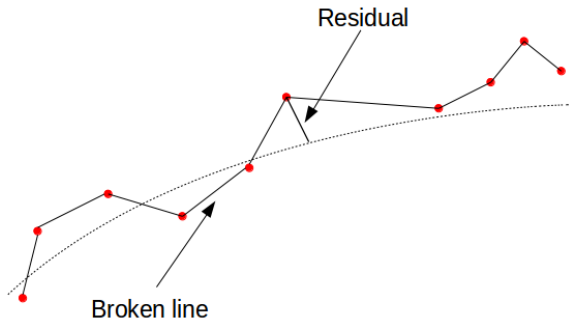
Prolongation hypotheses are made, taking into account multiple scattering. The best track candidate (in blue) is chosen according to the quality of the whole track.

# CONCLUSION



## Conclusion: new tracking techniques

- ▶ Kalman filter: most used → implementation of multiple scattering effects, measurement errors, (inhomogeneous) magnetic field.
- ▶ Has some drawbacks: very complicated implementation, iterative → starts from the beginning when something wrong.
- ▶ New techniques available → *broken line fit*:

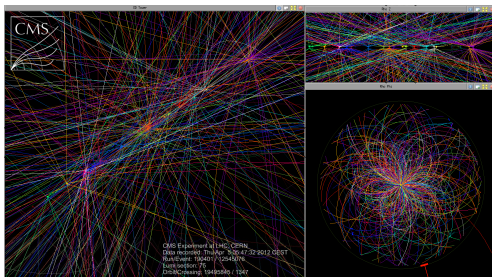


Fast track fit (Karimaki)+detailed fit (reduction of residuals) allowing *kinks*.





# Conclusion

What did we learn today?

- ▶ Particles in large collider experiments follow a helix.
- ▶ Fitting a circle or a helix is difficult (nonlinear problem) → use new parametrization!
- ▶ Physical effects make track reconstruction even more difficult.
- ▶ Kalman filter takes physical effects into account and
  - ▶ Predicts,
  - ▶ Filters,
  - ▶ Smooths the state vectors.
- ▶ A lot more of methods and techniques available: broken line fit, Hough transformations, multiple scattering fit, use of templates...





-  Alberto Caliva, *Low-mass dielectron measurement in Pb-Pb collisions at  $\sqrt{s_{NN}} = 2.76$  TeV with ALICE at the LHC.*
-  R. Frühwirth, *Application of Kalman filtering to track and vertex finding*, Institut für Hochenergiephysik der Österreichischen Akademie der Wissenschaften, Vienna, Austria, 1987.
-  V. Karimäki, *Effective circle fitting for particle trajectories*, SEFT, University of Helsinki, Helsinki, Finland, 1990.
-  Ferenc Siklér, *Combination of various data analysis techniques for efficient track reconstruction in very high multiplicity events*, Wigner RCP, Budapest, Hungary, 2017.