



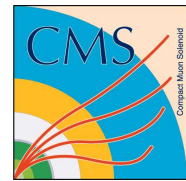
Plans for the implementation of a *Global Track Fitter* in CMS

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- Track fitting in CMS
 - ♦ Kalman Filter
 - ♦ Muon reconstruction: description and performance
 - ♦ strengths and weaknesses
- Need for a Global Fitter
 - ♦ concepts, working and benefits
 - ♦ applications and limits
- Future plans
 - ♦ what we have, what we need

In a magnetic field, the trajectory is a **helix** → **5 parameters**:

$x = (\text{charge/momentum, position and direction on a given surface})$

Reconstruction of the trajectory of charged particles from *position measurements*

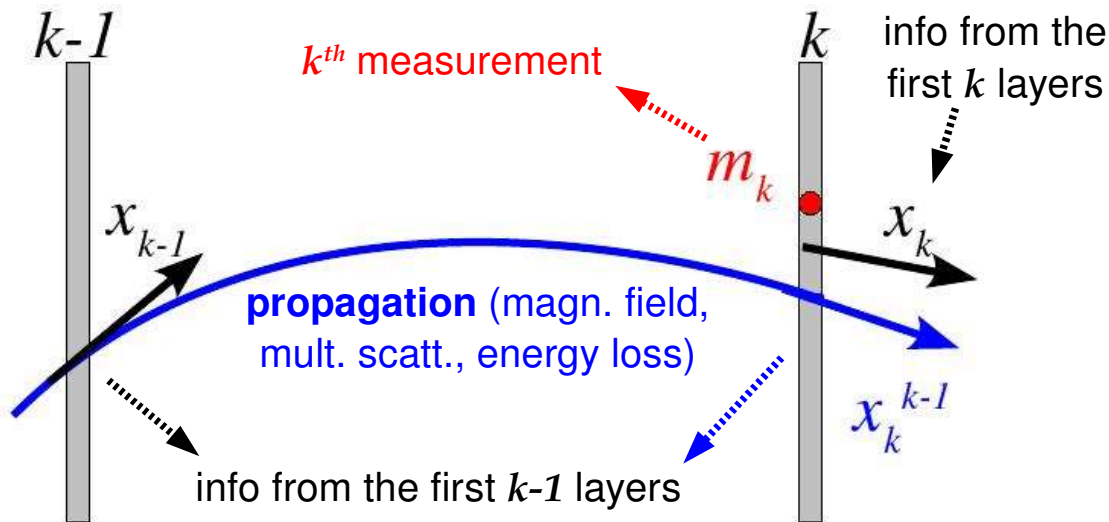
Requirements:

- account for *multiple scattering* and *energy loss*
- used both in **Tracker** (1/2-dim hits) and **Muon System** (1/2/3-dim hits/segments)
- it must provide
 - the **pattern recognition** → collection of hits
 - the **best estimation** of the track → minimum χ^2
- ... possibly in the **fastest** way! → well suited for HLT



Kalman Filter

Based on three basic steps: *prediction* (propagation), *filtering*, *smoothing*



Measurement on k^{th} layer:

$$m_k = H_k x_k^{\text{true}} + \epsilon_k$$

1/2/3 dim
5 dim
“noise”

Predicted state and covariance matrix:

$$x_k^{k-1} = F_{k-1} x_{k-1}$$

magn. field, energy loss
multiple scattering, straggling

$$C_k^{k-1} = F_{k-1} C_{k-1} F_{k-1} + M_{k-1}$$

Filtered state and covariance matrix:

$$x_k = x_k^{k-1} + K_k (m_k - H_k x_k^{k-1})$$

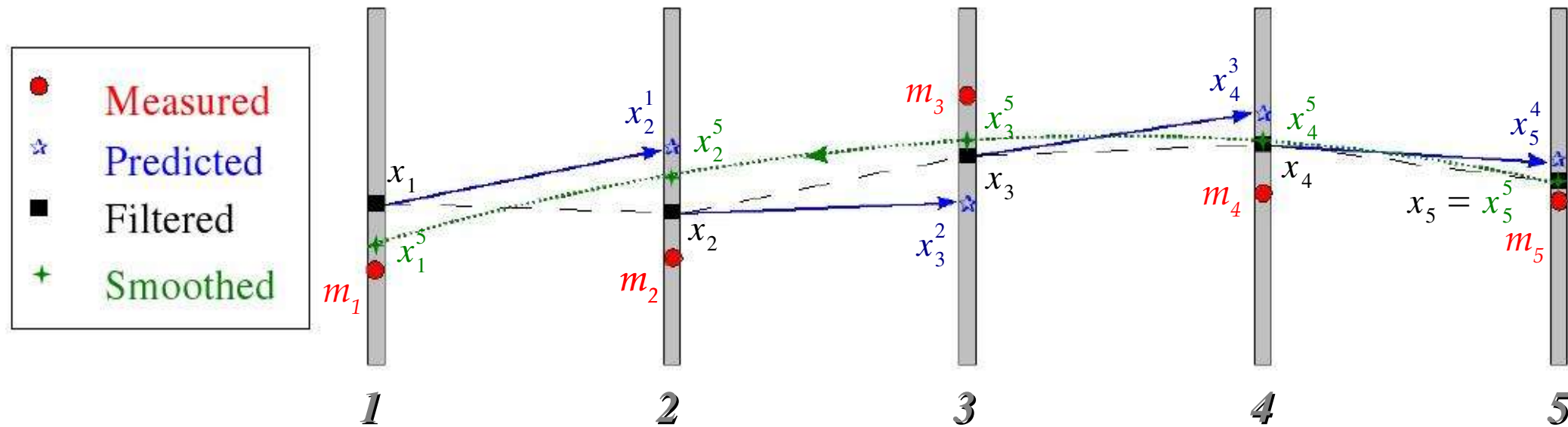
Kalman gain matrix

$$C_k = (1 - K_k H_k) C_k^{k-1}$$

On the k^{th} layer, the *filtered state* x_k contains information only from the **first k hits**

Once all the n hits have been collected, the **smoothing** is performed

→ each x_k is updated with the information from the last $n - k$ layers



Smoothed state and covariance matrix:

$$x_k = x_k^{k-1} + A_k (x_{k+1}^n - x_{k+1}^k)$$

↙ smoother gain matrix



The **smoothed** trajectory represents the **best estimate** (minimum χ^2) for the given set of hits

$$C_k^n = C_k + A_k (C_{k+1}^n - C_{k+1}^k) A_k^T$$

Muon transport in the detector accounting for *magnetic field* and *material effects*

Magnetic field, *mean* energy loss (Bethe-Block) → **state vector**

Multiple scattering, energy loss *fluctuations* → **covariance matrix**

1. Analytic

(used in the Tracker)

assumes a *uniform magnetic field* (perfect helix)

The state vector is propagated *from layer to layer*,
material effects are introduced in the *end-points*

2. Runge-Kutta

(used in the Tracker)

4th order Runge-Kutta method → *non-uniform magnetic field (radial component)*

The state vector is propagated *from layer to layer*,
material effects are introduced in the *end-points*

3. Stepping-Helix

(mainly outside the Tracker)

2nd order Runge-Kutta method → *uniform magnetic field*

The CMS volume is mapped in *cells* with *uniform magnetic field*

→ inside each cell the trajectory is a *helix*

→ at each step, the *magnetic field* is updated
and the *material effects* are introduced

The **track reconstruction** in the **Muon System** takes place in four steps:

1. **Estimation of the initial state** (*seed*)

- *on-line*: input from **Level 1** trigger
- *off-line*: built from **one** or **more** track **segments**

p_T parametrized as a function of ϕ (or $\Delta\phi$) of segments: $p_T = A - B/\Delta\phi$

2. **Pre-filter** or **forward filter** (*inside-out*)

- starts from the *seed state* (extrapolated at the *innermost* layer)
- **segments** (1D hits for RPC) are used for *pattern recognition*, on a χ^2 basis
- **segments** (1D hits for RPC) are used for *update* (*filtering*) of the trajectory
- needed to avoid possible *biases* from the seed

3. **Filter** or **backward filter** (*outside-in*)

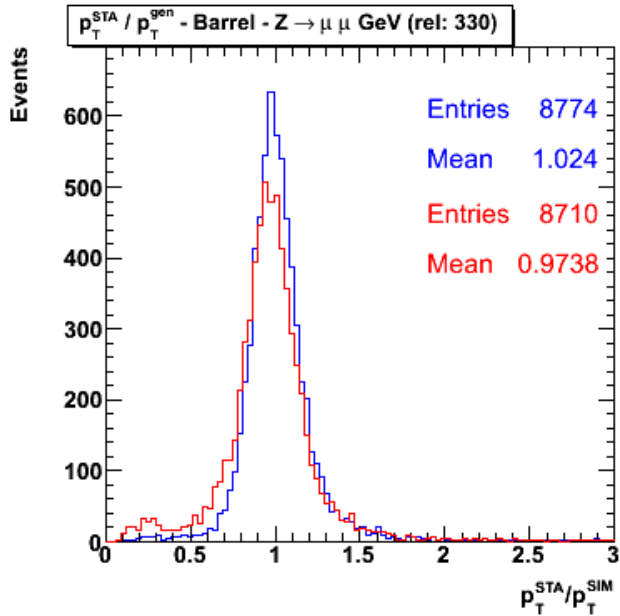
- starts from the *outermost* pre-filtered state
- **segments** (1D hits for RPC) are used for *pattern recognition*, on a χ^2 basis
- **single hits** (1D for DT/RPC, 2D for CSC) are used for the *update*

No smoothing!

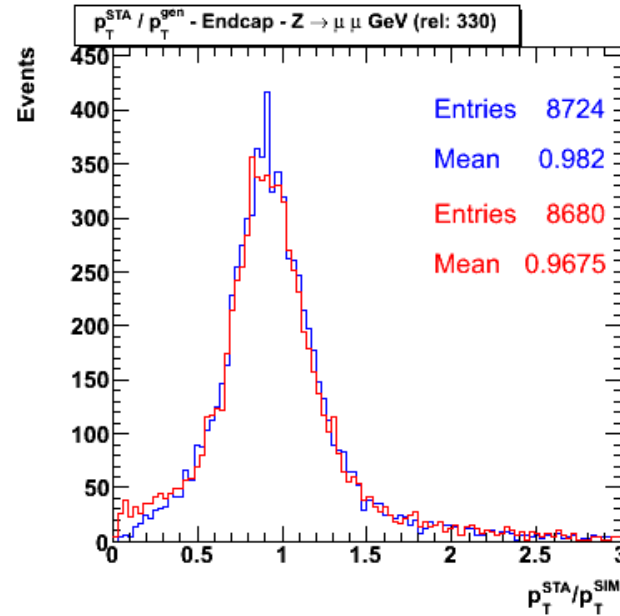
4. **Vertex constraint**

After the **ghost** suppression, the trajectory is extrapolated to the *point of closest approach* to the *beam line* and the *beam spot* is constrained to be a point of the track, to improve the p_T resolution

Barrel

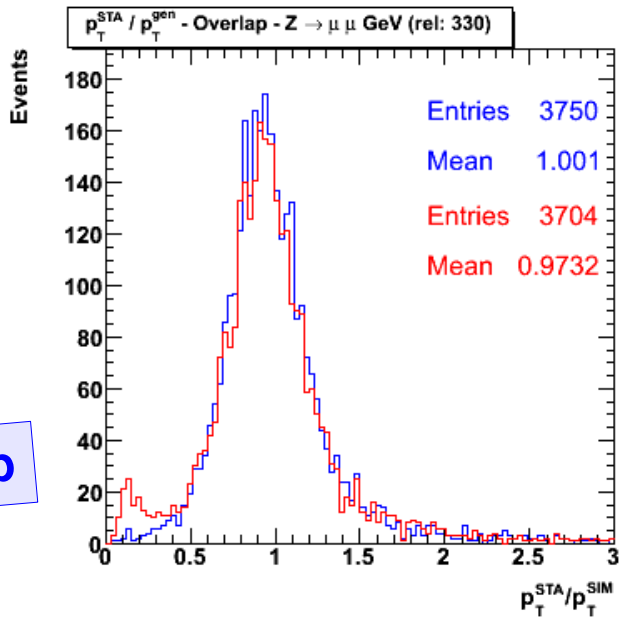


Endcap

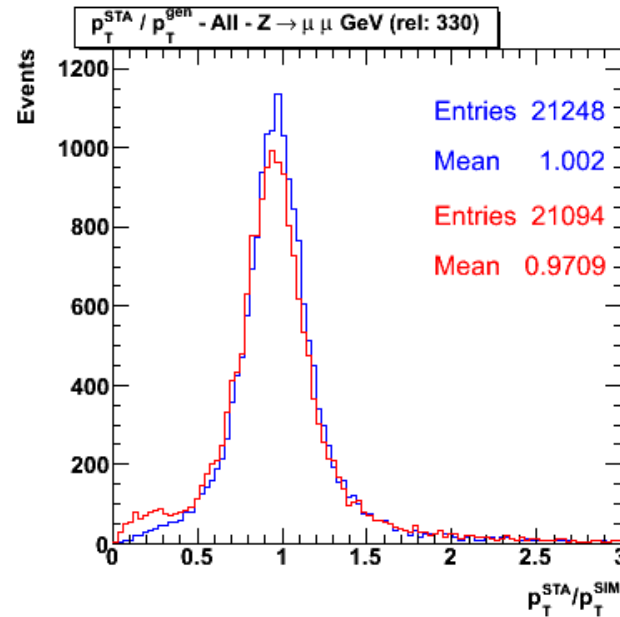


CMSSW_3_3_0

Overlap

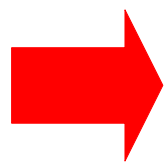


Total



— standard STA
— STA + smoothing

- Crucial point: initialization of the covariance matrix
 - too **large** initial errors → **too sensitive to possible low quality hits**
 - too **small** initial errors → **bias**
- recursive method proves more unstable
a single bad hit can irreparably damage the fit



efficiency loss

worsening of p_T estimation (in some cases)

Besides (not directly related to KF)

- calorimeters information is not exploited in the estimation of the energy loss (only simulated)

Non iterative method: all the collected measurements are fitted *simultaneously*

Function to be minimized:

$$\chi^2 = \underbrace{\sum_{meas} \frac{r_{meas}^2}{\sigma_{meas}^2}}_{residuals} + \underbrace{\sum_{scatt} \left(\frac{\theta_{scatt}^2}{\sigma_{scatt}^2} + \frac{\sin^2 \theta_{loc} \phi_{scatt}^2}{\sigma_{scatt}^2} \right)}_{multiple\ scattering} + \underbrace{\sum_{E_{loss}} \frac{(\Delta E - \overline{\Delta E})^2}{\sigma_{E_{loss}}^2}}_{energy\ loss}$$

Fit parameters:

- track parameters at vertex: $\alpha = (q/p_{T,0}, D_0, z_0, \phi_0, \lambda_0 = \cotg \theta_0)$
- scattering angles (ϕ_{scatt} , θ_{scatt}) for each layer
- energy loss ΔE ($\overline{\Delta E}$ from material description or measured in calorimeters)

Starting from the *initial state* of parameters α_0 , we propagate the trajectory layer by layer. So on each layer we have

- a *measurement* y_k
- a *propagated state* $y_k^{prop} = f_k(\alpha_0)$

The residuals are

$$\begin{aligned}
 r_k &= y_k - y_k^{fit} \\
 &= y_k - f_k(\alpha) \\
 &= \underbrace{y_k - f_k(\alpha_0)}_{\Delta y_k} - \sum_i \underbrace{\frac{\partial f_k}{\partial \alpha_i}(\alpha_{i,0})}_{A_{k,i}} \cdot \underbrace{(\alpha_i - \alpha_{i,0})}_{\eta_i} \\
 &= \Delta y_k - \sum_i A_{k,i} \cdot \eta_i
 \end{aligned}$$

Thus on each layer we have to pick up

- the (approximated) *residual* Δy_k
- its *derivatives w.r.t. the fit parameters* $A_{k,i}$

In matrix form: $\mathbf{r} = \Delta \mathbf{y} - \mathbf{A} \cdot \boldsymbol{\eta}$

$$\chi^2 = (\Delta \mathbf{y} - \mathbf{A} \cdot \boldsymbol{\eta})^t \mathbf{V}_y^{-1} (\Delta \mathbf{y} - \mathbf{A} \cdot \boldsymbol{\eta}) = \mathbf{r}^t \mathbf{V}^{-1} \mathbf{r}$$

with \mathbf{V}_y^{-1} being the *weight matrix*, inverse of the *covariance matrix* of the measurements y_i .

Minimizing, one gets: $\boldsymbol{\eta} = \mathbf{V}_A \mathbf{A}^t \mathbf{V}_y^{-1} \Delta \mathbf{y}$

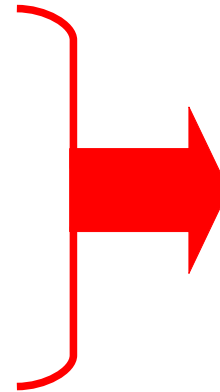
$$\text{with } \mathbf{V}_A = (\mathbf{A}^t \mathbf{V}_y^{-1} \mathbf{A})^{-1} = \mathbf{V}_\eta$$

Finally: $\boldsymbol{\alpha} = \boldsymbol{\alpha}_0 + \boldsymbol{\eta}$ and $\mathbf{V}_\alpha = \mathbf{V}_\eta = \mathbf{V}_A$

Notice that by replacing $\mathbf{V}_y \rightarrow \mathbf{V} = \mathbf{V}_y + \mathbf{V}_{\text{MS}}$, the *multiple scattering* contribution can be taken into account as well.

Fitting the *scattering angles* and the *energy loss* is more complicated.

- Only *initial state* is needed, no need to *initialize* the *covariance matrix* of α_0
- *Non-iterative* procedure



more stable
(no efficiency loss,
no resolution degrade)

Moreover...

- ... it yields the *scattering angles* and *residual derivatives* on each layer (e.g. used for alignment)
- ... it can be used (optionally) to resolve the *left-right ambiguity* and compute the *time pedestal* in the DT's
- ... it makes it easier to include *calorimeter measurements*

- Inversion of large matrices: for n measurements, \mathbf{V}_y is $n \times n$
 - if measurements are *all* uncorrelated, time for inversion $\sim O(n)$
 - if measurements are correlated (e.g. *multiple scattering*), time $\sim O(n^3)$
- Including scattering angles (2 per layer), many fit parameters
 - also \mathbf{V}_A is very large

→ Need for *fast matrix inversion* algorithms

e.g. the *Bunch-Kaufman* method (in CLHEP) is used in ATLAS and requires \sim **twice as much CPU time** as the Kalman Filter

Using approximated inverse matrices, the estimate of the parameters is still *unbiased*, but with **larger errors** (*non-optimal least squares* fitting)

- A Global Fitter is not yet available in CMS, but some tools are already there
 - `ReferenceTrajectory` code by G. Flucke *et al.* used for Tracker alignment
 - specific for Tracker, not immediately usable outside e.g. uses the Analytic Propagator
- Need to figure out how to
 - handle the **energy loss** and **multiple scattering** in the Muon Chambers
 - feed the **calorimeter deposits** in the track fitting
- Possible applications
 - fitter for the **stand-alone** tracks
 - additional fitter for **tracker** and **global** tracks



Back-up slides



The **stand-alone track** defines a *region of interest* (ROI) in the Tracker.
Then two different strategies are available.

- **Prompt reconstruction**

Tracker tracks are reconstructed *only* inside the ROI.
It is used in the **on-line trigger reconstruction** for its rapidity

- **Track matching**

Tracker tracks are built **independently** in the *whole* Tracker and the ones in the ROI are selected
It is used in the **off-line reconstruction**

Reconstruction in the inner Tracker

Two different **algorithms** can be used to resolve the **hit pattern** in the Tracker

- **Kalman Filter**, with *seeds* built from **2** or **3 consecutive hits**
- **Road Search**: starting from one hit in the **innermost layer** and one in the **outermost layer**, the hits are selected using **pre-set roads**

After the selection, the hits are fitted and the track is built.

The **most compatible** Tracker track is chosen and the **whole set of hits** is fitted
(**Tracker + Muon** hits)