

# Study of a new algorithm for tracker alignment using Machine Learning



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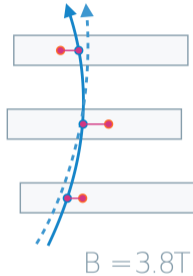


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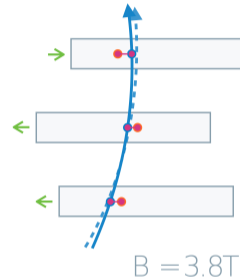
# Concept of misalignment

Misaligned modules



- charged particle
- fitted trajectory
- predicted hit
- measured hit
- residual

Aligned modules



taken from [Images for CMS Tracker alignment in Run 2](#)

# Calibration of the tracker with offline software:

## General idea of calibration algorithm

Starting geometry, e.g. design geometry, is assumed and track fit is done.

Define target function  $F(\mathbf{d}, \mathbf{t})$  in terms of detector parameter  $\mathbf{d}$  and track parameter  $\mathbf{t}$ .

Minimise  $F(\mathbf{d}, \mathbf{t})$  and update position detector modules.

With new geometry of the detector, perform the track fits again and update track parameter  $\mathbf{t}$ .

## With MillePede:

- Define  $F(\mathbf{d}, \mathbf{t})$  as  $\chi^2$   
$$\chi^2(\mathbf{d}, \mathbf{t}) = \sum_j^{\text{tracks}} \sum_i^{\text{hits}} \left( \frac{m_{ij} - f_{ij}(\mathbf{d}, \mathbf{t}_j)}{\sigma_{ij}^m} \right)^2$$
- Perform linearisation  $\mathbf{d} \rightarrow \mathbf{d} + \Delta\mathbf{d}$  and  $\mathbf{t} \rightarrow \mathbf{t} + \Delta\mathbf{t}$
- Problem can be reduced to solving the matrix equation  $\mathbf{C} \times \Delta\mathbf{d} = \mathbf{b}$

## Proposed algorithm using machine learning libraries (MLAligner)

- 👑 Usage of TensorFlow/PyTorch/etc. for the minimisation procedure
- 👑 Parameterise detector and tracks as trainable tensors
- 👑 The loss function will be  $F(\mathbf{d}, \mathbf{t})$ , parameterised as a  $\chi^2$

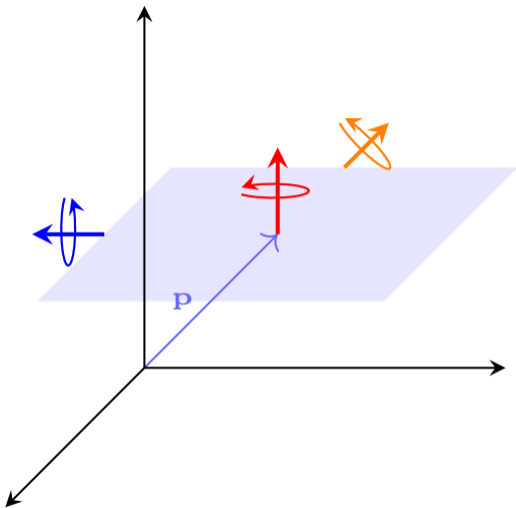
$$\chi^2(\mathbf{d}, \mathbf{t}) = \sum_j^{\text{tracks in batch}} \sum_i^{\text{hits}} \left( \frac{m_{ij} - f_{ij}(\mathbf{d}, \mathbf{t}_j)}{\sigma_{ij}^m} \right)^2$$

- 👑 Implement standard minimisation ML loop, update detector parameter each batch and refit tracks in each batch

## Advantages of this approach

- 👑 Usage of modern ML interface everybody is familiar with
- 👑 Straightforward implementation
- 👑 Low maintenance time/cost
- 👑 Running on GPUs is a trivial task

# Parametrisation of the detector in MLAligner



- 👑 For each module six free parameters
  - 👑 Three parameter for the vector to the center of the module, for now in Cartesian coordinates
  - 👑 Three Euler angles, with the parametrisation convention  $x-z'-x''$  intrinsic rotations
  - 👑 Planned for later: Parameter for global structures
- Each parameter will be a tensor, therefore "trainable"

## Detector simulation

- 👑 Generic detector using fast simulation (Fatras)
- 👑 Constant B-Field in z direction with 2 T
- 👑 Module level misalignment with gaussian smearings
  - ▶ Displacement of module center:  $\sigma_x^c = \sigma_y^c = 100 \mu\text{m}$ ,  $\sigma_z^c = 50 \mu\text{m}$
  - ▶ Rotational displacement around local axes:  $\sigma_x^{\text{rot}} = \sigma_y^{\text{rot}} = 20 \text{ mrad}$

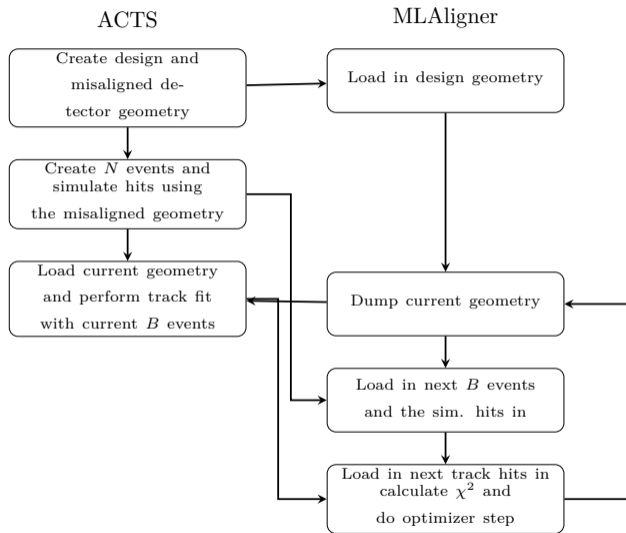
## Particle simulation

- 👑 Single muon events produced with a particle gun
- 👑  $p_T \in (1 \text{ GeV}, 30 \text{ GeV})$ ,  $\phi \in (0, 2\pi)$ ,  $\eta \in (-2.5, 2.5)$
- 👑 Origin in the center of the detector

## Seeding and tracking

- 👑 Standard (non-ML) seeding algorithm
- 👑 Tracking with Combinatorial Kalman Filter

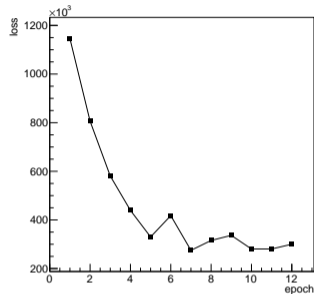
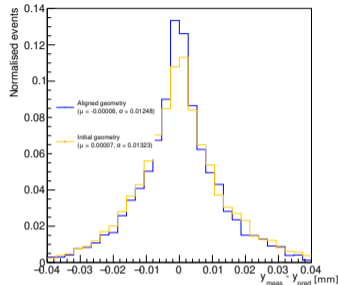
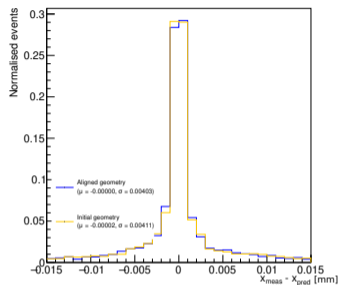
# Full training algorithm of ACTS and MLAligner



## Facts about the training

- 👑 80000 single muon events simulated
- 👑 Each batch contains 200 events  $\rightarrow$  400 total batches
- 👑 Adam Optimizer with a learning rate of  $10^{-4}$
- 👑 PyTorch used as backend ML library

# Look at first training output



## More questions than answers

- 👑 No improvement in x residuals, but in y residuals?
- 👑 Network converged after six epochs, nothing more to gain in terms of better residuals?
- 👑 What exactly has been learned (in which direction moved the modules?)



# Runtime breakdown

- 👑 Tested on CERN's lxplus with a single core execution
- 👑 Timed with `std::chrono::high_resolution_clock` from C++ standard library
- 👑 Following time stamps measured per batch

'Dump detector' Execution Time: 1061 ms

'Track fit' Execution Time: 1948 ms

'Load measured/track hits' Execution Time: 31 ms

'Track hits 3D to 2D' Execution Time: 154 ms

'Calc loss' Execution Time: 0 ms

'Backprop' Execution Time: 292 ms

'Update module parameter' Execution Time: 58 ms

# Conclusion

## Achieved so far

- 👑 New method for the alignment of a tracker system is presented
- 👑 Study based on simulation and tracking done by ACTS
- 👑 Build first iteration of core framework
- 👑 Complete set up is working and first training is shown

## List of things to do

- 👑 Study how/in which direction modules moved (weak modes?)
- 👑 Validate performance with other quantities besides residuals
- 👑 Use more realistic simulation set up
- 👑 Compare with MillePede
- 👑 ...

Tack för er uppmärksamhet!  
(Thanks for your attention!)

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