

On-the-fly measurement calibration with ACTS

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Connecting The Dots 2023
2023/10/11

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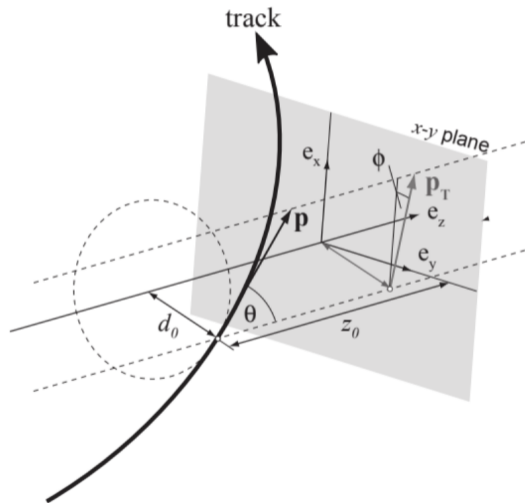
- ▶ Experiment-independent toolkit for tracking
- ▶ Free software (Mozilla Public License v2.0)
- ▶ Considered for use by **ATLAS**, **FASER**, Belle II, CEPC, sPHENIX, PANDA, EIC, ...
- ▶ Three overarching goals:
 1. Preserve current tracking approaches while enabling development for HL-LHC
 2. Serve as an algorithmic test bed incl. ML-based algorithms and accelerated hardware
 3. Enable rapid and realistic development of new tracking detectors
- ▶ Includes an [ONNX](#) plugin, to enable import of various ML models anywhere in the tracking workflow
- ▶ Ongoing R&D for GPU tracking ([tracc](#))



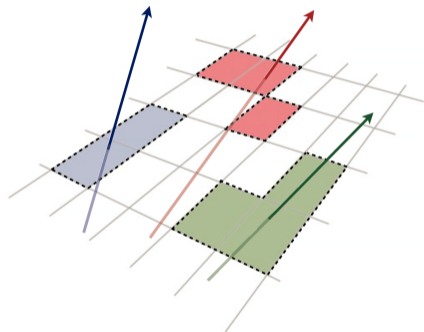
- ▶ Overview paper: [\[2106.13593\]](#)
- ▶ Project webpage: acts.readthedocs.io
- ▶ Code repository: github.com/acts-project/acts

Introduction: Kalman Filter

- ▶ ACTS Track state model: $(d_0, z_0, \theta, \phi, q/p, t)$
 - ▶ with associated covariance
- ▶ Estimated with measurements from detector
- ▶ E.g. for pixel detector: $m = (x, y)$
 - ▶ with associated covariance, usually diagonal
- ▶ Track state incorporates measurements via Kalman Filter formalism
 - ▶ Start from track seed parameters
 - ▶ **Predict parameters at next surface**
 - ▶ Search for matching measurements
 - ▶ **Kalman update stage:** Update track state using matching measurement
 - ▶ Repeat until no more surfaces
- ▶ Usually followed by Kalman "Smoothing"
 - ▶ Replace each local state estimate with an optimal estimate given a complete set of measurements
- ▶ [Nucl.Instrum.Meth.A 262 \(1987\) 444-450](#)

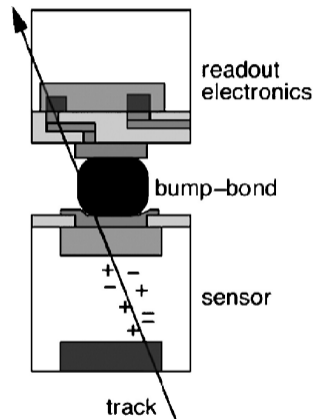


- ▶ From pixel detector, need measurements $m = (x, y)$
- ▶ However, only get individual pixels from readout
- ▶ → Use connected component analysis to obtain clusters
- ▶ Then can estimate measurement position:
 - ▶ $(x, y) =$ charge-weighted cluster center
 - ▶ $(\sigma_x, \sigma_y) = \text{pix. width} / \sqrt{12}$
- ▶ Possible to improve:
 - ▶ Take **direction** into account
 - ▶ Do fancier shape analysis
 - ▶ ...
- ▶ **Measurement calibration** paradigm: Apply corrections to estimated measurements during Kalman update stage
 - ▶ Simple scale-and-offset schemes
 - ▶ ATLAS: “Analogue clustering”, NN-based clustering
 - ▶ ... many other possibilities



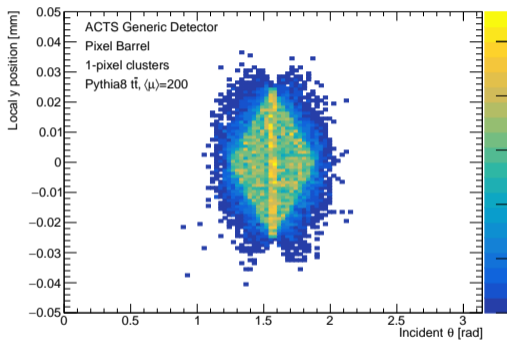
Example 1: Single pixel clusters

- ▶ Primarily rely on shape analysis to constrain position
- ▶ Edge case: 1-pixel clusters, “no” shape information
- ▶ However: Angles of incidence give some constraint!
 - ▶ $\approx 90^\circ$ crossing: Anywhere on surface
 - ▶ $\rightarrow 0^\circ$ crossing: Near center (else, ≥ 2 pixel)
- ▶ N.B. position defined at middle of Si bulk, by convention

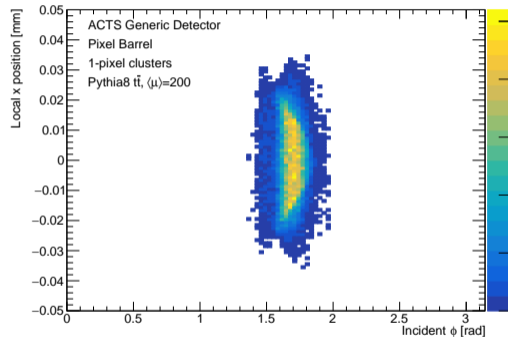


1-pixel cluster: Local positions vs Angles of incidence

- Clear relationship between $\sigma(\text{pos})$ and angle



- Transverse direction: Shift due to B field

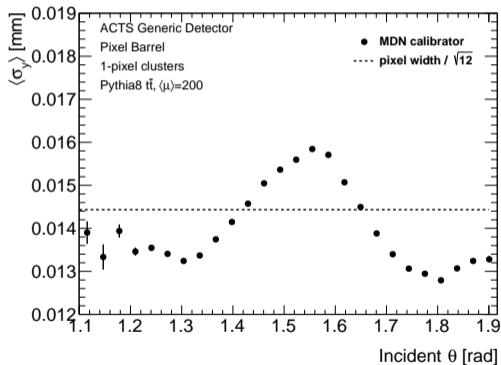


- ▶ MDN \equiv Mixture Density Network
- ▶ i.e. any neural network trained to output parameters of a gaussian mixture
- ▶ Model output: parameters π_i, μ_i, σ_i such that:

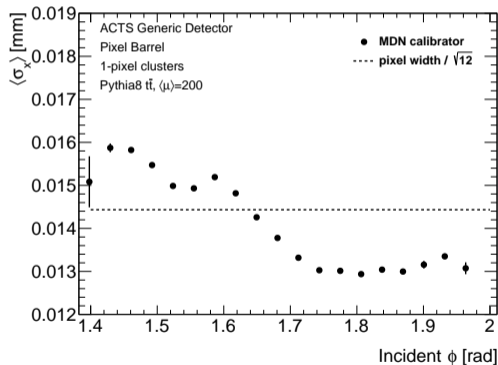
$$P(Y|X) \sim \sum_i \pi_i(X) \mathcal{N}(Y|\mu_i(X), \sigma_i(X))$$

- ▶ X is set of variables describing a measurement (e.g. charge, volume/layer, angles of incidence)
- ▶ Y is true crossing position in Si bulk (ground truth)
- ▶ $\pi_i(X)$: Prior probability for i -th component (if using ≥ 2 components)
- ▶ $\mu_i(X)$: Calibrated position estimate (Supervised learning)
- ▶ $\sigma_i(X)$: Uncertainty estimate (Unsupervised learning)
- ▶ If using single component, model is a simple normal distribution
- ▶ Trained using probabilistic programming paradigm: loss is directly $-\log P(Y|X)$
- ▶ At runtime, use $\mu_i \pm \sigma_i$ corresponding to highest π_i as position estimate
- ▶ This method naturally generalizes to clusters with ≥ 2 particles
- ▶ Method used by ATLAS collaboration for pixel measurement calibration
 - ▶ See e.g. [ATL-PHYS-PROC-2019-082](#)

- ▶ Clear relationship between $\sigma(\text{pos})$ and angle
 - ▶ Stronger constraint at large angles
 - ▶ Weaker constraint for head-on particles



- ▶ Asymmetry due to Lorentz Angle in transverse direction (known constant shift due to B-field and Si thickness \rightarrow easy to correct)



N.B. $\sigma_{x/y}$ are model-estimated uncertainties, not residuals

Calibration interface in ACTS

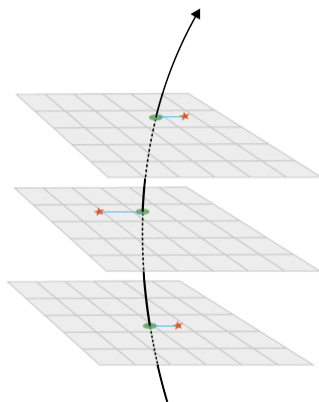
- ▶ The ACTS tracking toolkit contains Kalman Filter-based track finding & fitting algorithms
- ▶ Calibrations can be applied on-the-fly during track finding / track fitting
- ▶ Interface implemented using template-based delegation:

```
class KalmanFitterExtensions {  
    using Calibrator = Delegate<void(const GeometryContext&, const CalibrationContext&,  
                                     const SourceLink&, TrackStateProxy)>;  
  
    /// The Calibrator is a dedicated calibration algorithm that allows  
    /// to calibrate measurements using track information, this could be  
    /// e.g. sagging for wires, module deformations, etc.  
    Calibrator calibrator;  
  
    ...  
};
```

- ▶ Calibrator class acts directly on track state proxy, which holds the current measurement
- ▶ Dynamic geometry effects and intra-run calibration changes encapsulated via contextualization
- ▶ ONNX plugin: NN-based calibration methods are supported!
 - ▶ See [NeuralCalibrator](#) in ACTS Examples

Example 2: Detector alignment

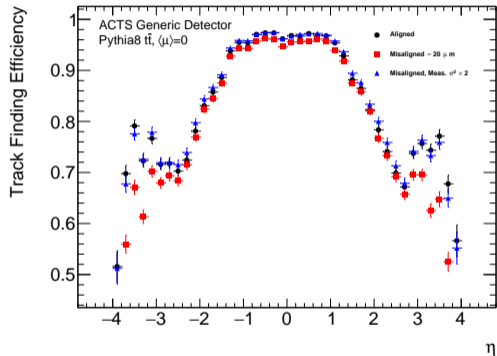
- ▶ Alignment \equiv deriving corrections to geometry description for shifts in element positions
- ▶ Work ongoing in ACTS on Kalman Filter-based alignment algorithm
- ▶ If detector is very misaligned, performance is degraded:
 - ▶ Track efficiency drops
 - ▶ measurements are lost
- ▶ Can “bootstrap” the alignment procedure with measurement calibration:
 - ▶ Scale measurement errors up
→ recover tracking efficiency
 - ▶ Perform alignment with unscaled errors



- ▶ Alignment minimizes track-hit χ^2
- ▶ c.f. [\[2007.07624\]](#)

Example 2: Detector alignment

- ▶ Simulated “large” misalignment: linear shift $\sim \mathcal{N}(0, 20\mu m)$ for each module
- ▶ Clear effect on efficiency & measurements per track
- ▶ Using the [ACTS ScalingCalibrator](#), apply a $\times 2$ factor to the measurement variances
 - ▶ Emulates artificially-large clusters
 - ▶ Efficiency is recovered



- ▶ Measurement Calibration: Correcting the measurement positions & errors on-the-fly during track finding & track fitting
- ▶ The ACTS Kalman Filter includes efficient template-based interface to measurement calibration
- ▶ Different examples are provided: Simple ScalingCalibrator, Fancy MDN-based NeuralCalibrator
- ▶ Future plans:
 - ▶ Provide documentation and tutorials for the interface and the examples
 - ▶ Explore more calibration methods (e.g. ATLAS “Analogue Clustering”)
 - ▶ Implement ATLAS-inspired dense environment calibration (Cluster splitting, positions for ≥ 2 particles, ...)