2D pixelated BNL AC-LGADs: From laser TCT to Test Beam characterization

Matias Senger

Ben Kilminster

Anna Macchiolo

Universität Zürich UZH

Gaetano Barone

BROWN

Gabriele Giacomini

Alessandro Tricoli

Brookhaven National Laboratory

AIDAinnova WP6 test-beam group

AIDA innova

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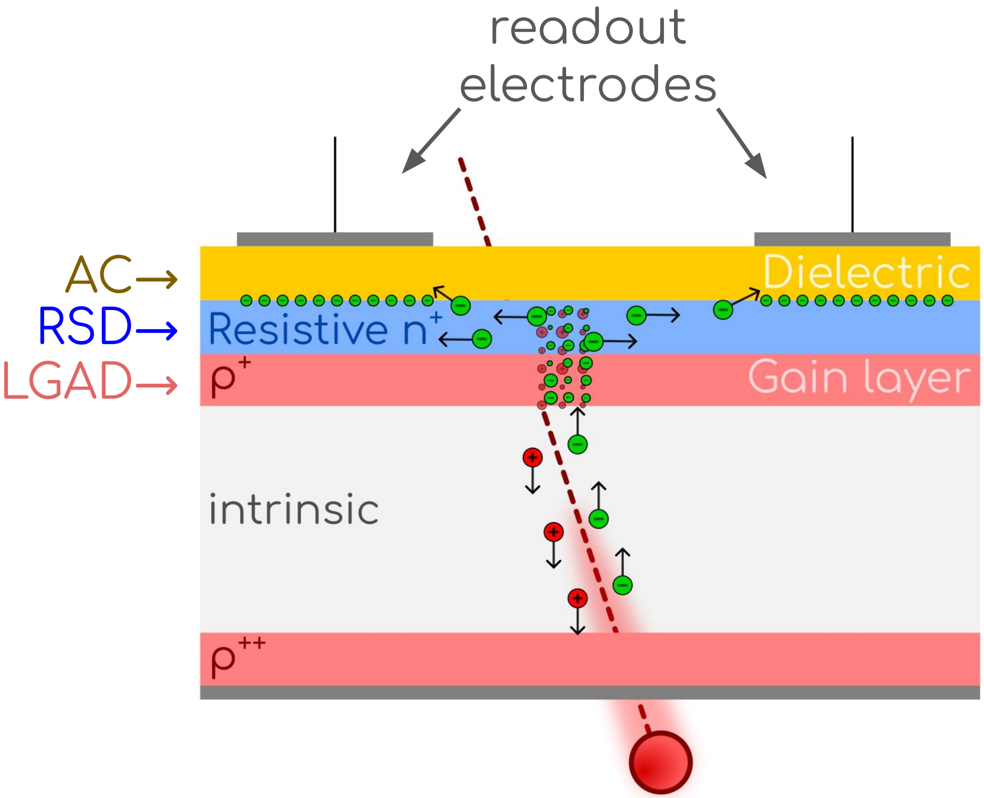
AIDAinnova WP6 test-beam group

- CNM-Barcelona (AIDAinnova): Oscar David Ferrer Naval
- IFCA (AIDAinnova + ETL): Ivan Vila Alvarez, Andres Molina Ribagorda, Jordi Duarte Campderros, Efren Navarrete Ramos, Marcos Fernandez Garcia, Ruben Lopez Ruiz
- IJS (AIDAinnova): Gregor Kramberger, Jernej Debevc
- University of Torino / INFN (AIDAinnova + ETL + EXFLU): Roberta Arcidiacono, Federico Siviero, Leonardo Lanteri, Luca Menzio, Roberto Mulargia, Valentina Sola, Marco Ferrero
- INFN Genova: Claudia Gemme
- UZH (AIDAinnova): Anna Macchiolo, Matias Senger
- Korea: D. Lee, W. Jun, T. Kim
- CERN: A. Rummler, V. Gkougkousis

Introduction

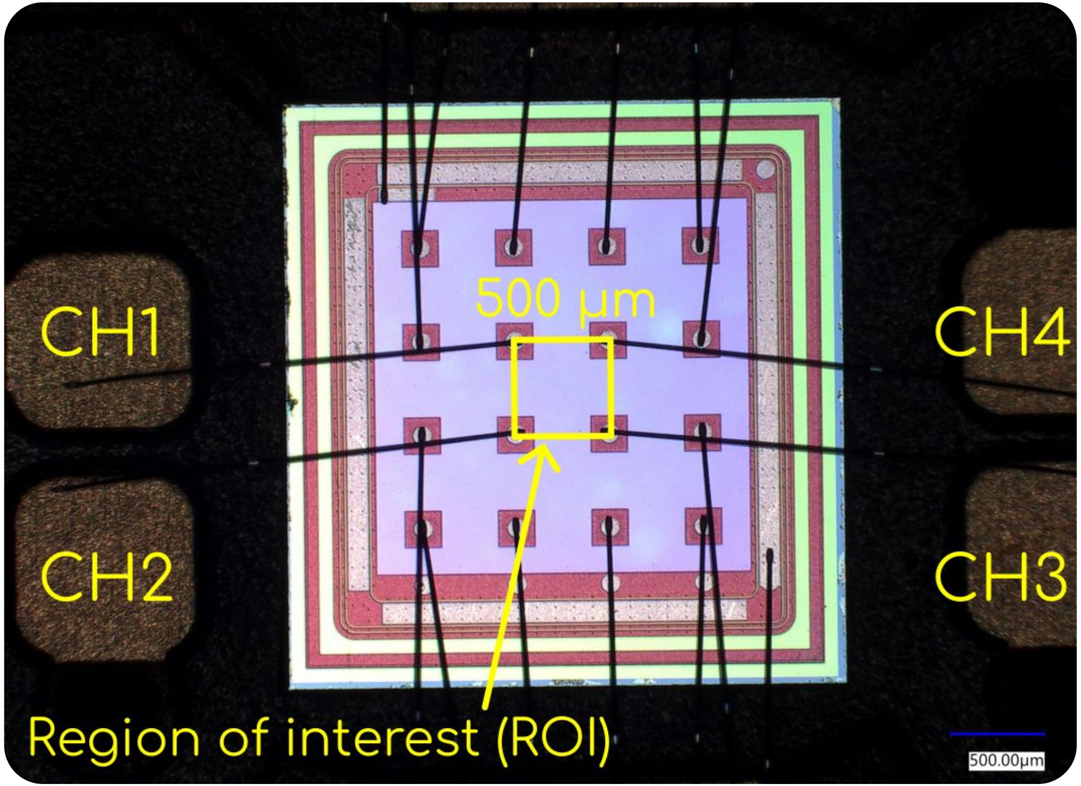
- AC-LGAD*: A single, large LGAD with a resistive and a dielectric layer on top, and small electrodes touching it.
- Fill factor = 100 % by construction. ✅
- Time resolution inherited from LGAD. ✅
- Spatial resolution improved by sharing the charge. 👏
- Efficiency? 🤔
- Radiation hardness? 🤔



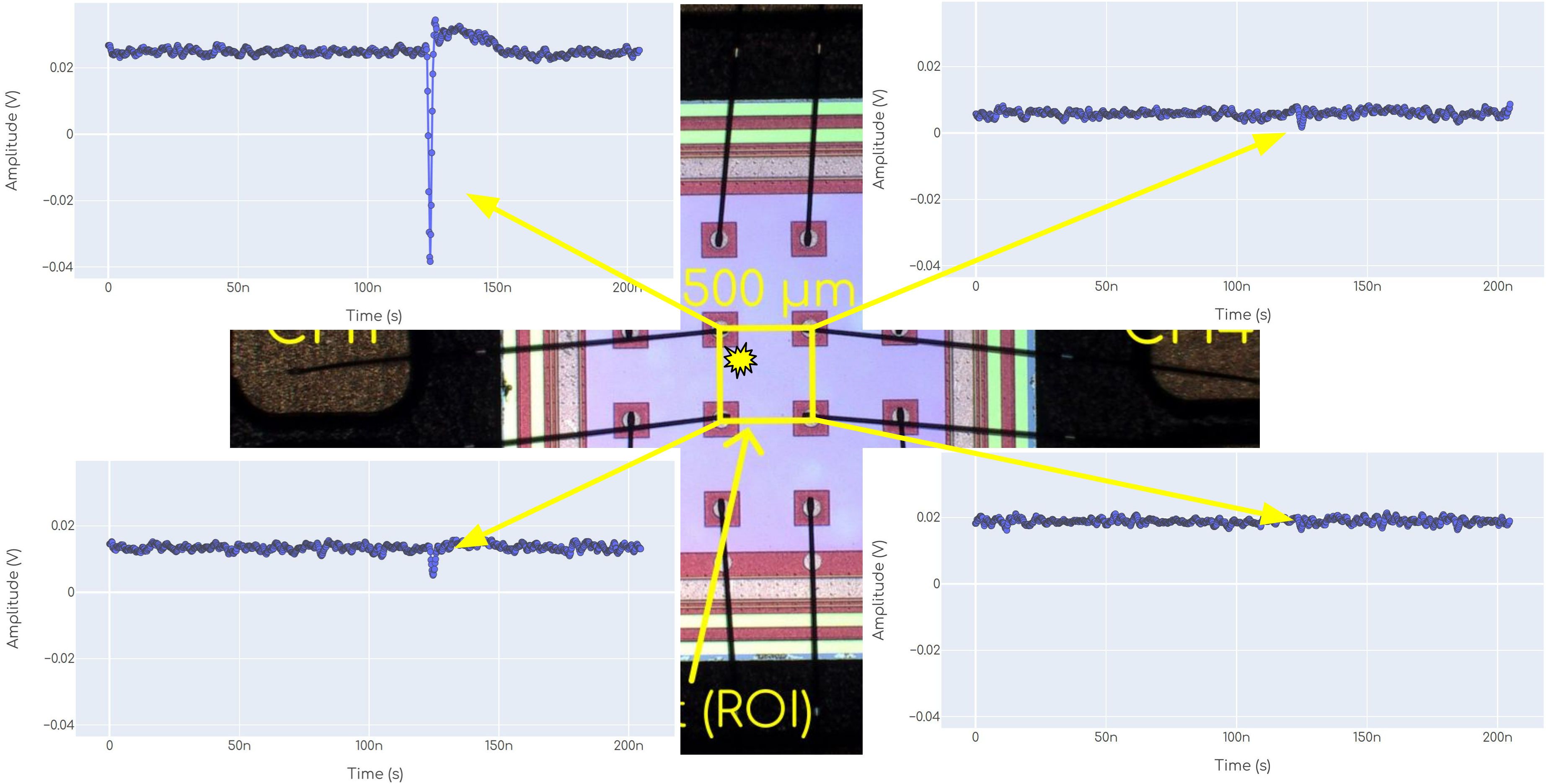
* Maybe a better name would be "AC-RSD-LGAD", see the cartoon.

Characterized devices

- 2 identical devices
- Manufactured at BNL
- Active thickness: 30 μm
- Pad size: 200 μm
- Pitch: 500 μm
- 2×2 pads readout
- Unused pads to GND
- Non irradiated



Charge sharing at the heart of this technology



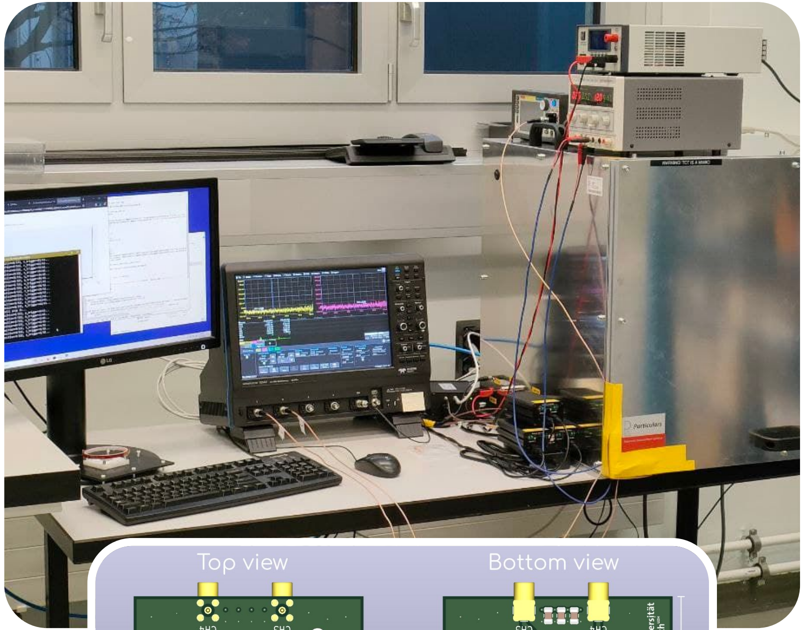
Laser TCT studies

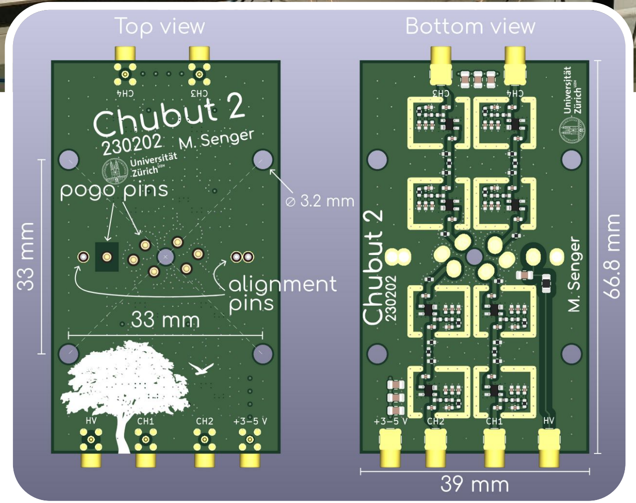
Goals of TCT characterization

- Understand working principles of this technology.
- Compare algorithms for:
  - Hit position reconstruction.
  - Hit time reconstruction.

UZH laser TCT setup

- Particulars Scanning TCT:
  - Infrared laser (1064 nm).
  - Laser spot Gaussian with σ ~ 9 μm.
  - ~1 μm spatial resolution.
  - Laser intensity set to match ≈ 1 MIP.
- Laser splitting+delay[1] with optic fiber for timing measurements provides two pulses separated by 100 ns.
- Oscilloscope LeCroy 640Zi.
  - 3 GHz, 20 GS/s.
- Chubut 2 readout board[2], 4 channels with 2 amplification stages.

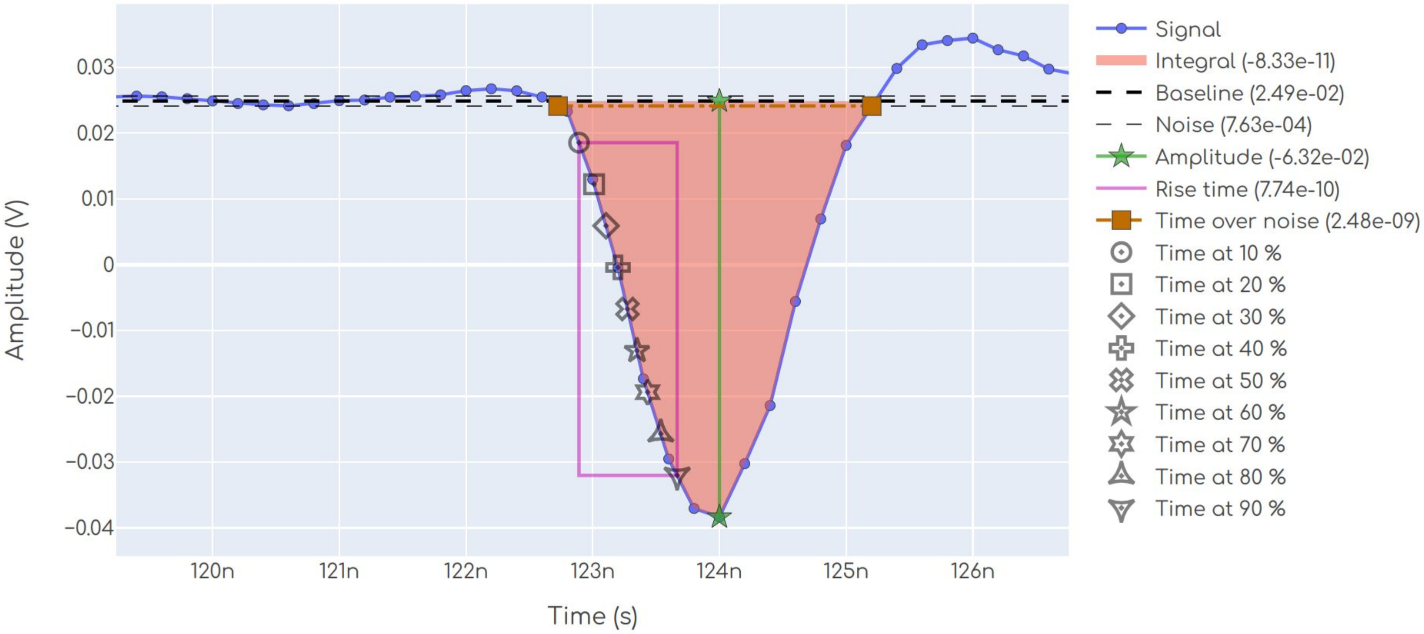




[1] https://msenger.web.cern.ch/laser-delay-system-for-the-scanning-tct/
[2] https://github.com/SengerM/Chubut_2

Waveforms analysis

We record the waveforms, then process them offline*. Example:



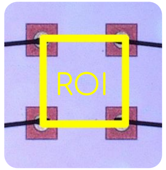
* https://github.com/SengerM/signals

Hit position reconstruction

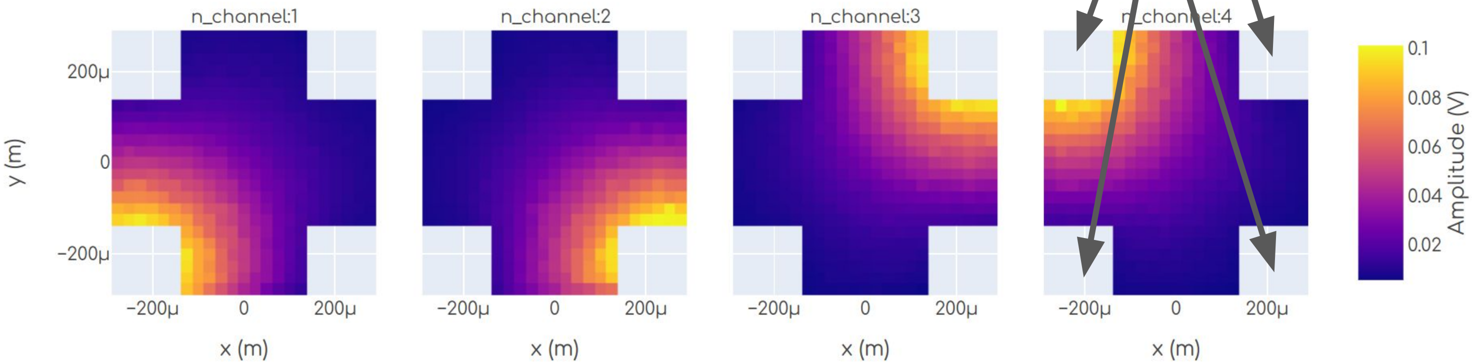
TCT scans

Two scans per DUT, training and testing scans, as shown:

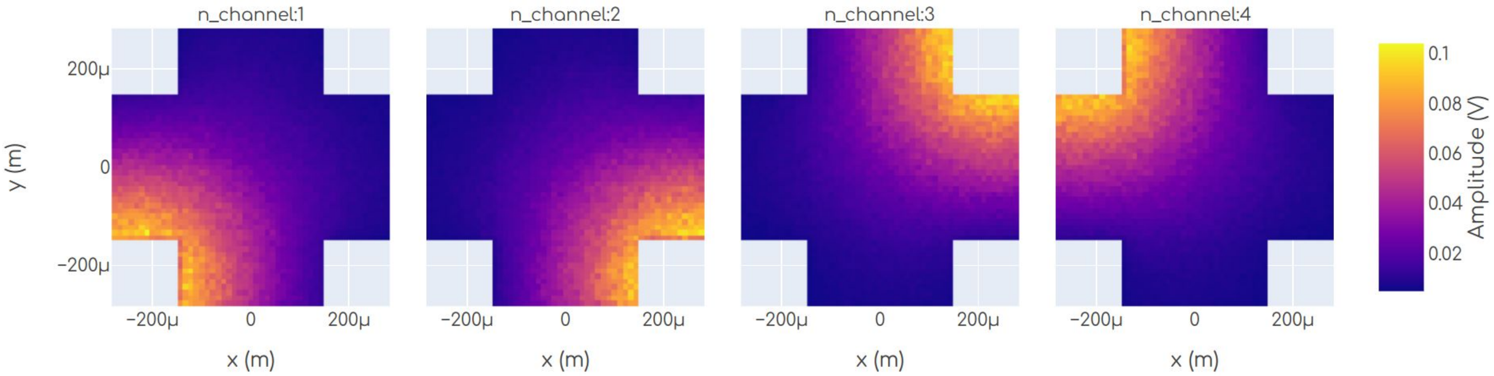
Readout metal pads position



Training scan:
25×25 μm² grid
111 events per position



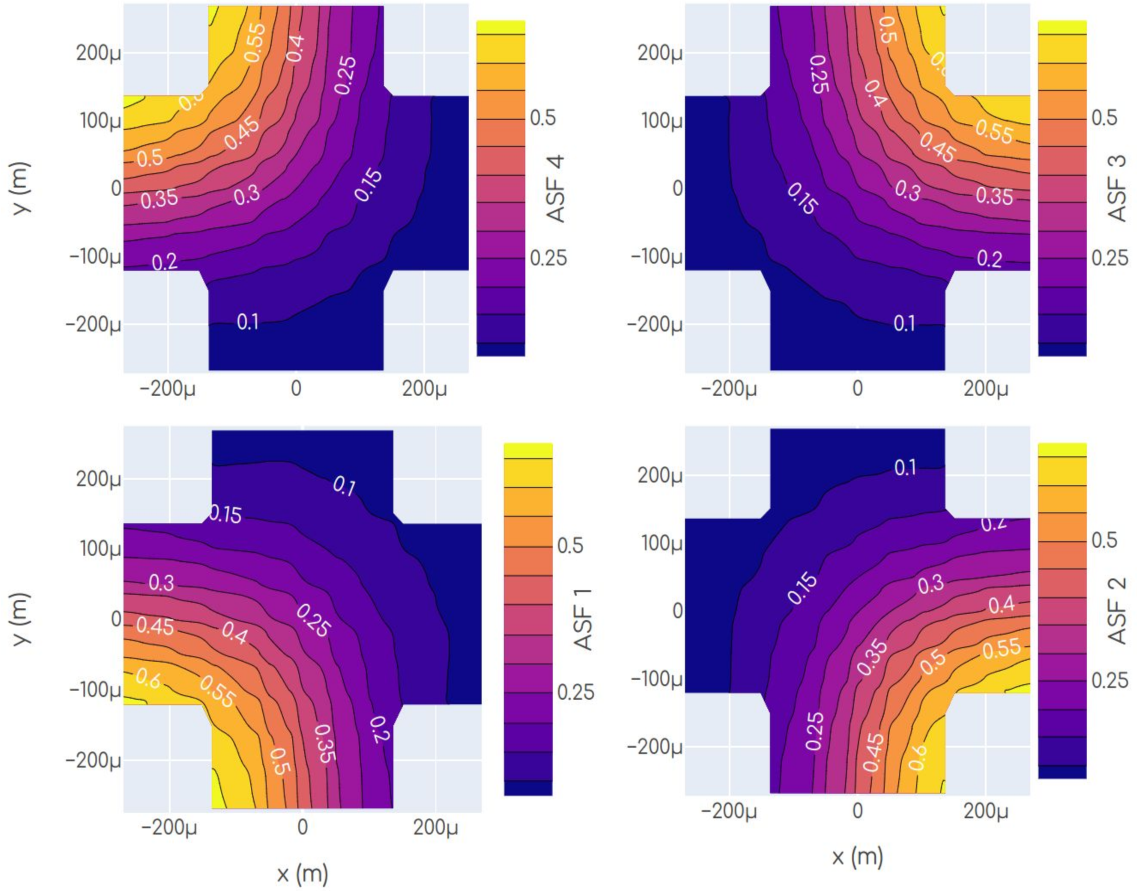
Testing scan:
11×11 μm² grid
22 events per position



Position reconstruction, step 1

Compute some meaningful quantity with strong spatial dependency, and preferably independent of total charge deposited. We chose the “amplitude shared fraction” (ASF):

$$\mathrm{ASF}_i = \frac{A_i}{\sum_j A_j}$$



Position reconstruction, step 2

Feed the data into a machine learning algorithm. We compare:

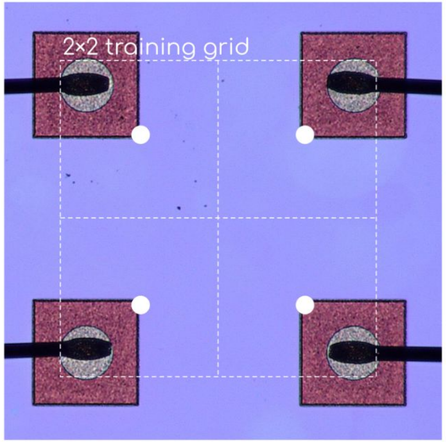
1. Deep neural network (DNN):
   - Popular, can solve anything.
   - PyTorch library: quick and easy.
2. Lookup table (LookupTable):
   - Sometimes, the simpler the better.
3. Maximum Likelihood Estimator (MLE):
   - Measure the likelihood function at each position, then simply compute the most likely x,y.

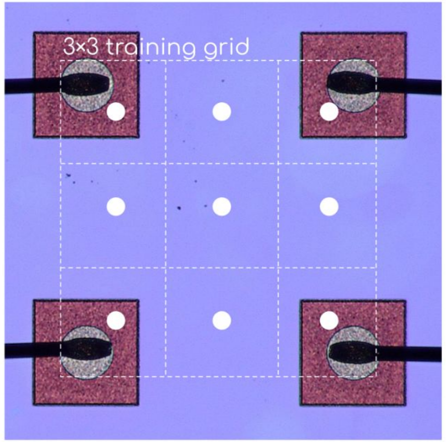
Position reconstruction, step 2.5

For the training process, the position data was discretized into a grid as shown.

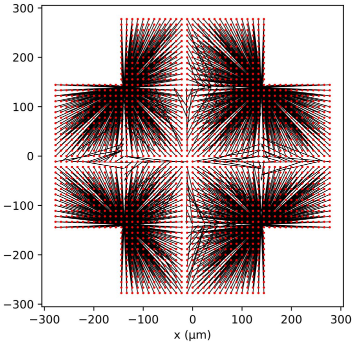
Why?

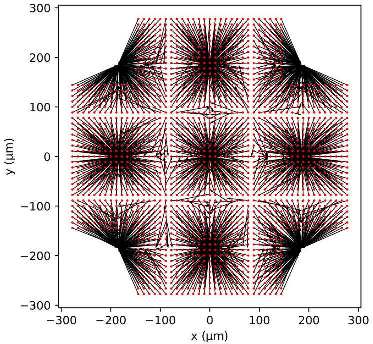
- Required for lookup table algorithm, no way around it.
- Gives a parameter to sweep and compare the algorithms. ✅
- As the grid gets smaller, better results are expected.





... etc...



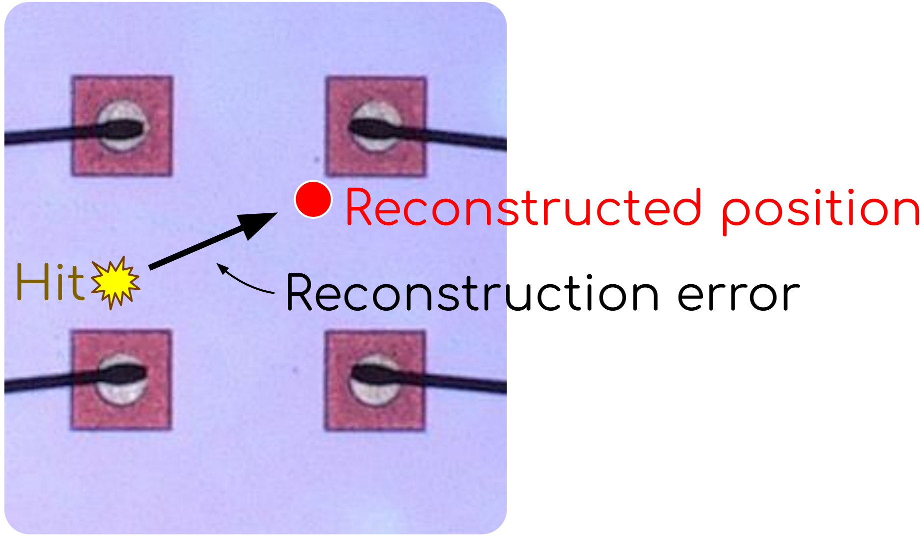


... etc...

Results

The results are measured using the reconstruction error:

$$\text{Reconstruction error} = \sqrt{\sum_{\xi \in \{x,y\}} \left(\xi_{\text{reconstructed}} - \xi_{\text{TCT}}\right)^2}$$



Results

The results are measured using the reconstruction error:

$$\text{Reconstruction error} = \sqrt{\sum_{\xi \in \{x,y\}} \left(\xi_{\text{reconstructed}} - \xi_{\text{TCT}}\right)^2}$$

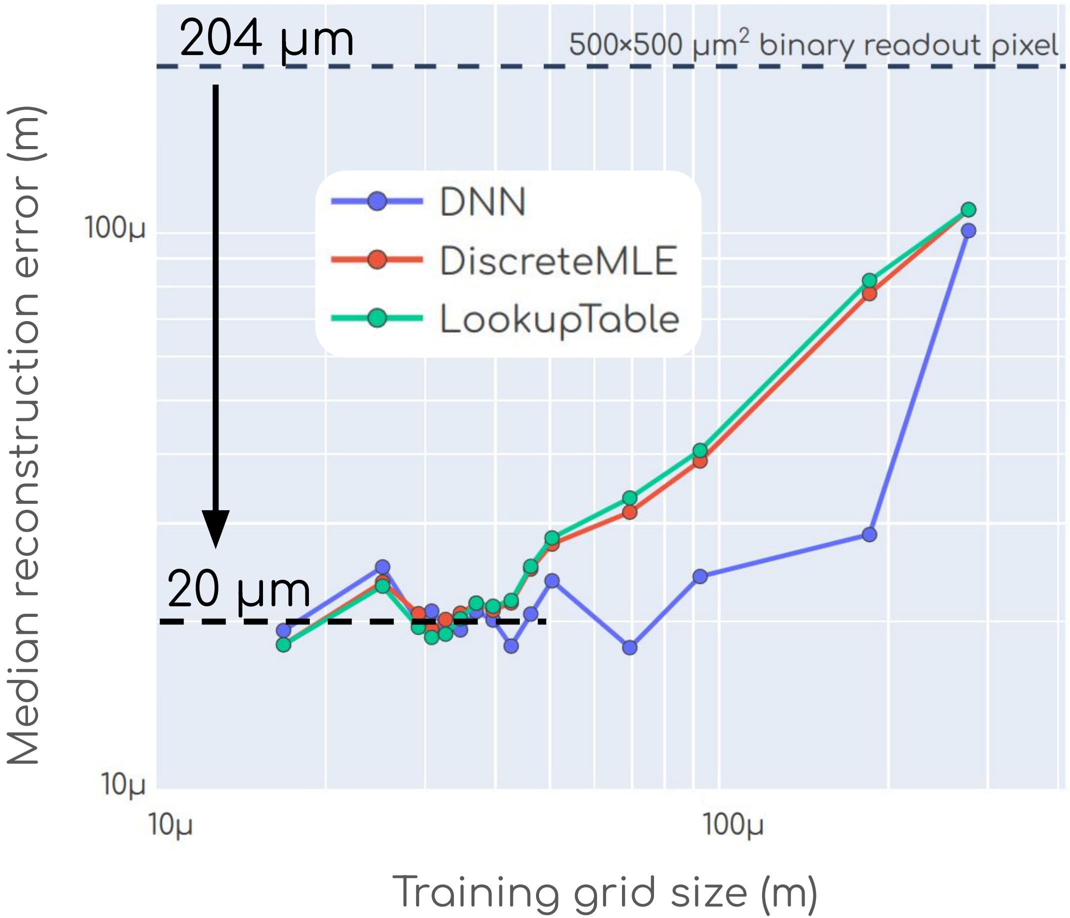
Before we do any comparison, for a square binary readout pixel:

$$\text{Reconstruction error}_{\text{square binary readout pixel}} \approx \text{pitch}\sqrt{\frac{2}{12}}$$ ✅ (204 µm)

$$\text{Reconstruction error}_{\text{square binary readout pixel}} = \frac{\text{pitch}}{\sqrt{12}}$$ ❌ (145 µm)

* See backup slides for more details.

Median reconstruction error vs training grid size



- DNN outperforms the others for large grids (because it learns to interpolate, even though it was not trained for that)
- For fine enough training grid, all algorithms behave similar.
- Converges to ≈20 μm for smaller and smaller grid sizes.
- Median reconstruction error is ~10 times smaller than for a 500×500 μm² binary readout pixel. 👏

Hit time reconstruction

Time reconstruction algorithms

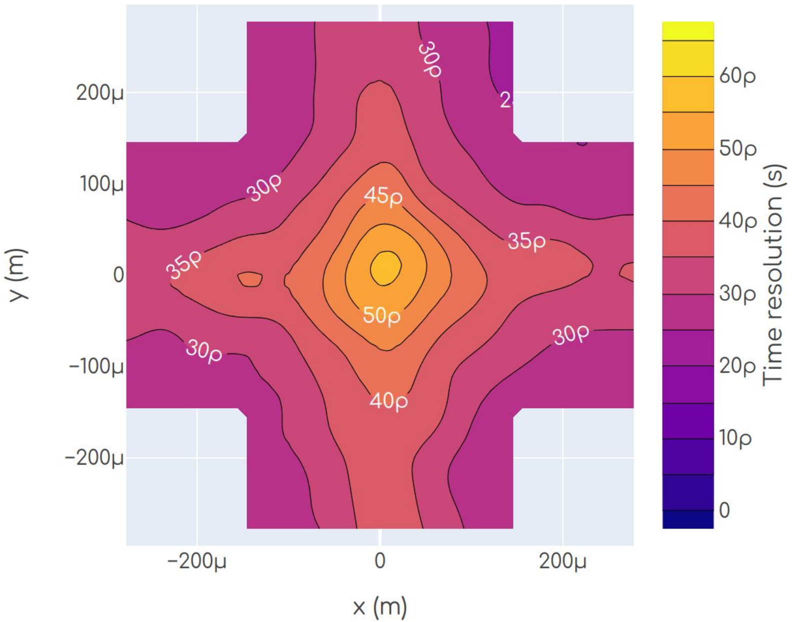
Two methods tested:

1. Single pad approach.
   - For each event just take the time from the leading waveform, ignore other channels.
2. Multiple pad weighted combination:
   - Amplitude weighted average from several pads.
   - No “hit position corrections”.

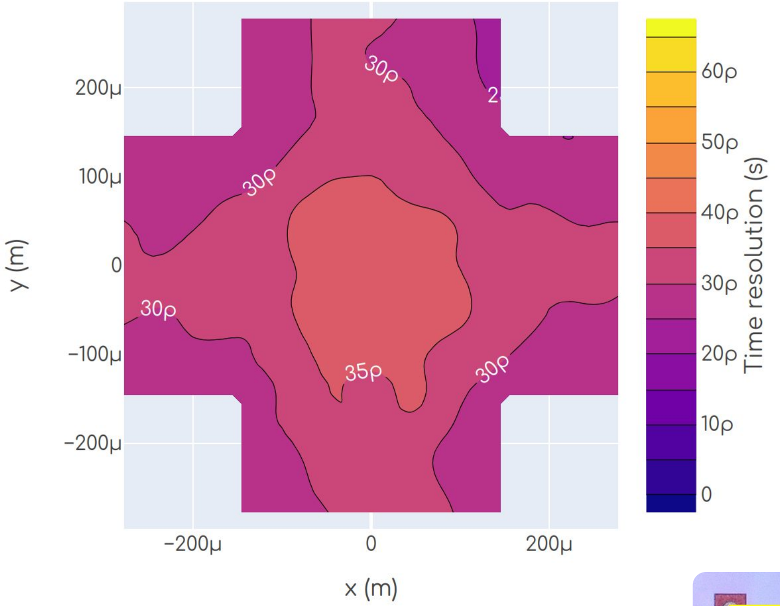
$$t_{\text{reco}} = \frac{\sum_i a_i^2 t_i}{\sum_i a_i^2}$$

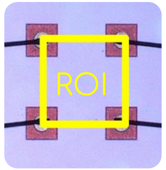
Time reconstruction algorithms

Single pad algorithm



Weighted average algorithm





- TDCs from all pads have to be active all the time to get the desired time resolution, one TDC out of 4 is not enough.
- ⚠️ Laser TCT lacks of Landau fluctuations

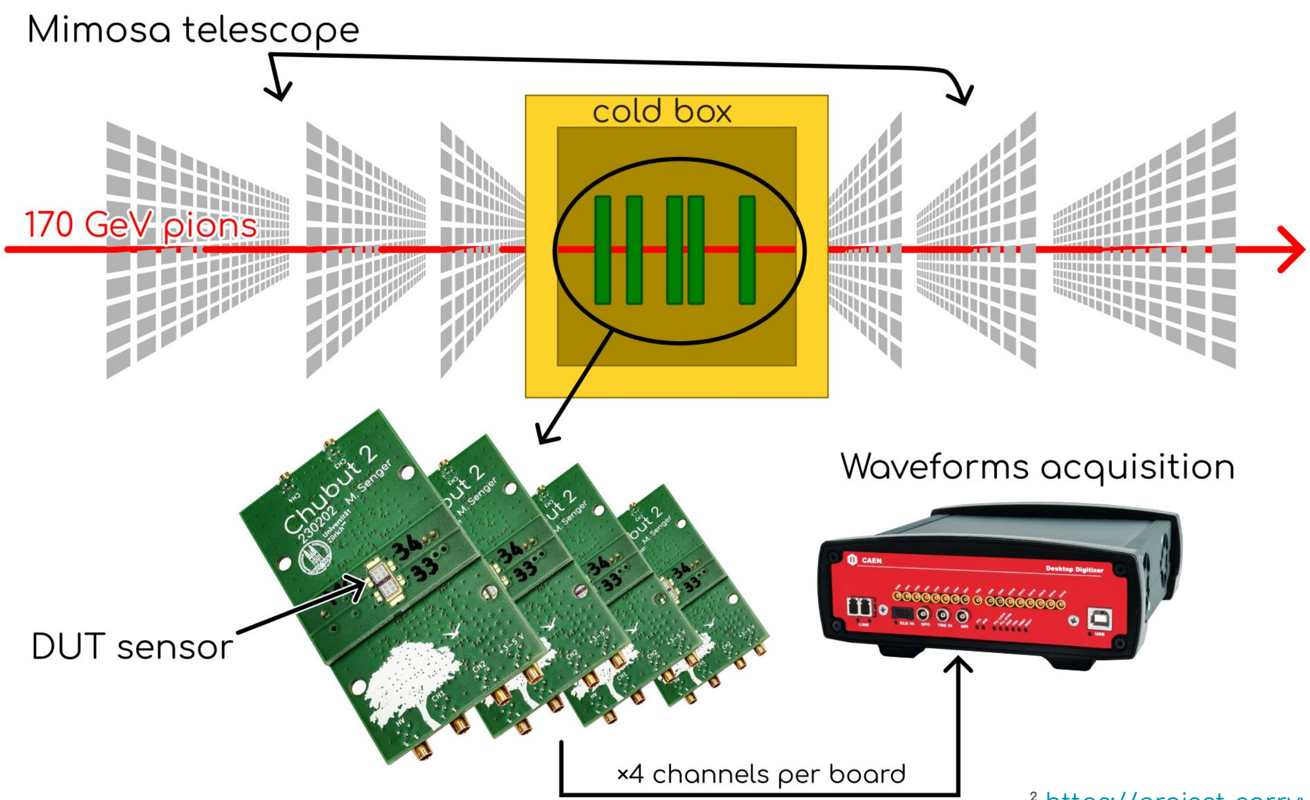
Test beam characterization

Goals of test beam characterization

- Test the technology with “real particles” (as opposed to laser pulses).
- Measure the efficiency.
- Study behavior of hits inside the pad area (impossible with laser).
- Compare results with laser TCT characterization.

Test beam setup

Simplified diagram:

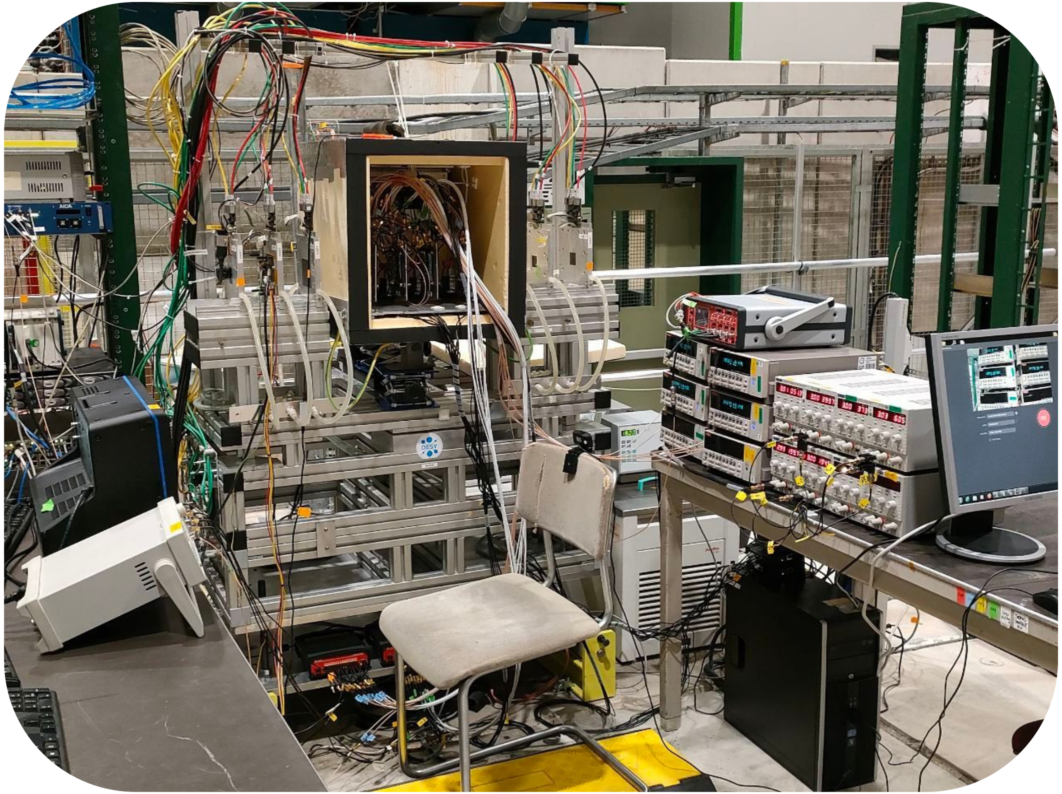


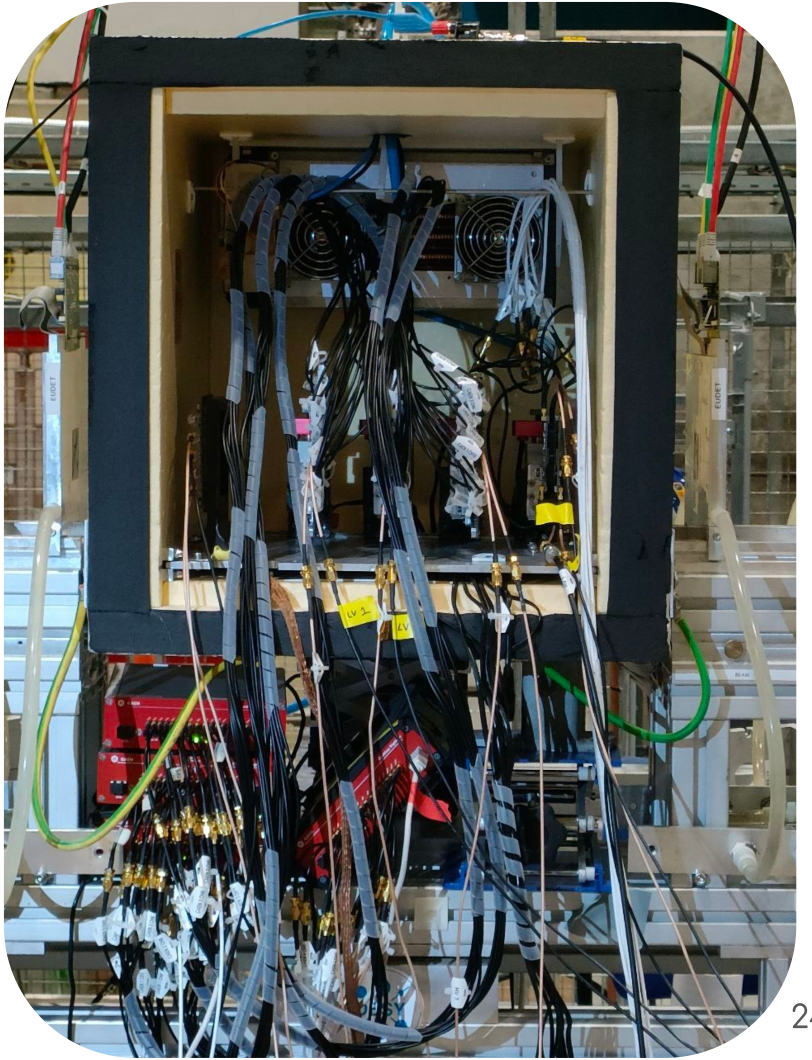
- CERN H6 beamline (120 GeV pions)
- Mimosa telescope
- Chubut 2, 4 channels readout board[1]
- CAEN DT5742 digitizer, 500 MHz @ 5 GS/s
- Cold box for irradiated DUTs, down to -12 °C
- Tracks reconstruction using Corryvreckan[2]

[1] https://github.com/SengerM/Chubut_2
[2] https://project-corryvreckan.web.cern.ch/project-corryvreckan/

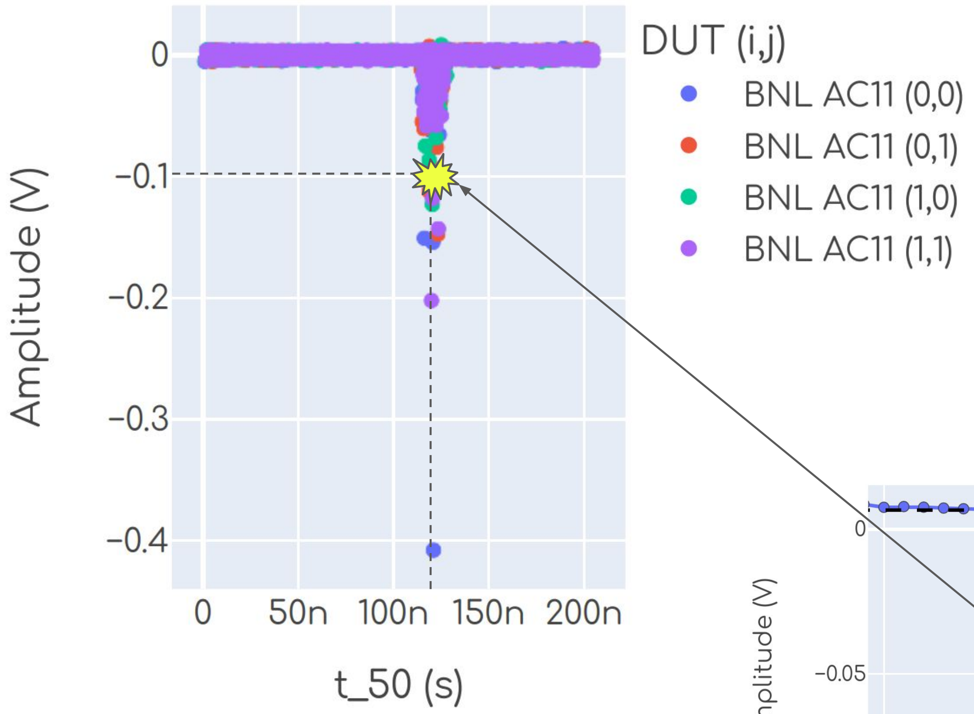
Test beam setup

Some photos:

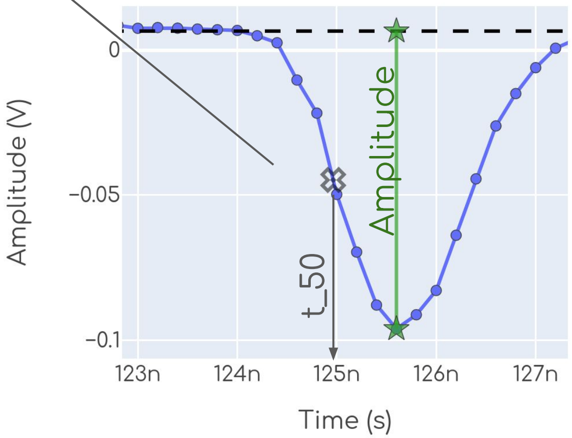




Waveforms distribution and events selection



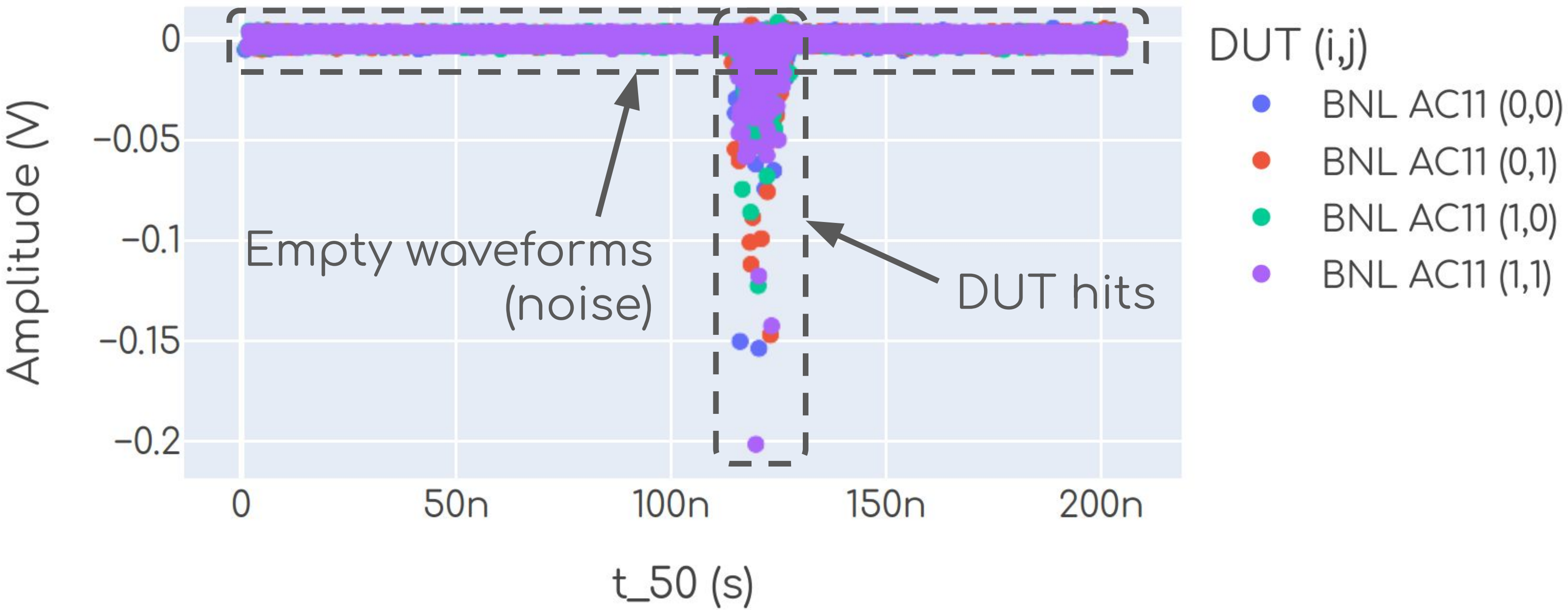
- Each dot is one waveform
- Color denotes channel



Example: This waveform has amplitude = 100 mV and t_50 = 125 ns

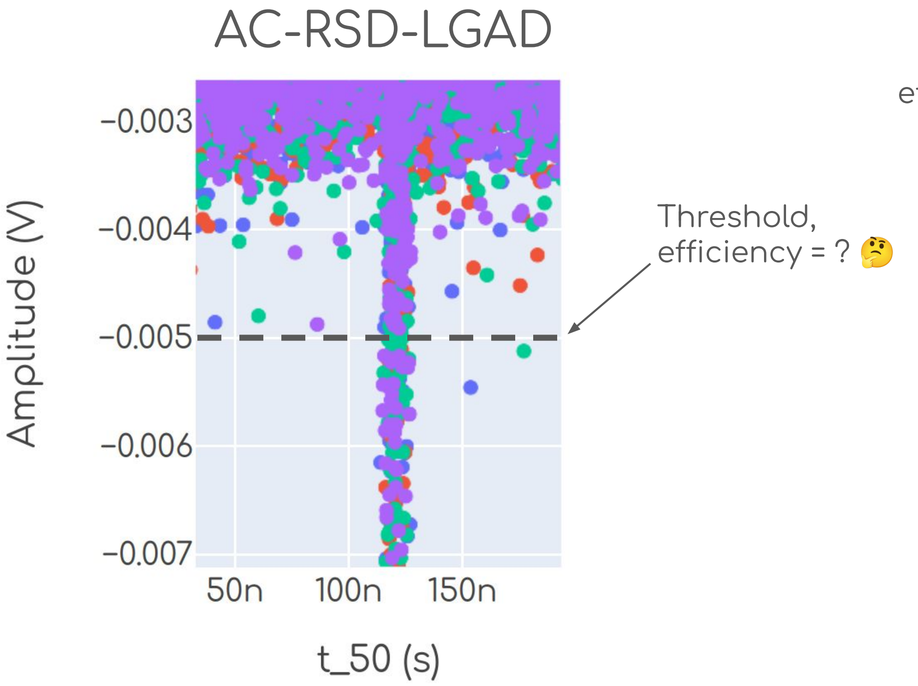
* This example is for one DUT, they all look similar.

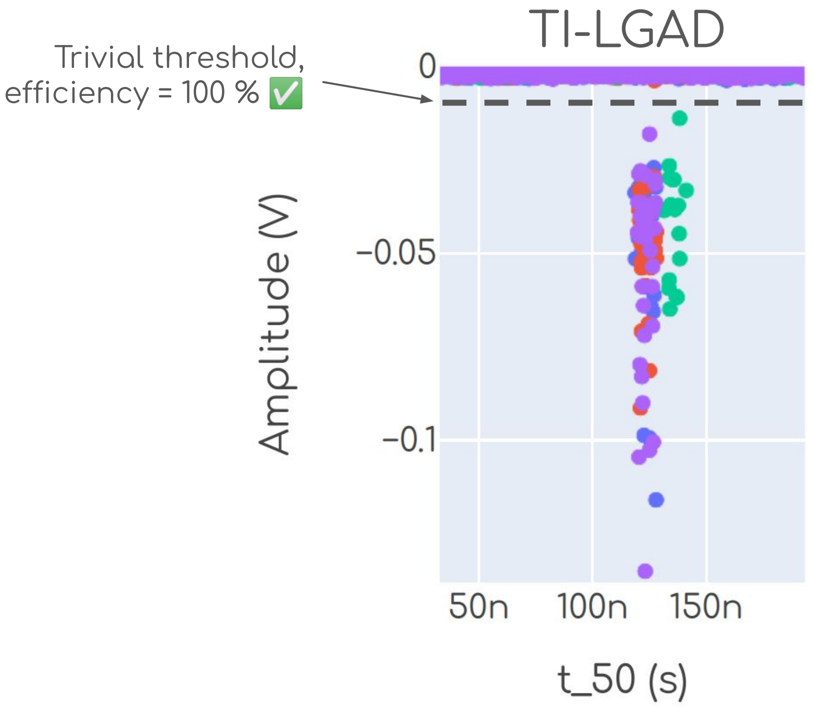
Waveforms distribution and events selection



The downside of charge sharing

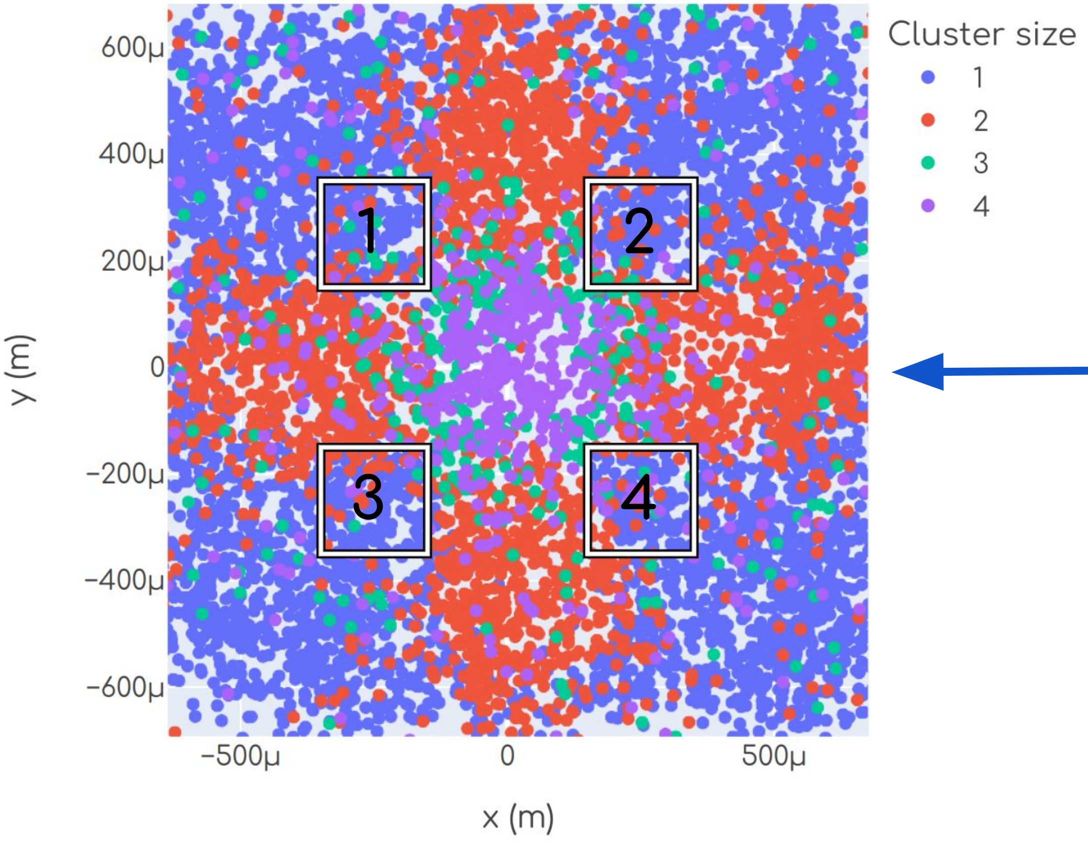
Threshold not trivial anymore, as opposed to a “normal LGAD” such as e.g. a TI-LGAD:

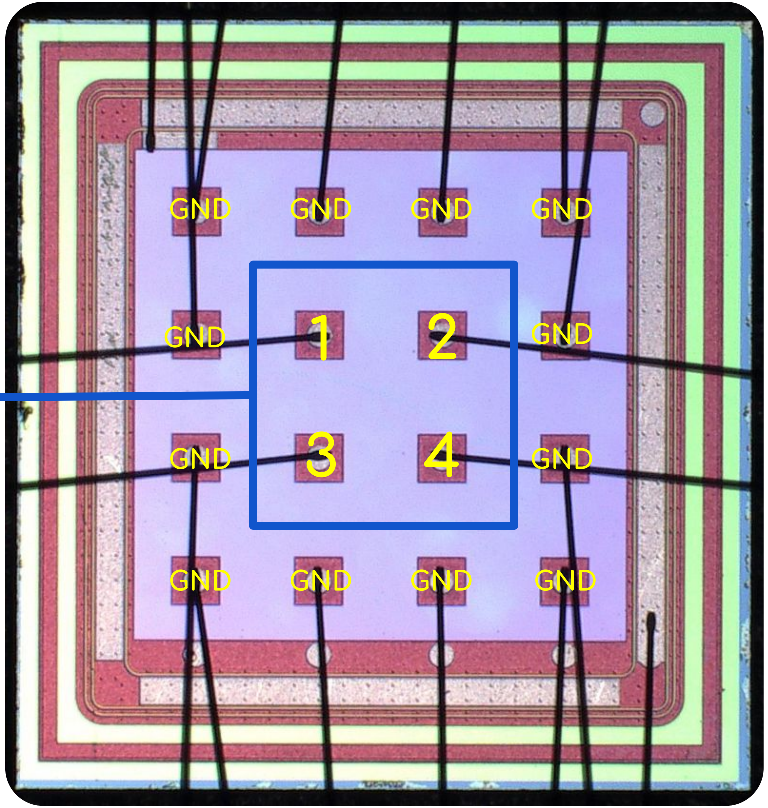




Charge sharing

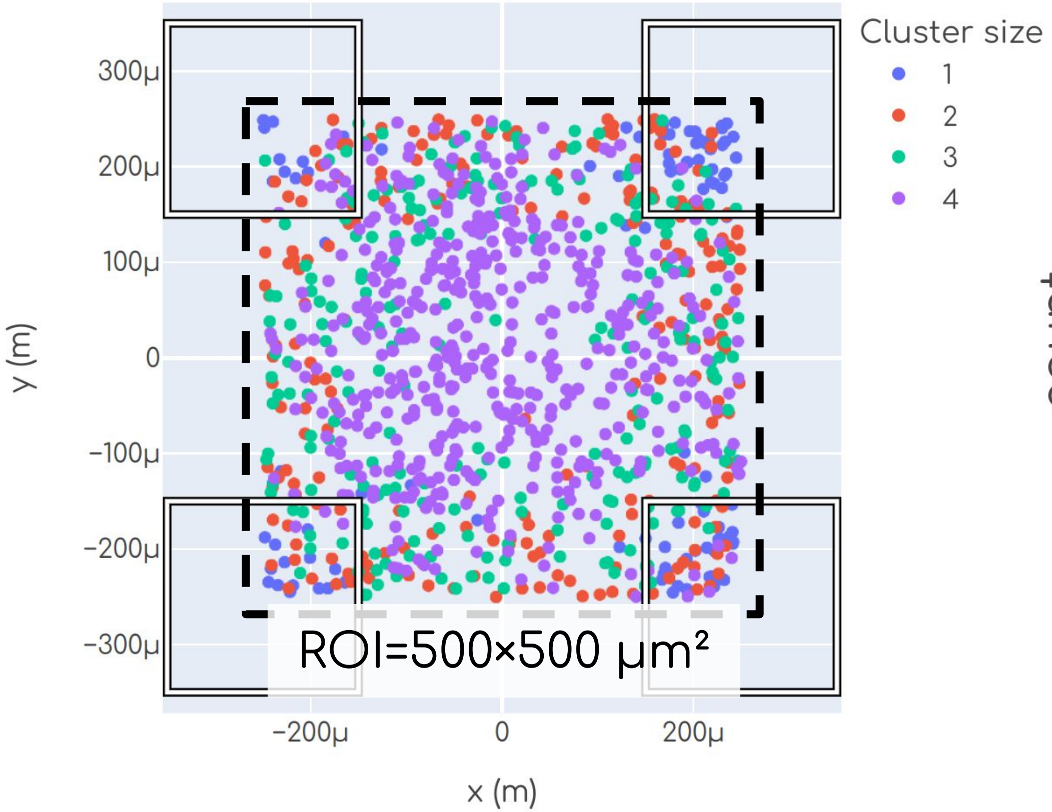
Charge sharing in action

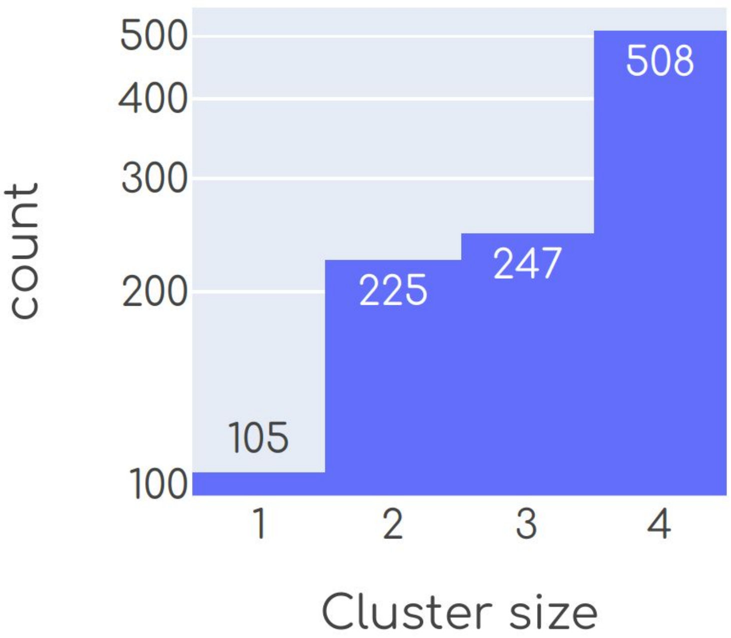




Charge sharing in action

Within ROI: Majority of events have large cluster size (desirable in this technology) ✅





Position resolution

Position reconstruction methods

Two methods were compared:

1. Charge imbalance formula. →

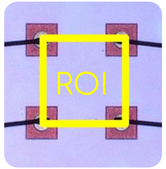
$$\begin{cases} x_{\text{reconstructed}} = \dfrac{\text{pitch}_x}{2} Q_{\text{imbalance } x} \\ y_{\text{reconstructed}} = \dfrac{\text{pitch}_y}{2} Q_{\text{imbalance } y} \end{cases}$$

$$\begin{cases} Q_{\text{imbalance } x} = \dfrac{Q_{11} + Q_{01} - Q_{00} - Q_{10}}{\sum Q_{ij}} \\ Q_{\text{imbalance } y} = \dfrac{Q_{00} + Q_{01} - Q_{11} - Q_{10}}{\sum Q_{ij}} \end{cases}$$

2. DNN.
   a. Using ASF, same as TCT.
   b. Training only on <2000 events.
   c. PyTorch library.

$$\text{ASF}_i = \frac{A_i}{\sum_j A_j}$$

Position reconstruction error results

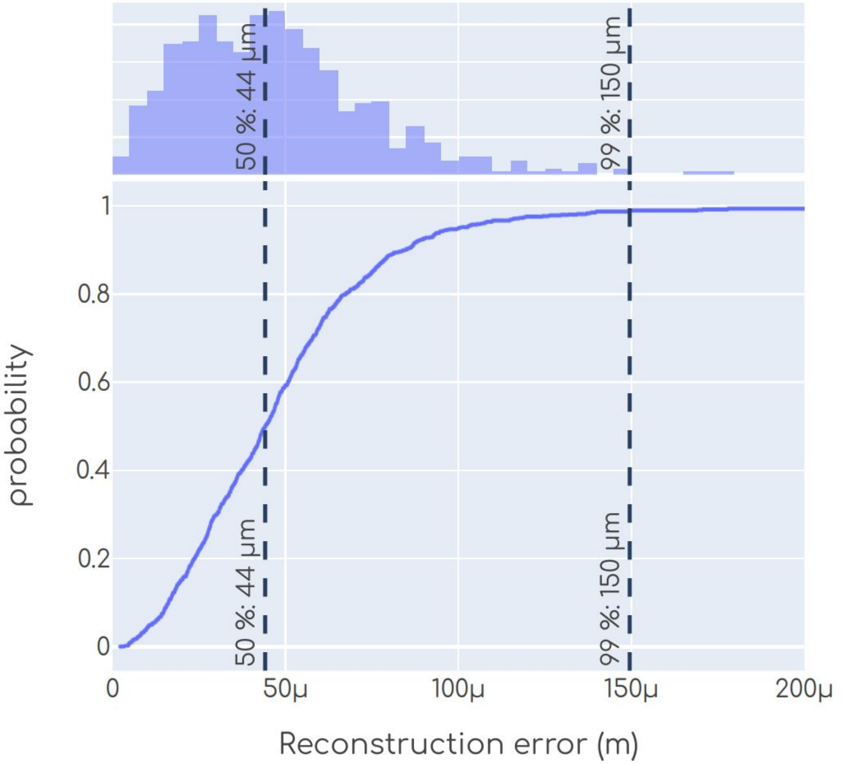


$$\text{reconstruction error} = \sqrt{\sum_{\text{coord}\in\{x,y\}} (\text{reconstructed}_{\text{coord}} - \text{telescope}_{\text{coord}})^2}$$

	Median	99 %
DNN	44 µm	150 µm
Charge imbalance formula	50 µm	173 µm
500×500 µm² SBRP*	204 µm	330 µm

quick comparison ↘

DNN reconstruction error distribution



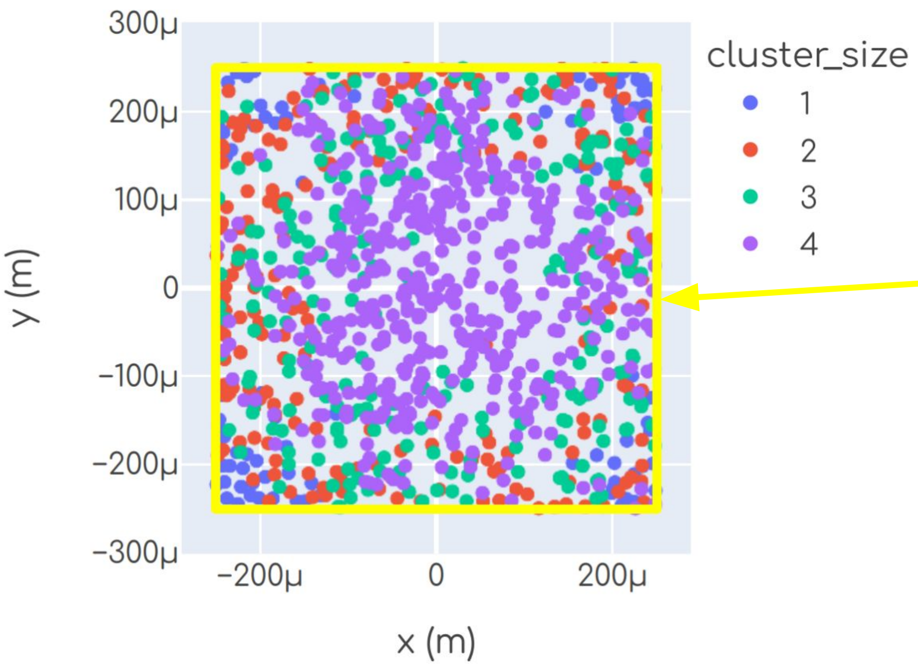
* SBRP = square binary readout pixel, see backup slides.
** Residuals in x and y also available in backup slides.

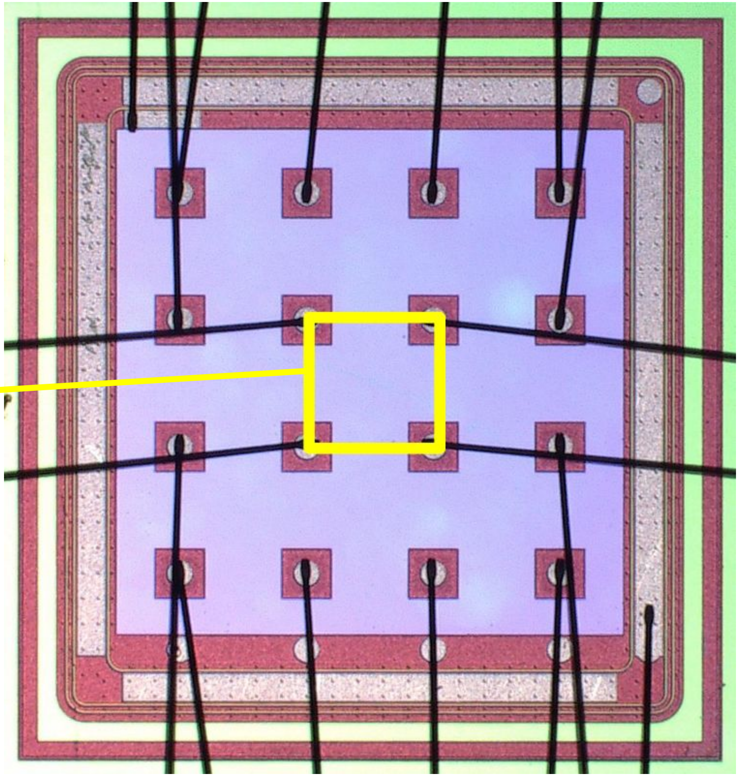
Efficiency

Efficiency

$$\text{Efficiency} = \frac{\text{Number of detected particles}}{\text{Number of particles that went through}}$$

- Measured efficiency: 100 % ✅
- 0 events undetected inside ROI (out of 1150 events)

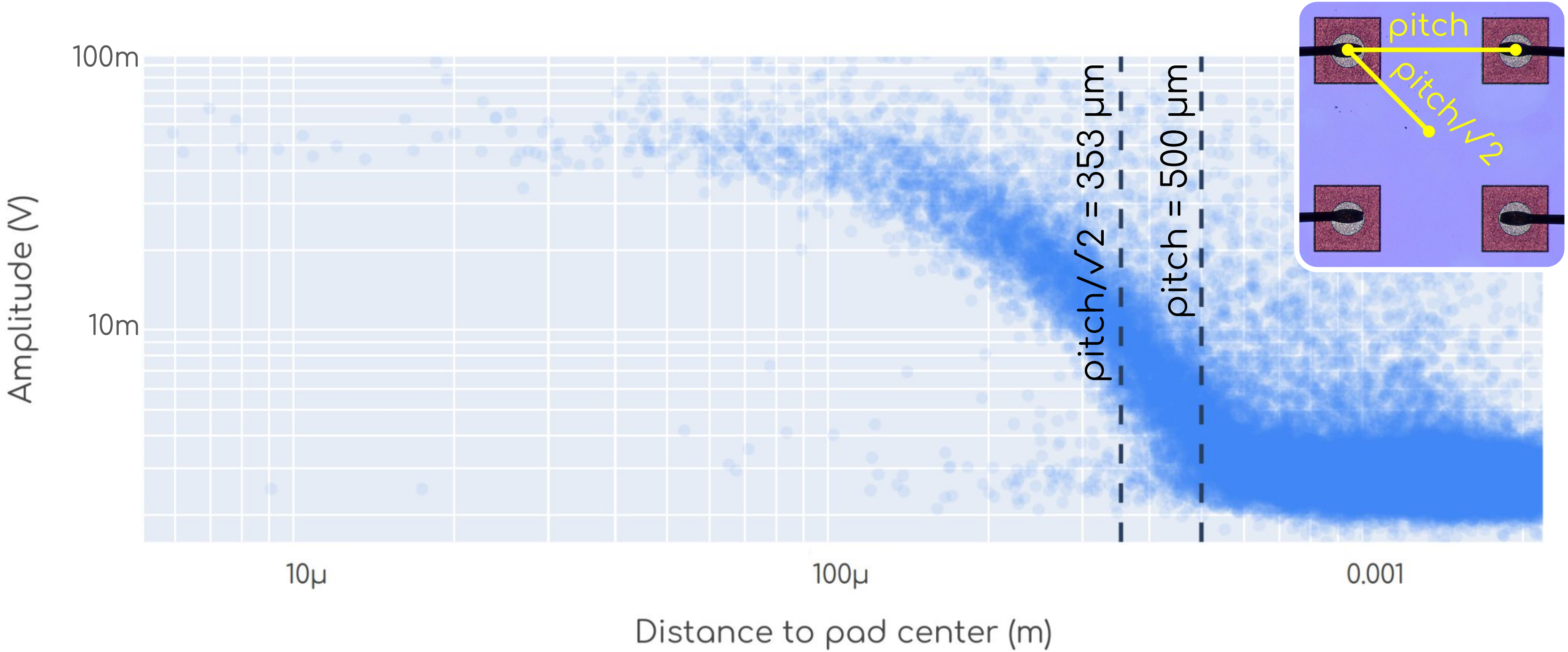




On the radiation hardness

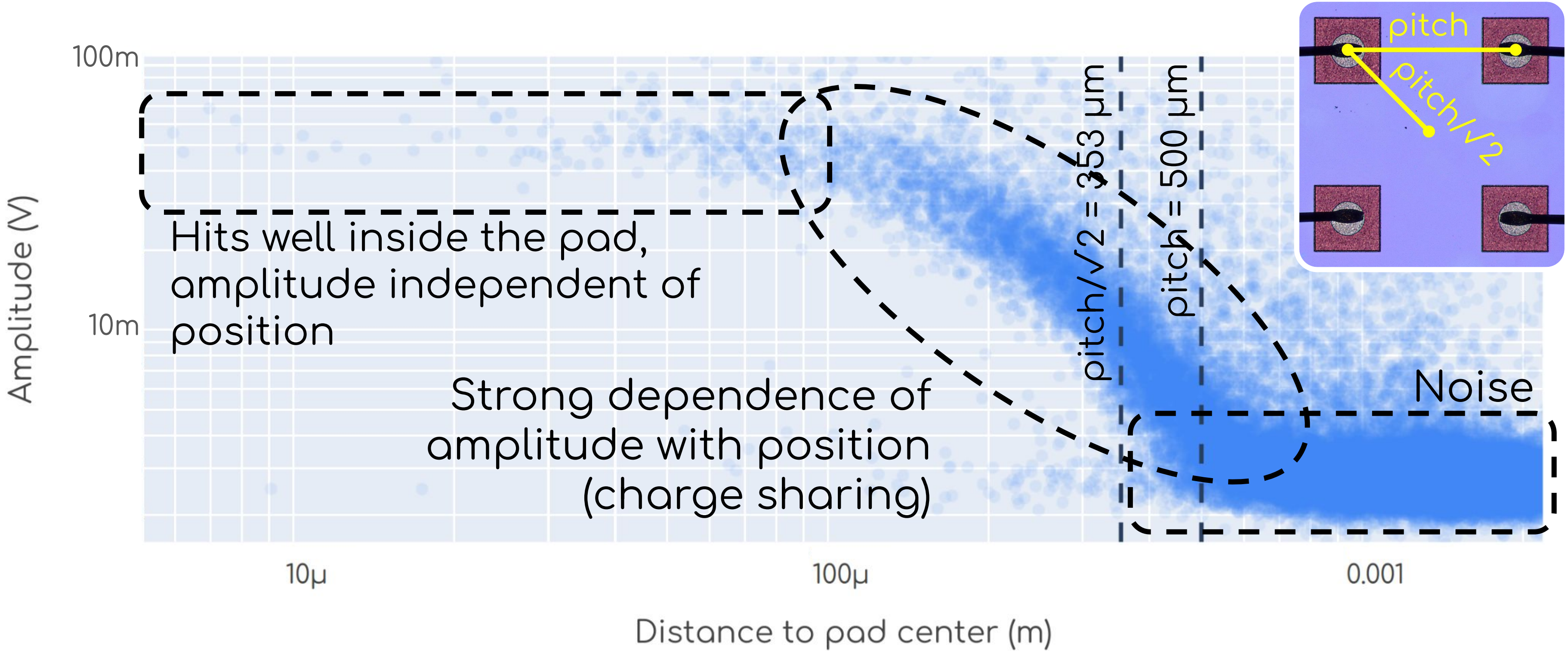
How much gain loss can we afford?

Let's look at this plot, amplitude vs distance to pad center (this is test beam data, each point is one waveform):



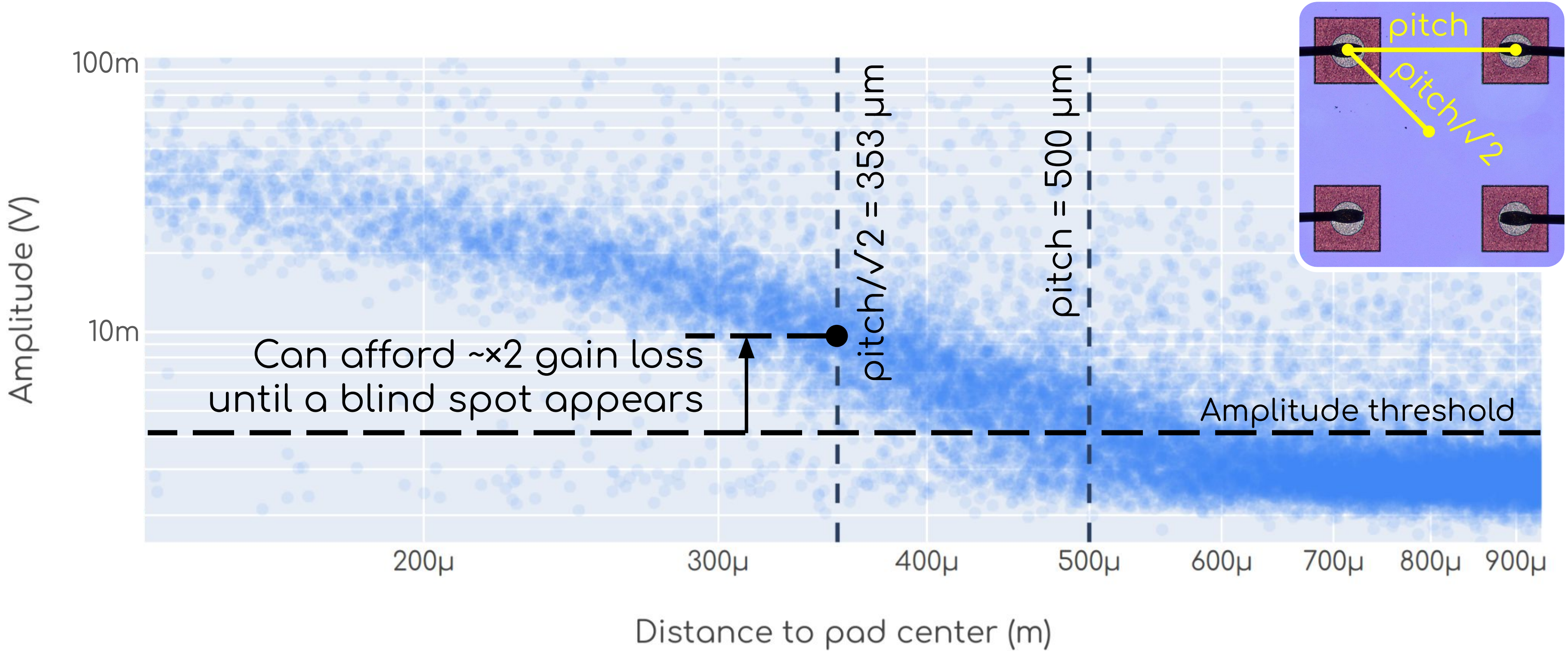
How much gain loss can we afford?

We can recognize these 3 different regimes:



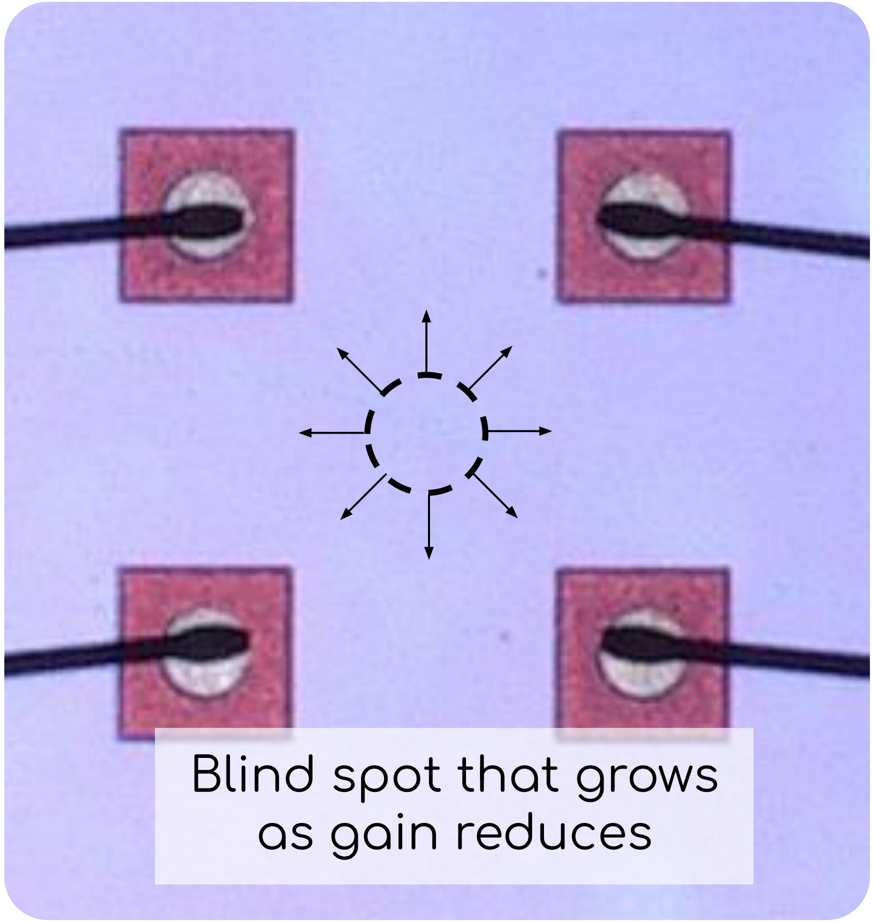
How much gain loss can we afford?

As long as the amplitude at the epicenter of the pads is higher than the noise, we can expect 100 % efficiency in all the surface, i.e. 100 % fill factor.



What happens after that?

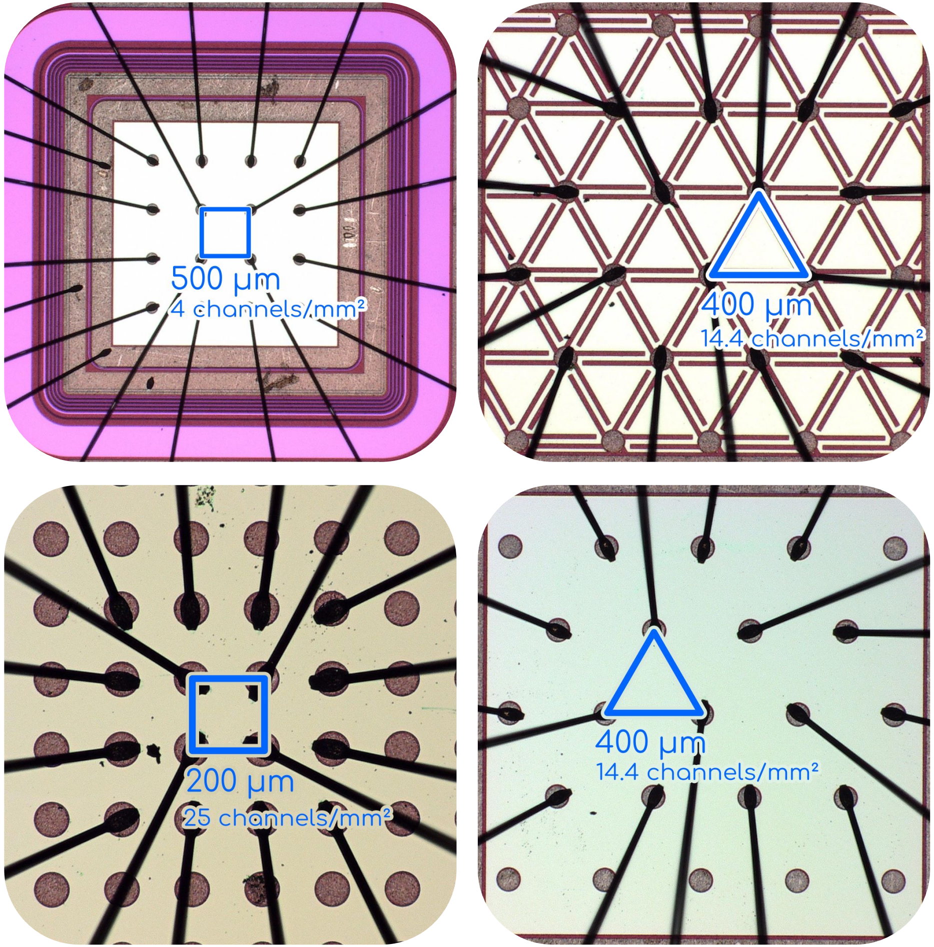
After gain loss goes beyond the “critical gain loss”, a blind spot will appear in the center and grow in size as gain further reduced, thus degrading the fill factor.



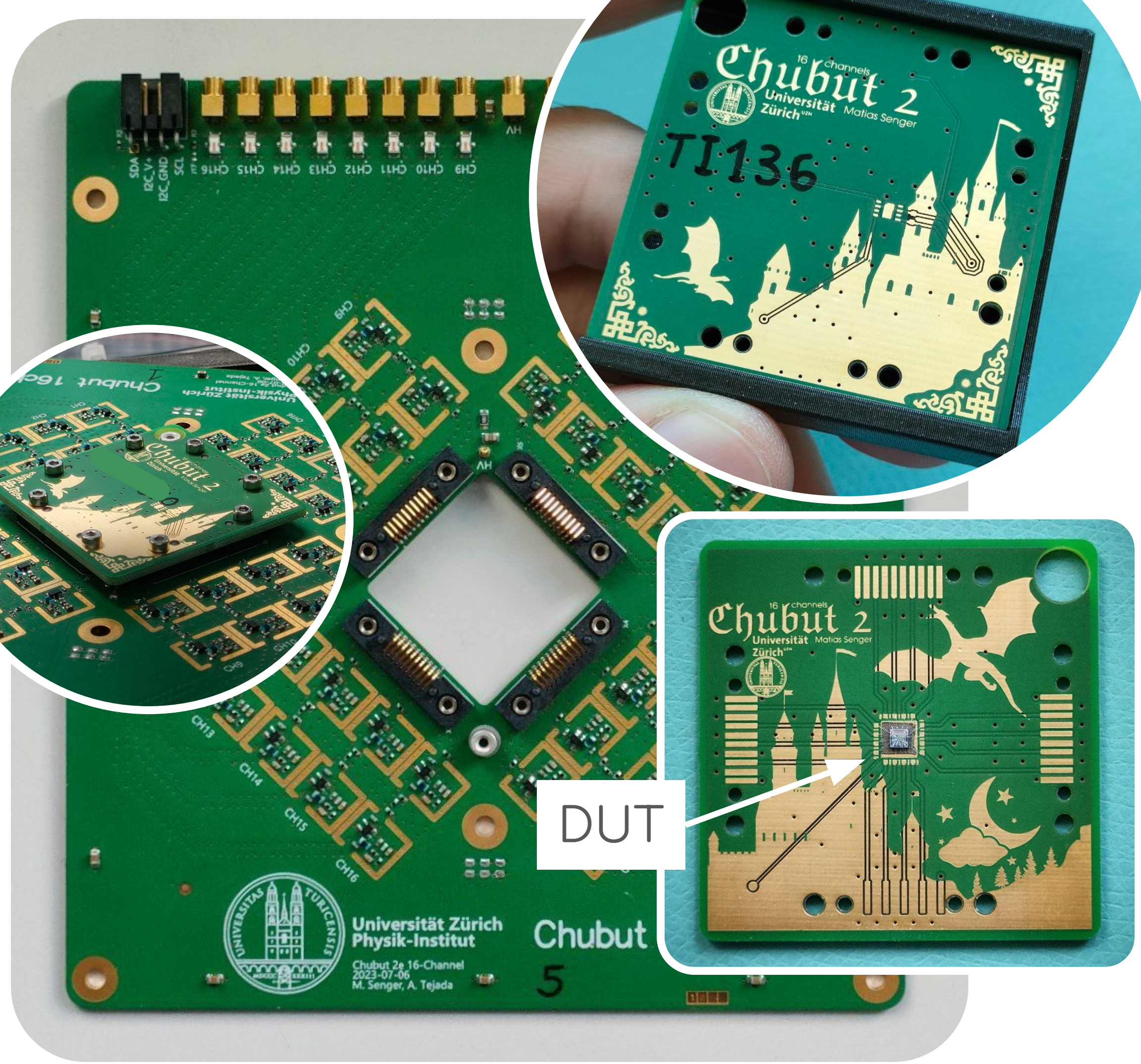
Future plans

Looking forward, near future

- New geometries
  - Square and triangular pad arrays
  - Varying pitch between 200 and 500 μm
- Irradiate samples
  - 1.0e15 n_{eq} cm^{-2}
  - 1.5e15 n_{eq} cm^{-2}
  - 2.0e15 n_{eq} cm^{-2}
- 16 channels readout board (next slide)



Chubut 2 16CH



- 16 independent channels
- 2 stages amplification (no need for external amps)
- Inexpensive and simple carrier board without any assembly required (other than mounting the DUT)
- Main board reusable many times
- Digital T + humidity sensor possible to mount in carrier board
- Developed at UZH 🙂

Conclusions

- Non irradiated AC-LGAD sensors from BNL studied with laser TCT and test beam setups.
- Good performance observed:
    - Efficiency at test beam: 100 %.
    - Median reconstruction error ×4.5 better than square binary readout pixel with same pitch obtained at test beam.
    - Time resolution comparable with regular LGAD measured at TCT setup.
- More results to come soon:
    - Irradiation studies.
    - More geometries with smaller pitch.
    - 16 readout channels study.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 Research and Innovation programme under Grant Agreement No 101004761.

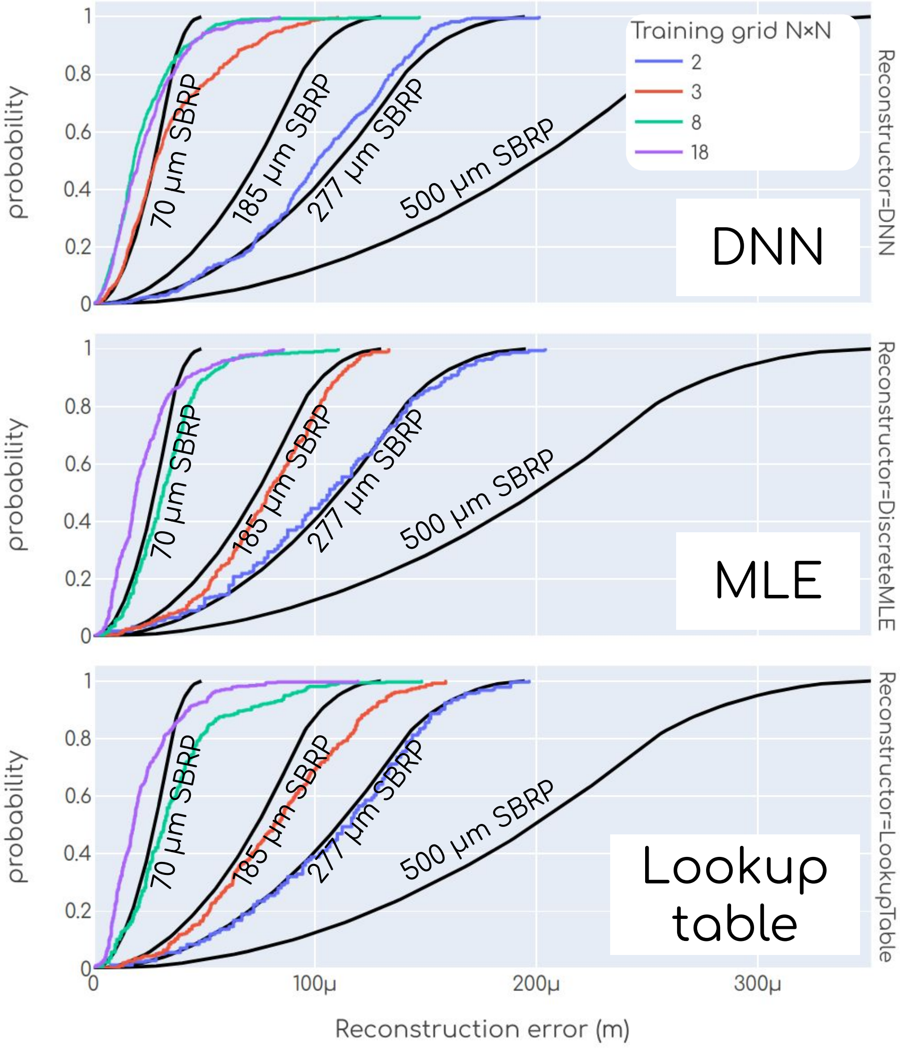
Backup slides

Algorithms detailed comparison (TCT data)

Plots show reconstruction error distribution (ECDF plots, the integral of histograms without bins).

- As the training grid gets finer, the results get better (as expected).
- Because of the discrete training grid, reconstruction error resembles that from a BRP of the same size.
- The DNN learns to interpolate, that's why it is better for e.g. training grid 3×3 (red).
- All cases are better than a 500 µm SBRP.
- For small enough training grid (N×N=18 in the plots), all algorithms behave roughly as a 70 µm SBRP.

* SBRP = square binary readout pixel

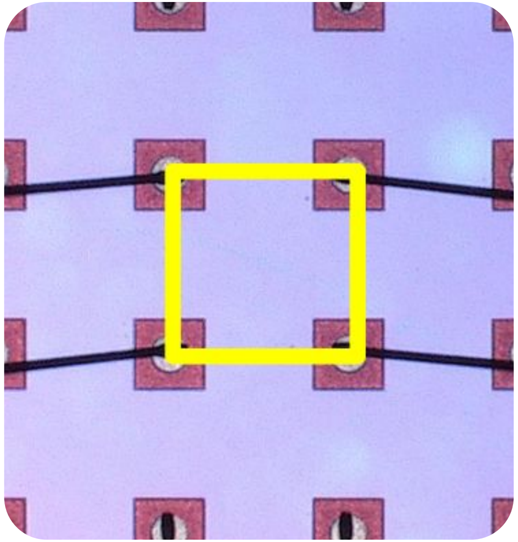


Position reconstruction using charge imbalance

$$\begin{cases} x_{\text{reconstructed}} = \frac{\text{pitch}_x}{2} Q_{\text{imbalance } x} \\ y_{\text{reconstructed}} = \frac{\text{pitch}_y}{2} Q_{\text{imbalance } y} \end{cases}$$

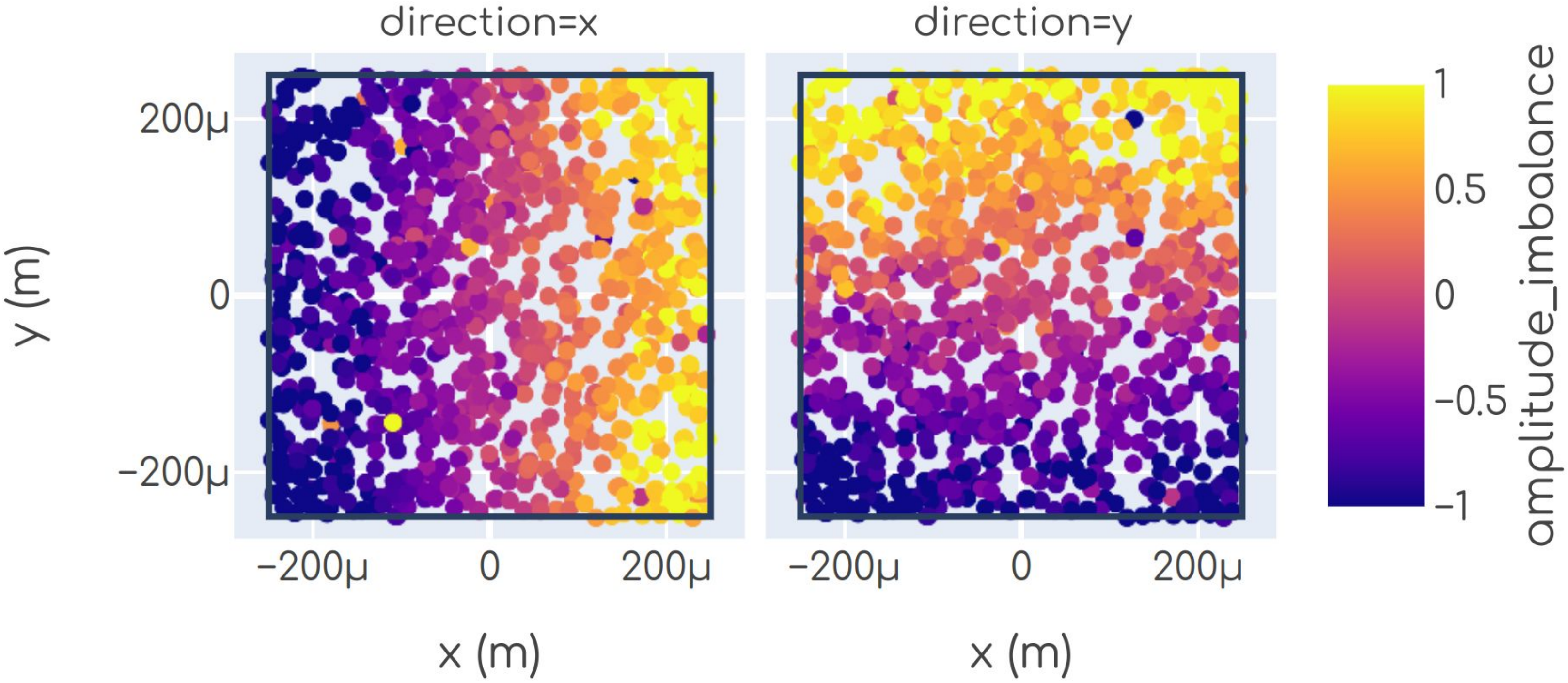
$$\begin{cases} Q_{\text{imbalance } x} = \frac{Q_{11} + Q_{01} - Q_{00} - Q_{10}}{\sum Q_{ij}} \\ Q_{\text{imbalance } y} = \frac{Q_{00} + Q_{01} - Q_{11} - Q_{10}}{\sum Q_{ij}} \end{cases}$$

- Pros
  - Easy
- Cons
  - Only applicable to very symmetric geometries (like this one 👍)
  - No special reason why this simple formula should be right one



Charge (amplitude) imbalance

$$\begin{cases} Q_{\text{imbalance } x} = \dfrac{Q_{11} + Q_{01} - Q_{00} - Q_{10}}{\sum Q_{ij}} \\ Q_{\text{imbalance } y} = \dfrac{Q_{00} + Q_{01} - Q_{11} - Q_{10}}{\sum Q_{ij}} \end{cases}$$



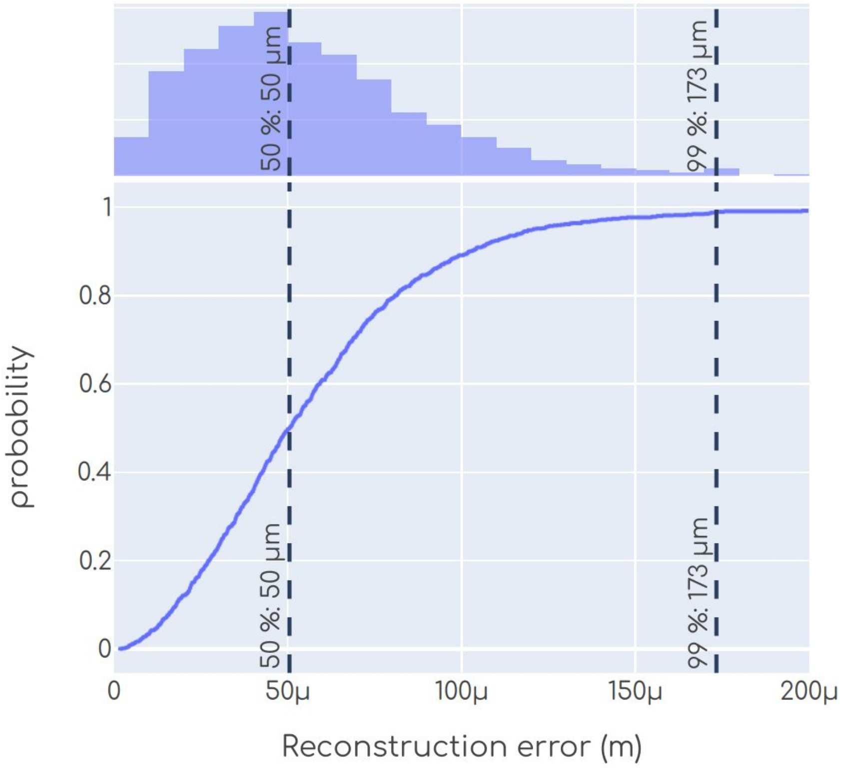
Charge imbalance reconstruction results (test beam)

$$\text{reconstruction error} = \sqrt{\sum_{\text{coord}\in\{x,y\}} (\text{reconstructed}_{\text{coord}} - \text{telescope}_{\text{coord}})^2}$$

- Median: 50 µm
- 99 %: 173 µm

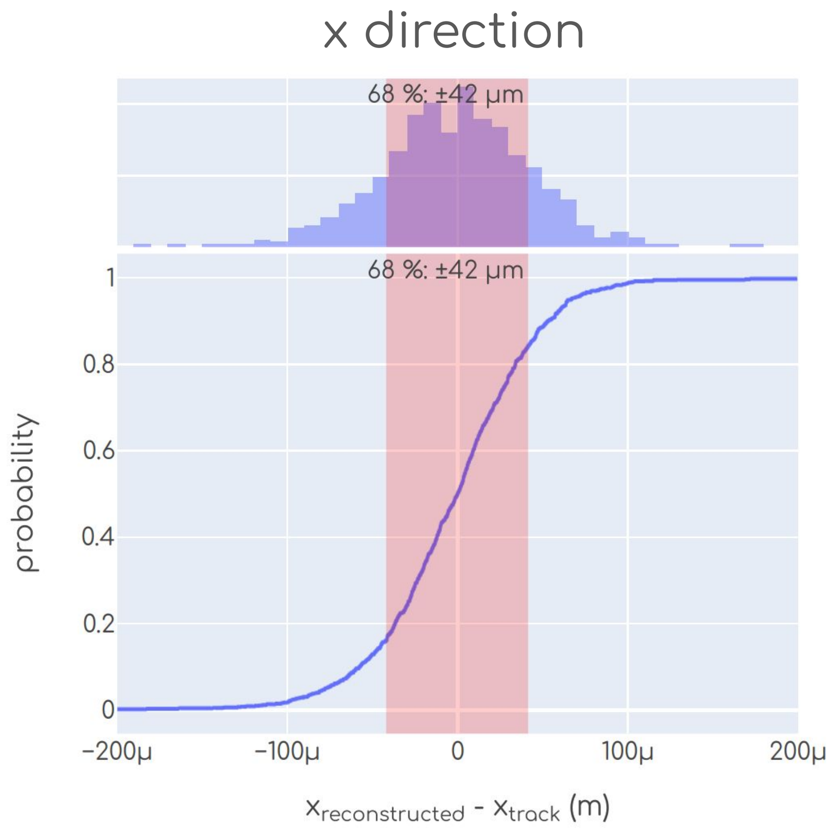
For a 500×500 µm² BRP*:

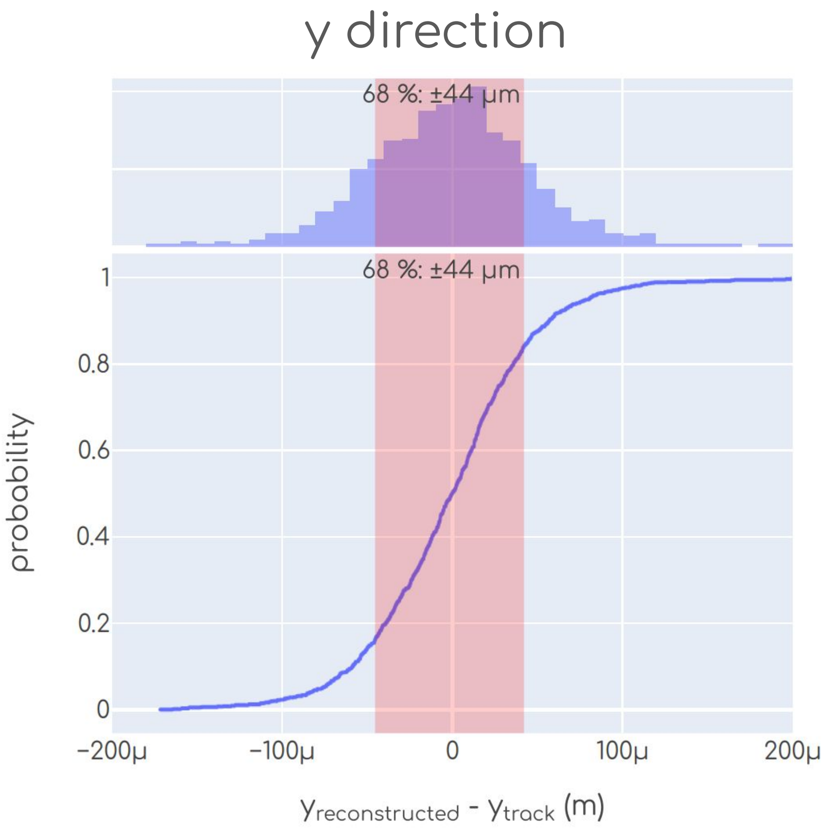
- Median ≈ 200 µm
- 99 % ≈ 330 µm



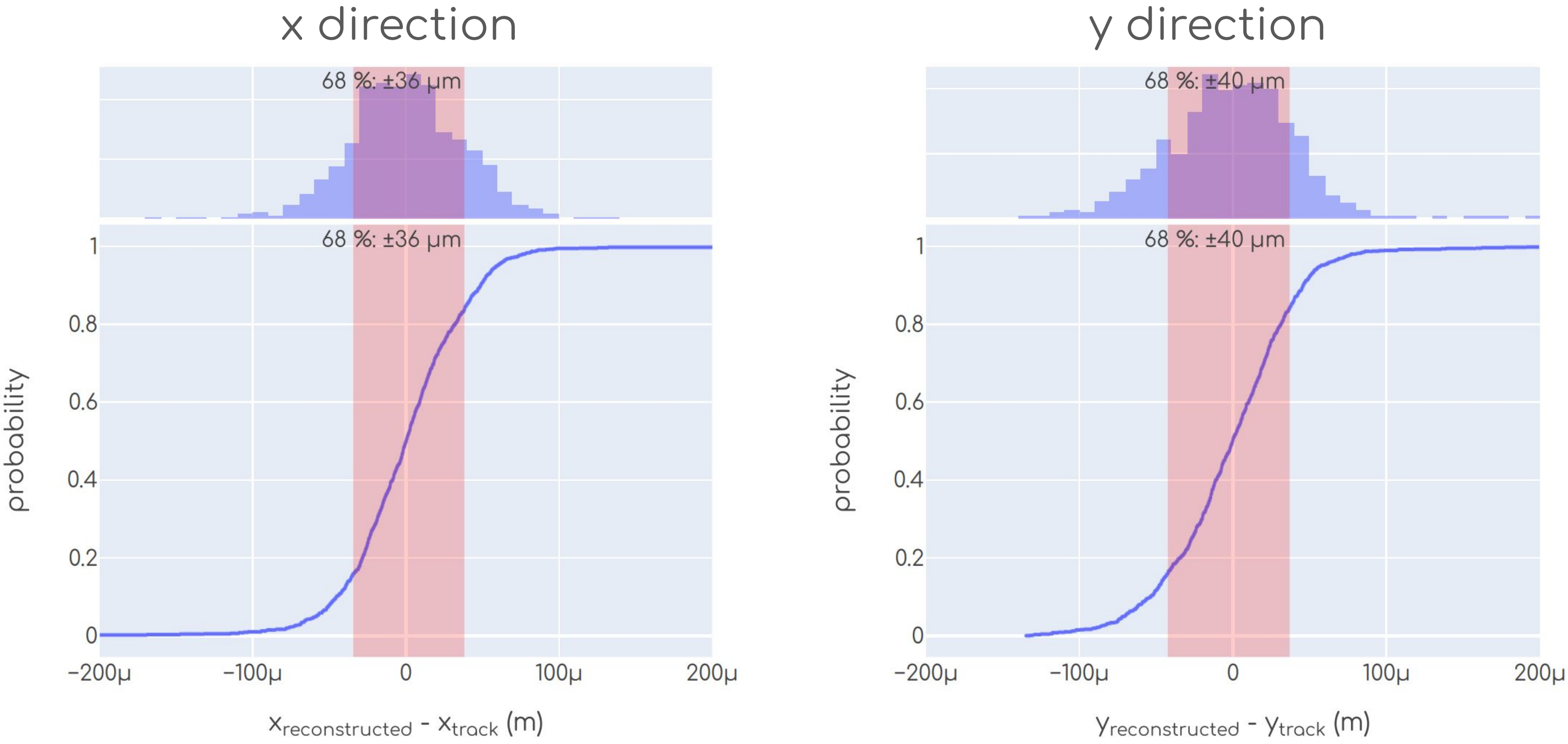
* See backup slides.
** Residuals in x and y also available in backup slides.

Charge imbalance reconstruction residuals (test beam)

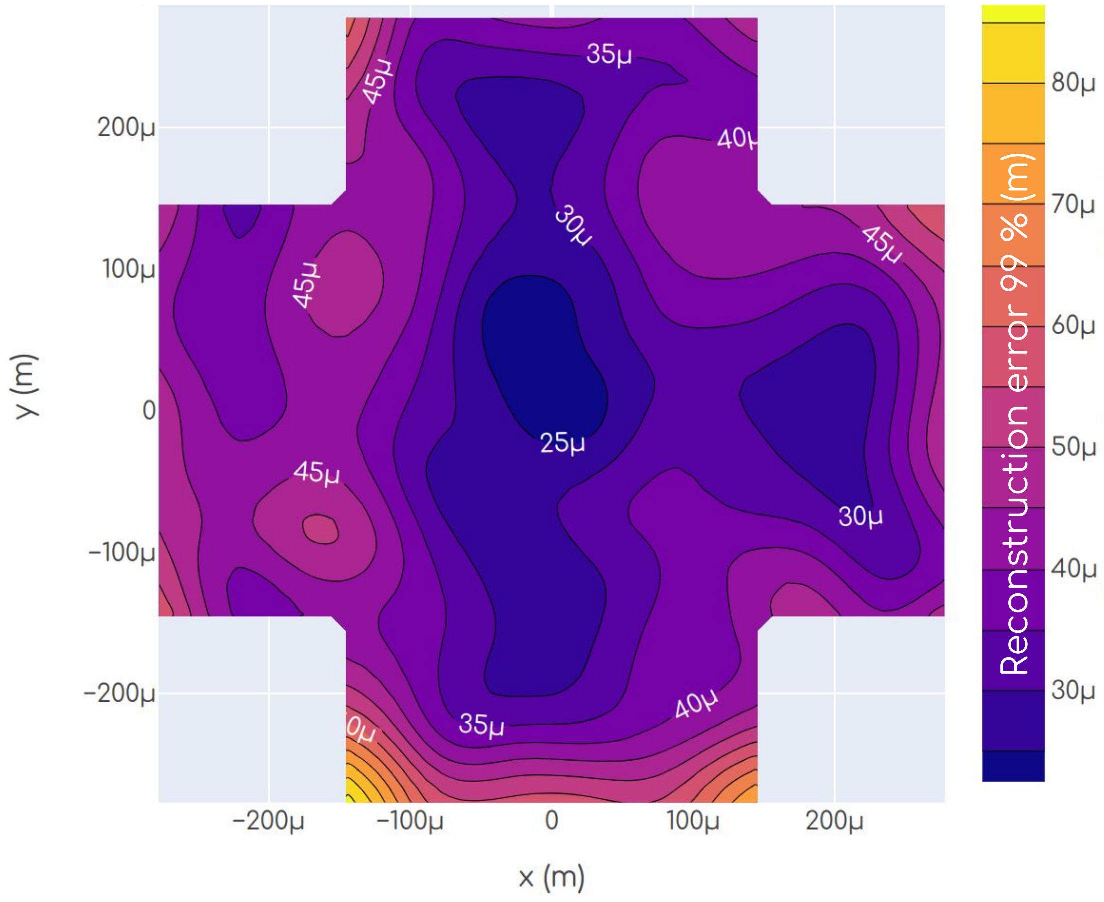




DNN reconstruction residuals (test beam)



Reconstruction error vs position



- TCT data
- DNN reconstruction
- Color is quantile 0.99, i.e. at each position, 99 % of hits got lower reconstruction error than shown

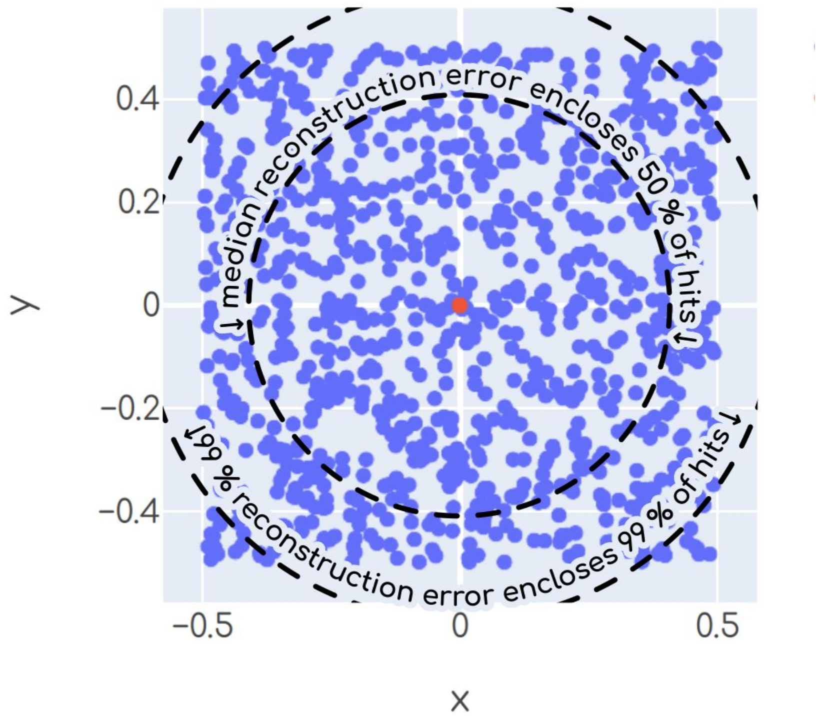
On the statistics used to measure the spatial resolution

Spatial resolution statistics table

Quantity	Formula in SBRP*	Meaning	Comment
Median reconstruction error	≈ pitch × √(2/12)	≡ 50 % of reconstructed hits will be closer than this to the actual hit	It is the radius of a circle in the xy plane around the reconstructed position
std of residuals in x,y, i.e. std of "$x_{reconstructed}$-x_{real}" and "$y_{reconstructed}$-y_{real}"	≡ pitch / √12	• Depends on the distribution • In a square SBRP*: ≈ 58 % of reconstructed hits will have x,y coordinates within ± this quantity (yes, 58, not 68)	• Not easy to interpret in a 2D arbitrary case (see slide with pathological example) • Beautiful interpretation for Gaussian distributions, but not for arbitrary distributions
99 % of reconstruction error	≡ pitch*0.66	≡ 99 % of reconstructed hits will be closer than this to the actual hit	Useful to account for plausible tails and measure "the worse case scenario"

* SBRP = square binary readout pixel

Median reconstruction error interpretation

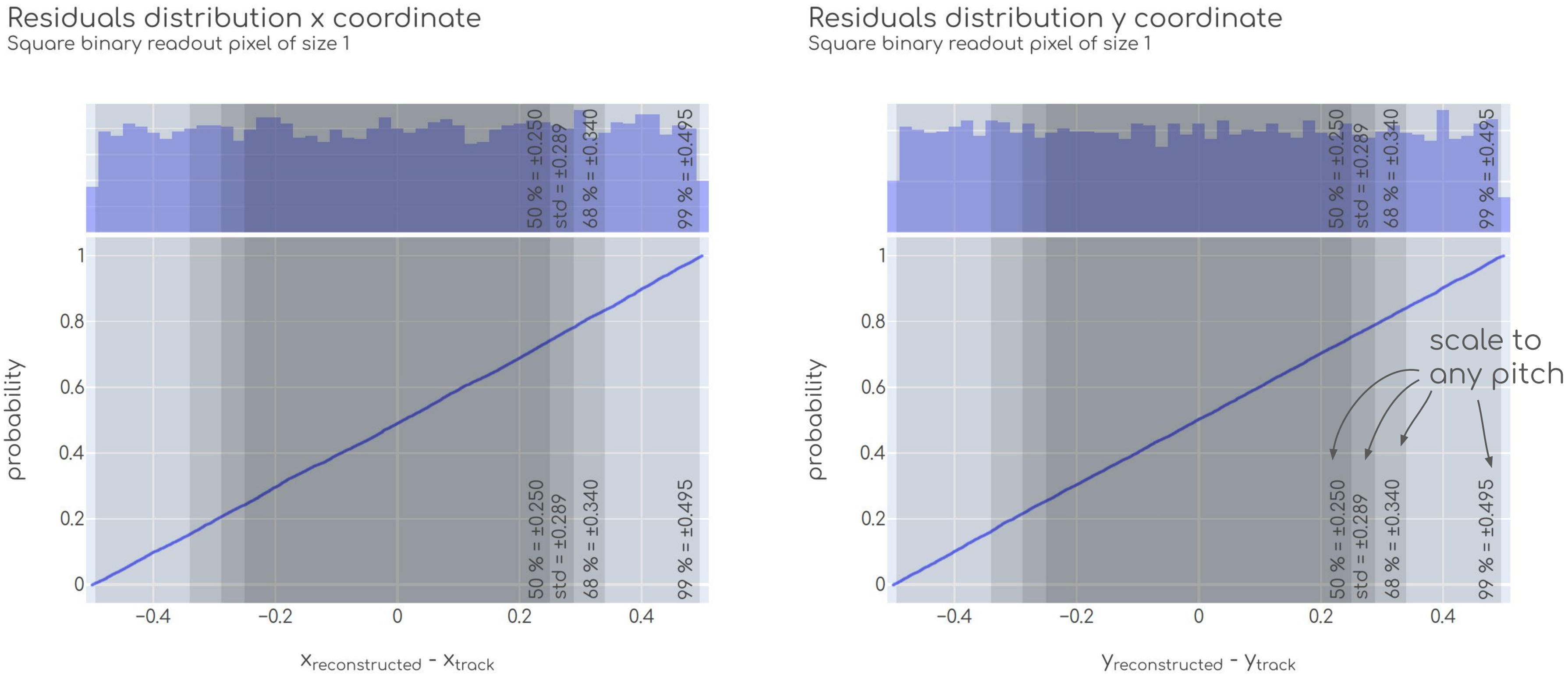


- ✅ The meaning of the statistics shown in the plot is independent of distribution (i.e. valid for binary readout pixels, AC-LGADs, whatever)
- ⚠️ pitch/√12 ≡ std ONLY for binary readout pixels
- ⚠️ Interpretation of std is different for different distributions (for sure it is different for AC-LGADs and binary readout pixels)
- In my opinion, the most meaningful statistics when comparing binary readout pixels and non-binary readout pixels (e.g. AC-LGAD) are the quantiles of the reconstruction error, since the meaning is the same in both cases

Residuals in a square binary readout pixel (BRP)

$$\frac{\text{pitch}}{\sqrt{12}} \equiv \text{std of square BRP} \approx 58\ \%\ \text{of hits}$$

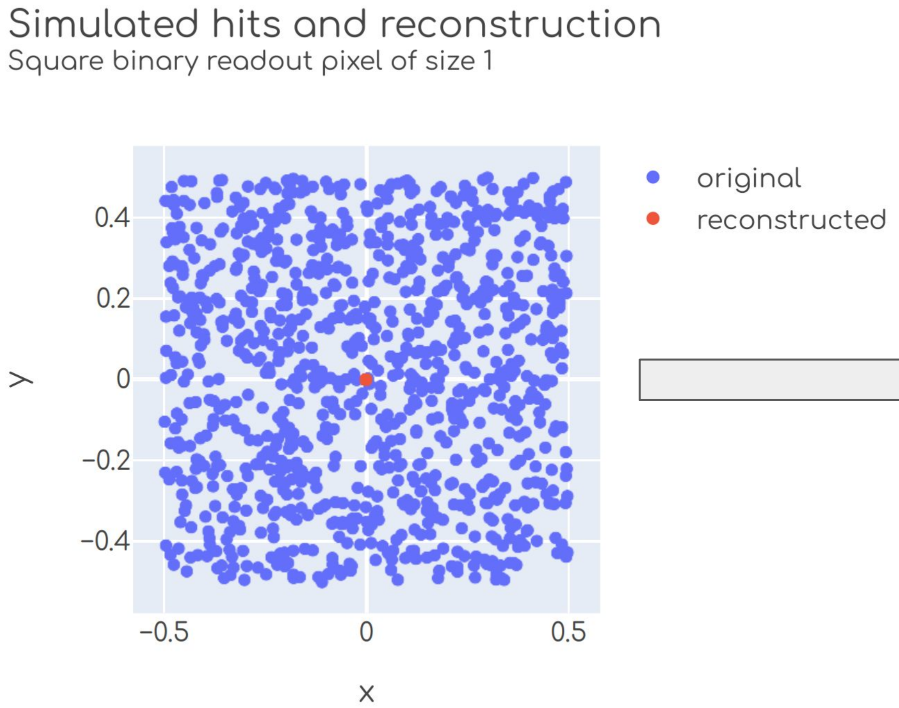
← The "magical formula" is the standard deviation of a uniform distribution (by definition), which is NOT the 68 % centered interval!!! (see plots) (It is so for a Gaussian, but this is not even close to a Gaussian)

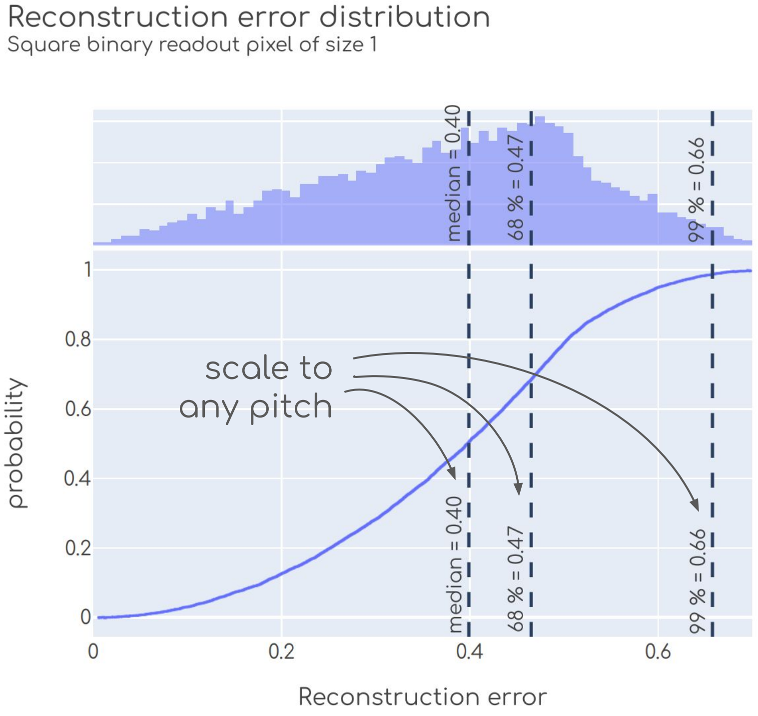


Reconstruction error in a square binary readout pixel

$$\text{Reconstruction error} \overset{\text{def}}{=} \sqrt{\sum_{\text{coord} \in \{x,y\}} \left(\text{coord}_{\text{reconstructed}} - \text{coord}_{\text{original}}\right)^2}$$

$$\begin{array}{c}\text{Median reconstruction error} \\ \text{in a square binary readout pixel}\end{array} \approx \text{pitch}\sqrt{\frac{2}{12}}$$

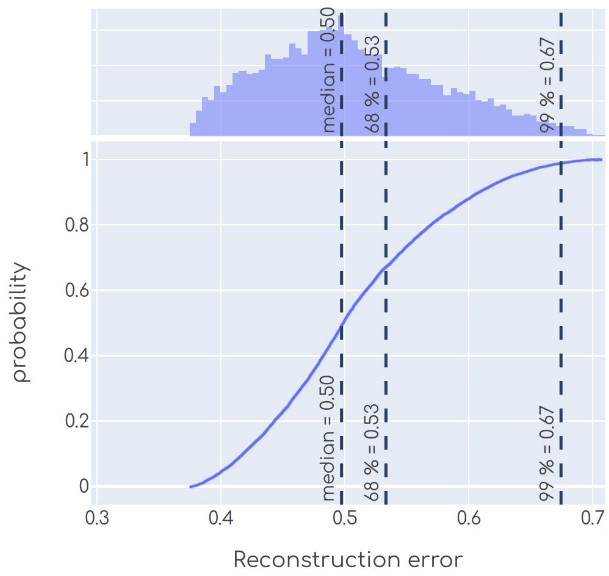




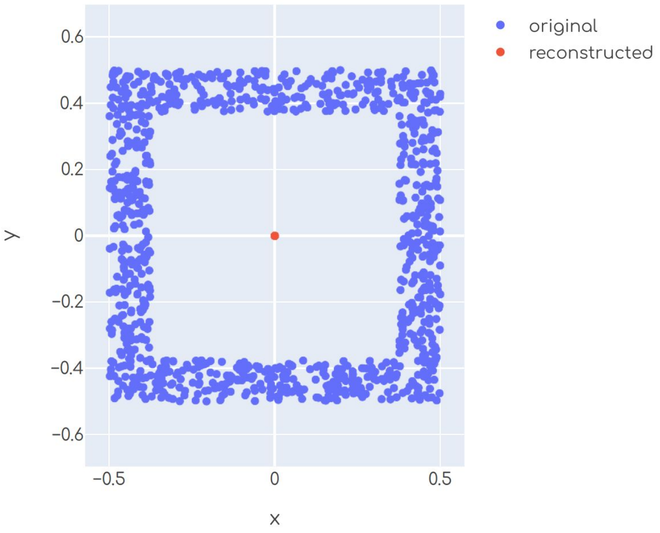
Pathological example

Consider this weird, still plausible pixel. Looking at the residuals in x,y we may be led to believe that ≈ 50 % of events are closer than 0.361 to the center. However, the minimum reconstruction error is actually 0.36. The reconstruction error quantiles, instead, never fail.

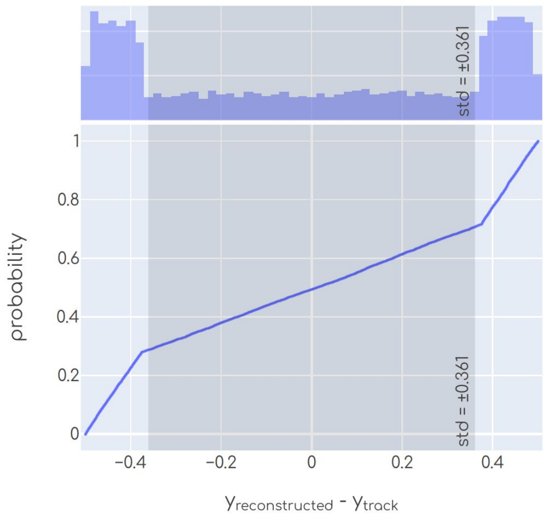
Reconstruction error distribution



Simulated hits and reconstruction



Residuals distribution y coordinate



Residuals distribution x coordinate