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Position reconstruction using machine learning algorithms applied to Resistive Silicon Detectors

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RSD

Outline

- ➢ Resistive Silicon Detectors design
    - ○ Signal attenuation law & position reconstruction method
- ➢ Optimization of the RSD design
- ➢ Multi-output regression algorithm
    - ○ Assessment of the algorithm resolution
- ➢ Machine learning algorithm validation with laser tests
- ➢ Validation with beam test data & future plans

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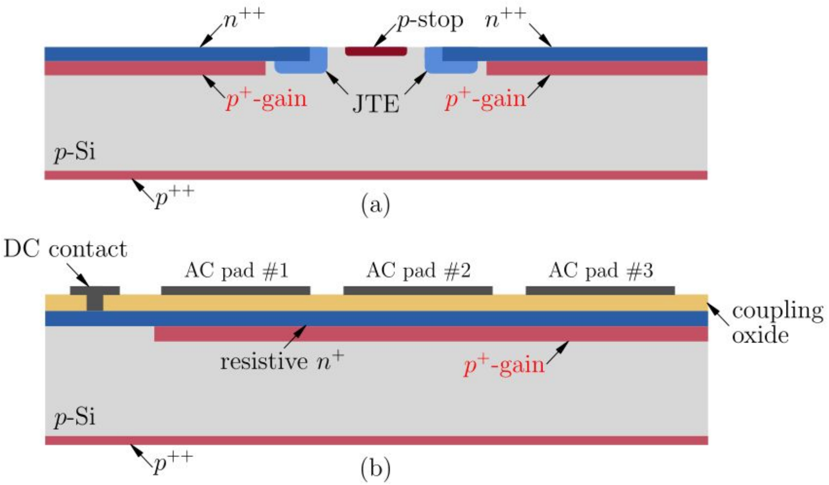
Resistive Silicon Detectors



See M.Tornago's talk for more details:

- RSD are based on LGAD technology
- Unsegmented gain layer spreading over the whole sensor area
- AC-coupling to metal pads
- Several geometries can be implemented by simply changing pads geometry
- 100% fill factor
- Signal sharing among many pads
- Parameters governing signal induction on AC-pads: coupling oxide thickness, n^{++} layer resistivity

Sensors presented in this talk are from the FBK RSD1 production

Signal attenuation law

- **Key feature** to reconstruct the hit position with RSD: **signal** generated by an impinging particle **spreads among 2-4 pads**
    - Reconstruction techniques that combine informations of many read-out channels
    - Similar to what happens in calorimeters

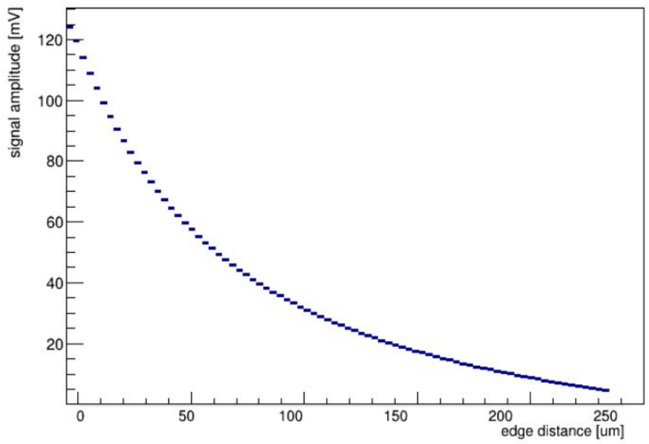
Signal attenuation law

- **Key feature** to reconstruct the hit position with RSD: **signal** generated by an impinging particle **spreads among 2-4 pads**
    - Reconstruction techniques that combine informations of many read-out channels
    - Similar to what happens in calorimeters
- We developed an **analytic signal attenuation law** (M.Tornago's talk)

  → signal amplitude seen by a read-out pad vs distance of the hit position from pad's edge

$$V(d) = [V_0 - \beta * d] * \left[tan^{-1}\left(\frac{\alpha}{\alpha + d}\right) / tan^{-1}\left(\frac{\alpha}{\alpha}\right)\right]$$

attenuation coefficient

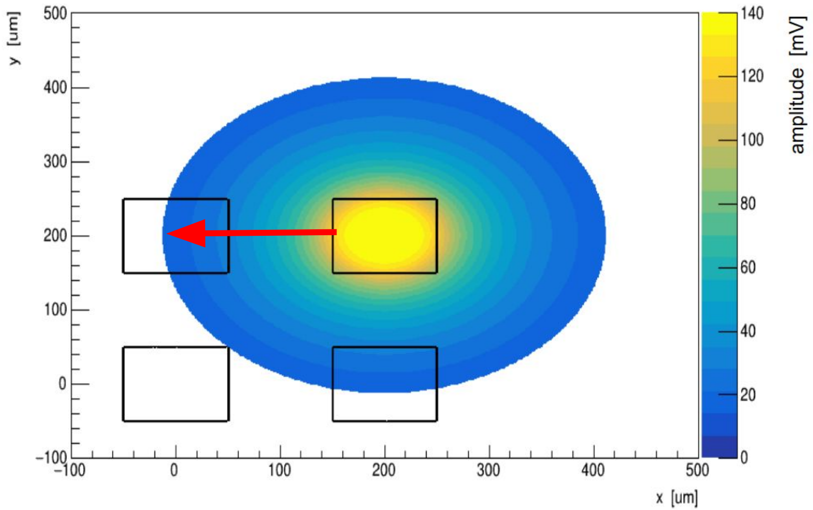


amplitude vs distance from the pad's edge (analytic law)

- **No signal sharing when the particle crosses a metal pad** → signal only seen by the hit pad

Signal attenuation law - 2

- **The attenuation law defines circumferences of equidistant positions that produce the same signal**
- All pads always see a signal, due to read-out noise
  - only those above noise level are used (fixed threshold ~ 15mV)
  - This sets the maximum distance at which a pad can be used
- Amplitude constant under the metal pad → no signal sharing there



Signal seen by a read-out pad vs x-y position
The max distance at which it can be used is shown

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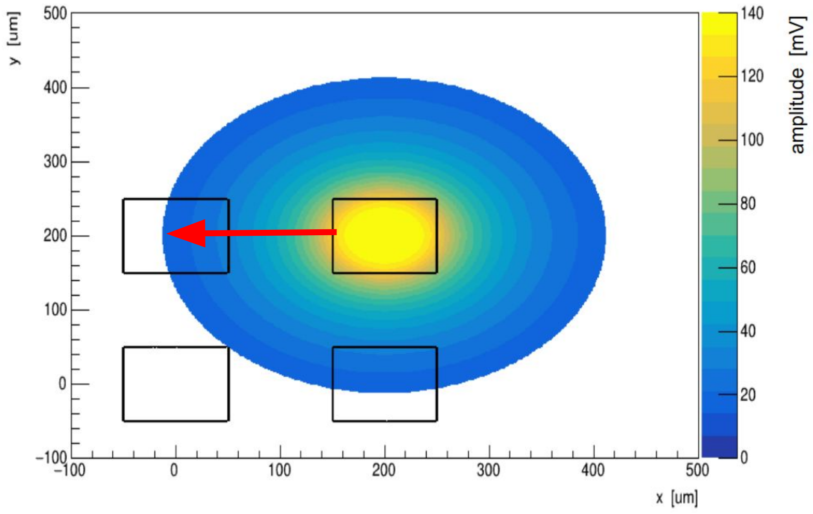
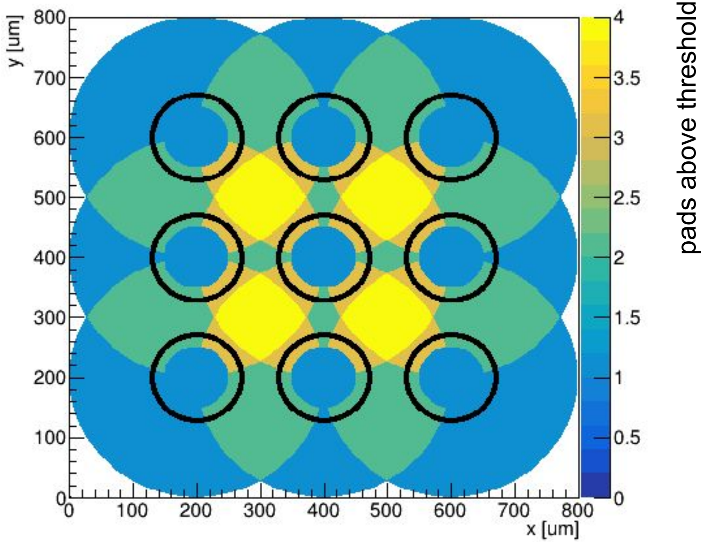
- Amplitude constant under the metal pad → no signal sharing there
- **We can reconstruct the hit position if at least 3 pads see a signal** → the intercept of 3 circumferences define a point



Signal seen by a read-out pad vs x-y position
The max distance at which it can be used is shown

Position reconstruction Efficiency

- Combining the attenuation laws of many read-out channels: x-y map representing, in each position, the number of pads that see a signal above threshold
- Regions where **less than 3 pads see a signal**: the reconstruction method is inefficient there → **we need to design RSD avoiding such regions**



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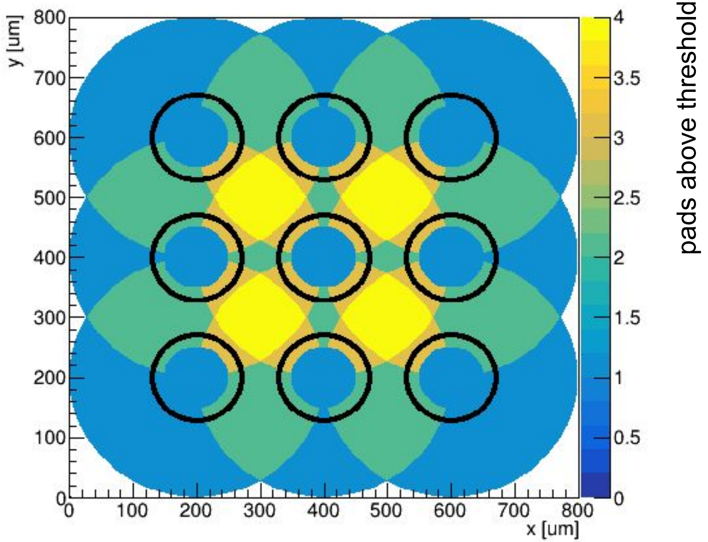
x-y map representing an RSD with 100-200* um geometry



- 3x3 pixel matrix (as all measured sensors)
- Circular metal pads drawn for simplicity (squared in real detectors, it doesn't change much)
- Blue / green regions: position reconstruction inefficient

**pad size -pitch*

Position reconstruction Efficiency

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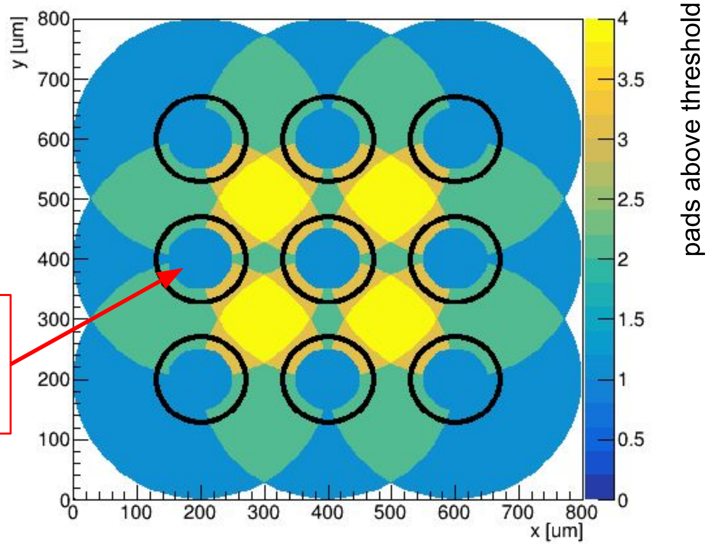
Only 1 pad reconstruct the position here, because signal is not shared



pitch -pad size

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Impact of pad geometry on position reconstruction

- In RSD, the **spatial resolution beneath the metal** pads is that of a standard silicon sensor with binary read-out **σ = *pixel size* / √12**
  - The RSD spatial resolution is much better than *pixel size* / √12 (next slides), as signal sharing enhances position reconstruction
  - Using squared pads, the spatial resolution is position dependent, worsening beneath the metal

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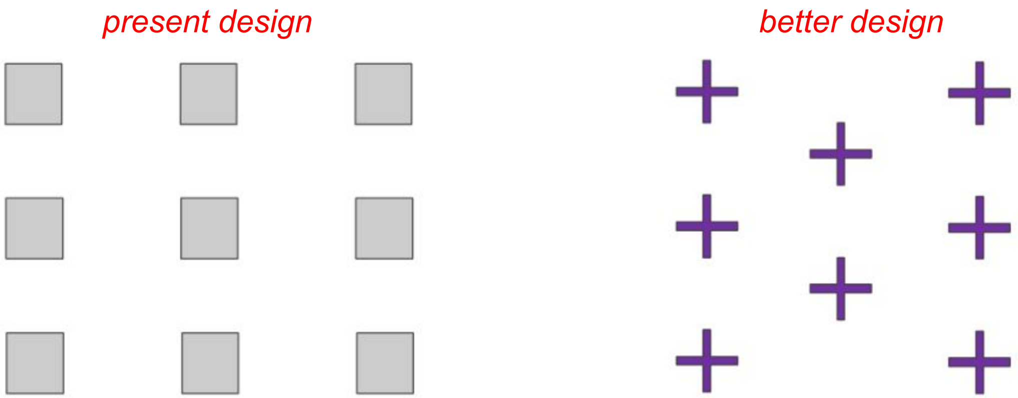
- **We should redesign RSD pixels in an innovative way, minimizing the area covered by metal**
  → achieve signal sharing everywhere in this way



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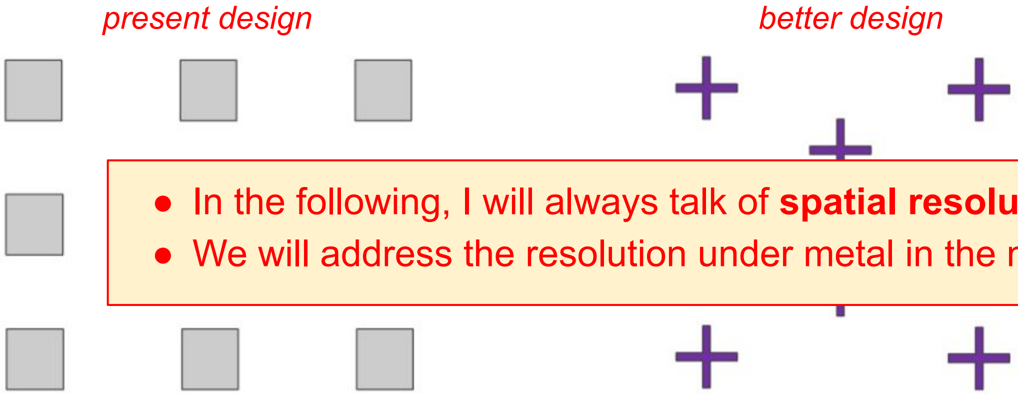
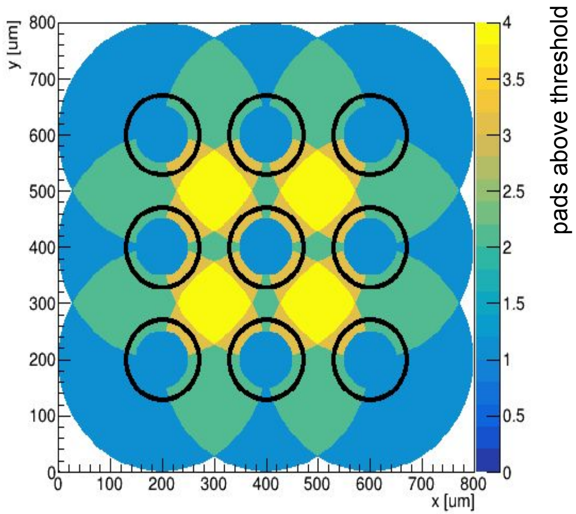


- In the following, I will always talk of **spatial resolution between pads**
- We will address the resolution under metal in the near future

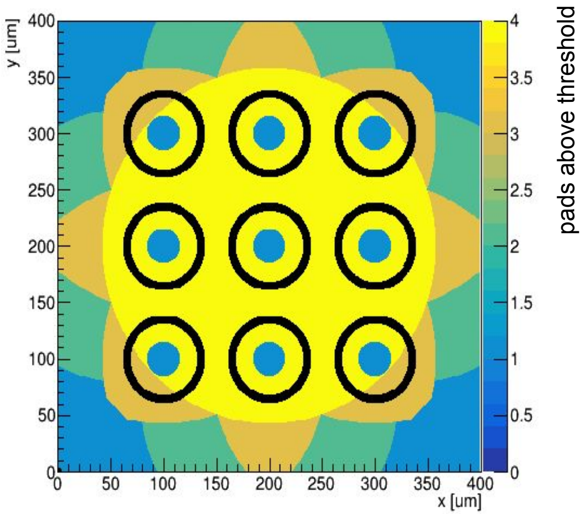
Impact of sensor geometry on position reconstruction

- 2nd parameter affecting position reconstruction efficiency: sensor area not covered by metal, given by ***pitch - pad size (“interpad”)***
- Small *interpad* → pads are closer, more likely to have 3 or more pads seeing the signal than with larger *interpad*

100-200 um



50-100 um



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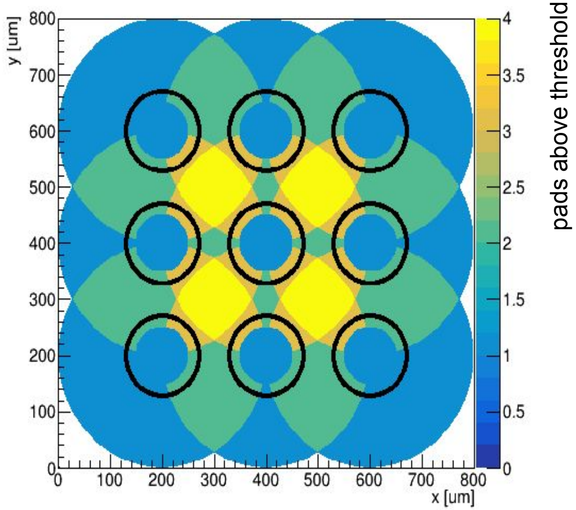

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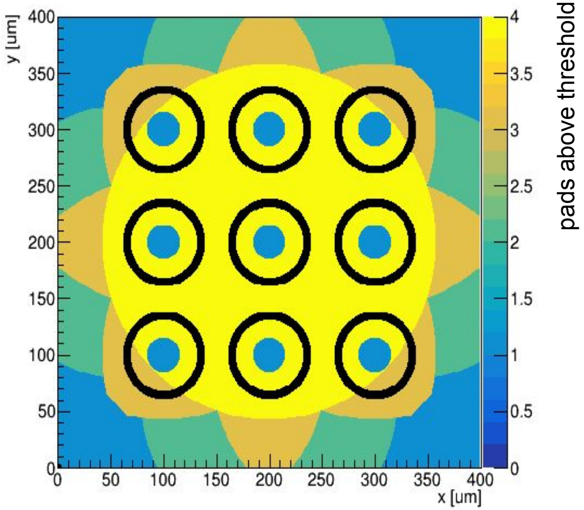


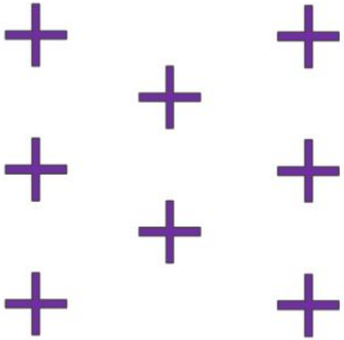
100-200 vs 50-100

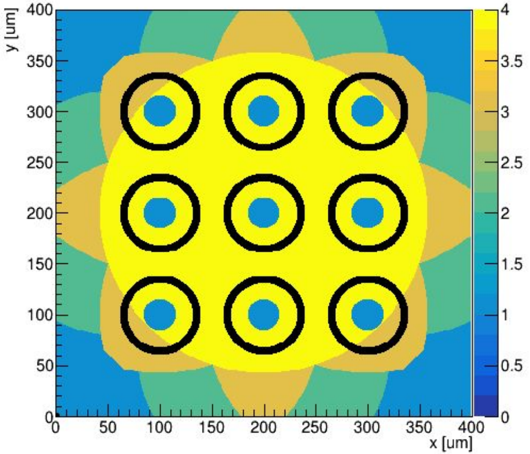
(both devices measured in this work):

- Same resistivity
- **100-200 has small inefficient regions**
- **50-100 reaches 100% 3-4 pad coverage** on its whole sensitive area

Optimized RSD design

- Using the previous results, we can define an optimized RSD design to precisely reconstruct the position:
  - **Cross-shaped metal read-out pads**: 100% signal sharing
  - **Small interpad**: 100% 3-4 pad coverage





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Machine learning applied to RSD

- Machine learning algorithms are suited to solve regression problems with many inputs and one (or multiple) output
- **We trained a** **[Multi-ouput regression algorithm]** **taking the RSD signal features as inputs and the x-y position as outputs** (it's a multi-output problem since we need 2 coordinates)
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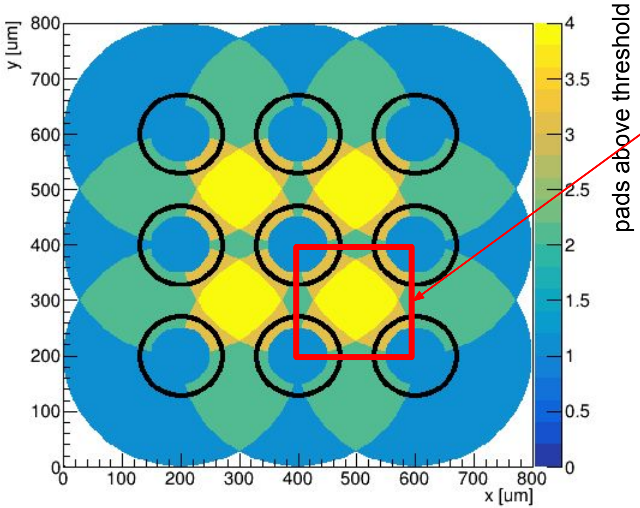
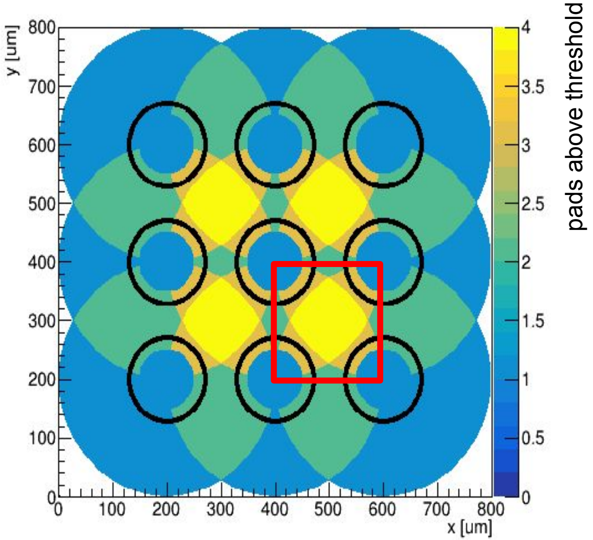


- Region considered for training, defined by the centers of 4 read-out pads
- Outside the red region, a different set of 4 read-out pads can be used to reconstruct the position
- Define the algorithm for 4 pads then get the full sensor by tessellation

Machine learning applied to RSD - 2

- ML algorithm trained with 8 input features: 4 pads' amplitudes (A_i) + the same 4 amplitudes normalized to the total amplitude ($A_i / \sum A_i$)
- **We used the signal attenuation law to train the ML algorithm, assessing in each x-y position the amplitude seen by each pad**



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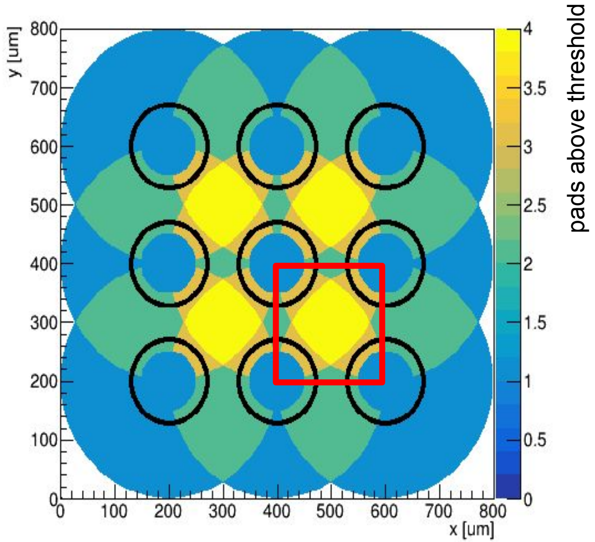

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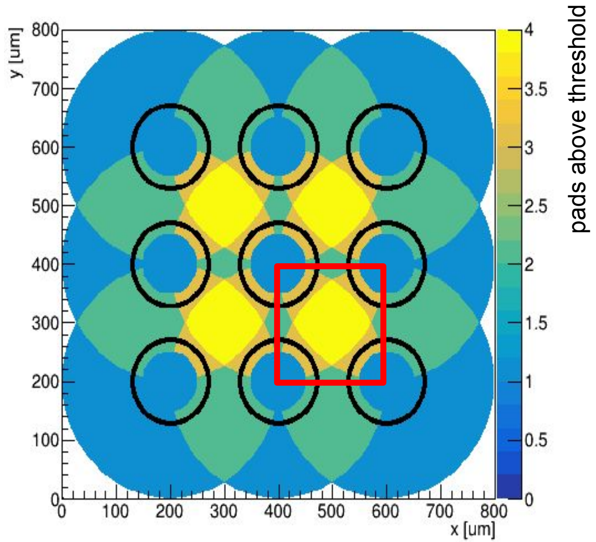

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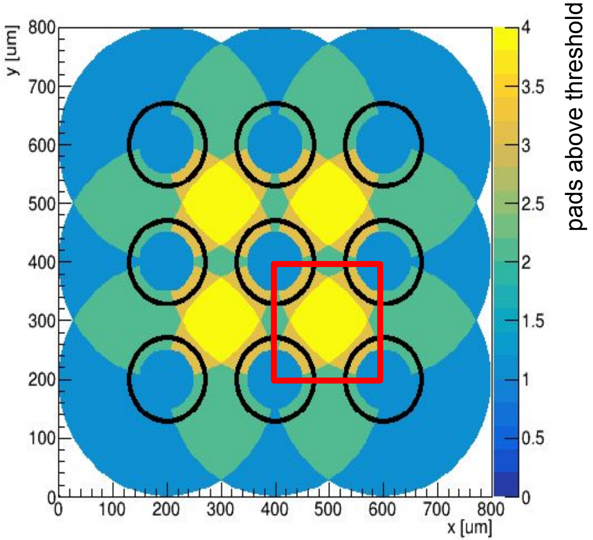
    - The attenuation coefficient (depending upon sensor resistivity and geometry) used in the attenuation law is tuned for each DUT
    - We add a **gaussian smearing** to the amplitudes → it's a way of **adding "noise" to the system, prevents overfitting**



Algorithm resolution

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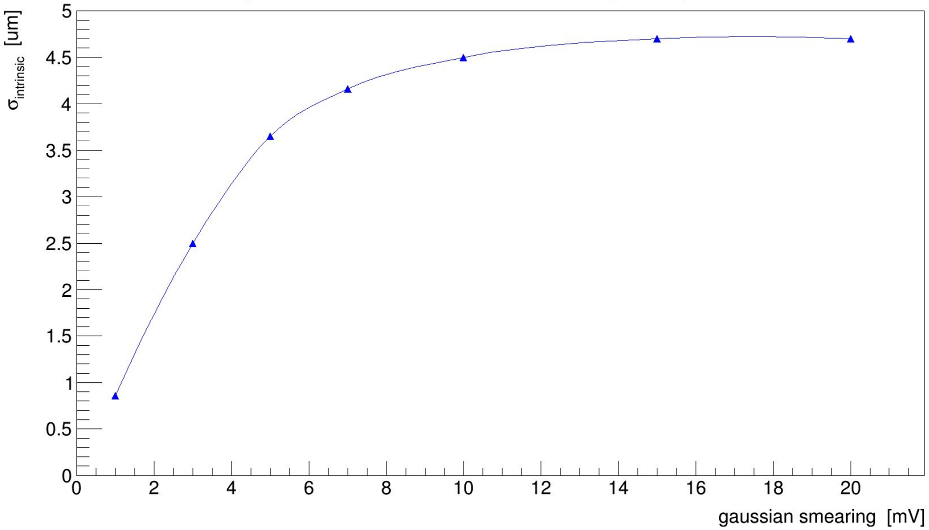
- Resolution can be obtained by predicting the same data used for training and calculating the width of $x_{predicted}$ - x_{truth} distribution
- The resolution saturates at about 10mV, reaching 4-5 um



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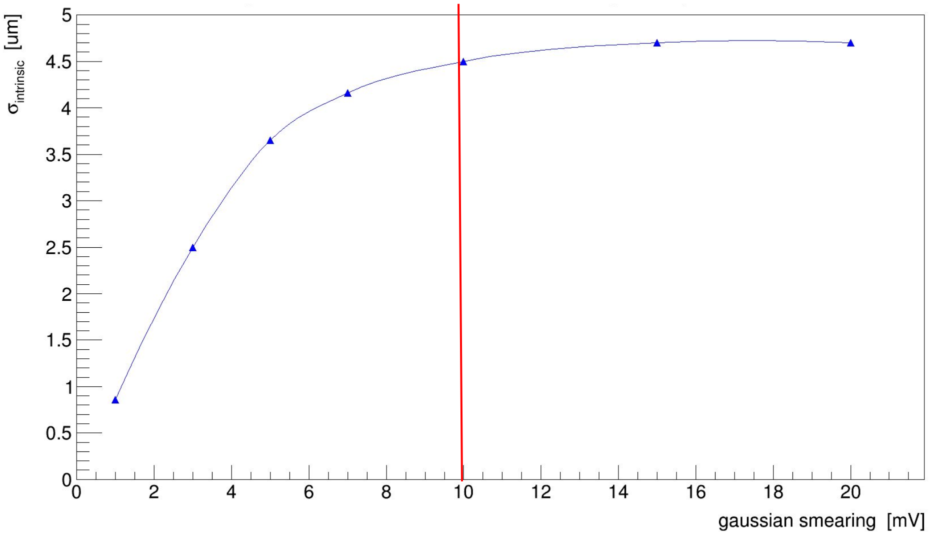
- The resolution saturates at about 10mV, reaching 4-5 um
- In order not to be too dependent on simulation parameters, we fixed the gaus smearing on the plateau, at 10 mV
- **The position reconstruction method will have therefore a resolution floor ($\sigma_{intrinsic}$) of 4-5 um due to the ML algorithm**



Read-out noise

- **2nd source of uncertainty contributing to the spatial resolution is the read-out noise** $\rightarrow \boldsymbol{\sigma_{total}^2 = \sigma_{intrinsic}^2 + \sigma_{noise}^2}$
- σ_{total} has been determined predicting 1000 times the same position but with sligthly different amplitudes each time, to reproduce the read-out noise

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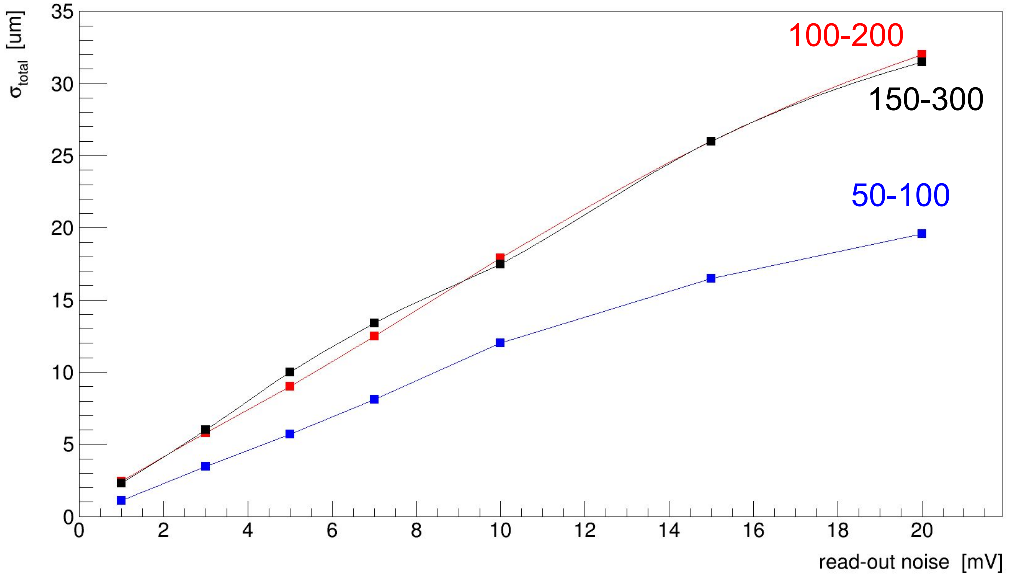
- σ_{total} has been determined predicting 1000 times the same position but with sligthly different amplitudes each time, to reproduce the read-out noise
- The total spatial resolution increases linearly with read-out noise and does not saturate
  → σ_{total} ∝ read-out noise
- σ_{total} for the 3 geometries considered in this work are shown: 50-100 um, 100-200 um, 150-300 um
- The effect of read-out noise is more pronounced in sensors with larger pitch



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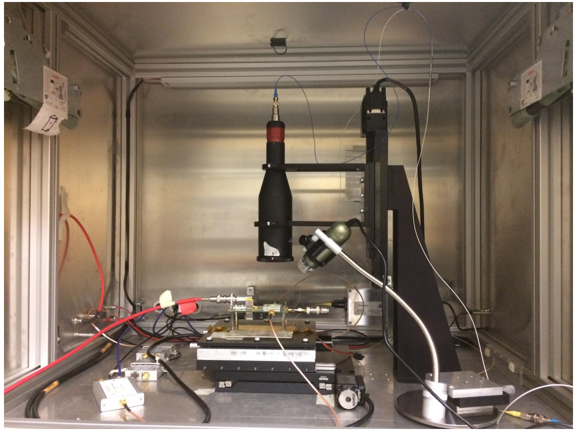
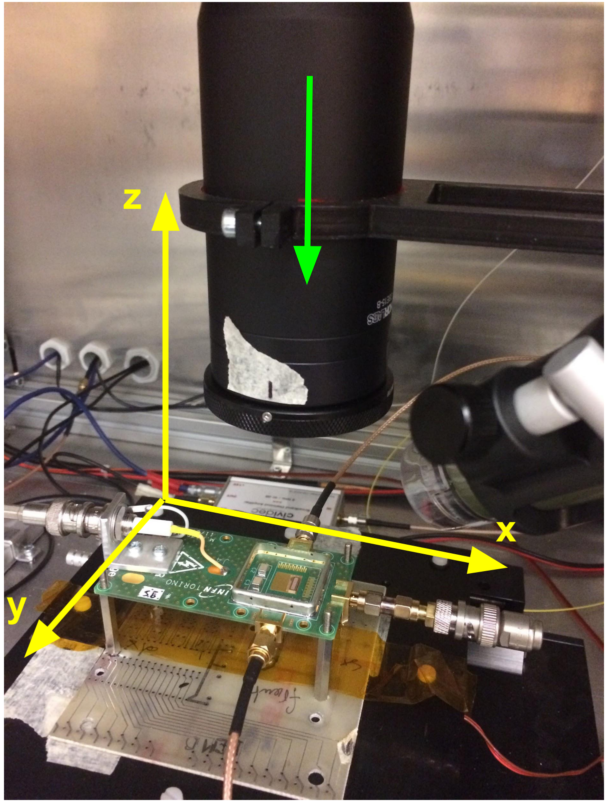
Algorithm validation using TCT setup

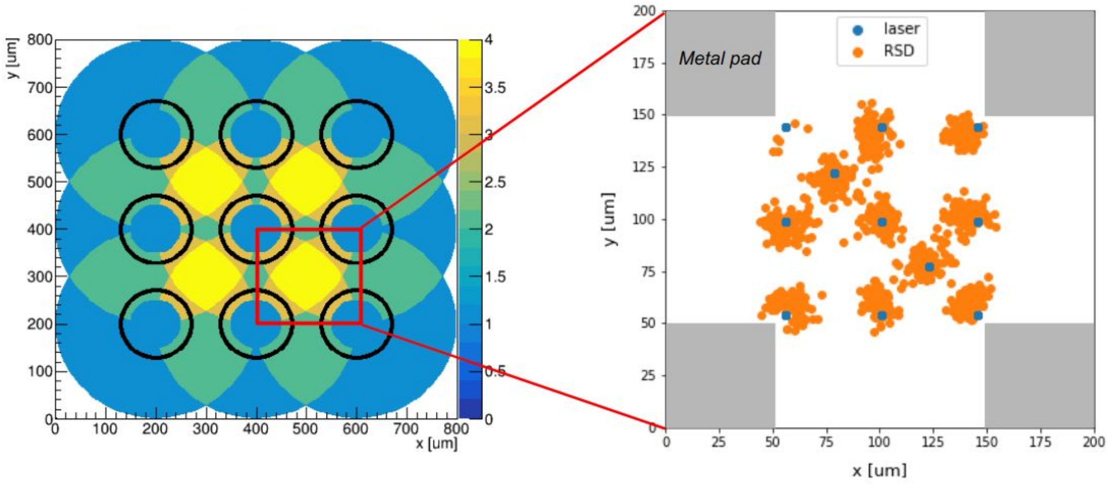
- ML algorithm has been firstly validated using a TCT setup
- IR pulsed laser (1060 nm) → 10-15 μm spot
- xy-stage with sub-μm precision → **laser shot position are known with <1 um resolution** → can be used as **reference positions to assess RSD predictions**





Laser results on 100-200 sensor

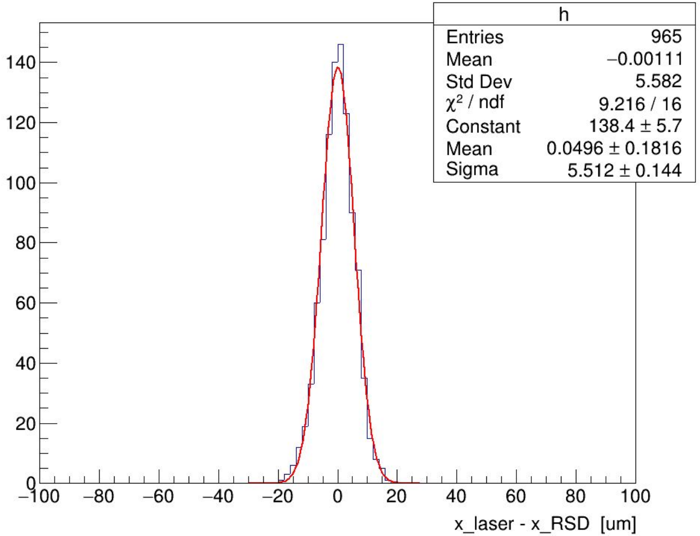
- 1st measured sensor: 3x3 matrix with 100-200 um geometry
- Gain = 15
- Focused on positions within the red region, as already explained
- Only regions where at least 3 pads can reconstruct the position are considered
- RSD spatial resolution: width of the x_{laser} - x_{RSD} distribution (negligible contribution from σ_{Laser})



Number of pads seeing a signal (left). Laser shot positions compared to RSD predictions (right)

Laser results on 100-200 sensor - 2

- A spatial resolution $\boldsymbol{\sigma_{total}}$ **~ 5.5 ± 0.1 (fit) ± 3.5 (syst.) um** has been measured
- That is **10 times better** than what would be achievable with **a pixel binary read-out**:
  σ = *pixel size* / √12 = 200 um / √12 ~ 55 um
- The optimized attenuation coefficient used (expressed in % of signal loss per um) is: β = 0.3% / um
- We added a systematic error of 3.5 um, which is the maximum variation of $\sigma_{intrinsic}$ depending on simulation parameters



Summary of laser results

- Three 3x3 **RSD** with different geometries have been **tested: 100-200, 50-100, 150-300**
- Gain = 15
- 4 pads read out
- **All 3 geometries provided a resolution ~ 5um**

Geometry	**Interpad**	**Resolution**	**β (%/um)**
100-200 um	100 um	**5.5** ± 0.1 (fit) ± 3.5 (syst.) um	0.3
50-100 um	50 um	**4** ± 0.1 (fit) ± 3.5 (syst.) um	0.33
150-300 um	150 um	**5.9** ± 0.1 (fit) ± 3.5 (syst.) um	0.3

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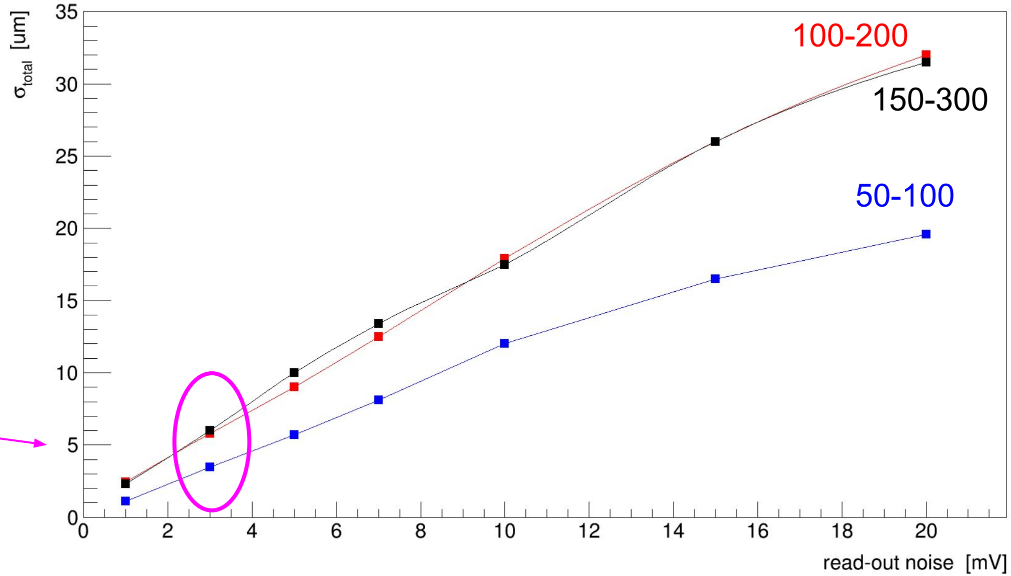
predictions of σ_{total} from simulation



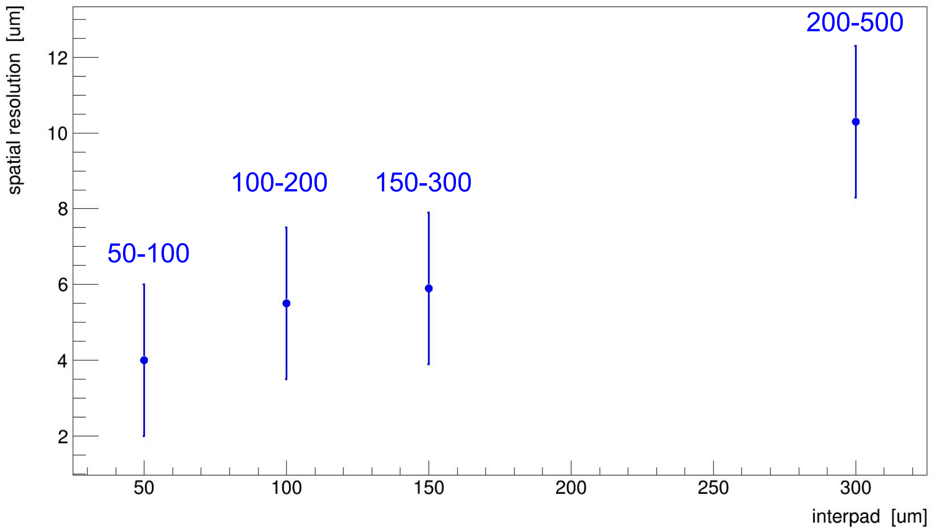
- The read-out noise during laser measurements is ~ 3 mV
- **Nice agreement with simulation predictions**

Summary of laser results - 2

- Also a **200-500 um** sensor has been measured, but without optimization

- Spatial resolution **~ 10um**
- Sensor with the largest interpad (300 um)
- The *interpad size* seems to have an important role in determining the spatial resolution

- We planned to measure other geometries, to further study this aspect of the RSD design, starting from an optimized training of the 200-500 geometry



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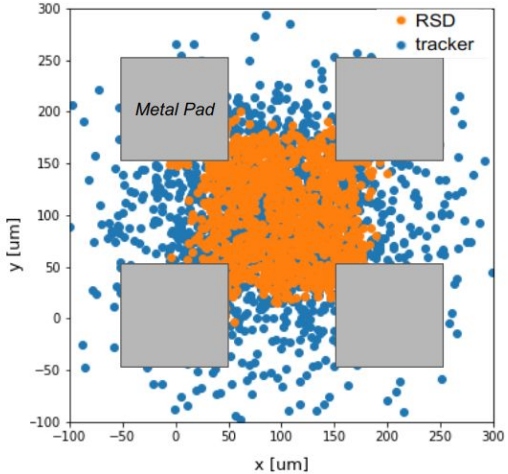
Results from FNAL beam test

- Beam test setup already described in M.Tornago's talk
- We measured the **100-200 um RSD**, reading out the same 4 pads of laser test
- Gain = 15
- The total resolution is given by the width of the $x_{Tracker}$ - x_{RSD} distribution
  - $\sigma_{Tracker}$ independently measured to be 45 um *



*due to non-standard run conditions, usually ~ 15 um

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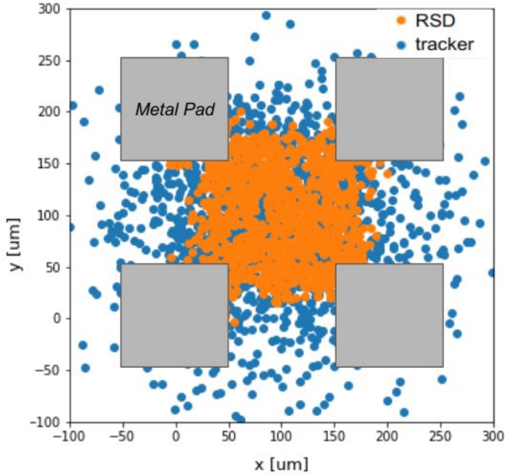

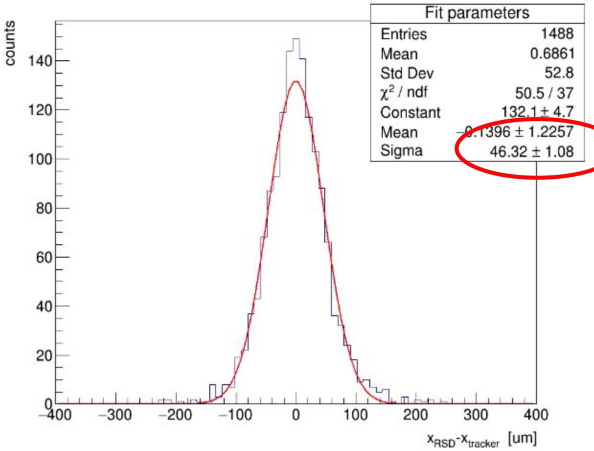

Resolution dominated by $\sigma_{tracker}$

consistent with σ_{RSD} ~ 5 um

Future plans

- **Train the ML algorithm using real beam test data taken with a very precise tracker**
  - No need to rely on analytic laws, which are based on our assumptions
  - Feed the network with a **wider range of input features**, whose attenuation laws cannot be derived analytically : signal width, signal derivative, risetime
    → **Deeper and more complex network**
- We believe the reconstruction method will further improve in this way
- Meanwhile: do the same training with TCT (although few drawbacks: laser spot has finite dimension, hard to simulate exactly 1 MIP)

4d-tracking with RSD

RSDs meet the requirements of 4d-tracking:

1. Timing resolution as standard LGAD: $\boldsymbol{\sigma_t}$ **~ 30 ps** (M.Tornago's talk)
2. **Radiation hardness** of standard LGAD
3. Spatial resolution : $\boldsymbol{\sigma_x}$ **~ 5 um** → 10 times better than with binary read-out
4. **Low power consumption** due to a reduced number of read-out channels:
    a. σ_x ~ 5 um with binary read-out is achieved with 25 um pixels
    → x64 more channels in the same area, compared to RSD
5. Plenty of **space for the electronics**, given the RSD pixel dimension

Summary & Outlook

- The distributed signal of RSD allows position reconstruction technique that combine the informations of many read-out channels
- The optimal RSD design features very small metal pads and a small interpad
- We trained a Multi-output regression algorithm to precisely reconstruct particles hit positions
  - Signal amplitude of 4 pads as inputs
  - x, y coordinates of the hit position as outputs
- The algorithm has been validated with laser tests:
  - 50-100, 100-200, 150-300 um geometries provided 5 um spatial resolution
  - 200-500 um provided 10 um spatial resolution
- RSDs meet the requirements of 4d-tracking
- In the near future, we will train the algorithm with precise beam test data → feed a deeper network, resulting in an enhanced position reconstruction

Thank You!

BACKUP

Systematic error on σ_{total}

- 3.5 um systematic error on measured spatial resolution
- This accounts for the maximum variability of $\sigma_{intrinsic}$, depending on the gaussian smearing parameter used in the algorithm training
- Since we do not know yet the best value for the smearing, we expect a change (considered in the systematic) in σ_{total} when the optimal value will be found