Position reconstruction using machine learning algorithms applied to Resistive Silicon Detectors

36th RD50 Workshop, CERN, 4th June 2020

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

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

  attenuation coefficient

- No signal sharing when the particle crosses a metal pad → signal only seen by the hit pad
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.
The attenuation law defines circumferences of equidistant positions that produce the same signal.

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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.
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**
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.

\[ \text{x-y map representing an RSD with 100-200* um geometry} \]

- 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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*\textit{pitch} - pad size

Only 1 pad reconstruct the position here, because signal is not shared
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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 $\sigma = \text{pixel size} / \sqrt{12}$
  - The RSD spatial resolution is much better than $\text{pixel size} / \sqrt{12}$ (next slides), as signal sharing enhances position reconstruction
  - Using squared pads, the spatial resolution is position dependent, worsening beneath the metal
Impact of pad geometry on position reconstruction

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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
Impact of pad geometry on position reconstruction

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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

  - 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*
Impact of sensor geometry on position reconstruction

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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
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 algorithms are suited to solve regression problems with many inputs and one (or multiple) output.

- We trained a **Multi-output 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):
  - Training performed using only 4 read-out pads.
Machine learning algorithms are suited to solve regression problems with many inputs and one (or multiple) output

- **We trained a Multi-output 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)
  - Training performed using only 4 read-out pads

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
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.
- ML algorithm trained with 8 input features: 4 pads’ amplitudes ($A_i$) + the same 4 amplitudes normalized to the total amplitude ($\frac{A_i}{\sum A_i}$)

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  - Amplitude values are randomly extracted from a Landau distribution with parameters taken from beam test data
Machine learning applied to RSD - 2

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We used the signal attenuation law to train the ML algorithm, assessing in each x-y position the amplitude seen by each pad

- **Amplitude** values are randomly extracted from a Landau distribution with parameters taken from beam test data
- 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

- **Amplitudes smearing**: x-y position not uniquely defined by one set of amplitudes → this leads to an intrinsic resolution of the algorithm
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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
Algorithm resolution

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- Resolution can be obtained by predicting the same data used for training and calculating the width of $x_{\text{predicted}} - x_{\text{truth}}$ distribution.

- 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 ($\sigma_{\text{intrinsic}}$) 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
  \[ \sigma_{\text{total}}^2 = \sigma_{\text{intrinsic}}^2 + \sigma_{\text{noise}}^2 \]
  
- \( \sigma_{\text{total}} \) has been determined predicting 1000 times the same position but with slightly different amplitudes each time, to reproduce the read-out noise
Read-out noise

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- \(\sigma_{\text{total}}\) has been determined predicting 1000 times the same position but with slightly different amplitudes each time, to reproduce the read-out noise.

- The total spatial resolution increases linearly with read-out noise and does not saturate
  \[ \sigma_{\text{total}} \propto \text{read-out noise} \]

- \(\sigma_{\text{total}}\) 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 $x_{\text{laser}} - x_{\text{RSD}}$ distribution (negligible contribution from $\sigma_{\text{Laser}}$)

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 $\sigma_{\text{total}} \sim 5.5 \pm 0.1 \text{ (fit)} \pm 3.5 \text{ (syst.) um}$ has been measured.

- That is **10 times better** than what would be achievable with a pixel binary read-out:
  \[ \sigma = \frac{\text{pixel size}}{\sqrt{12}} = \frac{200 \text{ um}}{\sqrt{12}} \sim 55 \text{ um} \]

- The optimized attenuation coefficient used (expressed in % of signal loss per um) is: $\beta = 0.3\% / \text{um}$

- We added a systematic error of 3.5 um, which is the maximum variation of $\sigma_{\text{intrinsic}}$ 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

<table>
<thead>
<tr>
<th>Geometry</th>
<th>Interpad</th>
<th>Resolution</th>
<th>$\beta$ (%/um)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100-200 um</td>
<td>100 um</td>
<td>$5.5 \pm 0.1$ (fit) $\pm 3.5$ (syst.) um</td>
<td>0.3</td>
</tr>
<tr>
<td>50-100 um</td>
<td>50 um</td>
<td>$4 \pm 0.1$ (fit) $\pm 3.5$ (syst.) um</td>
<td>0.33</td>
</tr>
<tr>
<td>150-300 um</td>
<td>150 um</td>
<td>$5.9 \pm 0.1$ (fit) $\pm 3.5$ (syst.) um</td>
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</tr>
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</table>
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

- 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 $\sim 10\text{um}$
- 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 $x_{\text{Tracker}} - x_{\text{RSD}}$ distribution
  - $\sigma_{\text{Tracker}}$ independently measured to be 45 um 

*due to non-standard run conditions, usually ~ 15 um
Results from FNAL beam test

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- 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 $x_{\text{Tracker}} - x_{\text{RSD}}$ distribution
  - $\sigma_{\text{Tracker}}$ independently measured to be 45 um

Resolution dominated by $\sigma_{\text{tracker}}$ consistent with $\sigma_{\text{RSD}} \sim 5$ 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: $\sigma_t \sim 30 \text{ ps}$ (M.Tornago’s talk)
2. **Radiation hardness** of standard LGAD
3. Spatial resolution: $\sigma_x \sim 5 \text{ um} \rightarrow 10$ times better than with binary read-out
4. **Low power consumption** due to a reduced number of read-out channels:
   a. $\sigma_x \sim 5 \text{ um}$ with binary read-out is achieved with 25 um pixels
      $\rightarrow$ 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!
Systematic error on $\sigma_{\text{total}}$

- 3.5 um systematic error on measured spatial resolution

- This accounts for the maximum variability of $\sigma_{\text{intrinsic}}$, 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 $\sigma_{\text{total}}$ when the optimal value will be found

max excursion = 3.5 um