

Silicon sensors with resistive read-out: ML and analytics techniques for ultimate spatial resolution

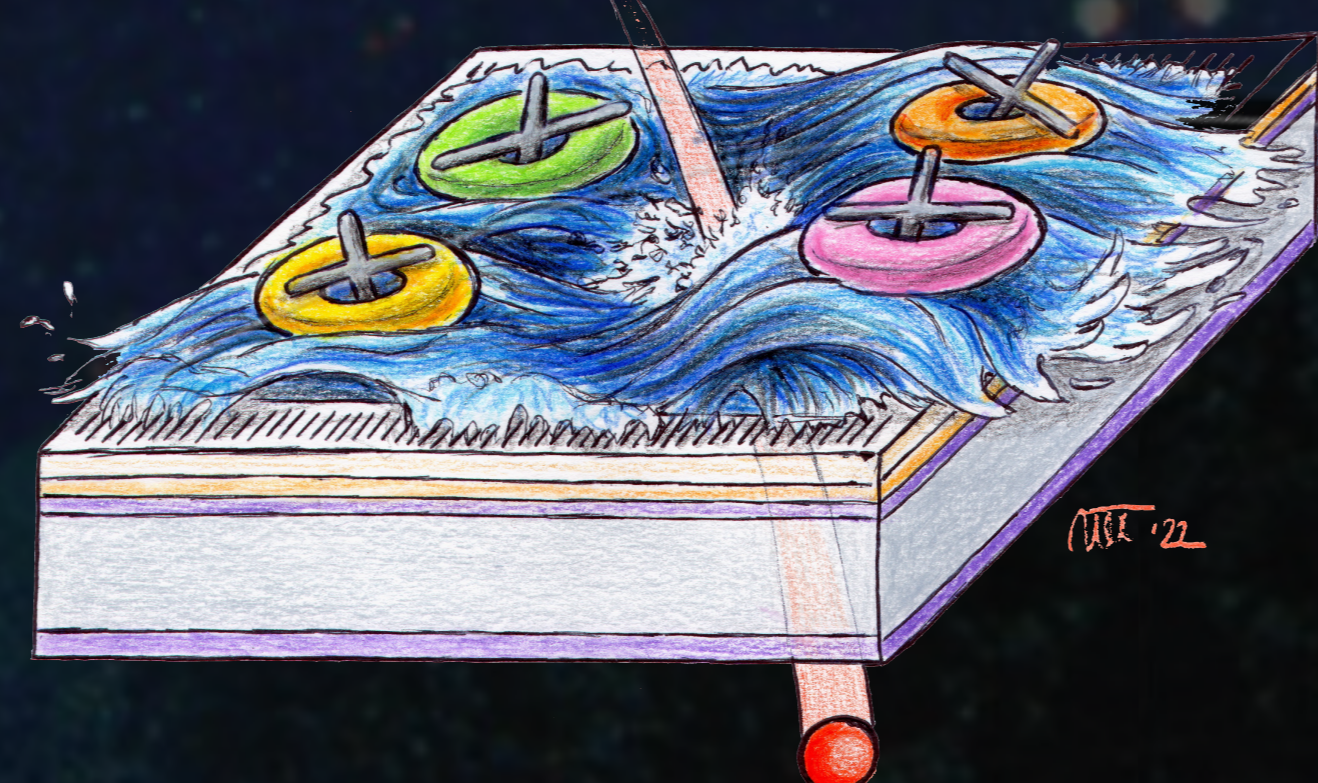
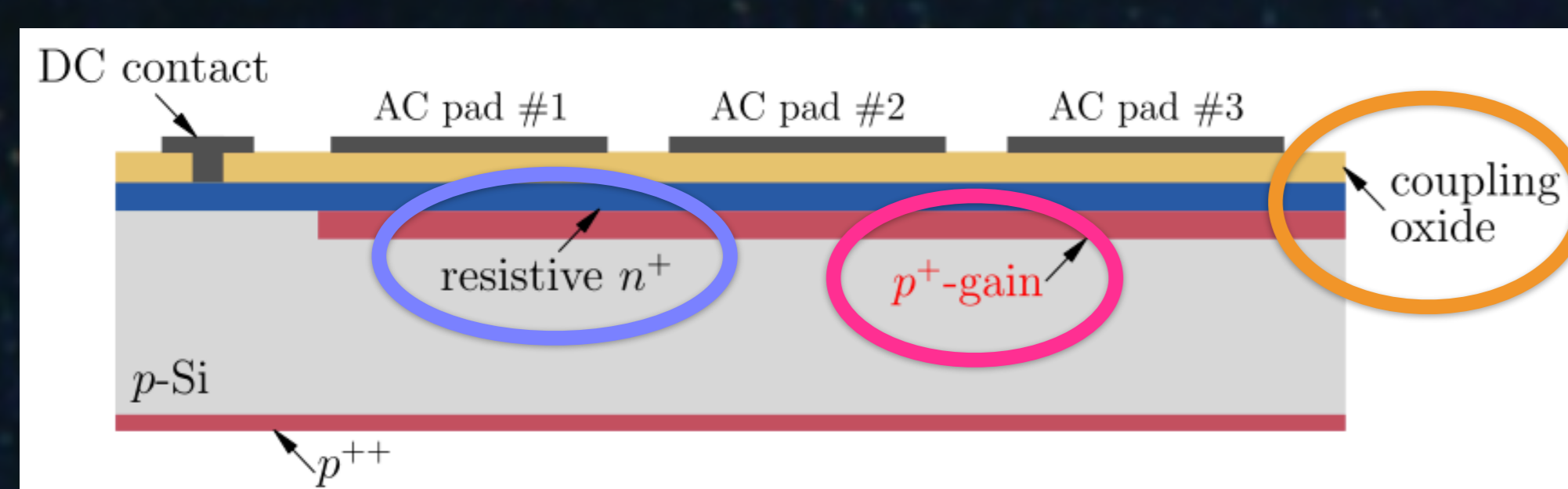
(1)(2) Tornago M., (8) Giobergia F., (1)(2) Menzio L., (2) Siviero F., (2)(3) Arcidiacono R., (2) Cartiglia N., (1)(2) Costa M., (2)(3) Ferrero M., (1) Gioachin G., (2) Mandurrino M., (7) Miserochci F., (2) Sola V., (2) Staiano A., (4)(6) Borghi G., (4)(6) Boscardin M., (4)(6) Centis Vignali M., (5)(6) Dalla Betta G.F., (4)(6) Ficorella F., (4)(6) Hammad Ali O., (5)(6) Pancheri L., (4)(6) Paternoster G.

(1) Università degli Studi di Torino, (2) INFN Torino, (3) Università del Piemonte Orientale (Novara), (4) Fondazione Bruno Kessler (Trento), (5) Università degli Studi di Trento, (6) TIFPA-INFN Trento, (7) D-ITET, ETH (Zurigo), (8) Politecnico di Torino

Resistive AC-Coupled Silicon Detectors

Resistive AC-coupled Silicon Detectors (RSD) are a new generation of n-in-p silicon sensors with 100% fill-factor designed for high-precision 4D tracking in experiments at future colliders

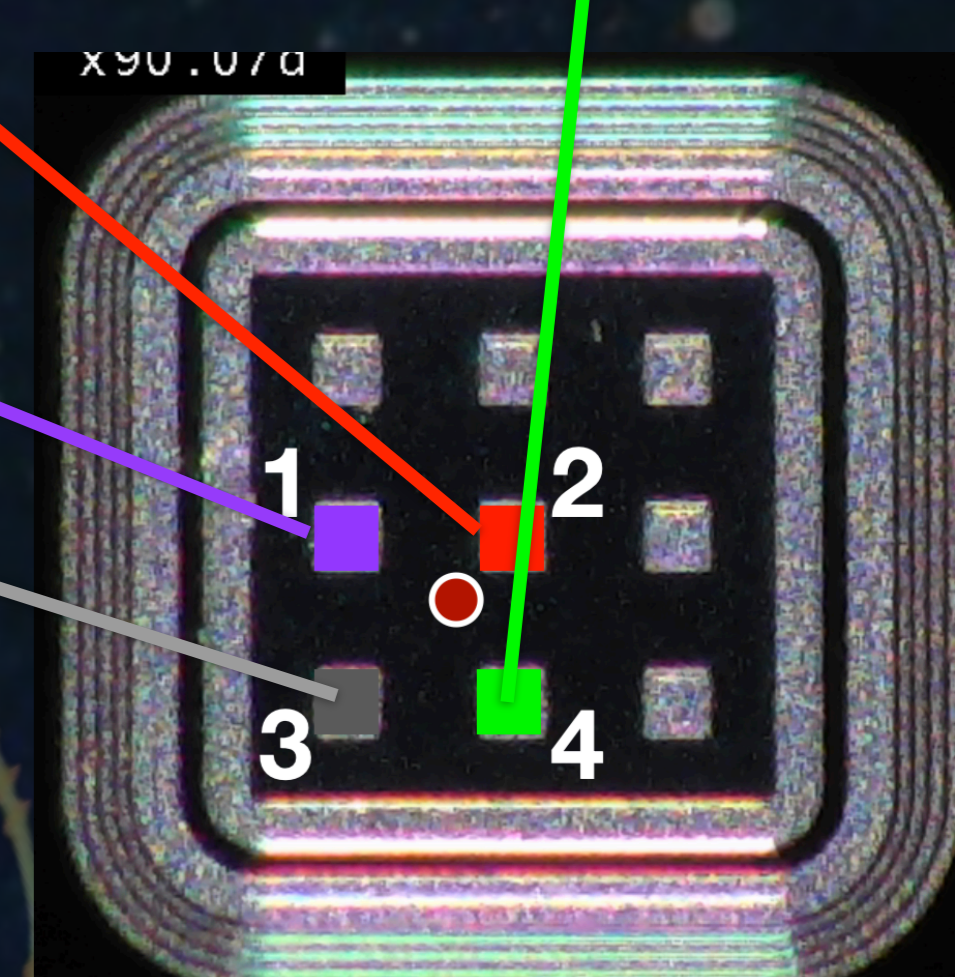
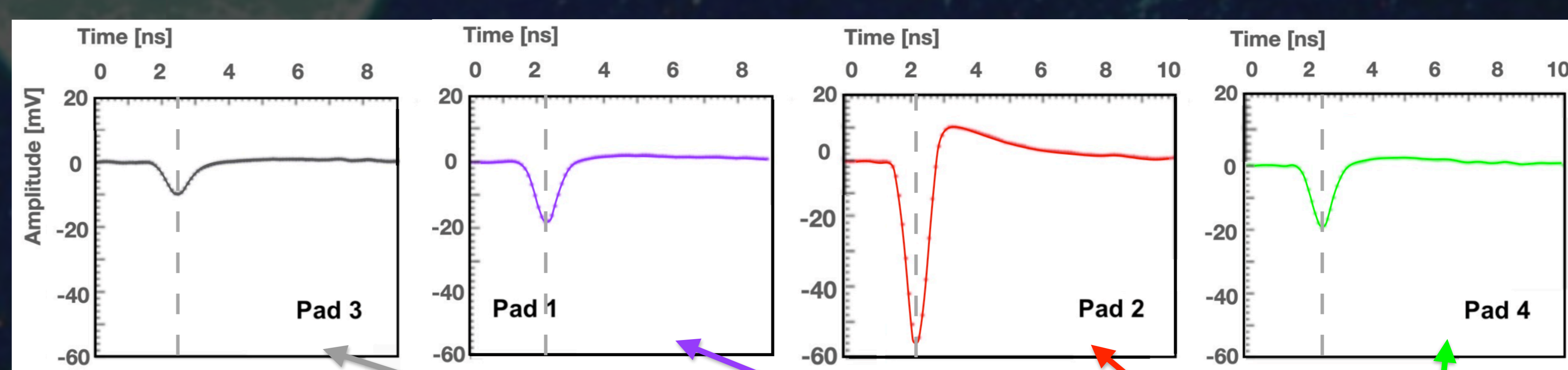
- Based on **LGAD technology**
 - improved by using **one continuous gain layer**
- Introduction of resistive read-out in silicon detectors:
 - AC coupling of the read-out occurring through a **dielectric layer**
 - a continuous **resistive n+ electrode** allowing charge sharing
 - spatial resolution up to a **factor 10 better than binary readout**



Signal sharing comes natural in RSDs

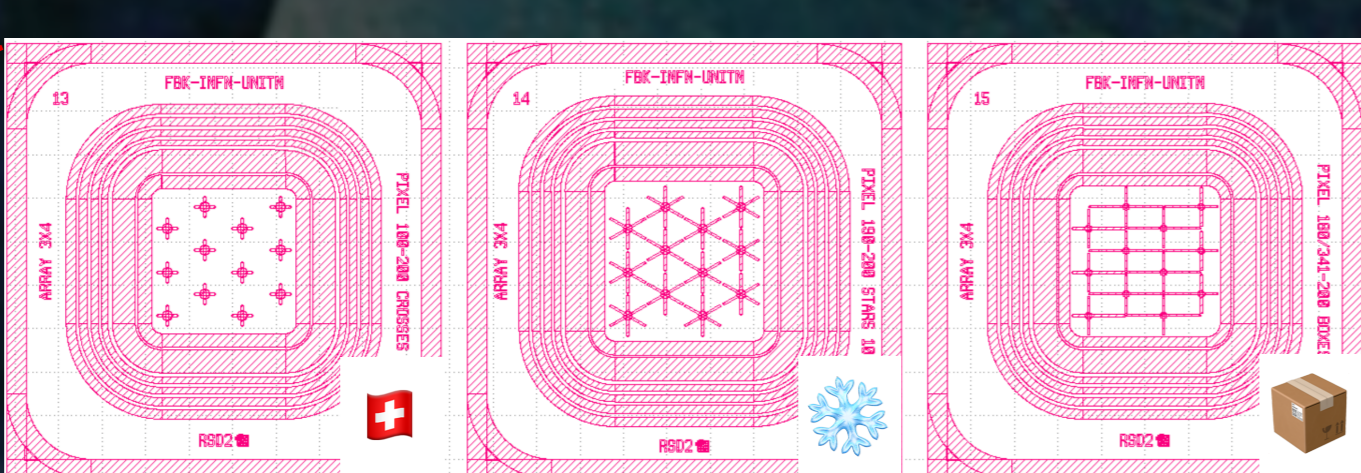
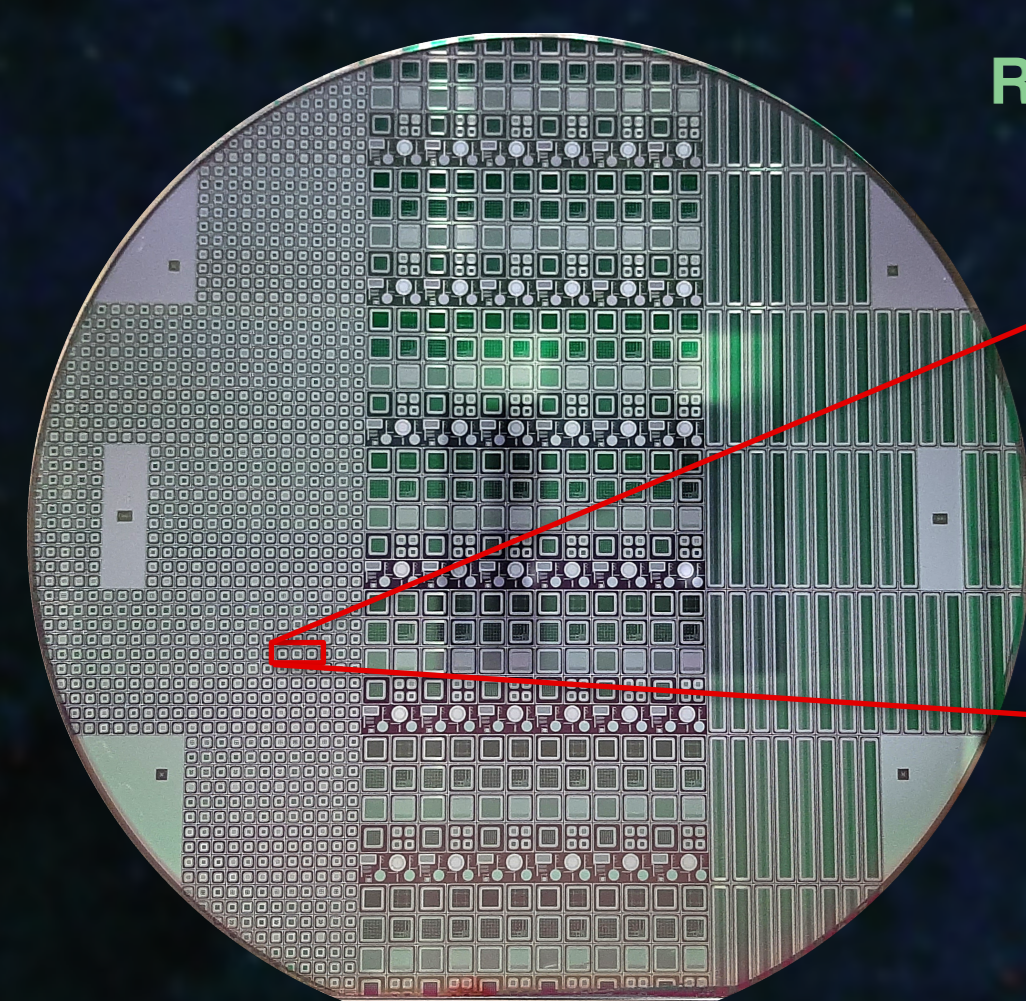
When a particle hits the sensor, each AC pad sees a signal which becomes **smaller and more delayed** with increasing distance from the **impinging point**

this is the RSD "recipe" to reach an unprecedented spatial resolution

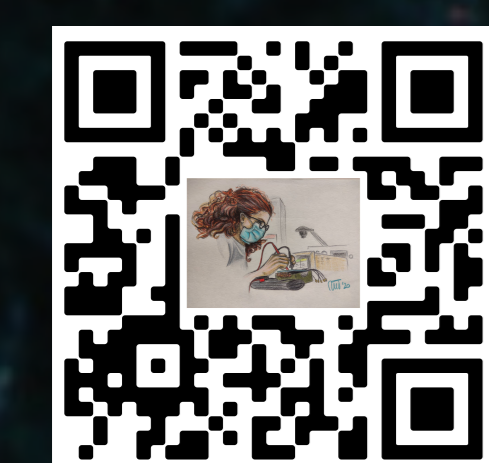


Laboratory Measurements

RSD2 is the second RSD batch produced by Fondazione Bruno Kessler in 2021



RSD2 wafers include sensors with different sizes, AC pads number and layout to explore signal sharing properties

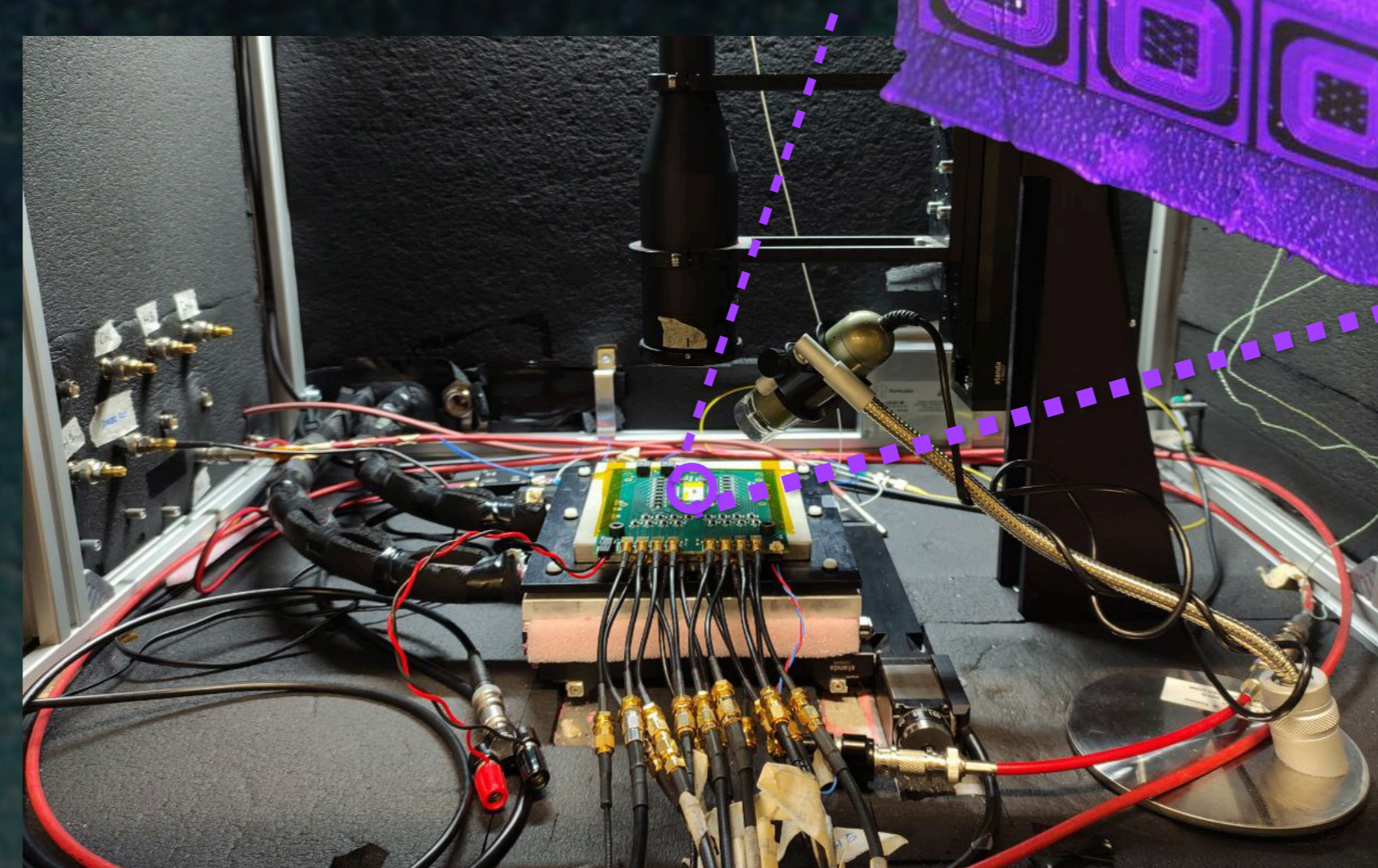
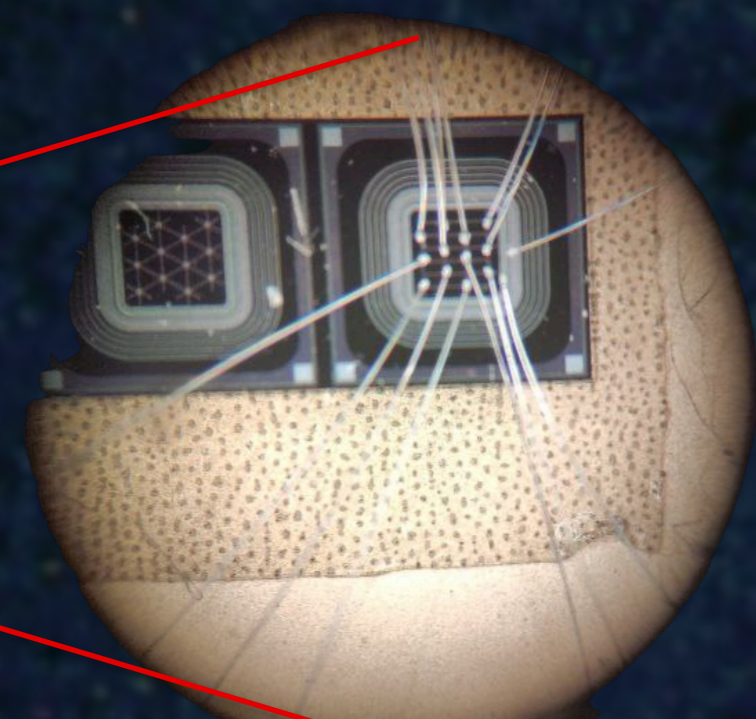
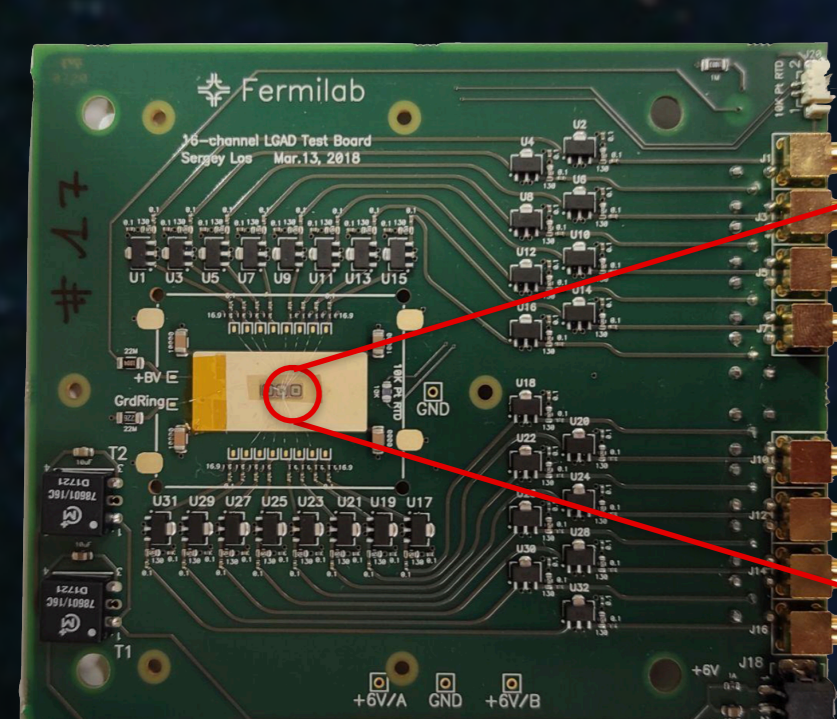


The **variety of AC pads shapes** is the result of studies performed on the previous RSD1 production (M. Tornago et al., *Resistive AC-Coupled Silicon Detectors principles of operation and first results from a combined laser-beam test analysis*)

Three 3x4 matrices with same dimension and different electrodes were selected to study their spatial resolution:

- #13, "Swiss crosses"
- #14, "Flakes"
- #15, "Boxes"

The devices under test were wire-bonded to a 16-channel Fermilab readout board



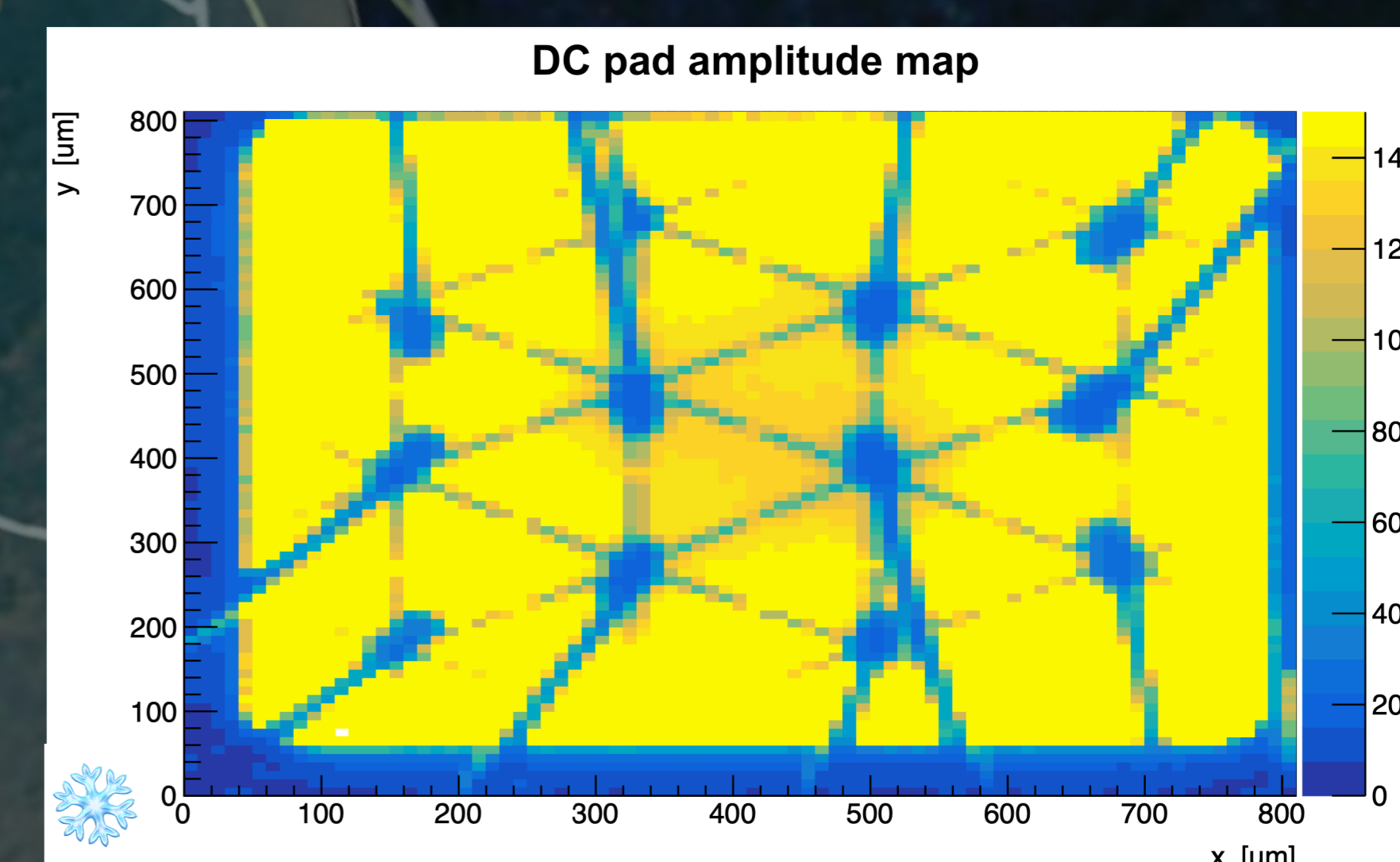
RSD2 arrays were tested with the Particulars **Transient Current Technique Setup (TCT)** in the **Laboratory for Innovative Silicon Sensors in Torino**

The setup is provided with:

- ★ **infra-red laser** simulating the passage of a MIP through the sensor
- ★ **x-y moving stages** with micrometrical precision
- ★ optical system that allows reaching a **minimum laser spot of ~10 μm**

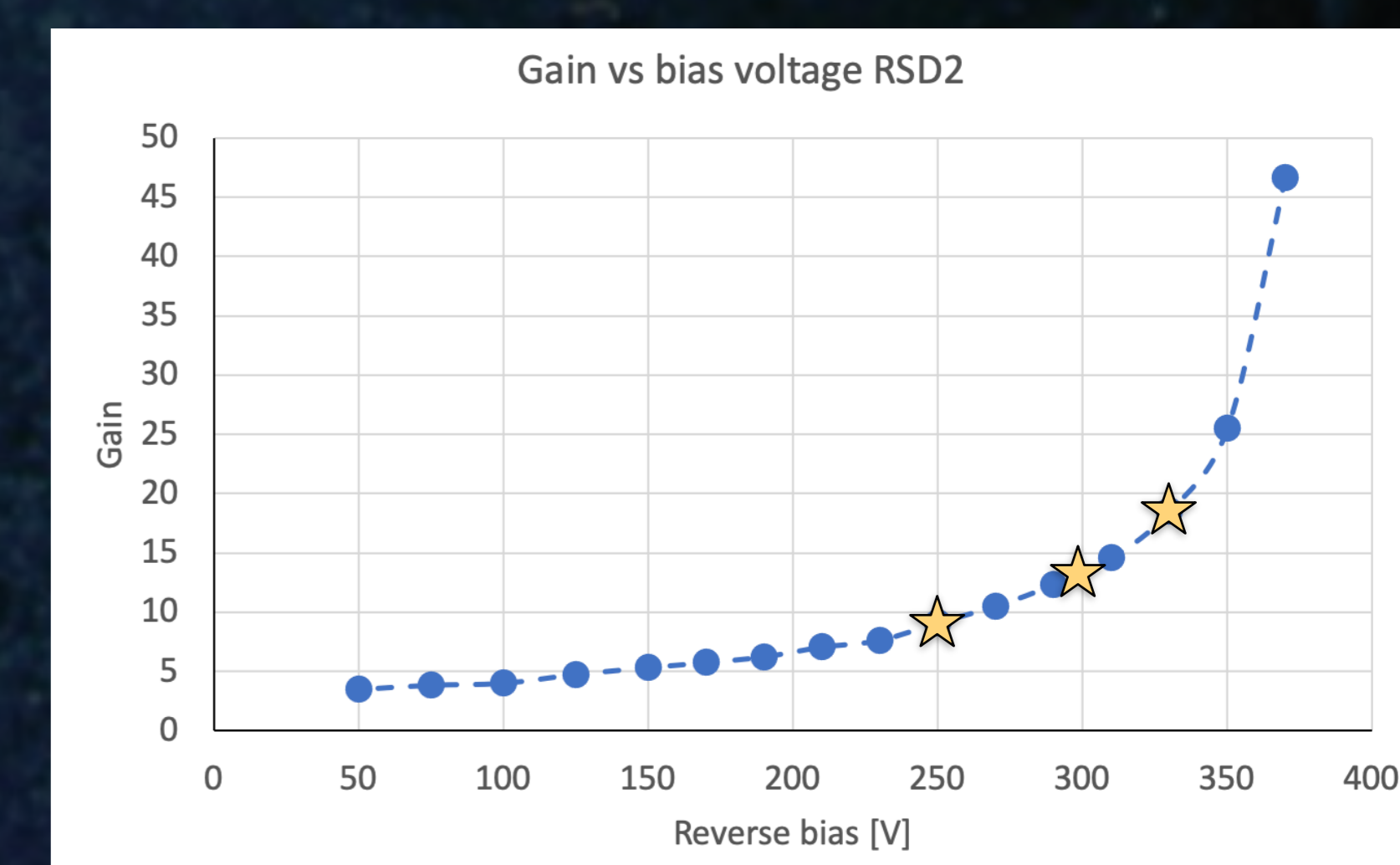
Data are acquired with a **16-channel digitizer**

Measurements are automated thanks to a **dedicated Python script**



All the DUTs surface is scanned with the TCT setup: the **laser is shot every 10 μm in x and y** and a fixed number of waveforms is acquired for each electrode in every point

The measurement is performed at three bias voltages (250 V, 300 V and 330 V), corresponding to **three different gain values of the sensors** ★



Results from Machine Learning Analysis

Position reconstruction is based on the combination of information on **signals from each AC pad**

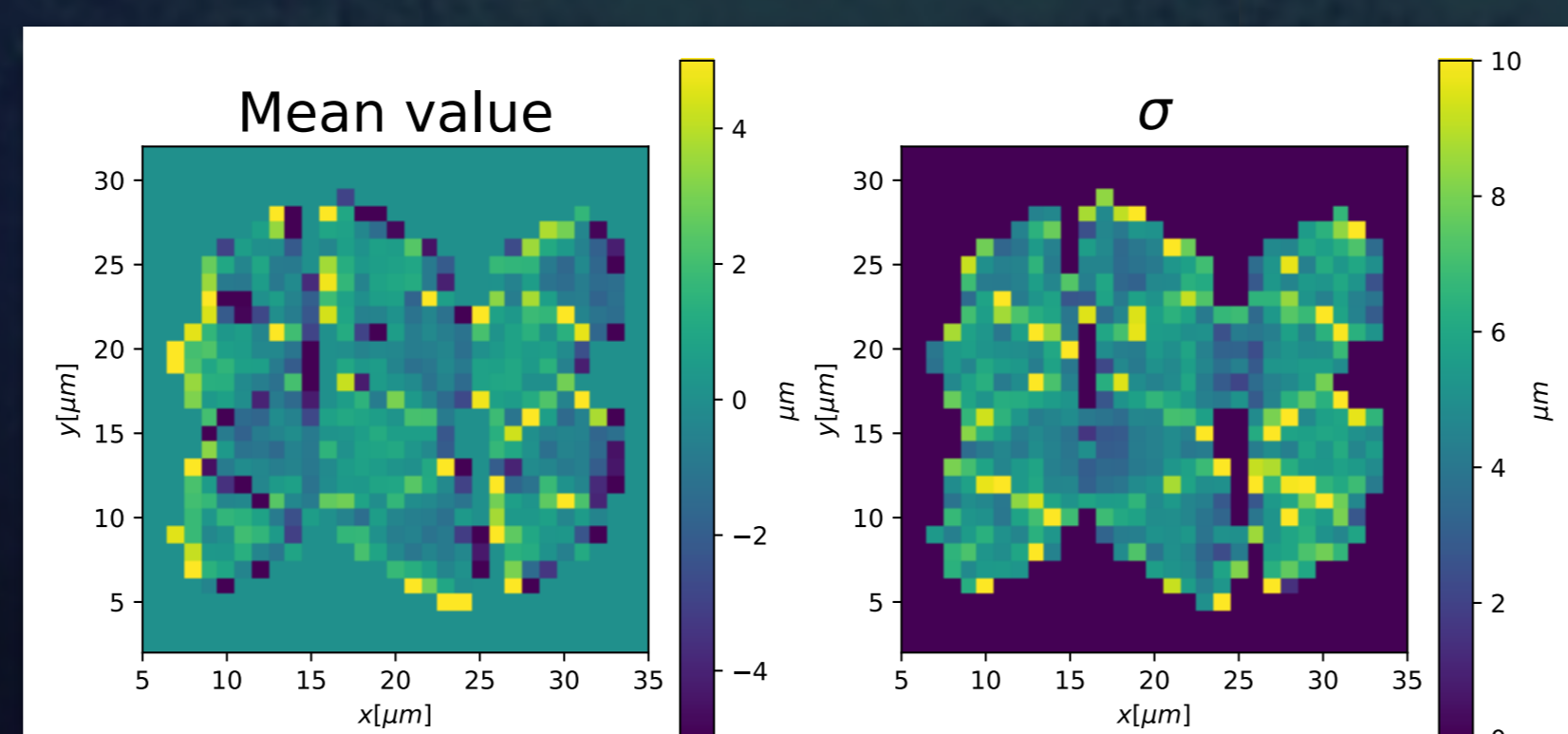
The correct analytic law describing the relation between signal properties and predicted coordinates is not easy to define

Task suited for a **Machine Learning algorithm**: signal properties are fed as input features, while the x-y coordinates are the output (F. Siviero et al., *First application of machine learning algorithms to the position reconstruction in Resistive Silicon Detectors*)

Procedure:

- **Feature extraction**: meaningful input features are extracted from experimental data
- Processed data are split into a **training** and a **test set**
- **Model training**: a **random forest regression model** is fit using the training dataset, in which 100 waveforms are acquired in each x-y position
- **Model evaluation**: the model performance is assessed on the test dataset to obtain final **results**

For the test set, 10 waveforms are acquired for each laser point; x-y positions are shifted of 5 μm with respect to the training ones to obtain non-overlapping datasets



Spatial resolution is computed by comparing the predicted positions with the laser reference ones, provided by the x-y stage

$$\sigma_{x,y} = \sqrt{\sigma_{RSD,x,y}^2 + \sigma_{laser,x,y}^2} \quad \sigma_{tot} = \sqrt{\sigma_{RSD,x}^2 + \sigma_{RSD,y}^2}$$

200-μm pitch RSDs can reach a total spatial resolution ~ 8 μm at a bias voltage corresponding to a gain value of 15-20

Much smaller than corresponding resolution from binary readout: $pitch/\sqrt{12} \sim 58 \mu m$

The main contribution to spatial resolution errors is represented by the **experimental setup uncertainty**; contribution from ML reconstruction has been calculated and is negligible

Better spatial resolution results are expected using point-like particles instead of a 10-μm spot laser and exploiting a setup provided with a precise tracking system

Spatial resolution vs Bias Voltage

