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

M. Tornago[a,b,*], F. Giobergia[d], L. Menzio[b,a], F. Siviero[a], R. Arcidiacono[c], N. Cartiglia[b], M. Costa[a], M. Ferrero[c], G. Gioachin[a], M. Mandurrino[b], V. Sola[b]

[a] *Università degli Studi di Torino, Torino, Italy*
[b] *INFN, Torino, Italy*
[c] *Università del Piemonte Orientale, Novara, Italy*
[d] *Politecnico di Torino, Torino, Italy*

Abstract

Resistive Silicon Detectors (RSDs) are based on the LGAD technology, characterized by a continuous gain layer, and by the innovative introduction of resistive read-out. Thanks to a novel electrode design aimed at maximizing signal sharing, the second FBK production of RSD sensors, RSD2, achieves a position resolution on the whole pixel surface of about 8 μm for 200-μm pitch. RSD2 arrays have been tested in the Laboratory for Innovative Silicon Sensors in Torino using a Transient Current Technique setup equipped with a 16-channel digitizer, and results on spatial resolution have been obtained with machine learning algorithms.

Keywords:
LGAD, AC-LGAD, Particle tracking detectors, Solid-state detectors, High Energy Physics

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1. Introduction

Resistive AC-coupled Silicon Detectors (RSDs) are a new generation of n-in-p silicon sensors with nearly 100% fill-factor designed for high-precision 4D tracking in experiments at future colliders. RSDs are based on the Low Gain Avalanche Diode (LGAD) technology but are featured with one single continuous gain layer. The segmentation of the device is realized thanks to the introduction of resistive AC-coupled read-out: (i) the AC coupling of the metal pads occurs through a dielectric layer, and (ii) a continuous resistive n+ electrode allows charge sharing. As a result, the signal is shared among multiple read-out pads. 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 RSD key feature allows reaching an unprecedented spatial resolution, up to a factor 10 better than the corresponding binary readout precision. After the first RSD production (2019) [3], a second batch, RSD2, has been manufactured by Fondazione Bruno Kessler (FBK) in 2021 [4]. It is featured with 15 wafers with varying resistivity, oxide thickness, and gain dose. Each wafer includes several sensors geometries, with different active areas, pitch, and AC pad number, size, and shape.

2. Laboratory measurements

RSD2 sensors have been tested in the Laboratory for Innovative Silicon Sensors (LISS) in Torino. Three 750×750 μm^2 RSD arrays with $200 - \mu m$ pitch and 3×4 AC pads have been selected for spatial resolution studies. The three matrices differ in the layout of the AC pads, which have shapes of "Swiss crosses", "flakes" and "boxes" 1. Measurements have been performed with the Particulars Transient Current Technique (TCT) setup [6], which exploits a laser to simulate the passage of a minimum ionizing particle (MIP) through the device under test (DUT). This setup is provided with (i) a picosecond infrared laser with 1064 nm wavelength, (ii) an optical system that allows reaching a minimum laser spot of ~ 10 μm, and (iii) an x-y moving stage with micrometrical precision where the sensor is mounted. Each array is wire-bonded to a 16-channel read-out board designed at Fermilab [9]. Data are acquired with a 16-channel CAEN DT5742 Desktop Digitizer, simultaneously recording all the detector channels. The whole DUT surface is scanned with the TCT setup: the laser is shot every 10 μm along x and y and 100 waveforms are acquired for each AC pad. When impinging on the sensor surface, the laser provides a signal equivalent to $\sim$ 5 MIPs. For each RSD2 matrix, the scan is repeated at three bias voltages, 250 V, 300 V, and 330 V, corresponding to gain values of $\sim$ 10, 15, and 20, respectively.

3. 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 [2]. This task is instead perfectly suited for a Machine Learning (ML) algorithm [5]: signal properties are fed as input features, while the predicted x-y coordinates are the output. The ML analysis of RSD data is based on the following steps: (i) *feature extraction*: meaningful input features are extracted from the experimental data,

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[*] Corresponding author
Email address: `marta.tornago@edu.unito.it` (M. Tornago)

such as the signal amplitudes; (ii) *train/test split*: the data extracted is split into a training set – used to build a regression model – and a test set, used to assess the performance of the model itself in terms of spatial resolution. We adopted an 80/20 train/test split. For a fair estimate of the model performance, we split the dataset so that all 100 waveforms collected for a specific x-y position are all either used for the training or the test; (iii) *model training*: a random forest regression model [7] is trained using the training dataset. The random forest is comprised of 100 trees independently trained on random subsets of the training set; (iv) *model evaluation*: the model performance is assessed on the test dataset to obtain the final results. The positions used for the test set differ from the ones used during training to assess the capability of the ML model to generalize to new, unseen positions.

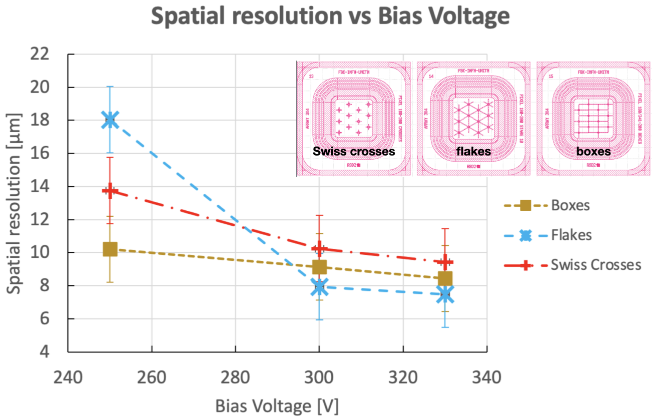

Figure 1: Results for total spatial resolution represented as a function of bias voltage for “boxes”, “flakes” and “Swiss crosses” $200 - \mu m$ pitch RSD2 arrays.

4. Experimental results

The spatial resolution for the DUTs has been computed by comparing the x-y predicted positions with the laser reference ones, which are provided by the TCT stage. The differences between predicted and reference coordinates are collected in a distribution that is fitted with a gaussian: its standard deviation represents the spatial resolution of the whole system, accounting for both the RSD and the laser resolution:

$$\sigma_{sys} = \sqrt{\sigma^2_{RSD} + \sigma^2_{laser}}. \qquad (1)$$

As the distributions are created separately for x and y coordinates, the total spatial resolution for a RSD array is the combination of the two resolutions:

$$\sigma_{RSD} = \sqrt{\sigma^2_{RSD,x} + \sigma^2_{RSD,y}}. \qquad (2)$$

The results are shown in figure 1, where spatial resolution values are represented as a function of bias voltage for the three geometries. $200 - \mu m$-pitch RSD2 matrices can reach a total spatial resolution $\sigma_{RSD,tot} \sim 8 \mu m$ at a bias voltage corresponding to a gain ~ 20. This result is much smaller than the corresponding binary readout precision, which would be $pitch\ size/\sqrt{12} \sim 58 \mu m$. Spatial resolution errors are mainly represented by the uncertainty on σ_{laser}, which is estimated to be ~ 2 *mum*. The contribution from ML reconstruction has been calculated and can be considered negligible [5]. Better spatial resolution results are expected using point-like particles instead of a $10 - \mu m$ spot laser and exploiting a setup provided with a precise tracking system.

5. Conclusions

This contribution describes the latest studies on the spatial resolution of three arrays from the FBK RSD2 production with $750 \times 750\ \mu m^2$ active area, 200 μm pitch, and 3×4 AC pads with different shapes: “Swiss crosses”, “flakes” and “boxes”. The sensors have been tested at the Laboratory for Innovative Silicon Sensors in Torino with a TCT setup equipped with a 16-channel digitizer. The characteristic charge sharing of RSDs allows performing position reconstruction by combining the information from signals of each AC pad. Machine Learning perfectly suits this task: a random forest regression model has been trained to analyze experimental data. Results demonstrate that RSD2 200-μm-pitch matrices can achieve a spatial resolution of ~ 8 μm at gain ~ 20 with a laser intensity corresponding to ~ 5 MIPs.

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