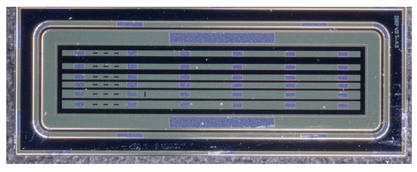
Neural-Network-Based Position Reconstruction for Strip AC-LGADs

Poster #B14

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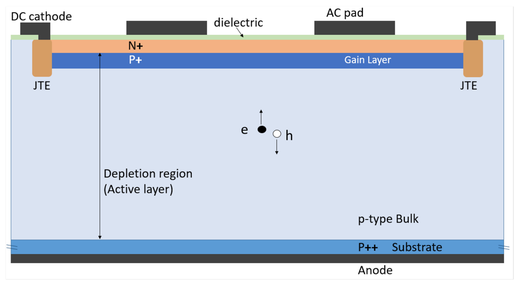
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Strip AC-LGAD sensor

AC-Coupled Low Gain Avalanche Diode



Structure of a Strip AC-LGAD sensor

Questions

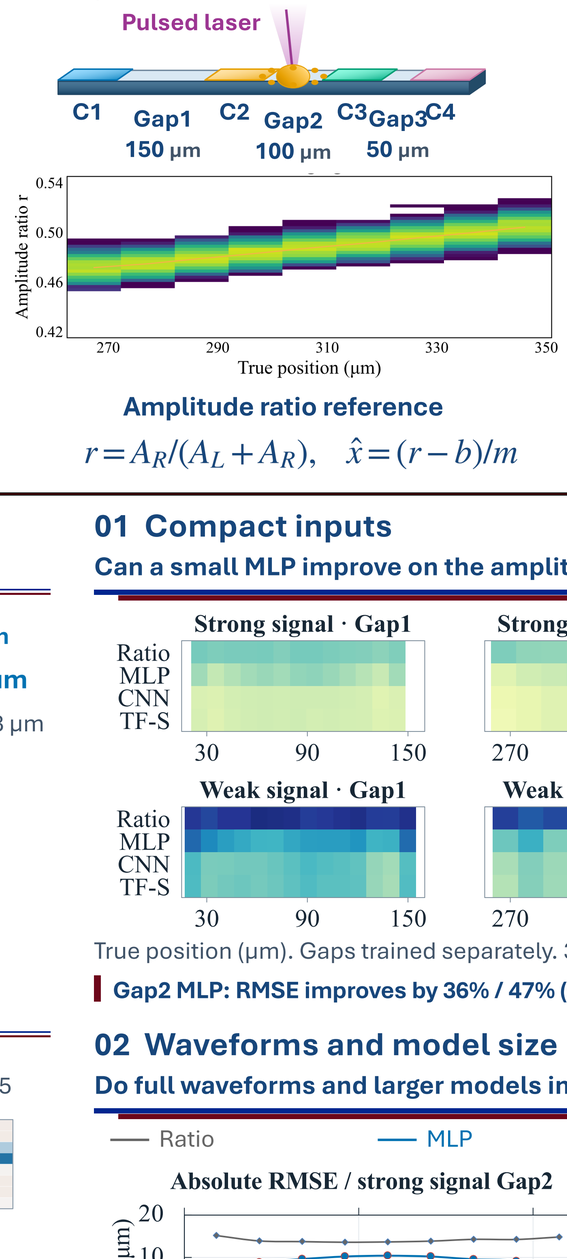
1 Can a small network with few amplitudes beat the ratio method?

2 Do full waveforms and larger networks improve reconstruction?

3 Can ToA and ToT improve amplitude-based reconstruction?

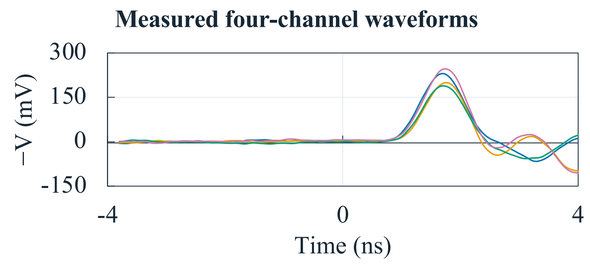
4 Can a model predict a gap excluded from training?

Experiment: TCT Laser Scan



Amplitude ratio reference

$$r = A_R/(A_L + A_R), \quad \hat{x} = (r - b)/m$$

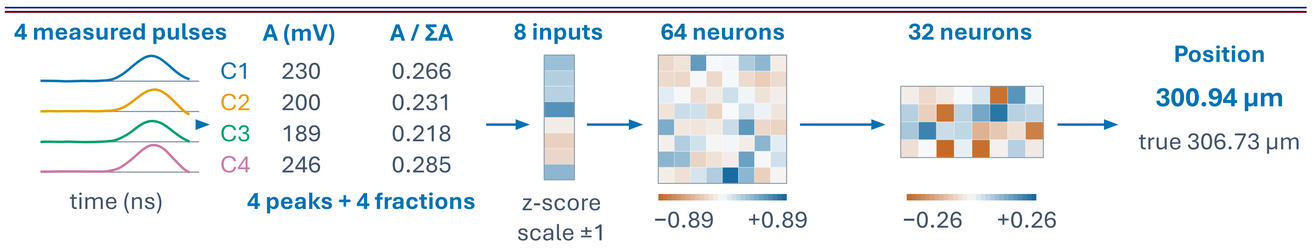


4 channels × 197 samples, 50 ps per sample

Gap2 RMSE: 14.14 µm strong
31.75 µm weak

MLP: compact amplitude features

Eight features encode position



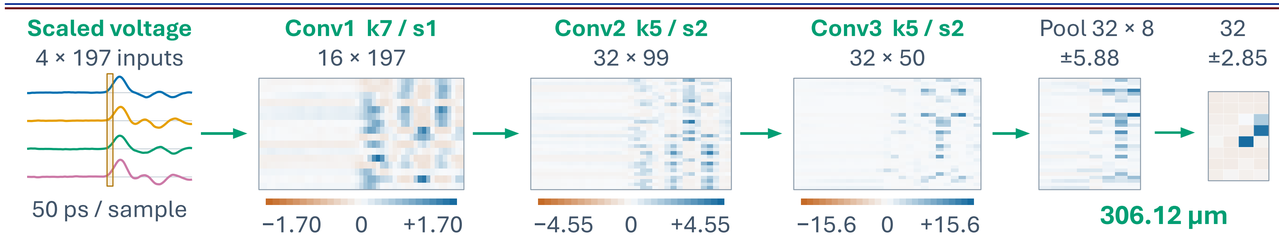
8 → 64 → 32 → 1 SiLU 2,689 parameters

$$h' = \mathrm{SiLU}(Wh + b)$$

h: features. W, b: learned weights and offsets.
Colours represent measured features and neuron activations.

Joint-channel CNN

Pulse shapes reveal more than amplitudes



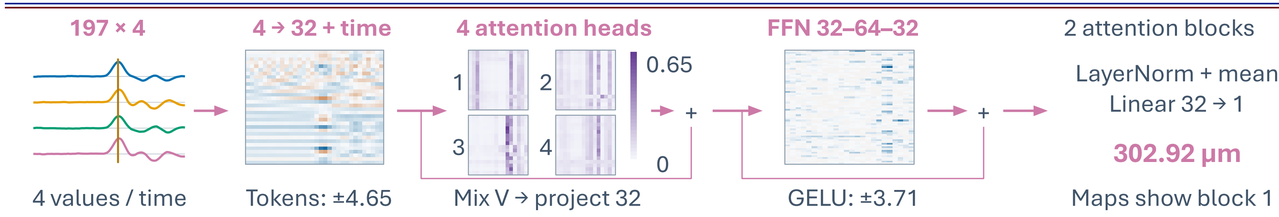
Time-local filters mix all four channels. 16,465 parameters.

$$H' = \mathrm{SiLU}(K * H + b)$$

K: learned filters. *: convolution over nearby samples.
The feature maps show an actual event at successive layers.

Time Transformer

Relationships across distant samples



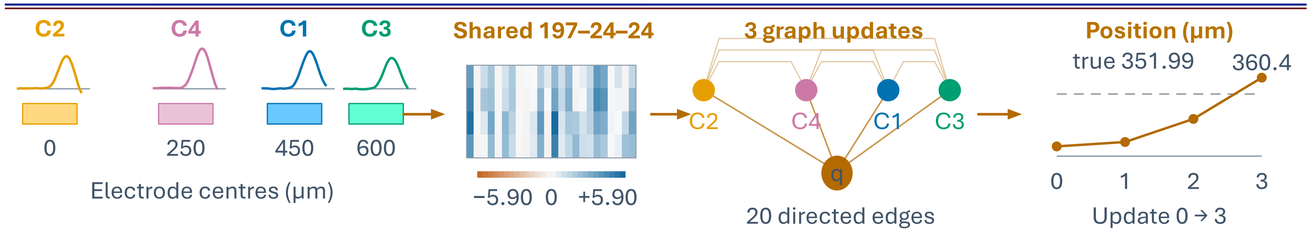
2 blocks, 4 heads, width 32, GELU. 17,345 parameters.

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(QK^T/\sqrt{8})\,V$$

Q, K: similarity. V: carried features.
Each attention head has width 8.

Anchored GNN

Electrode geometry support transfer to an unseen gap



Shared waveform encoder and 3 graph updates. 20,259 parameters.
AGNN-d0 removes radial messages but retains electrode anchors.

$$\hat{x}' = \hat{x} + 0.5\,\mathrm{mean}_i[(c_i - \hat{x})\,w_i]$$

c: electrode centres. x-hat: estimated hit.
w: learned weight between −1 and 1.

Train on Gap1 + Gap3, then predict Gap2.
Curves: seed means. Whiskers: seed range. Black: ideal.

Input definitions and training convention

Input	Numbers supplied to the position model
TT	ToA + ToT
A8	4 peaks + 4 peak fractions
TT+A	TT + 4 peaks
S16	Peaks, areas, relative ToA + validity flags
P16	16 learned principal components
CNN / TF-S	All four waveforms (788 samples)

CFD = 0.5 of each channel's own peak. TDC step = 20 ps.

Conclusions and outlook

1 RMSE Improvement: MLP 36% / 47%, TF 56% / 59% (strong / weak).

2 Larger models give no material gain in the matched capacity tests.

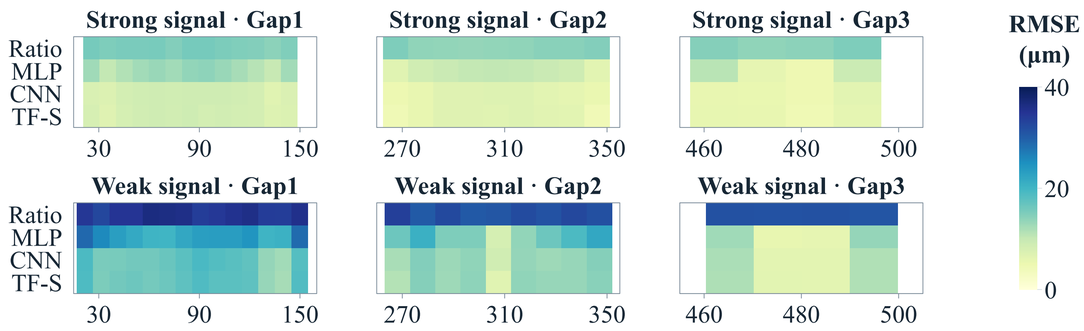
3 Timing alone is weak here. Amplitude or area information is needed.

4 Robust cross-gap observables remain to be found.

5 Small models show FPGA potential. Hardware tests remain necessary.

01 Compact inputs

Can a small MLP improve on the amplitude ratio?

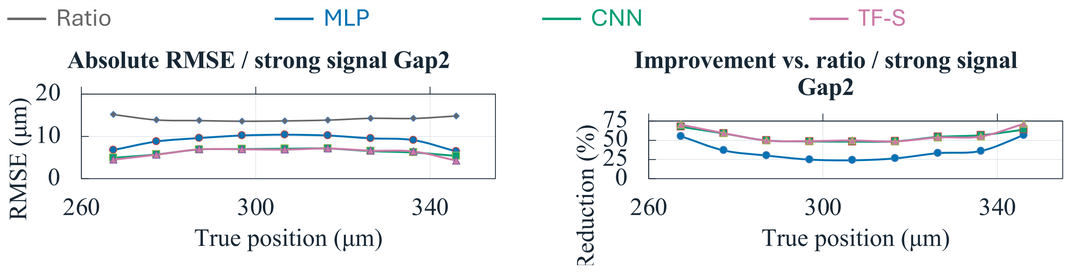


True position (µm). Gaps trained separately. 3 seeds. Gap3: 4 validation positions.

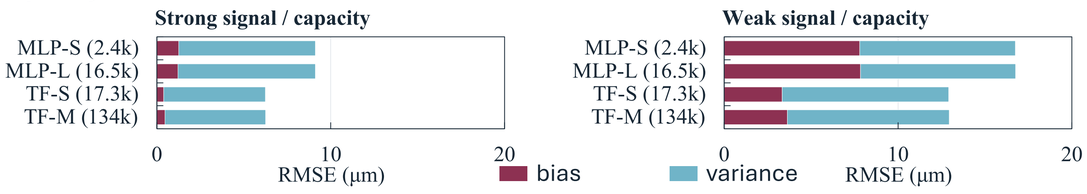
Gap2 MLP: RMSE improves by 36% / 47% (strong / weak).

02 Waveforms and model size

Do full waveforms and larger models improve accuracy?



Capacity control

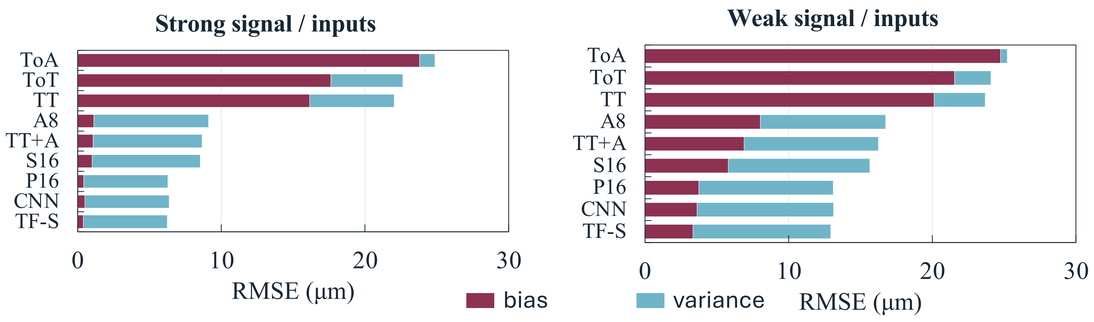


MLP-S/L: same four peaks. TF-S/M: same full waveforms.

Waveforms help. Larger models give no material gain.

03 Timing information

Can ToA and ToT improve amplitude-based reconstruction?



Total bar length = RMSE.
TT+A vs. A8: 4.9% / 3.0% lower RMSE (strong / weak).

Timing alone gives poor position sensitivity.

04 Cross-gap transfer

Train on Gap1 + Gap3. Can the model predict Gap2?



Gap2 RMSE (µm)	CNN-4L	AGNN	AGNN-d0
Strong	95.0	43.6	37.3
Weak	104.9	60.6	60.0

Anchors help, but bias and seed sensitivity remain.

Reference

[1] M. Tornago et al., Resistive AC-Coupled Silicon Detectors
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JINST 19, C01028 (2024).

[4] V. G. Satorras et al., E(n) Equivariant Graph Neural Networks.
ICML, PMLR 139, 9323–9332 (2021). arXiv:2102.09844.