Future Smart Detectors

Intelligent Pixel Detectors: Towards a Radiation Hard ASIC with On-Chip Machine Learning in 28nm CMOS

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Outline

Physics Motivation

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Real Time Tracking Challenges

Track Classification in 28nm

Motivation

We know there is physics to discover At particle colliders,

tracking is crucial

Illustrative Example

Mixed Higgs-scalar scenarios lead to many soft b-quarks (like di-Higgs).

- Overwhelmed by QCD background
- Swap cross section for lepton trigger from associated W/Z

 \rightarrow limited sensitivity

Just Scout It?

Perhaps use scouting to alleviate this? HLT resolution within 10% of offline. Ex. CMS scouting for RPV Higgsino's

Limited by the L1 (hardware) trigger!

The Limitation

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Current technology cannot handle O(PB/sec) data rates so we trigger.

This decision is made without tracking information.

CMS is similar numbers but will have outer tracker information (strips) for HL-LHC

Consequences [1706.04965](https://arxiv.org/abs/1706.04965), [1703.10485](https://arxiv.org/abs/1703.10485)

Lesson already learned adding tracking into jet reconstruction via particle flow (PFlow) algorithm \rightarrow resolution and fake rejection improve

After HLT save a higher data rate to a delayed stream, consume less online resources

- acceptance limited because of L1 trigger
- No way we can park O(PB/s) of data

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Shortcomings:

Motivation

Real time tracking is crucial

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CMS Phase-2 Outer Tracker (OT)

OT hits point back to displaced vertex

>10x Improvement with Full Tracker Not easy to implement online

Real Time Tracking Challenges

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Technical Challenges

To utilize tracking information, need readout chips capable of handling the physics conditions

Benchmark is the RD53 conditions for HL-LHC. Strict constraints so trigger rate at 1 MHz / 750 kHz

Talk by Flavio Loddo

[Horowitz in 45nm,](https://gwern.net/doc/cs/hardware/2014-horowitz-2.pdf) [UIUC Lectures,](https://misailo.web.engr.illinois.edu/courses/598sm/lec4.pdf) Nhar

Data Reduction at the Source

Aim to achieve tracking at 40 MHz within strict conditions

Key insight: moving data is expensive, doing computation $cheaper \rightarrow perform\ data$ reduction at the source could

Cost of Operations

Mark Horowitz. Energy table for 45nm process, Stanford VLSI wiki via Han et al., Learning both Weights and Connections for Efficient Neural Networks

Question: Can ML on chip perform effective data reduction at the source?

- operate on silicon within power, space, timing constraints
- deliver the required data reduction to meet bandwidth requirements

Key challenges:

 $\begin{array}{c} \bigcap_{u \in \mathcal{U}} \mathcal{L} \cup \$ Could imagine distributed ML across detectors more generally … *Smart Detectors*

- Examples:

Brand Contract of an analog networks and contract or analog networks of the state - Beam-induced background at a MuC
Dual readout calorimators - Beam-induced background at a MuC
	- Dual readout calorimeters
	- Duan reauval caronnicters
Illtre biob erepulsrituseempline eslerimentere - Ultra-high granularity sampling calorimeters
	- death saved to meet the meeting of the meeting of the meeting of the same of the same of the same of the same o
Pixel l ArTPCs - Pixel LArTPCs

Broader Applications

ASICs through oblong cavities cut in the data PCB.

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Track Classification in 28nm

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Physics Setup

Particle passing through a 100 µm thick single layer of silicon with small pitch 12.5 x 50 µm2 pixels

Non-exhaustive list of important details:

- Tracked data taken from CMS with p_T up to ~5 GeV.
- Untracked data not included and includes CMS acceptances
- PixelAV silicon simulation used
- Single 100µm thick layer of silicon with 12.5x50 µm² pixels
- Overall sensor area 16x16 mm²
- Bias voltage of -100 V
- Simulation assumes only pions input
- Charge deposition recorded every 200ps
- Sitting on a cylinder of radius 30 mm
- 3.8 TeV B-field parallel to x-coordinate

Example Tracks

Can see visually high (left) vs low (right) pT tracks bending in B-Field and different cluster shapes

Classification Network

Flat signal efficiency for track $p_T > 2$ GeV. Data reduction of 57.1 - 75%.

- Input: y-profile of charge, no timing
- Output: predict if $p_T > 200$ MeV
- QKeras quantized 2 Layer DNN
- Translated to silicon with CatapultAI
- Power consumption 300µW

Non-exhaustive list of important details:

Chip Tape-out

28nm CMOS demonstrated to be radiation tolerant by CERN. First tapeout in new technology node at Fermilab

- Layout:
- 2x2 pixel analog islands (within black boxes) surrounded by digital with DNN and test interface (purple space)
- Taped-out as super pixels (16x4) corresponding to 32x8 physical pixels

First Test: Check for Timing Violations

Loopback test to check for timing violation when a signal does not propagate through the circuits within the required time constraints, may cause unstable circuit behavior

No violations are seen

Now working on high statistics pattern pulsing to test the analog+DNN

Lots of work to do but lets assume everything works and mention exciting future directions

[Fermilab Test Beam Facility](https://ftbf.fnal.gov) Not our telescope but hopefully one day

- Build a bigger chip to bond to a real sensor and examine in a test beam - Analog NN: real edge computing,
- reduce digitization (1 ADC for entire chip as opposed to 1 per pixel)

[Opportunities for neuromorphic computing algorithms and applications](https://www.nature.com/articles/s43588-021-00184-y) Classical (~digital) vs Neuromorphic Computing (~analog)

Physics Motivation

To study the electroweak symmetry breaking and search for new physics we need real time tracking

Data reduction at the source with ML on chip is an exciting R&D avenue to *achieve real time tracking*

Real Time Tracking Challenges

Track Classification in 28nm

Developed a classification network to predict track momentum and taped it out in 28nm CMOS. First steps toward creating the new technology

Summary

Thank you from our team

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smartpixels

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Arghya Das

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UIC

BACKUP

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Physics Scenarios

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SM+s Scenario

Mixed Higgs-scalar scenarios lead to many soft b-quarks (like di-Higgs). Large QCD background overwhelms data rate, so swap cross section for leptonic trigger from associated W/Z. This makes analysis possible but limits sensitivity.

Displaced Track DM Scenario

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dark matter mass

Detector Considerations

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CMS/ATLAS Trigger Schemes

[2209.15519,](https://arxiv.org/pdf/2209.15519.pdf) [CERN-LHCC-2017-020](https://atlas.web.cern.ch/Atlas/GROUPS/PHYSICS/UPGRADE/CERN-LHCC-2017-020/)

Tracking [2010.13557,](https://arxiv.org/abs/2010.13557) [CERN-CMS-DP-2022-021](https://cds.cern.ch/record/2814728)

 $\langle L \rangle \sim 100$ mm × $\left(\frac{\text{F}}{\text{TeV}}\right)$ *E* TeV)

B-meson decay length

ATLAS Phase 2

 \sim 1.6 -1.8 ~ 2.0 -2.2 -2.4 -2.6
 -2.8
 -3.0 4.0 n

Classification Network on 28nm v1 chip

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Training Data

negatively charged low *p^T* particles (blue) and high *p^T* particles of both signs (black).

Neural Network Design

Chip Photos

Chip Tape-out Details

Technical:

- Analog island with amplifier and 2-bit ADC
- Digital logic surrounding with DNN inside (translated with CatapultAI)
- 28nm CMOS process from TSMC with Muse

Logistics:

- Received chip back last month June '24
- \sim \$14k/mm², 1.5 mm² tape-out \sim \$30k

Test Bench

Test bench that tests the core functionality of the chip. Reusable for future tape-outs. Builds upon Spacely (Adam Quinn)

