Accelerating the ATLAS Trigger System with Graphical Processing Units

8th IDPASC Student Workshop 16/10/2024

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LABORATÓRIO DE INSTRUMENTAÇÃO E FÍSICA EXPERIMENTAL DE PARTÍCULAS





ATLAS & Trigger

ATLAS and its Trigger System

- <u>**A**</u> Toroidal <u>**L**</u>HC <u>**A**</u>pparatu<u>s</u>: one of the two general-purpose detectors at the LHC
- The ATLAS Trigger is used to filter the detected events to ensure a manageable output rate
 - Two stages:
 - Hardware-based (Level 1/Level 0)
 - Software-based (High-Level Trigger/Event Filter)
- The High-Luminosity LHC Upgrade will increase the luminosity, making event reconstruction more computationally demanding
- The **Phase II ATLAS upgrade** needed for the High-Luminosity LHC increases event rate at the software-based stage from **1 kHz to 10 kHz**
- This higher computational load requires more computing power and/or better optimization
- Alternative: hardware acceleration
 - Ongoing studies for both FPGA and GPU acceleration



GPU Programming

GPUs and GPU Programming

- <u>Graphical Processing Units</u>
- Developed and designed to render 3D graphics
- Highly parallel operations \rightarrow highly parallel design
- "SIMT": *Single Instruction Multiple Threads*
- Branching is problematic



• Memory access patterns must be carefully considered

Calorimeter Clustering Algorithms

Topological Clustering

- Topological Clustering is the currently used approach for calorimeter reconstruction in ATLAS
 - Among the top 20th most computationally demanding algorithms within the ATLAS trigger
- Three main steps: cluster growing, cluster splitting, cluster moments calculation
- Clustering typically groups up **several tens of calorimeter cells**, **some clusters** may be **significantly larger**
- Several hundred to a few thousand clusters per event, depending on the physical process
- Significant dependence on the number of collisions per bunch crossing (μ) in terms of the execution time



Topo-Automaton Clustering

- Topological clustering is not accelerator-friendly: a different algorithmic approach is needed
 - Tags express the cluster assignment of the cells
 - Tag propagation rules to grow and split the clusters
- Formally equivalent to a **cellular automaton**, hence **Topo-Automaton Clustering**
- Fully implemented in the GPU using CUDA
- 100% agreement in cell assignment can be achieved between CPU and GPU, any reasons for differences if certain options are taken are fully understood
- Basic cluster properties (e. g.: energy, η , ϕ) yield similar values (within floating point accuracy)
- Some cluster moments have greater differences due to accumulated and compounded floating point errors
- The data structures used in the CPU part of the code cannot be used directly in the GPU, so we need to convert between the two representations



Results

Speed-up from GPU Acceleration in Relation to the CPU Implementation



We currently achieve a **speed-up of** ~5.9 **for di-jets**, ~8.9 **for** *tī*, considering all data conversions and transfers. The speed-up depends on the complexity of the event (number and size of the clusters), mostly due to CPU scaling.

Breakdown of GPU Execution Times

• Main bottleneck: converting the GPU data structures representing the clusters back to CPU-compatible structures

Step		$t-\bar{t}$ Events			Jet Events		
		Time (µs)	Fraction of Total Time		Time (µs)	Fraction of Total Time	
Pre-Clustering Conversion		1441 ± 225	$9.24 \pm 1.58\%$		1128 ± 88	$13.24 \pm 1.14\%$	
Pre-Clustering Transfer		266 ± 8	$1.71 \pm 0.18\%$		248 ± 15	$2.92\pm0.30\%$	
Growing	Cell Classification	61 ± 2	$15.76 \pm 1.77\%$	$2.53 \pm 0.35\%$	56 ± 3	$20.38 \pm 1.30\%$	$3.24 \pm 0.25\%$
	Neighbour Pair Creation	159 ± 8	$40.68 \pm 3.23\%$		114 ± 6	$41.45 \pm 1.98\%$	
	Tag Propagation	175 ± 46	$43.55 \pm 4.87\%$		106 ± 13	$38.17 \pm 2.59\%$	
	Total	396 ± 53			276 ± 16		
Post-Growing Property Calculation		74 ± 22	$0.47 \pm 0.14\%$		55 ± 2	$0.65 \pm 0.05\%$	
Splitting	Neighbour Pair Creation	409 ± 28	$29.23 \pm 2.73\%$	$9.02 \pm 1.16\%$	287 ± 14	$33.80 \pm 1.62\%$	$9.97 \pm 0.57\%$
	Local Maxima Identification	88 ± 7	$6.25 \pm 0.53\%$		57 ± 3	$6.77 \pm 0.33\%$	
	Secondary Maxima Exclusion	229 ± 16	$16.48 \pm 2.25\%$		230 ± 14	$27.15 \pm 2.11\%$	
	Main Tag Propagation	642 ± 194	$44.44 \pm 5.46\%$		236 ± 49	$27.53 \pm 3.54\%$	
	Finalization	50 ± 5	$3.60\pm0.31\%$		40 ± 3	$4.75 \pm 0.27\%$	
	Total	1417 ± 226			851 ± 67		
Cluster Moments		1422 ± 134	$9.07 \pm 0.58\%$		889 ± 52	$10.43 \pm 0.51\%$	
Post-Clustering Transfer + Conversion		10679 ± 137	$67.77 \pm 2.59\%$		5094 ± 690	$59.27 \pm 2.26\%$	
Total		15724 ± 1630	_		8565 ± 847		

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Summary and Future Efforts

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- Topo-Automaton Clustering fully implemented and working, for cluster growing, cluster splitting and cluster moments calculation, with configurability on a par with the CPU implementation (essentially, drop-in replacement)
 - First completed prototype for ATLAS Phase II, well ahead of schedule
- A very significant **speed-up** was found (factor of ~5.9 **for di-jet events**, ~8.9 **for denser** *tt* **events**)
 - A significant portion of the GPU event processing time (60~70%) is spent in data conversions
- A general solution to mitigate the data structure conversion overhead is under development (<u>Marionette</u>)
 - Integration with the current implementation of Topo-Automaton Clustering to follow
 - At least a **factor of 2** improvement on the current **speed-up** seems feasible
- Lessons learned and experience gained from this development have fed back into general hardware accelerationrelated development within ATLAS and in particular the ATLAS Trigger
 - Currently co-coordinator of HLT Calo, responsible for the calorimeter reconstruction in the High Level Trigger
- A final decision on using this approach in the ATLAS Trigger depends on a general technical assessment of the feasibility and/or performance of GPU-accelerated algorithms, being scheduled for next year
 - The approach is also being considered for offline reconstruction on grid sites where GPUs are available

Thank you for your attention!

Backup Slides

The ATLAS Experiment

- $\underline{A} \underline{T}$ oroidal \underline{L} HC \underline{A} pparatus
- One of the two **general-purpose detectors** at the LHC
- Three layers:
 - Inner Detector
 - Calorimeters
 - Muon Spectrometers
- 10⁸ electronic channels
 - 187652 calorimeter cells with multiple gain paths to optimize resolution *versus* dynamic range of operation



- Samples correspond to two kinds of **Monte-Carlo simulated** events:
 - $t\bar{t}$ events: 3000 events, $\mu = 80$
 - **di-jet events**: 10000 events, $\mu = 200$
- Results were obtained on a remote server provided by the Brookhaven National Laboratory: **GPU is a Tesla P100, CPU is a Xeon E5-2695 v4**
- Time measurements were based on a **per-thread clock**
 - For a single thread, "any clock" would work
 - The CPU GPU comparison is a bit lopsided, though...
 - For more threads, **timing and speed-up are representative**, **but throughput is a best-case estimate**
 - Essentially, we are assuming everything is always running in parallel
 - This is due to several limitations when trying to benchmark within the ATLAS software

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Importing	Cluster Number Transfer	21 ± 1	$0.20 \pm 0.03\%$	$67.77 \pm 2.59\%$	17 ± 1	$0.33 \pm 0.04\%$	$59.27 \pm 2.26\%$
	Cluster Info Transfer	250 ± 39	$2.35 \pm 0.27\%$		102 ± 20	$2.00 \pm 0.21\%$	
	Cluster Creation + Cell Info Transfer	395 ± 83	$3.68 \pm 0.46\%$		147 ± 24	$2.89\pm0.20\%$	
	Cell Cycle	2892 ± 444	$27.10 \pm 2.42\%$		1624 ± 117	$32.18 \pm 2.45\%$	
	Cluster Ordering	192 ± 41	$1.79 \pm 0.28\%$		77 ± 15	$1.52 \pm 0.16\%$	
	Cluster Filling	2022 ± 336	$18.88 \pm 1.41\%$		944 ± 165	$18.46 \pm 1.18\%$	
	Moments Transfer	3.7 ± 0.5	$0.04 \pm 0.01\%$		3.8 ± 1.0	$0.07 \pm 0.02\%$	
	Moments Filling	4903 ± 697	$45.96 \pm 3.43\%$		2178 ± 389	$42.54 \pm 2.36\%$	
	Total	10679 ± 1377			5094 ± 690		
Total		15724 ± 1630	_		8565 ± 847	47 —	

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Calorimeter Reconstruction Algorithms

• Reconstruction of **showers** generated by outgoing particles in the calorimeters of the ATLAS experiment



- Showers deposit their energy in a finite region of space: a calorimeter cell
- Calorimeter cells organized in up to **28 different sampling layers**
- Two main sources of **noise**: electronic read-out and pile-up
 - The **noise estimate** is typically a function of the gain of the cell
 - For the **Tile calorimeter**, the electronic noise can be estimated by a **two-Gaussian model**, which involves more sophisticated computations (inverse error function of error functions)



Topological Clustering

- Two main algorithmic stages:
 - Cluster growing: iteratively assign cells to clusters based on the SNR (classify cells as seed, growing or terminal, clusters grow out from the seeds to their neighbouring cells in an order defined by the SNR of the seed, clusters are merged if they touch through growing cells)



Cluster splitting: split the clusters around local maxima of the energy to distinguish different objects travelling
in the same direction (identify local maxima, exclude maxima from certain regions of the detector that overlap in
certain directions to favour layers with greater radiation depth, start growing the clusters to neighbouring cells in
an order defined by the energy of the cells, cells that can belong to more than one maximum are shared, shared
cells grow clusters only in the end and are weighted based on the energy and distance to the centroid)



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Limitations of Topological Clustering

- **Resizing** a container is **difficult to do in parallel**, and it goes **against the memory model** of both GPUs and FPGAs
- Topological Clustering involves keeping track of multiple lists¹ of cells, especially for cluster splitting
- The **clusters** themselves are also **expressed as lists**¹ which must be **resized** as we add and remove cells
- For a more **parallel-friendly** implementation, we can instead **mark the cells** that belong to each cluster with a "**tag**"
 - By constructing these tags appropriately, the sorting steps can be skipped entirely: floating point numbers that follow the IEEE-754 standard can be put in a "total ordering" where the bit patterns, interpreted as integers, are ordered in the same way as the original floating point numbers
 - By defining a set of rules for how these tags are propagated from a cell to its neighbours, one can replicate the entire behaviour of the iterative parts of cluster growing and cluster splitting while only considering each pair of neighbours independently from each other (potentially in parallel, as long as tag updates are thread-safe)
- Since we have both a **state** for each cell and can specify the **rules for how that state changes** based on the neighbourhood, this is equivalent to a **cellular automaton**, hence **Topo-Automaton Clustering**

¹– "List" is used here in the sense of an ordered collection of items; specifically, they correspond to dynamically allocated arrays, or "vectors" in C++.

Topo-Automaton Clustering

• **Cluster tags** are **64-bit integers** with **specific structure**:



- The tags are **propagated through pairs of neighbouring cells** satisfying the conditions for clusters to expand
 - We handle each **pair of cells in parallel**, using appropriate **atomic operations** when needed
- Additional logic (e.g. keeping a cell to cluster index table) reduces the number of iterations
- All necessary **temporary information stored** in the same block of memory meant to hold the **cluster moments** (calculated only at the end), **everything can be pre-allocated**
 - Total per event memory footprint is ~80 MB
 - Cell geometry and neighbourhood relations also need to be stored: ~100 MB of constant information

Topo-Automaton Cluster Growing – Anatomy of a Tag

High bit to distinguish valid tags from terminal and growing cells

Flag for preventing merges through seed cells (1 only in some edge cases with non-absolute value thresholds)

12 bit counter $(2^{12} - 1 - \# propagations)$

Assumptions:

- Less than $2^{16} = 65536$ clusters
- Less than 2¹² propagation steps

Signal-to-noise ratio in total ordering

Index of the seed cell



Topo-Automaton Cluster Splitting – Anatomy of a Tag

