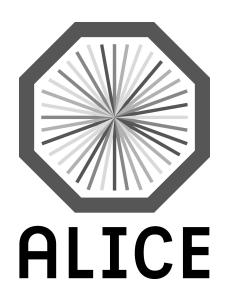
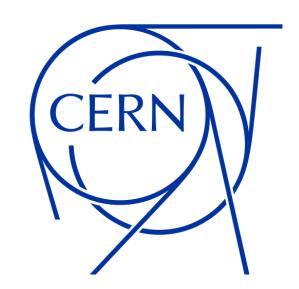
A vendor-unlocked GPU reconstruction for the ALICE Inner Tracking System

Matteo Concas, for the ALICE collaboration

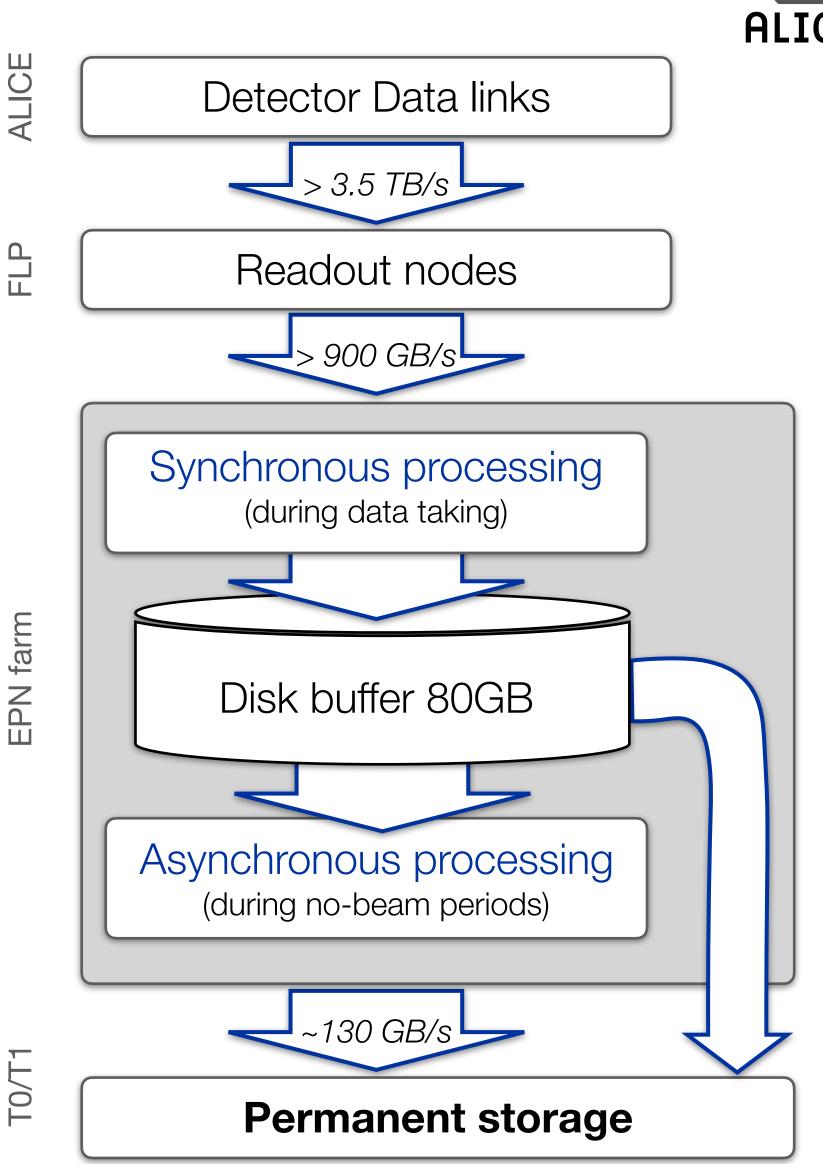




ALICE data processing for Run 3

ALICE

- Trigger-less acquisition: continuous readout
 - The stream of data is split into O(10ms) timeframes
 - L_{int} > 10 nb⁻¹ of PbPb data at 50kHz: 50x more than Run 2
- Online reconstruction and calibration for data compression^[1]
 - Synchronous: TPC full reconstruction and calibration
 - Asynchronous: all compressed data are reconstructed
 - Single computing framework for online-offline computing: O²
- Operate part of the reconstruction on GPUs is mandatory
 - Minimise the cost/performance ratio for online farm
 - 250x Event Processing Nodes (EPNs), 8x AMD MI50 GPUs
- Efficient utilisation of available computing resources is desired
 - Other detectors' reconstruction demands more resources
 - A larger fraction of GPUs available during the asynchronous phase

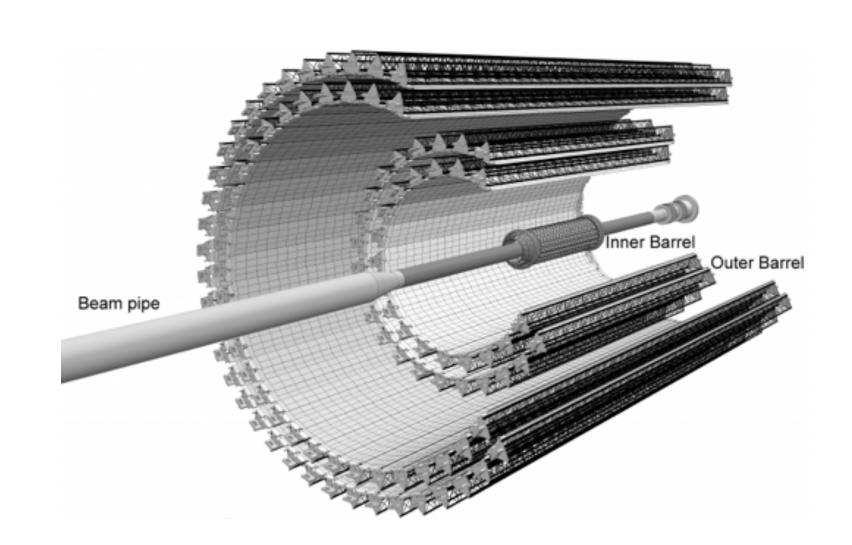


raw data (CTF)

ITS reconstruction in Run 3



- A new upgraded Inner Tracking System
 - A cylindrical silicon detector, is the innermost detector of the apparatus
 - Thin layers, 12.5 billion pixels and 10 m² of sensitive area
 - Provide spatial information in the form of clusters of fired pixels
- Continuous readout, continuous track reconstruction
 - Digital signals from pixels are clusterised and compressed
 - Timeframes are divided into Readout Frames (ROF): ~4µs
 - Collision data can split across multiple adjacent rofs
- New standalone vertexing and tracking algorithm
 - Single implementation steered via configuration (sync/async, collision system, ...)
 - During synchronous reconstruction focuses on primaries (7 clusters-long tracks)
 - During asynchronous reconstruction is sensitive to secondaries and tracks lower p_T
 - In- and cross-bunch pile-up ready



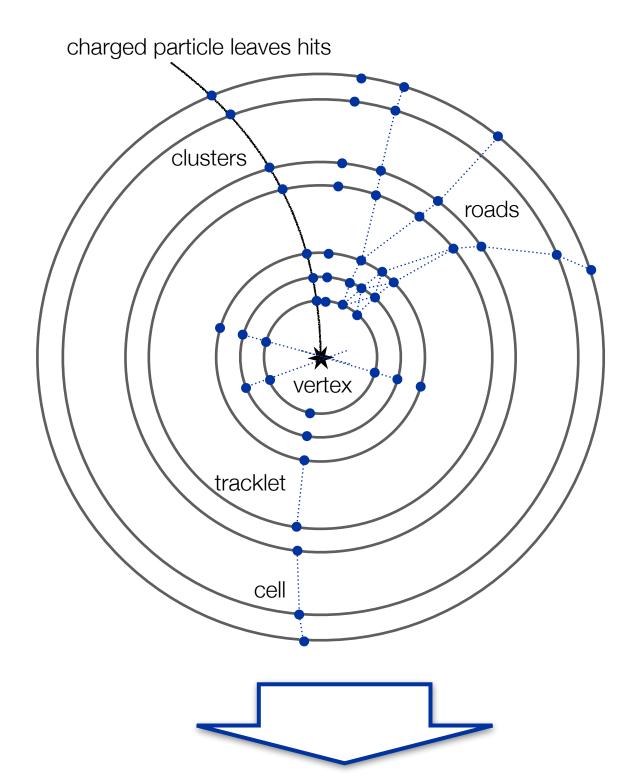


Timeframe				
ROF 0	ROF 1	ROF	ROF N	
compressed clusters of pixels	compressed clusters of pixels	•••	compressed clusters of pixels	

ITS vertexing and tracking



- Primary vertex seeding
 - Look for correlations between hits in the three innermost ITS layers
 - Combinatorial matching followed by linear extrapolations of tracklets
 - Unsupervised clustering to find the collision point(s)
- Track finding and track fitting
 - Uses vertex position to reduce the combinatorics in matching the hits
 - Connect segments of tracks, the *cells*, into a tree of candidates: *roads*
 - Kalman filter to fit tracks from candidates and apply quality cuts
- The algorithm is decomposable into multiple parallelisable steps
 - ALICE Data Processing Layer manages parallel Timeframe scheduling
 - Each ROF can be processed independently^(*)
 - In-frame combinatorics can be processed simultaneously
 - Current CPU implementation can profit from multi-threaded sections



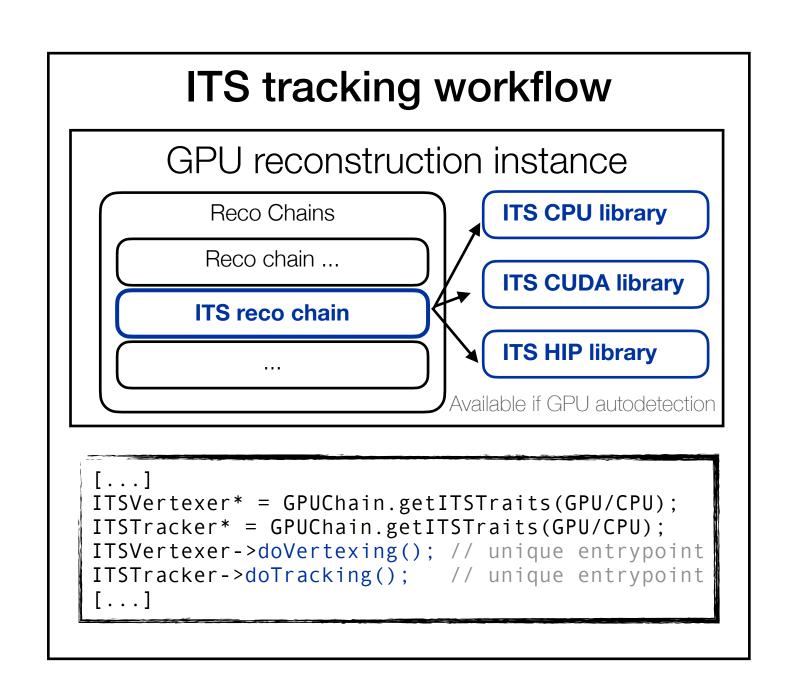
Timeframe				
ROF 0	ROF 1	ROF	ROF N	
- clusters - vertices - tracklets - cells - roads - tracks	- clusters - vertices - tracklets - cells - roads - tracks		- clusters - vertices - tracklets - cells - roads - tracks	

^(*) Information from adjacent ROFs can be used to recover from information splitting

A parallel implementation using GPUs



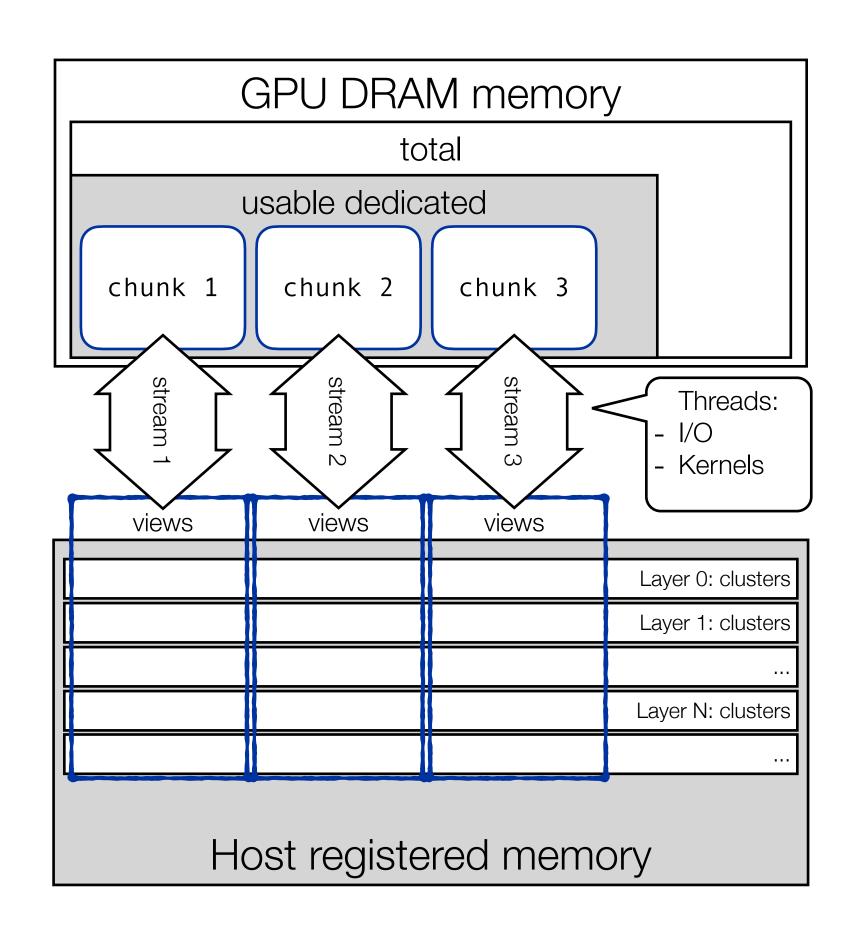
- Accelerate the processing using massively parallel architectures
 - Promising porting of some routines based on CUDA and OpenCL in the past
- Today: offload the whole vertexing and tracking on GPUs
 - Release the corresponding CPU cycles, improving resource usage efficiency
 - Integrate it into the broader reconstruction GPU chain by extending its coverage
- First phase: load and operate standalone GPU tracking for ITS
 - Mainstream reconstruction framework provides the interface for GPU lib loading
 - The ITS GPU library fully manages graphics card resource
 - Easy-to-contribute: plain C++ and CUDA code, focus on routines development
 - Supports CUDA and HIP with a single code base, no compatibility layer
- Second phase: build a GPU reconstruction chain including ITS
 - Centrally manage GPU memory and kernel scheduling for deeper integration
 - Easier to later add additional steps like the ITS-TPC matching



Cornerstones of the GPU implementation



- Resource usage flexibility via configuration
 - The amount of usable memory is a parameter that is passed to the algorithm
 - All required chunk sizes are set as a fraction of the total available memory
- Multi-threaded streams process bunches of ROFs in parallel
 - Each POSIX thread manages a stream, and the full tracking is independent
 - Optimise throughput by hiding memory loads behind kernel executions
 - Average timeframe size changes under different conditions: we cope with that!
- Use case extensibility via a generic N-layers implementation
 - All the routines in the vertexing and tracking are "local": no need to know N-layers
 - TrackerGPU<NLayers > offers native support for future use cases (ITS3/ALICE3)



Cross-platform on-the-fly code generation



- The O2 compilation via CMake, provides
 - Platform autodetection and production of corresponding target libraries
 - Custom commands setting dependencies between targets
- HIP code is generated in place from CUDA sources
 - Build source of targets parsing CUDA files and generating HIP versions
 - Currently based on hipify-perl: is run on all .cu files to produce HIP
 - Develop and maintain a single code base in place of two
 - No need to add a portability layer
- Headers files are shared across both the compilations
 - Negligible boilerplate (<0.1% LoCs) to cope with some architectural differences

```
// CUDA code
cudaMalloc(&A_d, Nbytes);
cudaMalloc(&C_d, Nbytes);
cudaMemcpy(A_d, A_h, Nbytes, cudaMemcpyHostToDevice);

vector_square <<<512, 256>>> (C_d, A_d, N);
cudaMemcpy(C_h, C_d, Nbytes, cudaMemcpyDeviceToHost);

// HIP code, translated
hipMalloc(&A_d, Nbytes);
hipMalloc(&C_d, Nbytes);
hipMemcpy(A_d, A_h, Nbytes, hipMemcpyHostToDevice);

hipLaunchKernelGGL(vector_square, 512, 256, 0, 0, C_d, A_d, N);
hipMemcpy(C_h, C_d, Nbytes, hipMemcpyDeviceToHost);
```

State of the development and testing



- Names of the steps are the main phases of the algorithms
 - GPU-ported implementations are usually more complex due to data organisation
 - Comparison with CPU is made when steps in both versions produce the same output
- The vertexing is fully operative in its GPU implementation
 - Timeframe chunking is natively supported, as no extra-ROF information is required
- The porting of tracking is being finalised
 - The last fully ported step is the neighbour finder for cells
 - Road finder is under development: size and number of found roads are not static
 - Track fitting had a POC, which requires an in-depth review
- Tested on both Nvidia and AMD cards
 - First setup: workstation with AMD Ryzen™ 9 7950X CPU and Nvidia™ TITAN Xp
 - Second setup: EPN node with 2x AMD EPYC™ 7452 and AMD Instinct™ MI50

Vertexer	
Tracklet Finder	~
Tracklet Selection	~
Vertex Fitter	~

Tracker			
Tracklet Finder	✓		
Trkl duplicate finder			
Cell finder	✓		
Cell neighbour finder	✓		
Road finder			
Track fitting	*		

	Clock (GHz)	RAM (GB)
AMD Ryzen™ 9 7950X	4.5-5.7	128
Nvidia™ TITAN Xp	1.586	12
AMD EPYC™ 7452	2.35-3.25	512
AMD Instinct™ MI50	1.725	32

Preliminary performance

ALICE

•	Total	timing	measured	on	real	data
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- A batch of 5 timeframes of pp collisions @500kHz
- CPU is run in single thread configuration

Three reported scenarios

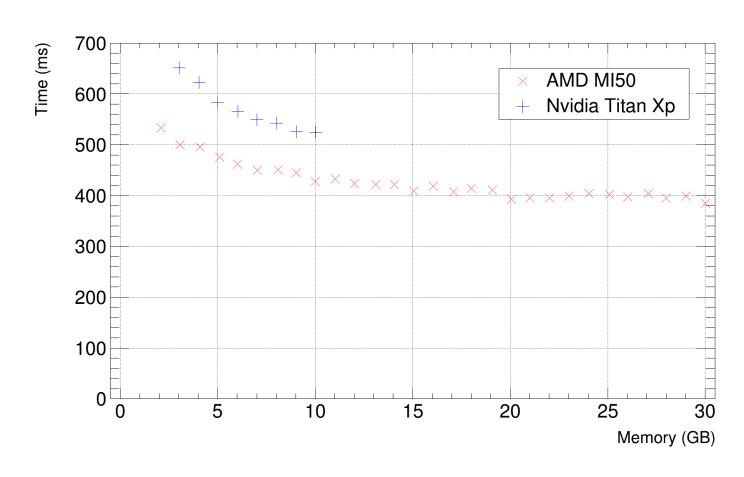
- Full vertex finding on GPU and CPU
- State-of-the-art tracking chain on CPU and GPU
- Full tracker run in the asynchronous configuration on CPU

Considerations

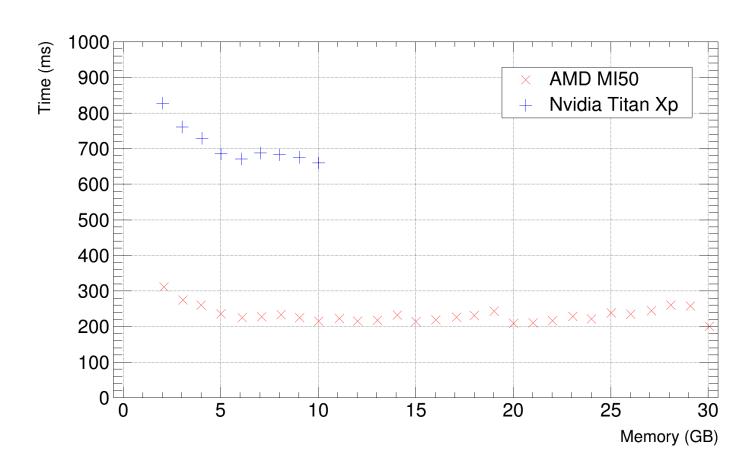
- The timing is promising if the primary goal is to trade GPUs for CPUs
- The most time-consuming part is the track fitting, high rewards expected
- Streaming chunks of a timeframe works successfully
- Timing decreases with memory increasing, then reaches a plateau

Elapsed Time [ms]	AMD EPYC™	AMD Ryzen™	AMD MI50	Nvidia™ TITAN Xp	1
Vertexer	2913±376	1416±183	291±38	478±64	
Tracker (Neigh. Finder)	550±71	287±37	211±27	779±105	
Tracker Full	13756±1780	6917±893	ini.		

GPU ITS vertexer elapsed time vs memory



GPU ITS tracker (neigh-finder) elapsed time vs memory



Conclusions and outlook



- ALICE plans to extend the coverage of GPU utilisation in the asynchronous reconstruction
 - The goal is to increase the efficiency in using the resources when TPC does not have the monopoly
- ITS is finalising the porting of the seeding vertexer and tracking
 - Road finding and track fitting, the last missing components, are under active development
 - Performance in pp collisions from actual data is not final but shows some promising margin
 - A full investigation of heavier conditions such as PbPb will show the fundamental capabilities and limitations
- Optimisation of the algorithms is to start after the finalisation of the porting
 - Tuning for GPU parameters can be performed with general-purpose tools for optimisation^[1]
- GPU adoption in the ITS software chain can be further extended
 - Signal digitisation and Clusterisation part are good candidates that are being considered

Backup

Heterogeneous-Compute Interface for Portability

- Support GPUs from two main vendors:
 - CUDA language and runtime for Nvidia
 - HIP language and ROCm runtime for AMD
- HIP: a C++ Runtime API and Kernel language
 - Portable AMD and NVIDIA applications from single source code
 - It is shaped around CUDA APIs to ease translation
 - CUDA libraries, like Thrust and CUB, have their HIP versions using ROCm
- ROCm has tools to translate CUDA to HIP automatically
 - hipify-clang: based on Clang, actual code translation
 - hipify-perl: script for line-by-line code conversion
- Strategy: maintain only the CUDA code and generate HIP

