Experience using GPUs for ATLAS Z finder algorithm

Second International Workshop for Future Challenges in Tracking and Trigger Concepts

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on behalf of the ATLAS collaboration

University of Edinburgh

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General Purpose GPUs

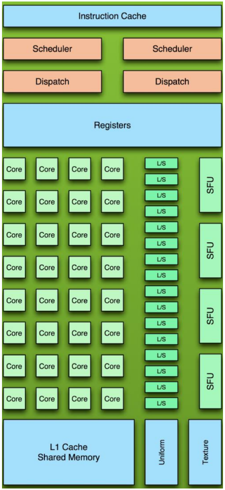
- GPU architectures are designed for running thousands of threads in parallel.
- Little additional overhead from running many threads.
- Suited to problems which can be performed in a data parallel manner.
- APIs allow the *host* to manage the GPU *device*.
- Several APIs and SDKs can be used for GPGPU programming: *Nvidia CUDA, OpenCL, AMD/ATI stream SDK.*

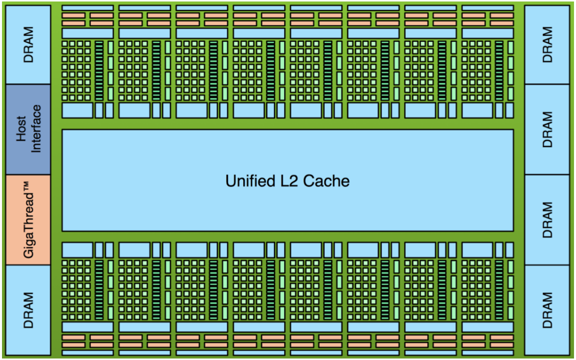
Where to start?

Nvidia CUDA zone

"Fermi" GPU

Images from Gernot Ziegler, Nvidia





CUDA Kernels and Thread Hierarchy

CUDA kernel

```
MyKernel <<< numBlocks, threadsPerBlock >>> (A, B, C);
```

- A CUDA kernel is a function which is executed in parallel by a number of threads on the GPU device.
- A *thread block* is a set of threads which execute together on a single multiprocessor.
- Thread blocks can be arranged into a one or two dimensional grids.

GPU memory

- CUDA devices contain different types of memory, each with their own properties.

Memory Type	**Size**	**Use**
Global	1GB+	Main memory storage on the GPU.
Shared	16/48KB (block)	Allows data to be shared between threads in the same block.
Registers	16/32KB (MP)	Stores kernel variable data (for each thread).
Local	16/512KB (thread)	Overflow for thread variable storage.
Constant	64KB	Automatically cached, read only.
Texture Memory	6-8KB (MP)	Streaming fetches with a constant latency.

GPU Projects at Edinburgh

- Number of GPU related projects at Edinburgh

- **Chris Jones** - *"Porting the Z finder algorithm to GPU"* (MSc in High Performance Computing)
- **Maria Rovatsou** - *"SIMT design of the High Level Trigger Kalman Fitter"* (MSc School of Informatics)
- **James Henderson** - *"An Investigation Into Particles Tracking and Simulation Algorithms using GPUs"*

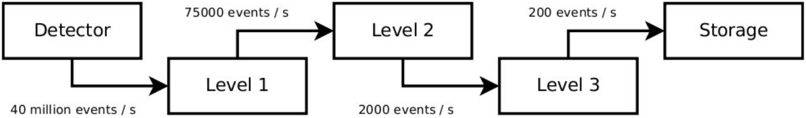
- Project reports and source code available at: ATLAS Edinburgh GPU Computing

Project Resources

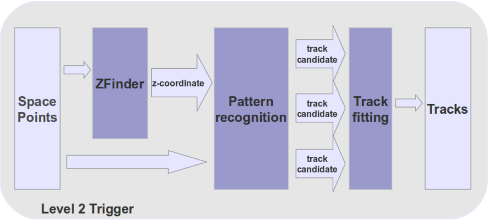
- Access to a number of dedicated GPUs with different architectures (*Tesla* and *Fermi*).
- CUDA code based on CUDA version 1.3

Properties	**Tesla C1060**	**GeForce GTX 470**	**Tesla C2050 (x4)**
CUDA Capability	1.3	2.0	2.0
Global Memory	4.3GB	1.3GB	2.8GB
Multiprocessors	30	14	14
Cores	240	448	448
Threads/block	512	1024	1024

The ATLAS Trigger



- Level 1: Custom built hardware with special processor units.
- **Level 2**: Software trigger operating independently on detector regions of interest (RoIs).
- Event filter (Level 3): Software trigger analysing whole event signatures.



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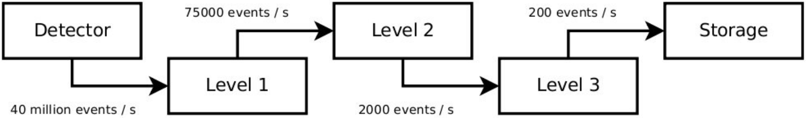

- Level 1: Custom built hardware with special processor units.
- **Level 2**: Software trigger operating independently on detector regions of interest (RoIs). **Ideal for GPGPUs**
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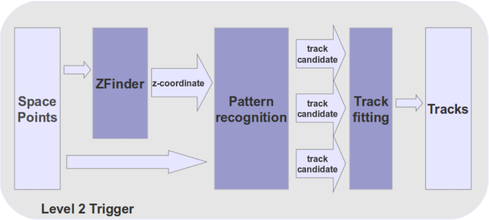
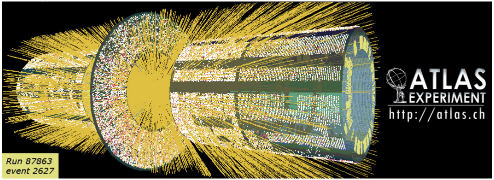
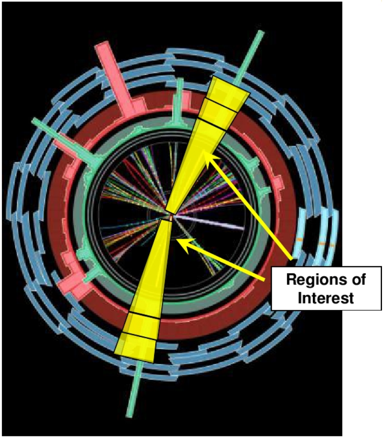


Z Finder GPU Motivation



- Already break an event up into regions of interest (ROIs) for distributed processing.
- Break ROIs into slices of ϕ and process independently.



Cross section view of the ATLAS detector

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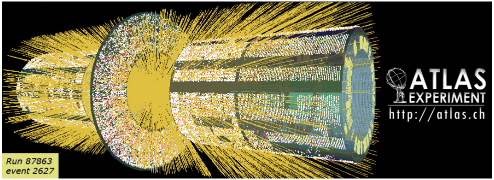
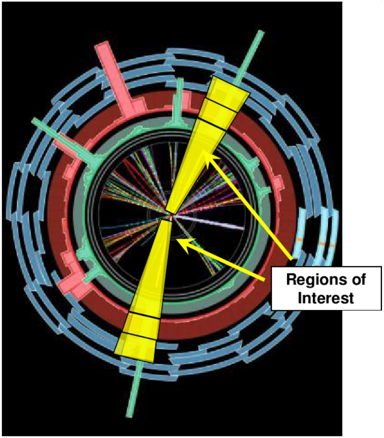


- Already break an event up into regions of interest (ROIs) for distributed processing.
- Break ROIs into slices of ϕ and process independently.
- Candidate for parallelisation using GPUs.



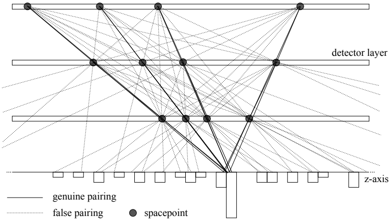
Cross section view of the ATLAS detector

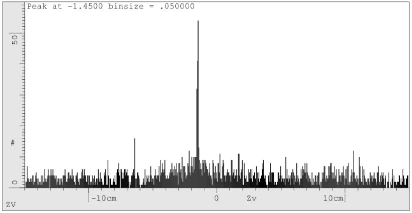
The Z Finder Algorithm

z_V calculation

$$z_V = \frac{z_2 \cdot \rho_1 - z_1 \cdot \rho_2}{\rho_1 - \rho_2}$$

- Process each combination of spacepoints and extrapolate back to the beam line.
- The histogram peak is the chosen interaction point.

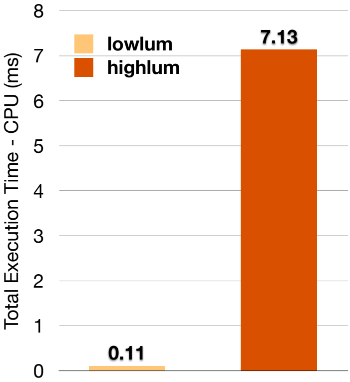




Z Finder Test Case

- Standalone version of Z finder code used for feasibility studies with CUDA.
- Initially optimised for calculating z_V using *pairs* of spacepoints.
- Timing performance measured using two samples of simulated events.

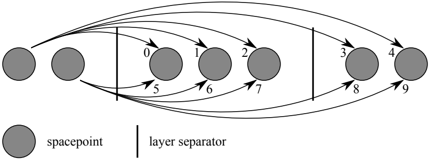
	lowlum	**highlum**
Luminosity ($cm^{-2}s^{-2}$)	$O(10^{32})$	$O(10^{34})$
Number of spacepoints	333	8104

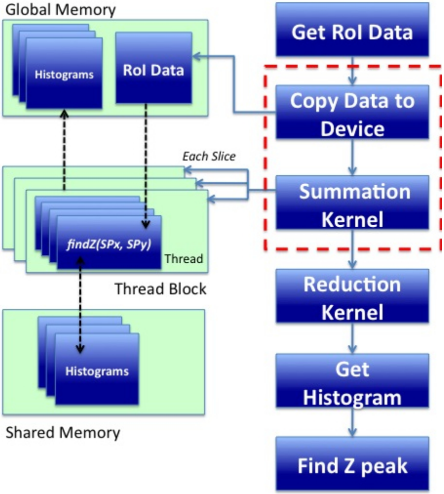


Z Finder Kernel: Histogram Summation

Code Iterations

- Single thread per ϕ slice.
- Thread block per ϕ slice.
- Histogram per thread block in shared memory.
- Improve spacepoint pair allocation method.





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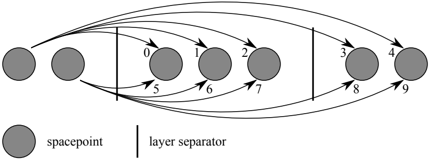

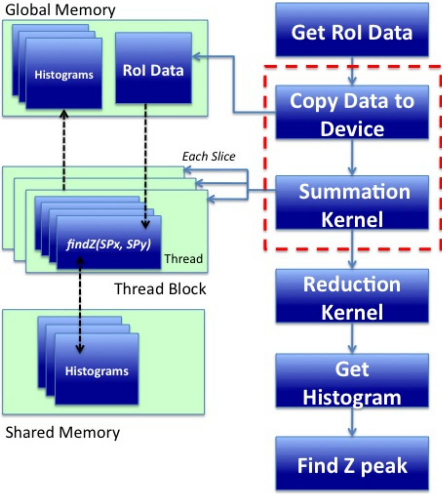

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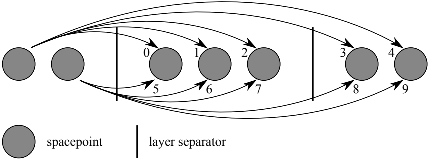

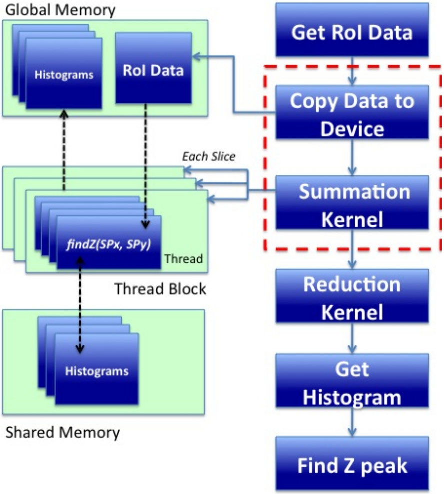

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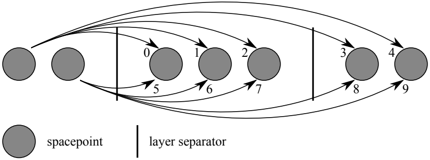
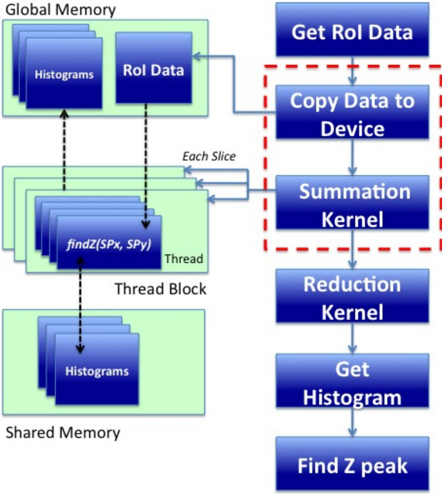
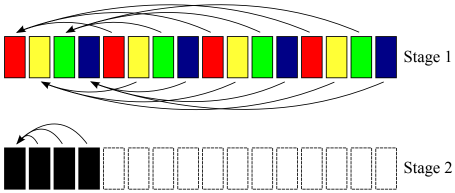


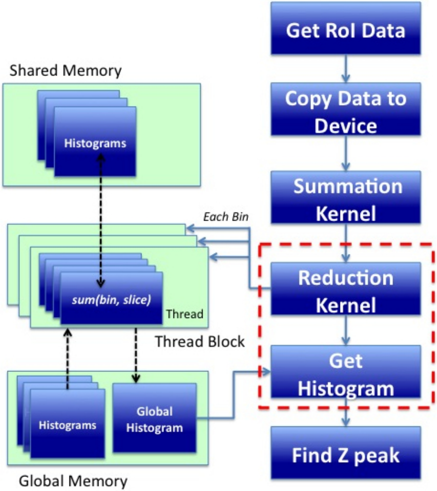


ZFinder Kernel: Histogram Combination

Code Iterations

- Combine histograms on the GPU ⇒ *reduce device to host data transfer by ∼500x.*
- Reduce the data to a single histogram in multiple steps.





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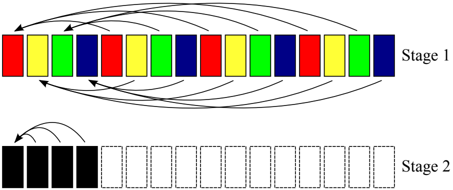
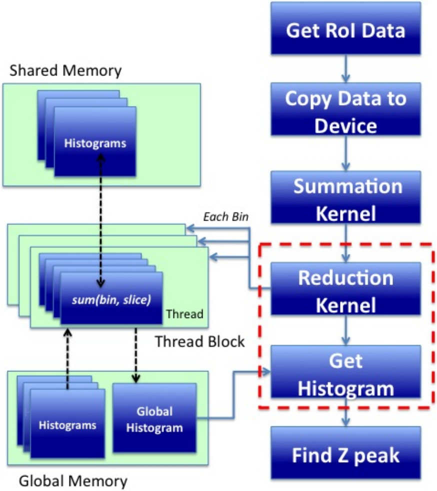
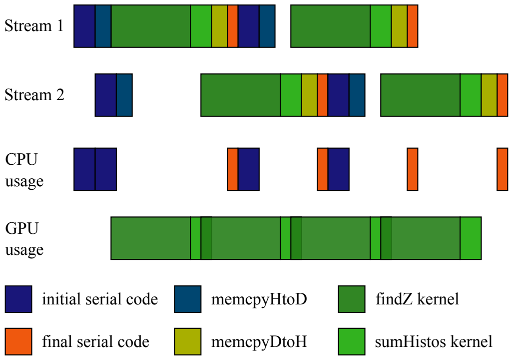


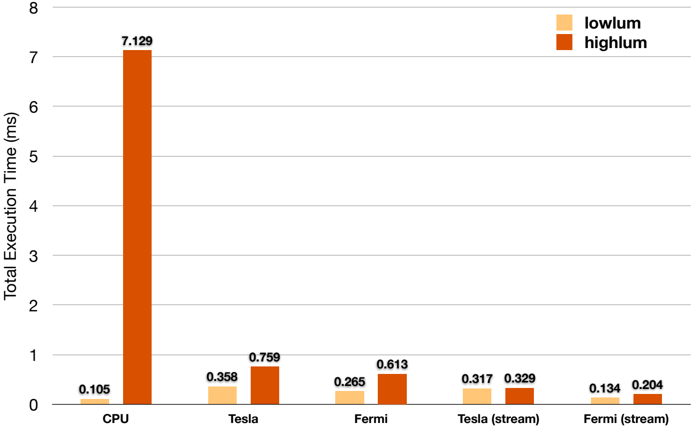


Z Finder Kernel: CUDA Streams



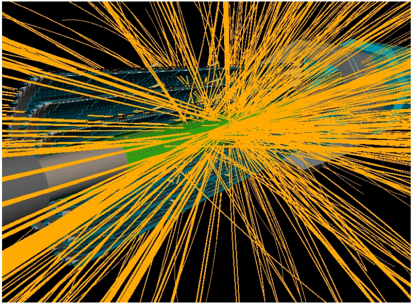
- Each RoI calculation independent ⇒ use CUDA streams.
- Successful in disguising any host to device transfer latency.

Timing Results



- Results for spacepoint pairs show up to *35x* speed-up (Fermi).
- Initial results for spacepoint *triplets* also show speed-up.

Kalman Filter GPU Motivation



- Potentially *thousands* of tracks to reconstruct for every event in the trigger.

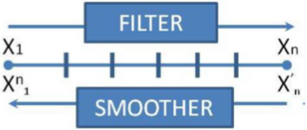
- Significant acceleration possible by reconstructing one track per GPU thread.

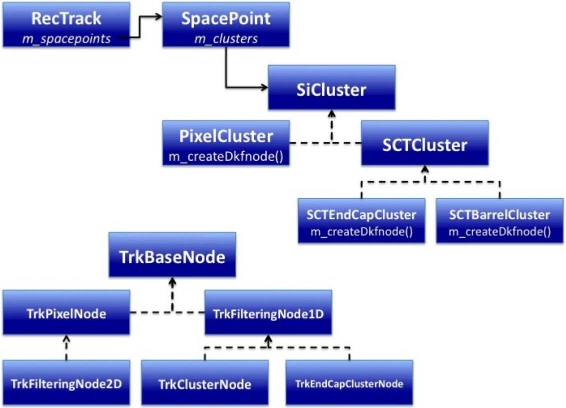
GPU benefits at other experiments

- Kalman Filter port to CUDA (GSI Scientific Report 2008, FAIR-EXPERIMENTS-38)
- ALICE TPC HLT code GPU based / future PANDA TPC code
- GPUs to be used for STS (Silicon Tracking System) within CBM (Compressed Baryonic Matter) experiment at FAIR/GSI.

Track Reconstruction in ATLAS

- Tracks reconstructed using the Kalman filter method.
- The trajectory of a track is predicted using detector hits as input.
- Backward smoothing filter applied after final Kalman Filter estimation.





C++ Class Hierarchy of Track Objects

Kalman Filter for CUDA

Initial Complications

- Class inheritance structure captures filter specialism for each sub-detector.
- Dynamic creation of objects in the main routine.
- Track state retention at each filtering step.
- Break down main routine for a smaller kernel.

Feasibility Studies (Maria Rovatsou)

- Standalone version successfully ported to C.
- Pre-allocated memory needed for track objects.
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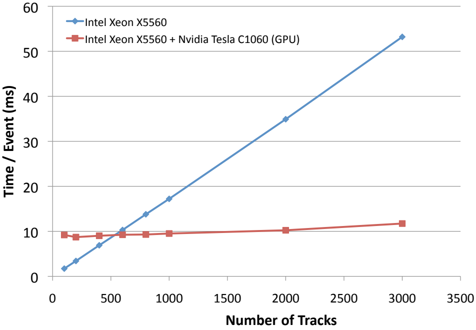
Kalman Filter for CUDA

D. Emeliyanov (first results)

- Standalone version successfully ported to C.
- Structs of arrays used to store track data.
- Vector data types (e.g. *float4*) for compact representation of data.
- One GPU thread per track.
- Modification of smoothing algorithm required for single precision arithmetic.



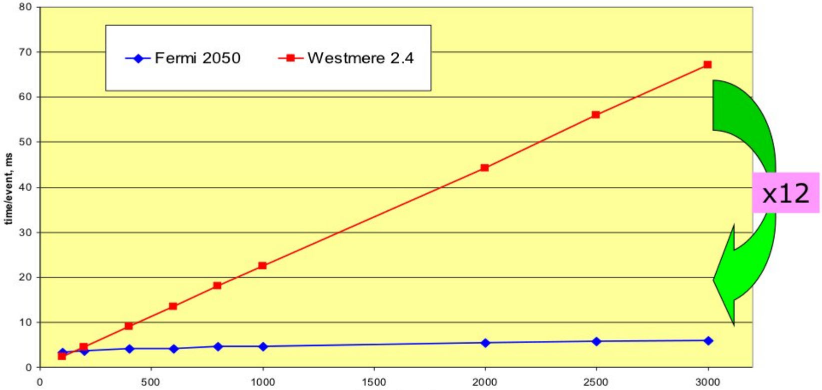
Muon tracks, p_T=10GeV, full MC simulation

- Over *5x* speed-up seen at 3000 tracks.

Kalman Filter for CUDA

D. Emeliyanov (latest results)

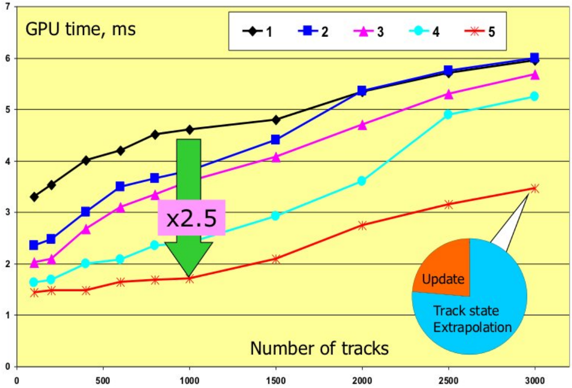
- CPU: Intel Westmere 2.4 GHz, GPU: NVIDIA Tesla C2050 (Fermi arch.)
- Data: full ATLAS Monte Carlo simulation
  - muon tracks, $p_T = 10\ GeV$, arranged into "events" with N tracks up to 3000



Kalman Filter Optimisations

D. Emeliyanov (latest results)

- A set of optimizations has been applied
- Optimised code gives ∼20x speed-up w.r.t. the CPU



1. Original code
2. 32 threads/block
3. Reduced memory footprint (fewer local variables, upper-triangular covariance matrix
4. Track state (cov. + parameters) stored in fast ("shared") memory
5. Jacobian in "shared" memory to speed-up JCJ^T calculation

Where is most HEP CPU consumed?

After triggering the LHC experiments still produce vast amounts of data!

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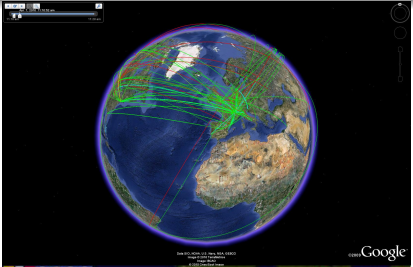
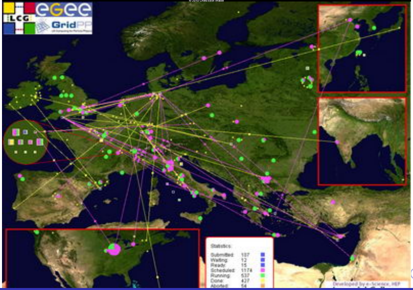
We developed worldwide LHC computing grid infrastructure

- Approximately 15 PB of data recorded per annum
- Currently $>$100,000 processors across Grid
- 130 sites in 34 countries





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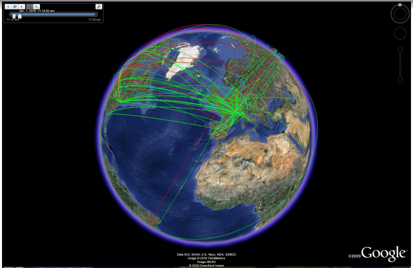
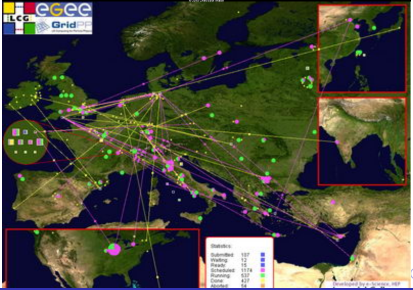
Geant4 simulation of detector response ($\sim$ 1000 cpu seconds per event)





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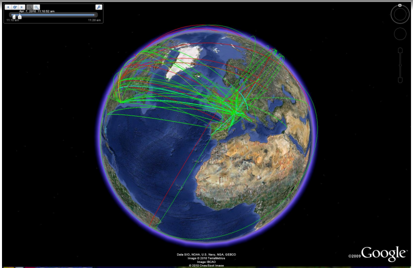
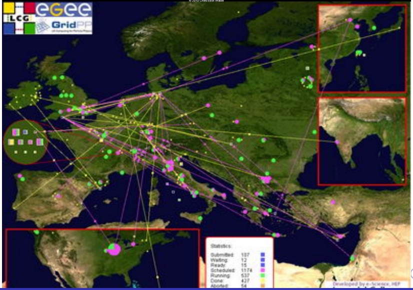
Geant4 simulation of detector response ($\sim$ 1000 cpu seconds per event)

Up to ten million events simulated daily

G4 failure rate is less than 10^{-6}





Particle tracking in a magnetic field

Preliminary GPGPU test case study

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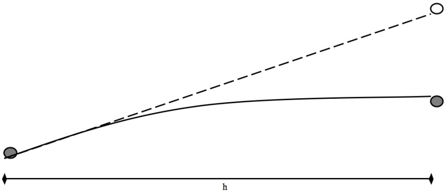
- Tracking charged particles in the magnetic field



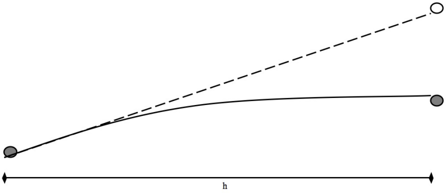
Particle tracking in a magnetic field

Preliminary GPGPU test case study

- Tracking charged particles in the magnetic field
- Lorentz force (perpendicular to plane of magnetic field)

$$\mathbf{F} = m\mathbf{a} = q \cdot (\mathbf{E} + \mathbf{v} \times \mathbf{B})$$

$$\frac{d\mathbf{v}}{dt} = \mathbf{a} = \frac{q}{m} \cdot (\mathbf{E} + \mathbf{v} \times \mathbf{B})$$



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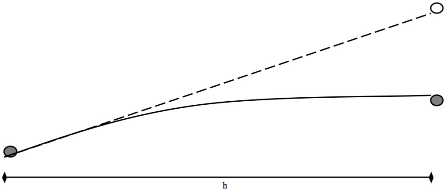
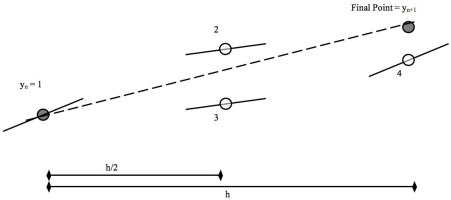
- Solve the differential equation with 4th order Runge Kutta Integration (called " Stepper" algorithm)





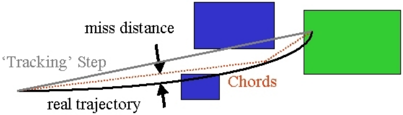
Steppers

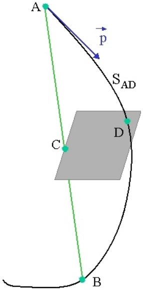
Steppers (EM field integration steps)
Various performance requirements:

- Miss Distance (chord sagitta),
- Boundary Intersection Error,
- Tolerable Integration Error, . . .

Lots of simulation time was spent on field calls...
Introduced adaptive stepper & caching
Different steppers:

- G4ClassicalRK4
  (EM field map: 10 calls per step)
- AtlasRK4
  (EM field map:2 calls per step





Acceleration with GPGPUs

Studied GPU acceleration of the standard 4th order Runge-Kutta (G4ClassicalRK4)

1. Using the GPGPU, pre-calculated a "look-up" table of derivative calculations for a space point matrix
   - Calculation time not a limiting factor (abandoned this idea)
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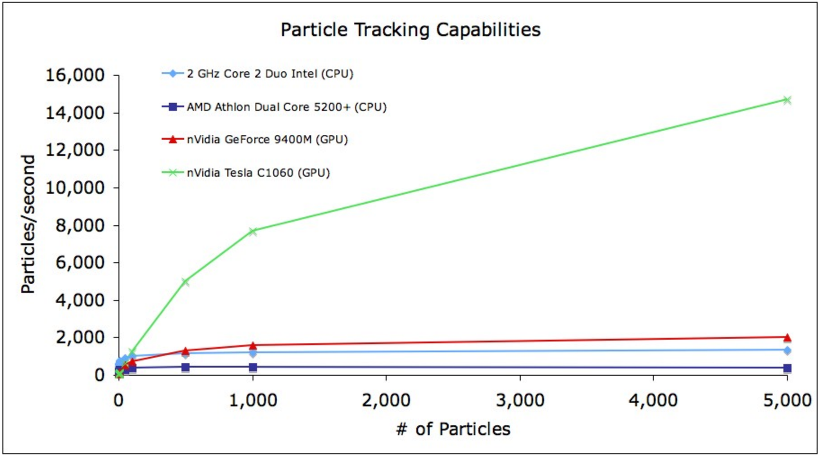
   - Still slower than the CPU. . .
3. Treated x,y,z coordinates in parallel (3 threads in block)
   - Cross-product ($\mathbf{v} \times \mathbf{B}$) calculation needs perp. coordinates
   - Set up the threads in the block to use shared memory
   - Speed was now closer to CPU

Acceleration with GPGPUs

Studied GPU acceleration of the standard 4th order Runge-Kutta (G4ClassicalRK4)

1. Using the GPGPU, pre-calculated a “look-up” table of derivative calculations for a space point matrix
   - Calculation time not a limiting factor (abandoned this idea)
   - Also lost accuracy due to rounding to nearest look up point
2. Increased calculation complexity to use adaptive stepping
   - Adjusting step size to be within an error tolerance
   - Still slower than the CPU...
3. Treated x,y,z coordinates in parallel (3 threads in block)
   - Cross-product ($\mathbf{v} \times \mathbf{B}$) calculation needs perp. coordinates
   - Set up the threads in the block to use shared memory
   - Speed was now closer to CPU
4. Next stage was to do many particle tracks in parallel...

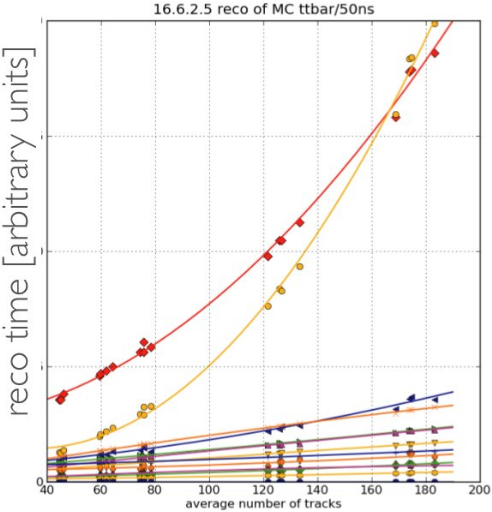
Magnetic Field Integration results



- Rapidly achieved a factor 32 speedup (more in progress)

Reconstruction: Tracking

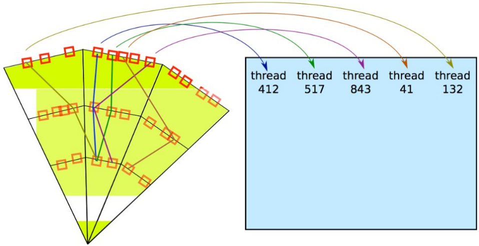
- Reconstruction time depends on multiplicity in the detector
- Track finding has worst combinatorial behaviour (expected) and starts to dominate already at modest multiplicities.



Reconstruction: Tracking

Christian Schmidt

- Initial prototyping of tracking on GPUs being done
- Single thread for each combination in every segment combination
- Assigns GPU-global hit data via thread index
- Preliminary results are showing GPU is at least 10 times faster than CPU



Summary

- The ATLAS trigger, particle tracking & simulation algorithms are key areas where GPUs can be used to improve performance.
- Significant enhancements to the trigger and reconstruction algorithms could prove invaluable for dealing with the rates from the LHC upgrade.
- Observed an initial *32x* speed-up for parallel Runge Kutta integration.
- Best case optimisation of *35x* speed-up for the Z Finder routine.
- Port of OO-based Kalman Filter algorithm showed GPU acceleration is feasible and scales to thousands of tracks.
- For much more information please see the talks at the recent workshop Future computing for Particle Physics