GPGPUs in HPC VILLE TIMONEN Åbo Akademi University

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Background

- Before GPGPU* "broke through", people mapped physics problems as graphics operations
- Programming using e.g. OpenGL shaders
- The specialized graphics HW was efficient for such operations

*) General-purpose computing on graphics processing units

Background

- On the graphics programming front, graphics libraries' abstractions are constantly being relaxed
- The usual HW is not limited to these abstractions and capable of much more
- -> Graphics is also asking for something that exposes the actual hardware better



Background

- The hardware had been ready..
- So there was need for GPGPU languages:

Graphics ----> GPGPU <--- General-purpose

Graphics wanted more freedom with the cost of performance (optimized pipelines) General-purpose computation wanted more performance with the cost of algorithmic freedom

How do GPUs pull off higher throughput

- It is important to understand where this performance comes from
- Let's begin by taking a commonly known CPU:



Remove logic that tries to keep the exec. units busy

And reduce the size of the cache :-(



Expand the SIMD units to process even more elements at once, and add registers to allow going for SIMT



- Multiply (up to 16-30 cores)
- Pack in fast memory and a capable memory controller



- It's all about how to use your transistor budget
- Summary:
 - Logic that tries to keep the execution units busy at all times is greatly reduced, and so is the cache
 - Expand SIMD
 - Make many cores
- Furthermore, GPUs have more transistors than CPUs
 Core i7-980X (6-core) has 1.2G, a GTX480 has 3G

- What about these 100x perf. improvement boasts?
 - Unfounded. Usually based on suboptimal/bloated/ single-threaded CPU implementations
 - There is up to 8 times the memory bandwidth, and up to 10 times the raw arithmetic throughput in a GPU

 The extra logic in CPUs cover up for badly optimized code -> In fact easier to get good performance with CPUs

The downside

GPUs are specialized, not for all problems:

- Doesn't parallelize -> don't consider GPGPU
- Parallelizes but is control-heavy -> poor perf.
- Depends on a large cache -> not available
- Data-intensive requiring a data set larger than 6GB
 -> CPU <-> GPU transfers will kill the perf.

The downside

An even larger issue is programming complexity

Making most of a GPU requires you to have either
 (i) Very simple algorithms
 (ii) Expert GPU programming skills

- Issues the same instruction to multiple exec. units
- w/ CPUs, we manually packed the vectors (SIMD, e.g. SSE)
- GPUs abstract this to concurrent threads (SIMT)
- Optimal perf. only when threads agree on exec. path



 Typical CPUs devote loads of transistors to logic that keeps the exec. units from stalling

 GPUs hide latencies and data dependencies by having thousands of threads in-flight to choose from

Switching between threads essentially a no-op

 GPUs have lots of registers (e.g. 128kB/core) to store contexts for so many threads

- They have small on-chip memory (e.g. 64kB/core) that can be manually accessed
 - Very little per thread, but good for communication

Fast global off-chip memory, be careful with accessing

Avoid bank conflicts with the on-chip memory

Very important:

- Global memory access patterns can make or break performance
- With the exception of Fermi, there's no cache, and requests map directly to controller transactions

The Fermi architecture

- The fastest version is the enthusiast GTX480 (1.5GB)
- Slightly slowed-down Teslas exist w/ larger memory
 - SGB or 6GB of ECC @ 144GB/s
 - 768kB L2 cache on top of the global memory
 - 14 cores (448 exec. units total -- i7-980x has 24)
 - Up to 1 Tflop/s single precision, 0.5 Tflop/s double (i7-980x does ~140G / 70G respectively)

The Fermi core

- 32 exec. units
- Dual-scheduler
- Capable of running a kernel independently
- On-chip mem. configurable as L1

Instruction Cache					
Warp Scheduler			Warp Scheduler		
Dis	patch U	nit	Dispatch Unit		
Register File (22,769 v 22 bit)					
Register File (32,768 x 32-bit)					
Core	Core	Core	Core	LD/ST LD/ST	
Core	Core	Core	Core	LD/ST LD/ST	SFU
Core	Core	Core	Core	LD/ST	
Core	Core	Core	Core	LD/ST LD/ST	SFU
Core	Core	Core	Core	LD/ST LD/ST	
Core	Core	Core	Core	LD/ST LD/ST	SFU
Core	Core	Core	Core	LD/ST	
Core	Core	Core	Core	LD/ST	SFU
Interconnect Network					
64 KB Shared Memory / L1 Cache					



Current situation & the future

Current vs. future

Throughput (Gops/s)

Specialization

ATI

NVidia

Intel

Scheduling logic Utilization Ease of programming

Generalization

Current vs. future

Could we combine a GPU and a CPU into a hybrid?

- They are architecturally different, that's the whole idea
- They both have global memory and a cache on top of it
 - We could probably unify these -> fast communication
 - CPU mem. is too slow currently

We could put the extra CPU logic to only some of the GPU cores!

Current vs. future

CUDA GPU Roadmap



- High level languages:
- OpenCL
- C for CUDA (NVidia)
- DirectX Compute (Microsoft)
- Cal/Brook+ (ATI, but prefer OpenCL)



- Khronos's GPGPU standard
- Everyone's in it: AMD, Intel, Apple, Nokia, NVidia...*
- So it moves slowly

*) Except Microsoft of course, who wants their proprietary solutions to triumph over the open ones

• <u>CUDA</u>

- NVidia's solution for early adopters
- Has been around the longest, most mature
- Support for every new hardware feature NVidia releases will be immediately available
- Has optimized libraries (by NVidia) for common tasks:
 - BLAS routines (all levels)
 - Sparse matrix operations
 - Pseudo random number generation
 - FFT routines, etc...

Choose OpenCL whenever you can

If you do something fancy you might need CUDA

If plan on using ready-made libs, today, choose CUDA

- The future?
 - Some compilers already make GPGPU code from C
 - Works decently for only the simplest of algorithms
 - Proper porting is still an expert task
 - The existing GPGPU libs/toolkits are easy-to-use
 - Do enough ops per data to avoid PCI-E bottleneck
 - Supercomputer network < PCI-E</p>

A tale of one algorithm



One thread per one line



Recursive algorithm executed at each iteration on a tree

Data set for one thread fits easily into CPU cache

Achieve 3.3 Gops/s on 2.5GHz Xeon, single-threaded

GPU implementation

- Recursion was new and broken when I started
- Manual implementation w/ global memory stack

At this point made over 10 revisions of the algorithm
 The fastest one also used in CPU

- With GPUs, 2k threads in-flight
- Cache usage becomes critical
- Spent significant amount of time optimizing
 - 5x boost in performance

- Result:
 - 65% of accesses caught by the L1 cache
 - 35% causes 58GB/s traffic

- Adjacent threads execute different amount of iterations of the "recursive" algorithm
- If one does 100 iterations, other 31 have to wait
- Measured utilization caused by this 18%

- We still achieve 71 Gops/s
 - (400 Gops/s if utilization were 100%)
 - 60% of the theoretical maximum
- It took 3 months to optimize, and I'm not new to this

- A sweep took 190ms on CPU, 3.13ms on GPU
- 60x improvement
- If we extrapolate to a faster 6-core CPU, and assume linear scaling w/ multithreading, it's 8x improvement
- Still not bad for an algorithm that at first looked like a suboptimal GPGPU candidate (recursive, low utilization, not enough cache, scattered reads)

Conclusion

GPUs

- 3x the performance per transistor
- Faster global memory
- The cost: removed logic
- Keeping the efficiency up is now up to the programmer

Conclusion

- Porting to GPGPUs is generally an expert task
- In my opinion will not be properly automatized in near future (except for simple loops)

- GPUs are specialized, but HPC can benefit from them
- Toolkits and external libs have optimized standard routines and are easy to use