CS377P Programming for Performance
Introduction to Accelerators

Sreepathi Pai

April 20, 2017

ICES

Outline

Introduction to Accelerators

GPU Architectures

GPU Programming Models

Outline

Introduction to Accelerators

GPU Architectures

GPU Programming Models

Accelerators

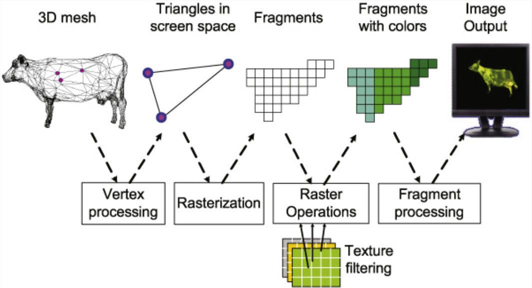
- Single-core processors
- Multi-core processors
- What if these aren't enough?
- Accelerators, specifically GPUs
  - what they are
  - when you should use them

Timeline

- 1980s
  - Geometry Engines
- 1990s
  - Consumer GPUs
  - Out-of-order Superscalars
- 2000s
  - General-purpose GPUs
  - Multicore CPUs
  - Cell BE (Playstation 3)
  - Lots of specialized accelerators in phones

The Graphics Processing Unit (1980s)

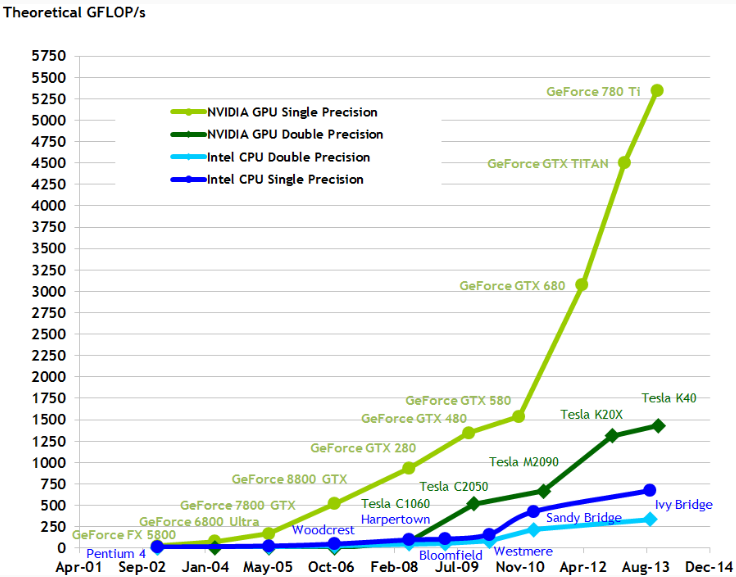
- SGI Geometry Engine
- Implemented the *Geometry Pipeline*
  - Hardwired logic
- Embarrassingly Parallel
  - $O(Pixels)$
  - Large number of logic elements
  - High memory bandwidth
- From Kaufman et al. (2009):



GPU 2.0 (circa 2004)

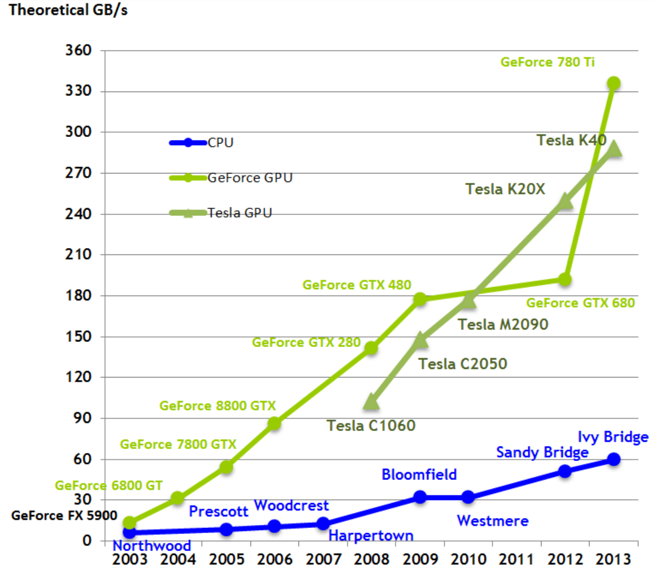
- Like CPUs, GPUs benefited from Moore's Law
- Evolved from fixed-function hardwired logic to flexible, programmable ALUs
- Around 2004, GPUs were programmable "enough" to do some non-graphics computations
    - Severely limited by graphics programming model (shader programming)
- In 2006, GPUs became "fully" programmable
    - GPGPU: General-Purpose GPU
    - NVIDIA releases "CUDA" language to write non-graphics programs that will run on GPUs

FLOPS/s



NVIDIA CUDA C Programming Guide

Memory Bandwidth



NVIDIA CUDA C Programming Guide

GPGPU Today

- GPUs are widely deployed as accelerators
- Intel Paper
  - 10x vs 100x Myth
- GPUs so successful that other accelerators are dead
  - Sony/IBM Cell BE
  - Clearspeed RSX
- Kepler K40 GPUs from NVIDIA have performance of 4TFlops (peak)
  - CM-5, #1 system in 1993 was 60 Gflops (Linpack)
  - ASCI White (#1 2001) was 4.9 Tflops (Linpack)

Pictures of Titan and Tianhe 1A from the Top500 website.

Accelerator Programming Models

- CPUs have always depended on co-processors
  - I/O co-processors to handle slow I/O
  - Math co-processors to speed up computation
  - H.264 co-processor to play video (Phones)
  - DSPs to handle audio (Phones)
- Many have been transparent
  - Drop in the co-processor and everything sped up
- Or used a function-based model
  - Call a function and it is sped up (e.g. "decode video")
- The GPU is not a transparent accelerator for general purpose computations
  - Only graphics code is sped up transparently
- Code must be rewritten to target GPUs

Using a GPU

- You must retarget code for the GPU
    - Rewrite, recompile, translate, etc.

Outline

The Two (Three?) Kinds of GPUs

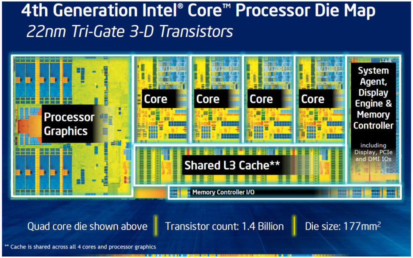
- Type 1: Discrete GPUs
  - More computational power
  - More memory bandwidth
  - Separate memory

NVIDIA

The Two (Three?) Kinds of GPUs #2

- Type 2: Integrated GPUs
  - Share memory with processor
  - Share bandwidth with processor
  - Consume Less power
  - Can participate in cache coherence

Intel



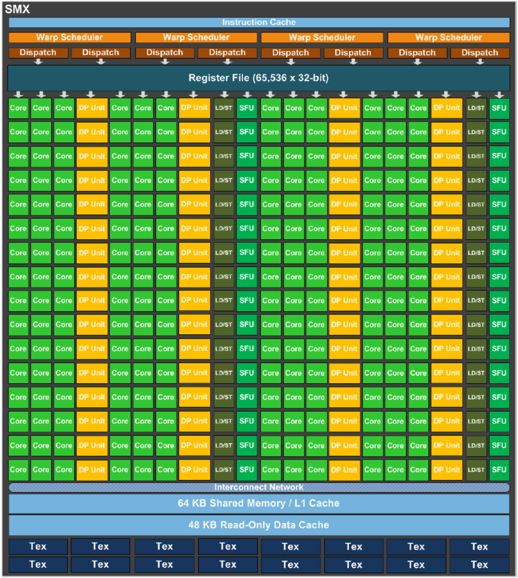
The NVIDIA Kepler

NVIDIA Kepler GK110 Whitepaper

Using a Discrete GPU

- You must retarget code for the GPU
    - Rewrite, recompile, translate, etc.
- Working set must fit in GPU RAM
- You must copy data to/from GPU RAM
    - "You": Programmer, Compiler, Runtime, OS, etc.
    - Some recent hardware can do this for you (it's slow)

NVIDIA Kepler SMX (i.e. CPU core equivalent)



NVIDIA Kepler SMX Details

- 2-wide Inorder
- 4-wide SMT
  - 2048 threads per core (64 warps)
  - 15 cores
  - Each thread runs the same code (hence SIMT)
- 65536 32-bit registers (256KBytes)
  - A thread can use upto 255 of these
  - *Partitioned* among threads (not shared!)
- 192 ALUs
- 64 Double-precision
- 32 Load/store
- 32 Special Functional Unit
- 64 KB L1/Shared Cache
  - Shared cache is software-managed cache

CPU vs GPU

Parameter	**CPU**	**GPU**
Clockspeed	> 1 GHz	700 MHz
RAM	GB to TB	12 GB (max)
Memory B/W	60 GB/s	> 300 GB/s
Peak FP	< 1 TFlop	> 1 TFlop
Concurrent Threads	O(10)	O(1000) [O(10000)]
LLC cache size	$>$ 100MB (L3) [eDRAM] O(10) [traditional]	< 2MB (L2)
Cache size per thread	O(1 MB)	O(10 bytes)
Software-managed cache	None	48KB/SMX
Type	OOO super-scalar	2-way Inorder superscalar

Using a GPU

- You must retarget code for the GPU
  - Rewrite, recompile, translate, etc.
- Working set must fit in GPU RAM
- You must copy data to/from GPU RAM
  - "You": Programmer, Compiler, Runtime, OS, etc.
  - Some recent hardware can do this for you
- Data accesses should be streaming
  - Or use scratchpad as user-managed cache
- Lots of parallelism preferred (throughput, not latency)
- SIMD-style parallelism best suited
- High arithmetic intensity (FLOPs/byte) preferred

Showcase GPU Applications

- Image Processing
- Graphics Rendering
- Matrix Multiply
- FFT

See “Debunking the 100X GPU vs. CPU Myth: An Evaluation of Throughput Computing on CPU and GPU” by V.W.Lee et al. for more examples and a comparison of CPU and GPU.

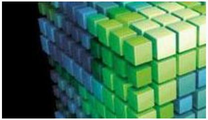
Outline

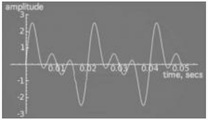
Hierarchy of GPU Programming Models

Model	GPU	CPU Equivalent
Vectorizing Compiler	PGI CUDA Fortran	gcc, icc, etc.
"Drop-in" Libraries	cuBLAS	ATLAS
Directive-driven	OpenACC, OpenMP-to-CUDA	OpenMP
High-level languages	pyCUDA	python
Mid-level languages	OpenCL, CUDA	pthreads + C/C++
Low-level languages	PTX, Shader	-
Bare-metal	SASS	Assembly/Machine code

“Drop-in” Libraries

- “Drop-in” replacements for popular CPU libraries, examples from NVIDIA:
    - CUBLAS/NVBLAS for BLAS (e.g. ATLAS)
    - CUFFT for FFTW
    - MAGMA for LAPACK and BLAS
- These libraries may still expect you to manage data transfers manually
- Libraries may support multiple accelerators (GPU + CPU + Xeon Phi)





GPU Libraries

- NVIDIA Thrust
  - Like C++ STL, but executes on the GPU
- Modern GPU
  - At first glance: high-performance library routines for sorting, searching, reductions, etc.
  - A deeper look: Specific "hard" problems tackled in a different style
- NVIDIA CUB
  - Low-level primitives for use in CUDA kernels

Directive-Driven Programming

- OpenACC, new standard for "offloading" parallel work to an accelerator
  - Currently supported only by PGI Accelerator compiler
  - gcc 5.0 support is ongoing
- OpenMPC, a research compiler, can compile OpenMP code + extra directives to CUDA
  - OpenMP 4.0 also supports offload to accelerators
  - Not for GPUs yet

```
int main(void) {
  double pi = 0.0f; long i;

  #pragma acc parallel loop reduction(+:pi)
  for (i=0; i<N; i++) {
     double t= (double)((i+0.5)/N);
     pi +=4.0/(1.0+t*t);
  }

  printf("pi=%16.15f\n",pi/N);
  return 0;
}
```

Python-based Tools (pyCUDA)

```
import pycuda.autoinit
import pycuda.driver as drv
import numpy
from pycuda.compiler import SourceModule

mod = SourceModule(""\"
__global__ void multiply_them(float *dest, float *a, float *b)
{
  const int i = threadIdx.x;
  dest[i] = a[i] * b[i];
}
""\")

multiply_them = mod.get_function("multiply_them")

a = numpy.random.randn(400).astype(numpy.float32)
b = numpy.random.randn(400).astype(numpy.float32)

dest = numpy.zeros_like(a)

multiply_them(
        drv.Out(dest), drv.In(a), drv.In(b),
        block=(400,1,1), grid=(1,1))

print dest-a*b
```

OpenCL

- C99-based dialect for programming heterogenous systems
  - Originally based on CUDA
  - nomenclature is different
- Supported by more than GPUs
  - Xeon Phi, FPGAs, CPUs, etc.
- Source code is portable (somewhat)
  - Performance may not be!
- Poorly supported by NVIDIA

CUDA

- "Compute Unified Device Architecture"
- First language to allow general-purpose programming for GPUs
    - preceded by shader languages
- Promoted by NVIDIA for their GPUs
- Not supported by any other accelerator
    - though commercial CUDA-to-x86/64 compilers exist
- We will focus on CUDA programs

CUDA Architecture

- From 10000 feet – CUDA is like pthreads
  - CUDA language – C++ dialect
- Host code (CPU) and GPU code in same file
- Special language extensions for GPU code
- CUDA Runtime API
  - Manages runtime GPU environment
  - Allocation of memory, data transfers, synchronization with GPU, etc.
  - Usually invoked by host code
- CUDA Device API
  - Lower-level API that CUDA Runtime API is built upon

CUDA Limitations

- No standard library for GPU functions
- No parallel data structures
- No synchronization primitives (mutex, semaphores, queues, etc.)
  - you can roll your own
  - only atomic*() functions provided
- Toolchain not as mature as CPU toolchain
  - Felt intensely in performance debugging
- It's only been a decade :)

Conclusions

- GPUs are very interesting parallel machines
- They're not going away
  - Xeon Phi might pose a formidable challenge
- They're here and now
  - Your laptop probably already contains one
  - Your phone definitely has one