MIC-GPU: High-Performance Computing for Medical Imaging on Programmable Graphics Hardware (GPUs)

SPIE Medical Imaging

Introduction

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First: A Big Word of Thanks!

SPIE Medical Imaging

… to the millions of computer game enthusiasts worldwide

Who demand an utmost of performance and realism of their game engines

And who create a market force for high performance computing that beats any federal-funded effort (DOE, NASA, etc.)

High Performance Computing on the Desktop

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PC graphics boards featuring GPUs:

- NVIDIA GeForce, ATI Radeon
- available at every computer store for less than $500
- set up your PC in less than an hour and play

the latest board:

NVIDIA GeForce GTX 580

“Just” Computing

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Compute-only (no graphics): NVIDIA Tesla c2050/c2070

True GPGPU

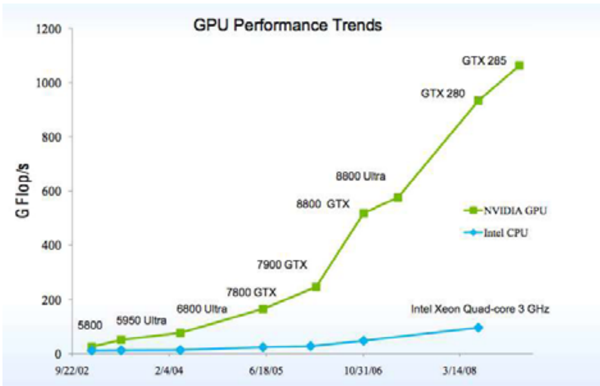
(General Purpose Computing using GPU Technology)

3/6 GB memory per card, 448 processors

$1,700/$2,300

Bundle 8 cards into a server: 3,584 processors, 48 GB memory

Incredible Growth



Performance gap GPU / CPU is growing

- currently 1-2 orders of magnitude is achievable (given appropriate programming and problem decomposition)

GPU Vital Specs

	GeForce 8800 GTX	GeForce GTX 580
Codename	G80	GF118
Release date	11/2006	11/2010
Transistors	681 M (90nm)	3,000 M (40nm)
Clock speed	1,350 MHz	1,544 MHz
Processors	128	512
Peak pixel fill rate	13.8 Gigapixels/s	37.6 Gigapixels/s
Pk memory bandwidth	86.4 GB/s (384 bit)	192 GB/s (384 bit)
Memory	768 MB	1536 MB
Peak performance	520 Gigaflops	1,581 Gigaflops

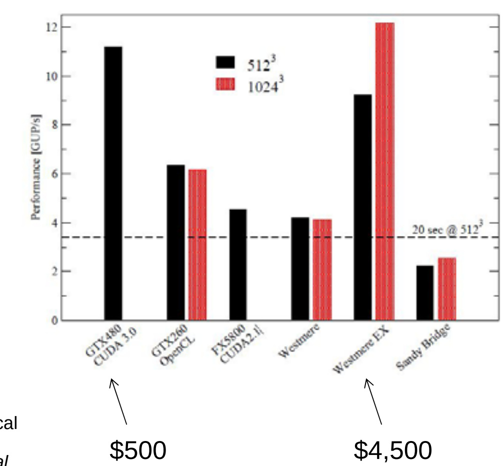
Comparison with CPUs

	Intel Xeon Westmere X5670	GeForce GTX 580
Price	$800	$500
Cores / Chip	6	16
ALUs / Core	1	32
Managed threads / Core	2	1536
Clock speed	3 GHz	1.5 GHz
Performance	96 Gigaflops	1,581 Gigaflops

Comparison with CPUs

Backprojection task

- 496 projections
- size 1248×960 each

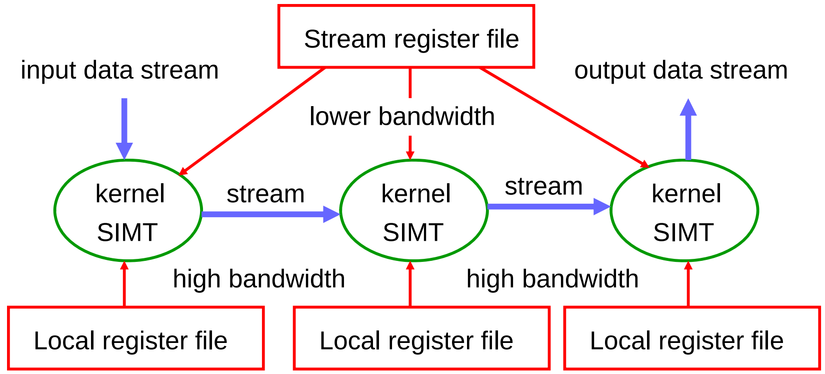


from Treibig et al. “Pushing the limits for medical image reconstruction on recent standard multicore processors,” *International Journal of High Performance Computing Applications*

Stream Processing

GPUs are *stream processors* [Kapasi '03]

(with some restrictions) [Venkatasubramanian '03]



History: Accelerated Graphics

1990s: accelerated graphics

- Silicon Graphics (SGI)
- expensive and non-programmable

Late 1990s: rise of consumer graphics chips

- Voodoo, ATI Rage, NVIDIA Riva
- chips still separate from memory

End 1990s: consumer graphics boards with high-end graphics

- the world's first GPU: NVIDIA GeForce 256 (NV 10)
- inexpensive, but still non-programmable

2000s: *programmable* consumer graphics hardware

- graphics cards: NVIDIA GeForce 3, ATI Radeon 9700
- HW programming languages: CG, GLSL, HLSL

Now: Focus Parallel Computing

2006: parallel computing languages appear

- dedicated SDK and API for parallel high performance computing (GPGPU)
- CUDA (Compute Unified Device Architecture)
  - developed by NVIDIA
- OpenCL (Open Computing Language)
  - initially developed by Apple
  - now with the Khronos Compute Working Group
- specific GPGPU boards: NVIDIA Tesla, AMD FireStream

Right Now: Focus "Serious" Parallel Computing

2009: next generation CUDA architectures announced

- NVIDIA Fermi, AMD Cypress
- substrate for supercomputing
- focused on "serious" high performance computing (clusters, etc)

Enrico Fermi (1901-1954)

- Italian physicist
- one of the top scientists of the 20th century
- developed the first nuclear reactor
- contributed to
  - quantum theory, statistical mechanics
  - nuclear and particle physics
- Nobel Prize in Physics in 1938 for his work on induced radioactivity

GPU vs. CPU

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One instruction-decode per kernel stream

- CPU needs a decode for each data item

Highly parallel

- GTX 580 has 512 processors
- Memory very close to processors → fast data transfer
- Threads are cheap to switch (light-weight)
  → use this to swap out waiting threads, swap in ready threads
- CPU requires lots of cache logic and communication to manage resources
- GPU has the resources close by

GPU vs. CPU

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High % of GPU chip real-estate for computing

- small in CPUs (example, 6.5% in Intel Itanium)

In many cases speedups of 1-2 orders of magnitude can be obtained by porting to GPU

- more details on the rules for effective porting later

GPU Architecture: Overview

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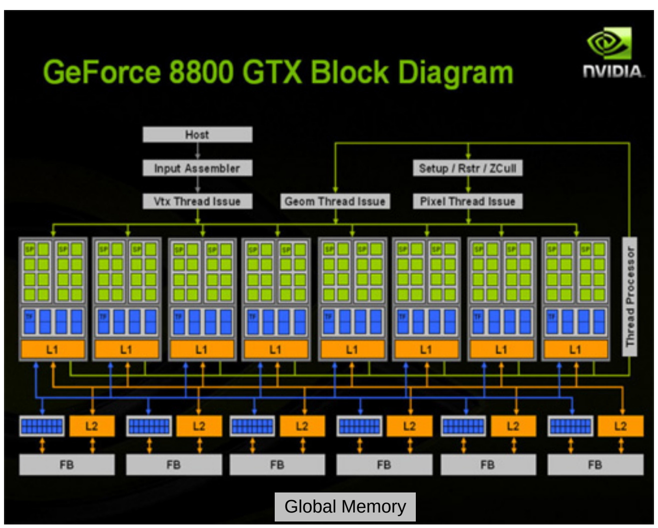

128 processors → 8 multi-processors of 16 processors each

local cache L1 (4k)

shared cache L2 (1M)

DRAM (global memory)

GPU Architecture: Overview

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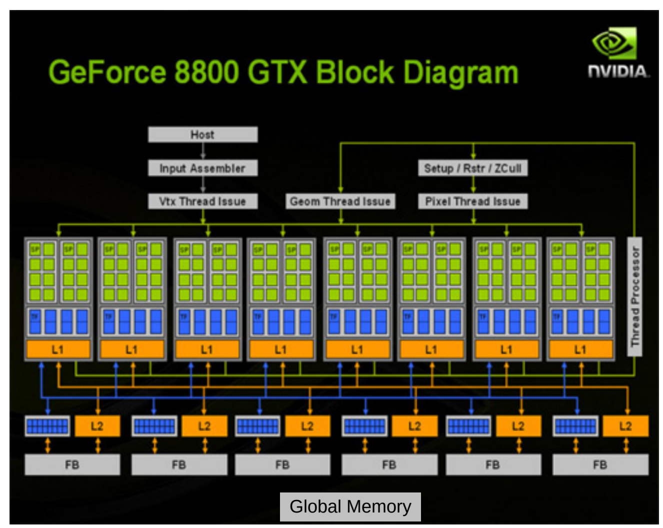

Memory management is key!

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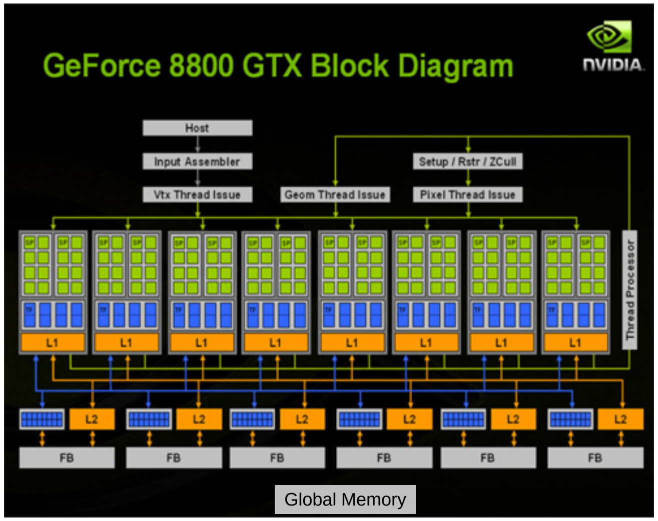
GPU Architecture: Overview



Memory management is key!

Thread management is key!

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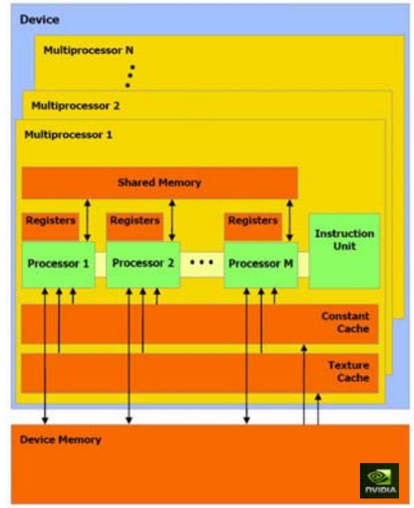
GPU Architecture: Different View



each multiprocessor is a SIMT (Same Instruction, Multiple Thread) architecture

equipped with a set of local 32-bit registers (L1 and L2 caches)

the (multi-processor level) shared Constant Cache and Texture Cache are read-only

the (device-level shared) Device Memory (Global Memory) has read-write access (with caching soon)

GPU Specifics

All standard graphics ops are hardwired
- linear interpolations
- matrix and vector arithmetic (+, -, *)

Arithmetic intensity
- the ratio of ALU arithmetic per operand fetched
- needs to be reasonably high, else application is memory-bound

GPU memory 1-2 orders of magnitude slower than GPU processors
- computation often better than table look-ups
- indirections can be expensive

Be aware of GPU 2D-caching protocol (for texture memory)
- data is fetched in 2D tiles (recall graphics bilinear texture filtering)
- promote data locality in 2D tiles

Latency Hiding

GPUs provide *hardware multi-threading*
- kicks in when threads within a core ALU stall (waiting for memory, etc)
- then another (light-weight) SIMT thread group is swapped in for execution
- this *hides the latency* for the stalled threads
- GTX 480 allows 48x more threads to be maintained than currently SIMT- executed

Hardware multi-threading requires memory
- contexts of all these threads must be maintained in memory
- this typically limits the amount of threads that can be simultaneously maintained for latency hiding

Programmability

GPU hardware can be programmed with
- shading languages (NVIDIA CG, OpenGL GLSL, Microsoft HLSL)
- parallel programming language (CUDA, OpenCL)

Shading languages
- require computer graphics knowledge
- give access to all fixed function pipelines (fast, ASIC-accelerated)
  - texturing: data interpolation, filtering
  - rasterization: mapping into the data domain
  - culling: clipping, early thread removal (early fragment kill)
- this can provide performance benefits

Parallel programming languages
- ease programming, eliminate need to study (some) graphics

Parallel Programming Languages

CUDA (C-interface: *C for CUDA*, also Fortran), OpenCL

Expose details on GPU memory and thread management
- memory hierarchy, latencies, operation costs, etc
- shading languages don't make this explicit
- give programmers better control over memory, threads, and arithmetic intensity (via occupancy calculator, profiler)

Promote computations as SIMT threads, executed in kernels
- synonymous to fragments in shading languages

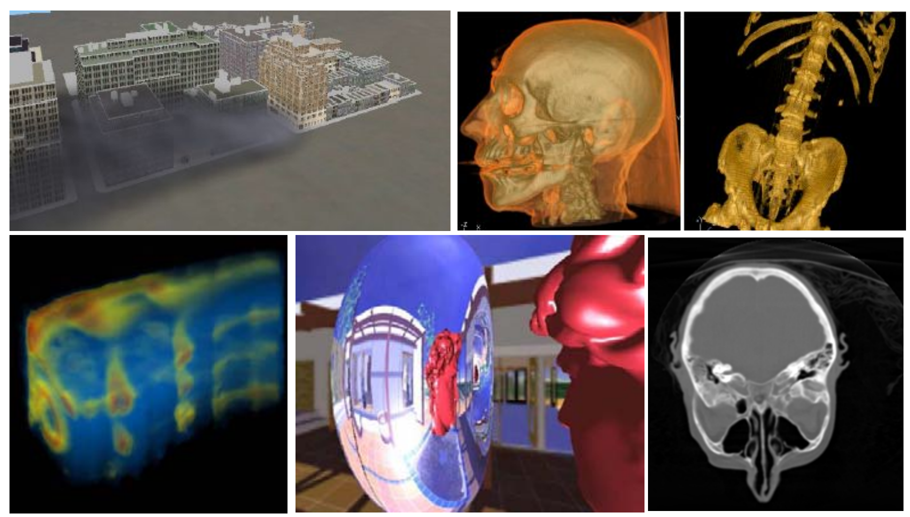
But still require (for optimal performance):
- careful computation flow planning, memory management, and analysis before coding
- no magic here; no pain, no gain

GPGPU

GPGPU = General Purpose Computation on Graphics hardware (GPU)
- massive trend to use GPUs for main stream computing
- see http://www.gpgpu.org

Accelerate
- volume rendering and advanced graphics effects
- computer vision
- scientific computing and simulations
- audio and image & video processing
- database operations, numerical algorithms and sorting
- data compression
- medical imaging
- and many others

GPGPU Example Applications



Course Schedule

1:30 – 1:45:	Introduction (Klaus)
1:45 – 2:00:	Parallel programming primer (Klaus)
2:00 – 2:15:	GPU hardware (Ziyi)
2:15 – 3:00:	CUDA API, threads (Ziyi)
	Coffee Break
3:30 – 4:00:	CUDA memory optimization (Eric)
4:00 – 4:15:	CUDA programming environment (Ziyi)
4:15 – 4:45:	Parallelism in CT reconstruction (Klaus)
4:45 – 5:25:	CT reconstruction examples (Eric)
5:25 – 5:30:	Closing remarks (Klaus)