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

SPIE Medical Imaging

Parallel Programming Primer

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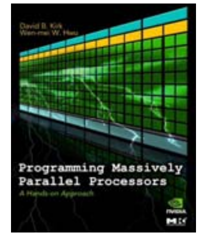
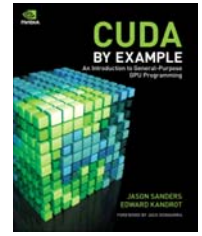
Recommended Literature

SPIE Medical Imaging

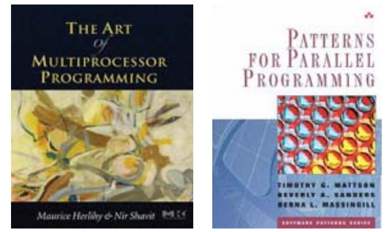


text book



reference book

programming guides available from nvidia.com



more general books on parallel programing

Speedup Curves

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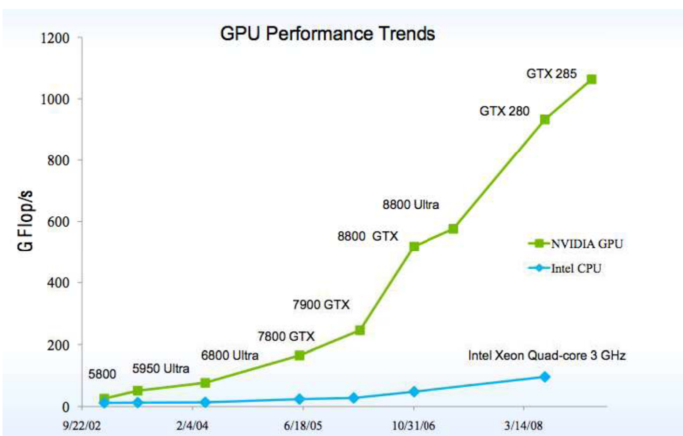

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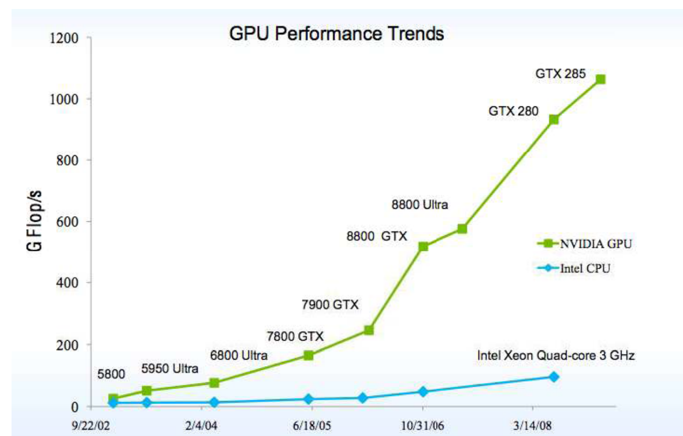

but wait, there is more to this…..

Amdahl's Law

Governs theoretical speedup

$$S = \frac{1}{(1-P) + \frac{P}{S_{parallel}}} = \frac{1}{(1-P) + \frac{P}{N}}$$

P: parallelizable portion of the program
S: speedup
N: number of parallel processors

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S: speedup
N: number of parallel processors

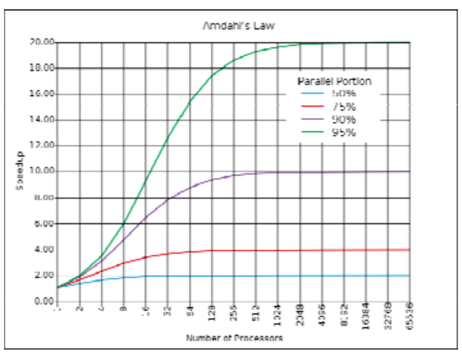
P determines theoretically achievable speedup

- example (assuming infinite N): P=90% → S=10
  P=99% → S=100

Amdahl's Law

How many processors to use

- when P is small → a small number of processors will do
- when P is large (embarrassingly parallel) → high N is useful



Focus Efforts on Most Beneficial

Optimize program portion with most 'bang for the buck'

- look at each program component
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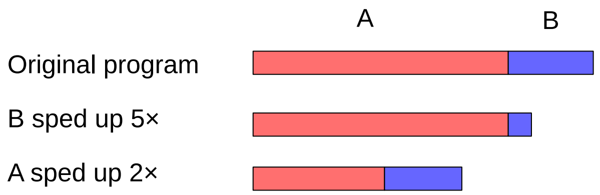
Example:

- program with 2 independent parts: A, B (execution time shown)



- sometimes one gains more with less

Beyond Theory....

Limits from mismatch of parallel program and parallel platform

- man-made 'laws' subject to change with new architectures

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Support for hardware access → drivers, APIs

Device Transfer Costs

Transferring the data to the device is also important
- computational benefit of a transfer plays a large role
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Adding two (N×N) matrices:

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Multiplying two (N×N) matrices:

- transfer back and from device: 3 N^2 elements
- number of multiplications and additions: N^3

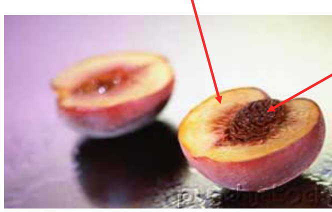
→ operations-transfer ratio = O(N) grows with N

Programming Strategy

Use GPU to complement CPU execution

- recognize parallel program segments and only parallelize these
- leave the sequential (serial) portions on the CPU

parallel portions (enjoy)



sequential portions (do not bite)

PPP (Peach of Parallel Programming – Kirk/Hwu)

Course Schedule

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