GPU Parallel Computing Architecture and CUDA Programming Model

John Nickolls

Outline

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- Data Parallel Problem Decomposition
- Parallel Memory Sharing
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Parallel Computing on a GPU

- NVIDIA GPU Computing Architecture is a scalable parallel computing platform
- In laptops, desktops, workstations, servers
- 8-series GPUs deliver 50 to 200 GFLOPS on compiled parallel C applications
- GPU parallel performance pulled by the insatiable demands of PC game market
- GPU parallelism is doubling every year
- Programming model scales transparently
- Programmable in C with CUDA tools
- Multithreaded SPMD model uses application data parallelism and thread parallelism

NVIDIA 8-Series GPU Computing

- Massively multithreaded parallel computing platform
- 12,288 concurrent threads, hardware managed
- 128 thread processor cores at 1.35 GHz == 518 GFLOPS peak
- GPU Computing features enable C on Graphics Processing Unit
SM Multithreaded Multiprocessor

- SM has 8 SP Thread Processors
  - 32 GFLOPS peak at 1.35 GHz
  - IEEE 754 32-bit floating point
  - 32-bit integer
- Scalar ISA
  - Memory load/store
  - Texture fetch
  - Branch, call, return
  - Barrier synchronization instruction
- Multithreaded Instruction Unit
  - 768 Threads, hardware multithreaded
  - 24 SIMD warps of 32 threads
  - Independent MIMD thread execution
  - Hardware thread scheduling
- 16KB Shared Memory
  - Concurrent threads share data
  - Low latency load/store

SM SIMD Multithreaded Execution

- Weaving: the original parallel thread technology is about 10,000 years old
- Warp: the set of 32 parallel threads that execute a SIMD instruction
- SM hardware implements zero-overhead warp and thread scheduling
- Each SM executes up to 768 concurrent threads, as 24 SIMD warps of 32 threads
- Threads can execute independently
- SIMD warp diverges and converges when threads branch independently
- Best efficiency and performance when threads of a warp execute together
- SIMD across threads (not just data) gives easy single-thread scalar programming with SIMD efficiency
Programmer Partitions Problem with Data-Parallel Decomposition

CUDA Programmer partitions problem into Grids, one Grid per sequential problem step
- Programmer partitions Grid into result Blocks computed independently in parallel
- GPU thread array computes result Block
- Programmer partitions Block into elements computed cooperatively in parallel
- GPU thread computes result element

Cooperative Thread Array
CTA Implements CUDA Thread Block

A CTA is an array of concurrent threads that cooperate to compute a result
- A CUDA thread block is a CTA

Programmer declares CTA:
- CTA size 1 to 512 concurrent threads
- CTA shape 1D, 2D, or 3D
- CTA dimensions in threads

CTA threads execute thread program
- CTA threads have thread id numbers
- CTA threads share data and synchronize
- Thread program uses thread id to select work and address shared data
SM Multiprocessor Executes CTAs

- CTA threads run concurrently
  - SM assigns thread id #s
  - SM manages thread execution
- CTA threads share data & results
  - In Memory and Shared Memory
  - Synchronize at barrier instruction
- Per-CTA Shared Memory
  - Keeps data close to processor
  - Minimize trips to global Memory
- CTA threads access global Memory
  - 76 GB/sec GDDR DRAM

Data Parallel Levels

- Thread
  - Computes result elements
  - Thread id number
- CTA – Cooperative Thread Array
  - Computes result Block
  - 1 to 512 threads per CTA
  - CTA (Block) id number
- Grid of CTAs
  - Computes many result Blocks
  - 1 to many CTAs per Grid
- Sequential Grids
  - Compute sequential problem steps
Parallel Memory Sharing

- **Local Memory**: per-thread
  - Private per thread
  - Auto variables, register spill
- **Shared Memory**: per-CTA
  - Shared by threads of CTA
  - Inter-thread communication
- **Global Memory**: per-application
  - Shared by all threads
  - Inter-Grid communication

**Thread**

- **Local Memory**

**CTA**

- **Shared Memory**

**Grid 0**

- Global Memory

**Grid 1**

Sequential Grids in Time

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How to Scale GPU Computing?

- **GPU parallelism varies widely**
  - Ranges from 8 cores to many 100s of cores
  - Ranges from 100 to many 1000s of threads
  - GPU parallelism doubles yearly

- **Graphics performance scales with GPU parallelism**
  - Data parallel mapping of pixels to threads
  - Unlimited demand for parallel pixel shader threads and cores

**Challenge:**

- Scale **Computing** performance with GPU parallelism
  - Program must be insensitive to the number of cores
  - Write one program for any number of SM cores
  - Program runs on any size GPU without recompiling
Transparent Scalability

- Programmer uses multi-level data parallel decomposition
  - Decomposes problem into sequential steps (Grids)
  - Decomposes Grid into computing parallel Blocks (CTAs)
  - Decomposes Block into computing parallel elements (threads)

- GPU hardware distributes CTA work to available SM cores
  - GPU balances CTA work load across any number of SM cores
  - SM core executes CTA program that computes Block

- CTA program computes a Block independently of others
  - Enables parallel computing of Blocks of a Grid
  - No communication among Blocks of same Grid
  - Scales one program across any number of parallel SM cores

- Programmer writes one program for all GPU sizes
- Program does not know how many cores it uses
- Program executes on GPU with any number of cores

CUDA Programming Model: Parallel Multithreaded Kernels

- Execute data-parallel portions of application on GPU as kernels which run in parallel on many cooperative threads

- Integrated CPU + GPU application C program
  - Partition problem into a sequence of kernels
  - Kernel C code executes on GPU
  - Serial C code executes on CPU
  - Kernels execute as blocks of parallel threads

- View GPU as a computing device that:
  - Acts as a coprocessor to the CPU host
  - Has its own memory
  - Runs many lightweight threads in parallel
Single-Program Multiple-Data (SPMD)

CUDA integrated CPU + GPU application C program
- Serial C code executes on CPU
- Parallel Kernel C code executes on GPU thread blocks

CUDA Programming Model: Grids, Blocks, and Threads
- Execute a sequence of kernels on GPU computing device
- A kernel executes as a Grid of thread blocks
- A thread block is an array of threads that can cooperate
- Threads within the same block synchronize and share data in Shared Memory
- Execute thread blocks as CTAs on multithreaded multiprocessor SM cores
CUDA Programming Model: Thread Memory Spaces

- Each kernel thread can read:
  - Thread Id per thread
  - Block Id per block
  - Constants per grid
  - Texture per grid

- Each thread can read and write:
  - Registers per thread
  - Local memory per thread
  - Shared memory per block
  - Global memory per grid

- Host CPU can read and write:
  - Constants per grid
  - Texture per grid
  - Global memory per grid

CUDA: C on the GPU

- Single-Program Multiple-Data (SPMD) programming model
  - C program for a thread of a thread block in a grid
  - Extend C only where necessary
  - Simple, explicit language mapping to parallel threads

- Declare C kernel functions and variables on GPU:
  ```c
  __global__ void KernelFunc(...);
  __device__ int GlobalVar;
  __shared__ int SharedVar;
  ```

- Call kernel function as Grid of 500 blocks of 128 threads:
  ```c
  KernelFunc<<< 500, 128 >>>(args ...);
  ```

- Explicit GPU memory allocation, CPU-GPU memory transfers
  ```c
  cudaMemcpy( ), cudaMemcpy2D( ), ...
  ```
CUDA C Example: Add Arrays

C program

```c
void addMatrix(float *a, float *b, float *c, int N)
{
    int i, j, idx;
    for (i = 0; i < N; i++) {
        for (j = 0; j < N; j++) {
            idx = i + j*N;
            c[idx] = a[idx] + b[idx];
        }
    }
}

void main()
{
    .....  
    addMatrix(a, b, c, N);
}
```

CUDA C program

```c
__global__ void addMatrixG(float *a, float *b, float *c, int N)
{
    int i = blockIdx.x*blockDim.x + threadIdx.x;
    int j = blockIdx.y*blockDim.y + threadIdx.y;
    int idx = i + j*N;
    if (i < N && j < N)
        c[idx] = a[idx] + b[idx];
}

void main()
{
    dim3 dimBlock (blocksize, blocksize);
    dim3 dimGrid (N/dimBlock.x, N/dimBlock.y);
    addMatrixG<<<dimGrid, dimBlock>>>(a, b, c, N);
}
```

CUDA Software Development Kit

- **CUDA Optimized Libraries:** FFT, BLAS, ...
- **Integrated CPU + GPU C Source Code**
- **NVIDIA C Compiler**
- **NVIDIA Assembly for Computing (PTX)**
- **CUDA Driver**
- **Debugger Profiler**
- **CPU Host Code**
- **Standard C Compiler**
- **GPU**
- **CPU**
Compiling CUDA Programs

- C/C++ CUDA Application
- NVCC
- PTX Code
- GPU to Target Translator
- Target Code
- GPU

GPU Computing Application Areas

- Computational Geoscience
- Computational Chemistry
- Computational Medicine
- Computational Modeling
- Computational Science
- Computational Biology
- Computational Finance
- Image Processing
Summary

NVIDIA GPU Computing Architecture
- Computing mode enables parallel C on GPUs
- Massively multithreaded – 1000s of threads
- Executes parallel threads and thread arrays
- Threads cooperate via Shared and Global memory
- Scales to any number of parallel processor cores
- Now on: Tesla C870, D870, S870, GeForce 8800/8600/8500, and Quadro FX 5600/4600

CUDA Programming model
- C program for GPU threads
- Scales transparently to GPU parallelism
- Compiler, tools, libraries, and driver for GPU Computing
- Supports Linux and Windows

http://www.nvidia.com/Tesla
http://developer.nvidia.com/CUDA