Introduction to GPU (Graphics Processing Unit) Architecture & Programming

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Some of slides are from M. Hall of Utah CS6235







- Programming model
- Example



Historical PC



FIGURE A.2.1 Historical PC. VGA controller drives graphics display from framebuffer memory. Copyright © 2009 Elsevier, Inc. All rights reserved.



Intel/AMD CPU with GPU



FIGURE A.2.2 Contemporary PCs with Intel and AMD CPUs. See Chapter 6 for an explanation of the components and interconnects in this figure. Copyright © 2009 Elsevier



GPU Evolution

Highly parallel, highly multithreaded multiprocessor optimized for graphic computing and other applications

- New GPU are being developed every 12 to 18 months
- Number crunching: 1 card ~= 1 teraflop ~= small cluster.
- 1980's No GPU. PC used VGA controller
- 1990's Add more function into VGA controller
- 1997 3D acceleration functions: Hardware for triangle setup and rasterization Texture mapping Shading
- 2000 A single chip graphics processor (beginning of GPU term)
- 2005 Massively parallel programmable processors



GPU Programming API

- CUDA (Compute Unified Device Architecture) : parallel GPU programming API created by NVIDA
 - Hardware and software architecture for issuing and managing computations on GPU
 - Massively parallel architecture. over 8000 threads is common
 - API libaries with C/C++/Fortran language
 - Numerical libraries: cuBLAS, cuFFT,
- **OpenGL** an open standard for GPU programming
- **DirectX** a series of Microsoft multimedia programming interfaces





SP: scalar processor 'CUDA core'

Executes one thread

SM streaming multiprocessor 32xSP (or 16, 48 or more) <u>Fast</u> local 'shared memory'

(shared between SPs) 16 KiB (or 64 KiB)



• GPU:

≻SMs

o 30xSM on GT200,o 14xSM on Fermi

For example, GTX 480:

14 SMs x 32 cores= 448 cores on a GPU

GDDR memory 512 MiB - 6 GiB



HOST

В

More Detailed GPU Architecture View



FIGURE A.2.5 Basic unified GPU architecture. Example GPU with 112 streaming processor (SP) cores organized in 14 streaming multiprocessors (SMs); the cores are highly multithreaded. It has the basic Tesla architecture of an NVIDIA GeForce 8800. The processors connect with four 64-bit-wide DRAM partitions via an interconnection network. Each SM has eight SP cores, two special function units (SFUs), instruction and constant caches, a multithreaded instruction unit UCSB and a shared memory. Copyright © 2009 Elsevier, Inc. All rights reserved.

CUDA essentials

- developer.nvidia.com. Download
 - Driver
 - Toolkit (compiler nvcc)
 - SDK (examples) (recommended)
 - CUDA Programmers guide

Other tools:

- 'Emulator'. Executes on CPU. Slow
- Simple profiler
- cuda-gdb (Linux)



How To Program For GPUs

Parallelization

Decomposition to threads

Memory

- shared memory, global memory
- Enormous processing power
- Thread communication
 - Synchronization, no interdependencies



Application Thread blocks

- Threads grouped in thread blocks
 - 128, 192 or 256 threads in a block

BLOCK 1		
THREAD	THREAD	THREAD
(0,0)	(0,1)	(0,2)
THREAD	THREAD	THREAD
(1,0)	(1,1)	(1,2)

- <u>One thread block executes on one</u>
 <u>SM</u>
 - All threads sharing the 'shared memory'
 - 32 threads are executed simultaneously ('warp')



Application Thread blocks

- Blocks execute on SMs
 - execute in parallel
 - execute independently!
- Blocks form a GRID
- Thread ID unique within block
- Block ID unique within grid







Thread Batching: Grids and Blocks

- A kernel is executed as a grid
 of thread blocks
 - All threads share data memory space
- A thread block is a batch of threads that can cooperate with each other by:
 - Synchronizing their execution
 - For hazard-free shared memory accesses
 - Efficiently sharing data through a low latency shared memory
- Two threads from two different blocks cannot cooperate





- Computation partitioning (where to run)
 - Declarations on functions __host__, __global__, __device_
 - Mapping of thread programs to device: compute <<<gs, bs>>>(<args>)
- Data partitioning (where does data reside, who may access it and how?)
 - Declarations on data __shared__, __device__, __constant__, …
- Data management and orchestration
 - Copying to/from host: e.g., cudaMemcpy(h_obj,d_obj, cudaMemcpyDevicetoHost)
- Concurrency management
 - E.g. __synchthreads()



Code that executes on GPU: Kernels

Kernel

- a simple C function
- executes on GPU in parallel
 - as many times as there are threads
- The keyword __global____tells the compiler nvcc to make a function a kernel (and compile/run it for the GPU, instead of the CPU)
- It's the functions that you may call from the host side using CUDA kernel call semantics (<<<...>>>).

Device functions can only be called from other device or global functions. ______device___ functions cannot be called from host code



Minimal Extensions to C + API

- Declspecs
 - global, device, shared, local, constant
- Keywords
 - threadIdx, blockIdx
- Intrinsics
 - __syncthreads
- Runtime API
 - Memory, symbol, execution management
- Function launch

```
device float filter[N];
 global void convolve (float *image)
  shared float region[M];
region[threadIdx] = image[i];
   syncthreads()
 image[j] = result;
// Allocate GPU memory
void *myimage = cudaMalloc(bytes)
```

// 100 blocks, 10 threads per block
convolve<<<100, 10>>> (myimage);

Setup and data transfer

- cudaMemcpy
 - transfer data to and from GPU (global memory)
- cudaMalloc
 - Allocate memory on GPU (global memory)
- GPU is the 'device', CPU is the 'host'
- Kernel call syntax



NVCC Compiler's Role: Partition Code and Compile for Device



CUDA Programming Model: How Threads are Executed

- The GPU is viewed as a compute device that:
 - Is a coprocessor to the CPU or host
 - Has its own DRAM (device memory)
 - Runs many threads in parallel
- Data-parallel portions of an application are executed on the device as kernels which run in parallel on many threads
- Differences between GPU and CPU threads
 - GPU threads are extremely lightweight
 - Very little creation overhead
 - GPU needs 1000s of threads for full efficiency
 - Multi-core CPU needs only a few



Block and Thread IDs

- Threads and blocks have IDs
 - So each thread can decide what data to work on
 - Block ID: 1D or 2D (blockIdx.x, blockIdx.y)
 - Thread ID: 1D, 2D, or 3D (threadIdx.{x,y,z})
- Simplifies memory addressing when processing multidimensional data



Courtesy: NDVIA

Simple working code example

- What does it do?
 - Scan elements of array of numbers (any of 0 to 9)
 - How many times does "6" appear?
 - Array of 16 elements, each thread examines 4 elements, 1 block in grid, 1 grid

threadIdx.x = 3 examines in_array elements 3, 7, 11, 15

distribution

CUDA Pseudo-Code

MAIN PROGRAM:

Initialization

- Allocate memory on host for input and output
- Assign random numbers to input array

Call host function

Calculate final output from per-thread output

Print result

GLOBAL FUNCTION:

Thread scans subset of array elements Call *device* function to compare with "6" Compute local result

HOST FUNCTION:

Allocate memory on device for copy of *input* and *output* Copy input to *device* Set up grid/block Call *global* function Synchronize after completion Copy *device* output to host

DEVICE FUNCTION:

Compare current element and "6"

Return 1 if same, else 0

Main Program: Preliminaries

...

MAIN PROGRAM:

Initialization

- Allocate memory on host for input and output
- Assign random numbers to input array

Call host function

Calculate final output from per-thread output

Print result

#include <stdio.h>
#define SIZE 16
#define BLOCKSIZE 4

int main(int argc, char **argv) { int *in_array, *out_array;

Main Program: Invoke Global Function

MAIN PROGRAM:

Initialization (OMIT)

- Allocate memory on host for input and output
- Assign random numbers to input array

Call *host* function

Calculate final output from per-thread output

Print result

```
#include <stdio.h>
#define SIZE 16
#define BLOCKSIZE 4
 _host___ void outer_compute (int
*in_arr, int *out_arr);
int main(int argc, char **argv)
 int *in_array, *out_array;
 /* initialization */ ...
 outer_compute(in_array, out_array);
```


Main Program: Calculate Output & Print Result

MAIN PROGRAM:

Initialization (OMIT)

- Allocate memory on host for input and output
- Assign random numbers to input array

Call host function

Calculate final output from per-thread output

Print result

```
<u> #include <stdio h></u>
#define SIZE 16
#define BLOCKSIZE 4
 _host___ void outer_compute (int
*in_arr, int *out_arr);
int main(int argc, char **argv)
 int *in_array, *out_array;
 int sum = 0:
 /* initialization */ ...
 outer_compute(in_array, out_array);
 for (int i=0; i<BLOCKSIZE; i++) {
  sum+=out_array[i];
 printf ("Result = %d\n",sum);
```


Host Function: Preliminaries & Allocation

HOST FUNCTION:

Allocate memory on device for copy of *input* and *output*

Copy input to *device*

Set up grid/block

Call global function

Synchronize after completion

Copy *device* output to host

_host___ void outer_compute (int *h_in_array, int *h_out_array) {

int *d_in_array, *d_out_array;

cudaMalloc((void **) &d_in_array, SIZE*sizeof(int));

cudaMalloc((void **) &d_out_array, BLOCKSIZE*sizeof(int));

Host Function: Copy Data To/From Host

HOST FUNCTION:

Allocate memory on device for copy of *input* and *output*

Copy input to *device*

Set up grid/block

Call global function

Synchronize after completion

Copy *device* output to host

_host__ void outer_compute (int *h_in_array, int *h_out_array) { int *d_in_array, *d_out_array;

cudaMalloc((void **) &d_in_array, SIZE*sizeof(int));

cudaMalloc((void **) &d_out_array, BLOCKSIZE*sizeof(int));

cudaMemcpy(d_in_array, h_in_array, SIZE*sizeof(int), cudaMemcpyHostToDevice);

... do computation ...

cudaMemcpy(h_out_array,d_out_array, BLOCKSIZE*sizeof(int), cudaMemcpyDeviceToHost);

Host Function: Setup & Call Global Function

HOST FUNCTION:

- Allocate memory on device for copy of *input* and *output*
- Copy input to *device*
- Set up grid/block
- Call global function
- Synchronize after completion
- Copy *device* output to host

_host___ void outer_compute (int *h_in_array, int *h_out_array) { int *d_in_array, *d_out_array;

- cudaMalloc((void **) &d_in_array, SIZE*sizeof(int));
- cudaMalloc((void **) &d_out_array, BLOCKSIZE*sizeof(int));
- cudaMemcpy(d_in_array, h_in_array, SIZE*sizeof(int), cudaMemcpyHostToDevice);
- cudaThreadSynchronize();
 - cudaMemcpy(h_out_array, d_out_array, BLOCKSIZE*sizeof(int), cudaMemcpyDeviceToHost);

Global Function: How to distribute tasks?

GLOBAL FUNCTION:

- Thread scans subset of array elements
- Call *device* function to compare with "6"
- Compute local result

_global___ void compute(int *d_in,int *d_out) { d_out[threadIdx.x] = 0; for (int i=0; i<SIZE/BLOCKSIZE; i++) { int val = d_in[i*BLOCKSIZE + threadIdx.x];

d_out[threadIdx.x] += compare(val, 6);

3 6 7 5 3 5 6 2 9 1 2 7 0 9 3 6 threadIdx.x = 0 examines in_array elements 0, 4, 8, 12 threadIdx.x = 1 examines in_array elements 1, 5, 9, 13 threadIdx.x = 2 examines in_array elements 2, 6, 10, 14 threadIdx.x = 3 examines in_array elements 3, 7, 11, 15

Device Function

DEVICE FUNCTION:

Compare current element and "6"

Return 1 if same, else 0

___device___ int compare(int a, int b) { if (a == b) return 1; return 0; }

Summary of Lecture

- Introduction to CUDA: C + API supporting heterogeneous data-parallel CPU+GPU execution
 - Computation partitioning
 - Data partititioning (parts of this implied by decomposition into threads)
 - Data organization and management
 - Concurrency management
- Compiler nvcc takes as input a .cu program and produces
 - C Code for host processor (CPU), compiled by native C compiler
 - Code for device processor (GPU), compiled by nvcc compiler

