ECE569 Module 8



• Vector addition kernel code

Kernel

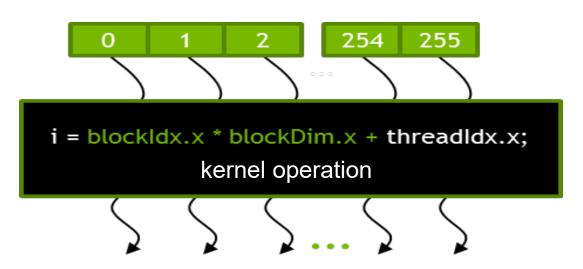
Looks like serial program

- Write your program as if it will run on one thread
 - C[i] = A[i] + B[i]
- From the CPU we decide the number of instances for the kernel
 - GPU will run the program on many threads
- GPU is good at
 - Launching large number of parallel threads
 - Latency for a thread may be longer than CPU!

Arrays of Parallel Threads

- A CUDA kernel is executed by a grid (array) of threads
 - All threads in a grid run the same kernel code (Single Program Multiple Data)
 - Each thread has indexes that it uses to compute memory addresses and make control decisions

Example with 1 block,
With 256 threads per blocks
blockIdx =?
blockDim=?



ECE569

Assume array size is 2048 targeting Tesla K20

	Compute Capability											
Technical Specifications	3.0	3.2	3.5	3.7	5.0	5.2	5.3	6.0	6.1	6.2	7.0	7.5
Maximum number of resident grids per device (Concurrent Kernel Execution)	16	4		3	32 16		16	128	32	16	12	28
Maximum dimensionality of grid of thread blocks	3											
Maximum x- or y-dimension of a block	1024											
Maximum z-dimension of a block	64											
Maximum number of threads per block	1024											
Warp size	32											
Maximum number of resident blocks per multiprocessor	16				32							16
Maximum number of resident warps per multiprocessor	64									32		
Maximum number of resident threads per multiprocessor	2048									1024		
Maximum amount of shared memory per multiprocessor		48 KB		112 KB	64 KB	96 KB	64 KB		96 KB	64 KB	96 KB	64 KB
Maximum amount of shared memory per thread block	48 KB 96 KB								96 KB	64 KB		
Cache working set per multiprocessor for texture memory	Between 12 KB and 48 KB Between 24 KB and 48 KB						and 48	32 ~ 128 KB	32 or 64 KB			

What is the proper thread block configuration?

- a) 1 block, 2048 threads per block
- b) 2 blocks, 1024 threads per block
- c) 4 blocks, 512 threads per block
- d) 8 blocks, 256 threads per block

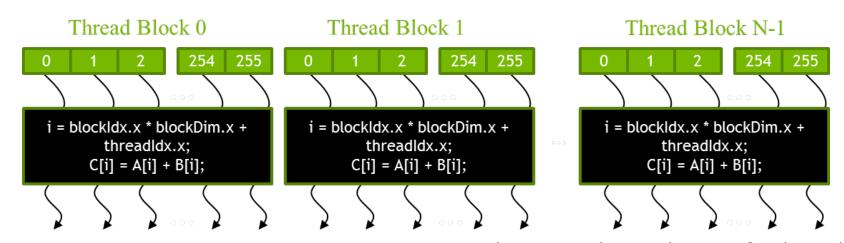
Tesla K20 3.5

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Thread Blocks: Scalable Cooperation

Divide thread array into multiple blocks

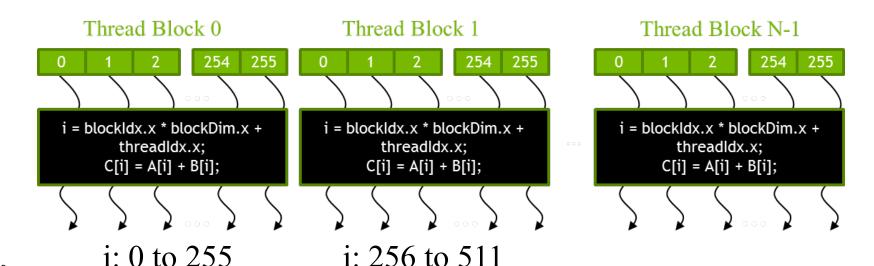
- Threads within a block cooperate via shared memory and barrier synchronization
- Threads in different blocks do not interact



i: c to d

Thread Blocks: Scalable Cooperation

- Divide thread array into multiple blocks
 - Threads within a block cooperate via shared memory and barrier synchronization
 - Threads in different blocks do not interact
 - blockDim.x allows striding with size of 256 (block size)



Vector addition kernel

```
// Compute vector sum C = A+B
// Each thread performs one pair-wise addition
__global__
void vecAddKernel(float* A, float* B, float* C, int n)
{
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    C[i] = A[i] + B[i]
}
```

CUDA Function Declarations

__global__ defines a kernel function,

Must return void

		Executed on the:	Only callable from the:
device floa	t myDeviceFunc()	device	device
global void	myKernelFunc()	device	host
host floa	t myHostFunc()	host	host

 By default, all functions in a CUDA program are host functions if they do not have any of the CUDA keywords in their declaration.

CUDA Function Declarations

- one can use both "__host__" and "__device__"
 in a function declaration.
 - to generate <u>two versions</u> of object files for the same function.
 - One is executed on the host and the on the device
 - Many user library functions will likely fall into this category.

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```
// Assume array size 1000 and block size is 256 threads
vecAddKernel<<<???, ???>>>(d_A, d_B, d_C, n);
```

set the grid and thread block dimensions

```
// Run ceil(n/256) blocks of 256 threads each
vecAddKernel<<<ceil(n/256.0), 256>>>(d_A, d_B, d_C, n);
```

- first parameter: number of thread blocks in the grid.
 - To ensure that we have enough threads to cover all the vector elements, we apply the C ceiling function to n/256.0
 - Using floating point value 256.0 ensures that we generate a floating value for the division so that ceiling function rounds up correctly.
- second parameter: number of threads per block.
- What is the total number of threads that we launch if n is 1000?

```
// Run ceil(n/256) blocks of 256 threads each
vecAddKernel<<<ceil(n/256.0), 256>>>(d_A, d_B, d_C, n);
```

- first parameter: number of thread blocks in the grid.
 - To ensure that we have enough threads to cover all the vector elements, we apply the C ceiling function to n/256.0
 - Using floating point value 256.0 ensures that we generate a floating value for the division so that ceiling function rounds up correctly.
- second parameter: number of threads per block.
- if n is 1000
 - launch ceil(1000/256.0) = 4 thread blocks.
 - statement will launch 4*256=1024 threads.
- In this case which elements of the A and B arrays will be accessed by thread (threadidx.x = 232, blockldx.x = 3)?

```
// Run ceil(n/256) blocks of 256 threads each
vecAddKernel<<<ceil(n/256.0), 256>>>(d_A, d_B, d_C, n);
    - if n is 1000
```

- launch ceil(1000/256.0) = 4 thread blocks.
- statement will launch 4*256=1024 threads.
- In this case which elements of the A and B arrays will be accessed by thread (threadidx.x = 232, blockldx.x = 3)?

```
i = threadIdx.x + blockDim.x * blockIdx.x; // i=1000
C[i] = A[i] + B[i] // out of boundary!!!
```

Threads 1000-1023 should not participate in the computation! **How do we achieve that?**

Vector addition kernel

```
// Compute vector sum C = A+B
// Each thread performs one pair-wise addition
__global__
void vecAddKernel(float* A, float* B, float* C, int n)
{
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    if (i<n)
        C[i] = A[i] + B[i];
}</pre>
```

Observations:

- 1. No more loop in the code! Replaced with grid of threads
- 2. With (i<n) we can operate on arbitrary length arrays

CUDA threads

main mechanism for exploiting of data parallelism

- Hierarchical thread organization
- Launching parallel execution
- Thread index to data index mapping

Threads and Blocks: Why an hierarchy?

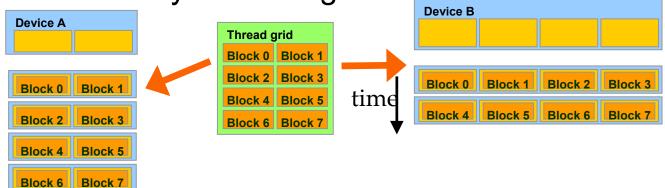
- Why not launch millions of threads instead of organizing them into blocks?
 - Each block can have 1024 threads, but you can launch massive number of blocks 2³²-1
 - Each GPU can run some number of blocks concurrently, executing some number of threads simultaneously
 - With the extra level of abstraction, higher performance GPUs can simply run more blocks concurrently and chew through the workload quicker with absolutely no change to the code!

Scalability!

Transparent Scalability

- Each block can execute in any order relative to others.
- Hardware is free to assign blocks to any processor at any time

 A kernel scales to any number of parallel processors automatically for each generation of GPU



Reading

- CUDA Programming Guide
 - Chapter 1: Introduction
 - Chapter 2: Programming Model
 - Appendix A: CUDA-enabled GPUs
 - Appendix B, sections B.1 B.4
 - Appendix I, section I.1: features of different GPUs

blockldx and threadldx

 Each thread uses indices to decide what data to work on

- blockldx: 1D, 2D, or 3D

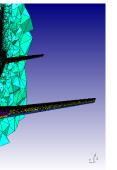
- threadIdx: 1D, 2D, or 3D

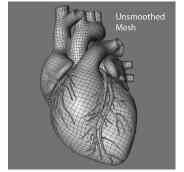
 Simplifies memory addressing when processing multidimensional data

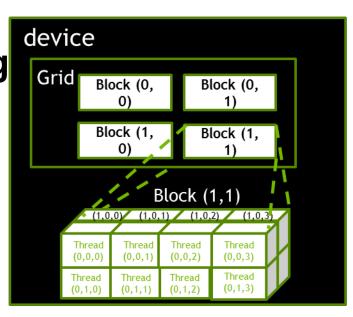
Image processing

Solving PDEs on volumes

- ...







Compute Capability

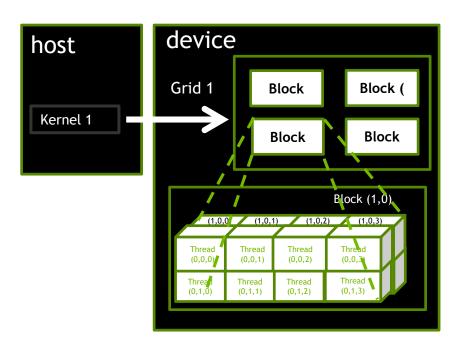
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dim3 Data Type

- 3D structure (C struct) or vector type with three unsigned integers (x,y,z)
 - dim3 threads(256); // x=256, y and z=1
 - dim3 blocks(100,100); // x and y = 100, z=1
 - dim 3 another (10, 20, 40);
- Each thread is individual and knows the following:
 - threadIdx : Thread index within the block
 - blockldx: Block index within the grid
 - blockDim: Block dimensions in threads
 - gridDim: Grid dimensions in blocks
 - Each of these are dim3 structures and can be read in the kernel to assign particular workloads to a thread.

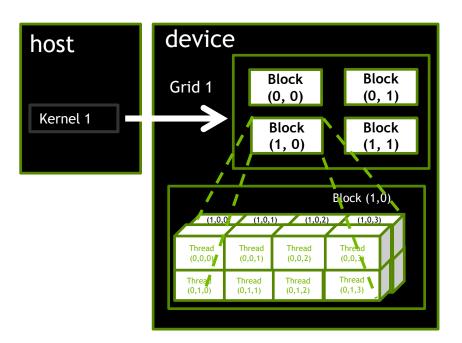
A Multi-Dimensional Grid Example

- dim3 dimGrid(?,?,?)
 - -? blocks
- dim3 dimBlock(?,?,?)
 - ? threads/block



A Multi-Dimensional Grid Example

- dim3 dimGrid(2,2,1)
 - 4 blocks
- dim3 dimBlock(4,2,2)
 - 16 threads/block



CUDA Parallelism Model – Multidimensional

Vector Addition Kernel Launch (Host Code)

```
host void vecAdd(float* h A, float* h B, float*
h C, int n)
dim3 DimGrid((n-1)/256 + 1, 1, 1);
dim3 DimBlock (256, 1, 1);
vecAddKernel<<<DimGrid,DimBlock>>> (d A, d B, d C, n);
                          Grid
                              GPU
                                            global
                                     Mk
                                            void vecAddKernel(float *A,
                                               float *B, float *C, int n)
                                              int i = blockIdx.x * blockDim.x
                                                     + threadIdx.x;
                                              if(i < n) C[i] = A[i] + B[i];
```

Next

- Launching interactive jobs
 - Printing from kernel code, time utility, thread block configuration experiment
- Debugging and profiling tools