GPU Programming Using CUDA

Michael J. Schnieders
Depts. of Biomedical Engineering & Biochemistry
The University of Iowa
&
Gregory G. Howes
Department of Physics and Astronomy
The University of Iowa

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Outline

• Concepts for GPU Computing

• Programming Model for GPU Computing using CUDA C

• CUDA C Programming

• Advanced CUDA Capabilities
Graphics Processing Units (GPUs) have been developed in response to strong market demand for realtime, high-definition 3D graphics (video games!)

GPUs are highly parallel, multithreaded, manycore processors

- Tremendous computational horsepower
- Very high memory bandwidth

We hope to access this power for scientific computing
GPU Programming Languages

- **CUDA** (Compute Unified Device Architecture) is the proprietary programming language for NVIDIA GPUs
- **OpenCL** (Open Computing Language) is portable language standard for general computing that can exploit capabilities of GPUs from any manufacturer.
- **OpenACC** (Open Accelerators) is portable like OpenCL, but features a directive syntax that is compatible with OpenMP

Each language provide extensions to C (as well as other languages) that enable the programmers to access the powerful computing capability for general-purpose computing on GPUs (GPGPU)

Today we will focus on the basics of CUDA C programming
Different computer architectures suggest three approaches to parallel computing:

1) Message Passing (MPI)

2) Multithreading (OpenMP)

3) GPU (CUDA)
More Transistors to Data Processing

CPUs devote a significant fraction of transistors to data caching and flow control

GPUs devote more transistors to data processing (arithmetic and logic units, ALU)
GPU vs. CPU Peak Performance

Floating point Operations Per Second (FLOPS)

Memory Access Bandwidth (GB/s)
Many Languages for GPU Computing

NVIDIA’s diverse offerings for GPU Computing

GPU Computing Applications

Libraries and Middleware
- cuFFT, cuBLAS, cuRAND, cuSPARSE
- LAPACK, CULA, MAGMA
- Thrust, NPP, cuDPP
- VSIPL, SVM, OpenCurrent
- PhysX, QuIX
- Unity, RealityServer
- MATLAB, MathWorks

C | C++ | Fortran | Java, Python Wrappers | Direct Compute | OpenCL™ | Directives (e.g. OpenACC)

**NVIDIA GPU**
with the **CUDA** Parallel Computing Architecture

<table>
<thead>
<tr>
<th>Fermi Architecture (compute capabilities 2.x)</th>
<th>GeForce 400 Series</th>
<th>Quadro Fermi Series</th>
<th>Tesla 20 Series</th>
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</thead>
<tbody>
<tr>
<td>Tesla Architecture (compute capabilities 1.x)</td>
<td>GeForce 200 Series</td>
<td>Quadro FX Series</td>
<td>Tesla 10 Series</td>
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<td>GeForce 9 Series</td>
<td>Quadro Plex Series</td>
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<td>GeForce 8 Series</td>
<td>Quadro NVS Series</td>
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Entertainment | Professional Graphics | High Performance Computing
Outline

• Concepts for GPU Computing

• Programming Model for GPU Computing using CUDA C

• CUDA C Programming

• Advanced CUDA Capabilities
CUDA C Programming Language

• Minimal set of extensions to the C programming language

• Core concepts:
  - Hierarchy of thread groups
  - Shared memory
  - Barrier synchronization

1) Kernel:
• C function executed $N$ times in parallel by $N$ CUDA threads
• Called by the Host (CPU) but executed on the Device (GPU)

2) Thread Hierarchy:
• Grid: Contains many blocks that can be solved independently in parallel
• Block: Contains many threads that can be solve cooperatively in parallel

3) Memory Functions:
• Allocate and Free memory space on Device (GPU),
• Copy data from Host (CPU) to Device (GPU), and vice versa
Thread Hierarchy: Grid of Blocks

Grid: Full problem to be solved by GPU is broken into blocks.

Each block is independent. The blocks can be executed, in any order, concurrently or sequentially.

The Streaming Multiprocessors (SMs) control the execution of each block.

This model enables excellent scalability for a varying number of cores per GPU.
Thread Hierarchy: Block of Threads

Each block contains many threads.

Threads within a block are executed in parallel, either cooperatively or independently.
Very high memory bandwidth can be achieved using a hierarchy of memory.

Each thread has private local memory.

Each thread block has fast access to shared memory.

All threads have slower access to global memory.

All threads can also access read-only Constant and Texture memory, optimized for different memory usages.
General Flow of CUDA C Program

C Program
Sequential Execution

Serial code

Parallel kernel
Kernel0<<<>>>()

Host

Device

Grid 0

Block (0, 0)  Block (1, 0)  Block (2, 0)
Block (0, 1)  Block (1, 1)  Block (2, 1)

Serial code

Host

Parallel kernel
Kernel1<<<>>>()

Device

Grid 1

Block (0, 0)  Block (1, 0)
Block (0, 1)  Block (1, 1)
Block (0, 2)  Block (1, 2)
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Programming in CUDA C

• Comparison of Multithreading and GPU Computing

• The Kernel
  - Thread Hierarchy

• Memory Functions

• Examples
Comparison to OpenMP Multithreading

General Implementation:
- Multithreading using OpenMP
- Parallel Computation on GPU device

All of this executes on the multicore host CPU with access to shared memory.

Kernel

Copy data from host memory to device memory

Copy data from device memory to host memory
The Kernel in CUDA C

Kernels:

• CUDA C enables the programmer to define C functions, called kernels, that are executed N times in parallel on the GPU device.

• Declaration specifier: Kernels are defined using \texttt{__global__}.

\begin{verbatim}
__global__ void VecAdd(int *a, int *b, int *c)
\end{verbatim}

• Kernels are called from the host (CPU) using a new \textit{execution configuration} syntax,

\begin{verbatim}
<<blocksPerGrid,threadsperBlock>>>
VecAdd<<blocksPerGrid,threadsperBlock>>>(d_a,d_b,d_c);
\end{verbatim}

\textbf{NOTE:} Kernel functions are called from the host, but executed on the device!
Blocks and Threads

Thread Hierarchy:
- The execution configuration specifies:
  
  \text{blocksPerGrid}
  
  \text{threadsPerBlock}

- These variables are 3-component integer vectors of type \text{dim3}

- For example,
  
  \text{dim3 threadsPerBlock(N,N);
  
  defines 2D thread blocks of size } N \text{ by } N

- In the kernel function, the thread ID is accessed through the variable
  
  \text{threadIdx, where the two dimensions are given by
  
  threadIdx.x \text{ and
  
  threadIdx.y}
Blocks and Threads

**Blocks:**
- The block ID and block dimensions are similarly accessed through `blockIdx` giving `blockIdx.x` and `blockIdx.y` and `blockDim` giving `blockDim.x` and `blockDim.y`.

- A general formula for computing the appropriate index based on multiple blocks is
  ```
  int i = blockIdx.x*blockDim.x + threadIdx.x;
  ```

**Limitations:**
- The maximum number of threads per block is the number of GPU cores, 512 for the GeForce GTX580.
- The number of blocks per grid is unlimited, and is determined by the number of blocks required to do the entire calculation.

- For a 2D computation of size $N$ by $N$
  ```
  dim3 numBlocks(N/threadsPerBlock.x,N/threadsPerBlock.y);
  ```
CUDA Kernel

**Standard serial C function**

```c
/* Function to compute y=a*x+y */
void saxpy_serial(int n, float a, float *x, float *y){
    for (int i=0; i < n; i++)
        y[i]= a*x[i] + y[i];
}

/* Call Function from main() */
saxpy_serial(4096*256, 2.0, x, y);
```

**Parallel CUDA C kernel**

```c
__global__ void saxpy_parallel(int n, float a, float *x, float *y)
{
    int i=blockIdx.x*blockDim.x + threadIdx.x;
    if (i < n)  y[i]= a*x[i] + y[i];
}

/* Call Function from main() */
saxpy_parallel<<<4096,256>>>(4096*256, 2.0, x, y);
```
CUDA Kernel

General Comments:
• The kernel contains only the commands within the loop
• The kernel call is asynchronous
  - After the kernel is called, the host can continue processing before the GPU has completed the kernel computation

<table>
<thead>
<tr>
<th><strong>device</strong></th>
<th><strong>global</strong></th>
<th><strong>host</strong></th>
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<tbody>
<tr>
<td>float DeviceFunc()</td>
<td>void KernelFunc()</td>
<td>float HostFunc()</td>
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<table>
<thead>
<tr>
<th>Executed on the:</th>
<th>Only callable from the:</th>
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<tbody>
<tr>
<td>device</td>
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</tr>
<tr>
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<td>host</td>
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• The computations in the kernel can only access data in device memory
Therefore, a critical part of CUDA programming is handling the transfer of data from host memory to device memory and back!
CUDA Memory Functions

• Device memory is allocated and freed using
  
  cudaMalloc()
  cudaFree()

  Example:
  
  size_t size = N * sizeof(float);
  float* d_A;
  cudaMalloc(&d_A, size);

• Data is transferred using
  
  cudaMemcpy()

  Example:
  
  /* Allocate array in host memory */
  float* h_A = (float*)malloc(size);
  /* Copy array from host memory to device memory */
  cudaMemcpy(d_A, h_A, size, cudaMemcpyHostToDevice);
#include<stdio.h>
#include<cuda.h>

#define N 100 /* Size of vectors */

/* Define CUDA kernel */
__global__ void add( int *a, int *b, int *c ) {
  int tid = blockIdx.x*blockDim.x+threadIdx.x;
  if (tid < N)
    c[tid] = a[tid] + b[tid];
}
Example CUDA code for Vector Addition

```c
int main() {
    int a[N], b[N], c[N];
    int *dev_a, *dev_b, *dev_c;
    /* allocate the memory on the GPU */
    cudaMalloc( (void**)&dev_a, N * sizeof(int) );
    cudaMalloc( (void**)&dev_b, N * sizeof(int) );
    cudaMalloc( (void**)&dev_c, N * sizeof(int) );
    /* Copy the arrays 'a' and 'b' from CPU host to GPU device*/
    cudaMemcpy( dev_a, a, N * sizeof(int), cudaMemcpyHostToDevice );
    cudaMemcpy( dev_b, b, N * sizeof(int), cudaMemcpyHostToDevice );
    int threadsPerBlock=512;
    int blocksPerGrid=(N+threadsPerBlock-1)/threadsPerBlock;
    add<<<blocksPerGrid,threadsPerBlock>>>( dev_a, dev_b, dev_c );
    /* Copy the array 'c' back from GPU device to CPU host*/
    cudaMemcpy( c, dev_c, N * sizeof(int), cudaMemcpyDeviceToHost );
    /* Free the memory allocated on the GPU device*/
    cudaFree( dev_a );
    cudaFree( dev_b );
    cudaFree( dev_c );
}
```
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Advanced CUDA Capabilities

• Shared Memory

• Concurrent memory copy and kernel execution

• Asynchronous concurrent execution

• Lower-level CUDA driver API

• Multiple devices on host system with peer-to-peer memory access

• Texture and surface memory

• Graphics functions with OpenGL and Direct3D Application Programming Interfaces (APIs)
Starter Code for CUDA Vector Addition

```c
#include <stdio.h>
#include <stdlib.h>
#include <math.h>

// CUDA kernel. Each thread takes care of one element of c
__global__ void vecAdd(double *a, double *b, double *c, int n)
{
    int id = ??? // Get our global thread ID
    // Make sure we do not go out of bounds
    if (id < n)
        c[id] = a[id] + b[id];
}

int main( int argc, char* argv[] )
{
    int n = 100000; // Size of vectors
    // Declare host vectors
    // Declare device input vectors
    size_t bytes = n*sizeof(double); // Size, in bytes, of each vector
    // Allocate memory for each vector on host
    // Allocate memory for each vector on GPU

    int i;
    // Initialize vectors on host
    for( i = 0; i < n; i++ ){
        h_a[i] = sin(i)*sin(i);
        h_b[i] = cos(i)*cos(i);
    }
    cudaMemcpy( d_a, h_a, bytes, cudaMemcpyHostToDevice); // Copy host vectors to device

    int blockSize, gridSize;
    blockSize = 1024; // Number of threads in each thread block
    gridSize = (int)ceil((float)n/blockSize); // Number of thread blocks in grid
    // Execute the kernel
    // Copy array back to host
    // Sum up vector c and print result divided by n, this should equal 1 within error
    double sum = 0;
    for(i=0; i<n; i++)
        sum += h_c[i];
    printf("final result: %f\n", sum/n);
    // Release device memory
    // Release host memory
    return 0;
}
```
Starter Code for CUDA Monte Carlo

```c
#include <stdio.h>
#include <stdlib.h>
#include <cuda.h>
#include <curand.h>
#include <time.h>

__global__ void kernel(int* count_d, float* randomnums) {
}

int main(int argc, char* argv[]) {
    //NOTE: if threads and/or blocks is changed, niter needs to be changed to reflect
    //that change (niter=threads*blocks)
    int niter = 100000;
    float* randomnums;
    double pi;

    //Allocate the array for the random numbers
    cudaMalloc((void**)&randomnums, (2*niter)*sizeof(float));
    //Use CuRand to generate an array of random numbers on the device
    int status;
    curandGenerator_t gen;
    status = curandCreateGenerator(&gen, CURAND_RNG_PSEUDO_MRG32K3A);
    status |= curandSetPseudoRandomGeneratorSeed(gen, 4294967296ULL^time(NULL));
    status |= curandGenerateUniform(gen, randomnums, (2*niter));
    status |= curandDestroyGenerator(gen);
    if (status != CURAND_STATUS_SUCCESS) {
        printf("CuRand Failure\n");
        exit(EXIT_FAILURE);
    }

    int threads = 1000;
    int blocks = 100;
    int* count_d;
    int* count = (int*)malloc(blocks*threads*sizeof(int));
    unsigned int reducedcount = 0;

    //Allocate the array to hold a value (1,0) whether the point in is the circle (1) or not (0)
    cudaMalloc((void**)&count_d, (blocks*threads)*sizeof(int));
    //Launch the kernel
    kernel <<<blocks, threads>>> (count_d, randomnums);
    cudaDeviceSynchronize();

    //Copy the resulting array back
    int i = 0;
    // Reduce array into int
    // Free the cudaMalloc'd arrays
    // Find the ratio
    pi = ((double)reducedcount/niter)*4.0;
    printf("Pi: \%f\n", pi);
    return 0;
}
```