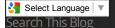
CUDA OGRAMMING

The Complexity of the Problem is the Simplicity of the Solution

HOME FEATURE PAGE BOOKS CUDA C/C++ PROGRAMMING CUDA CONCEPT TUTORIALS CUDA TOOLKIT AND DRIVERS CUDA EDUCATION AND TRAINING CONTACT US SITE MAP SUGGESTION PAGE

Prefer Your Language



Search

TAGS

CUDA BASICS

CUDA PROGRAMMING CONCEPT

RELATED POSTS

- : How to Query Device Properties and Handle Frrors in CUDA
- : How to Implement Performance Metrics in CUDA C/C++ | Optimization in CUDA
- : How to specify architecture while compiling CUDA program in Visual profiler How to change command line flag in CUDA
- · Further Optimization in histogram CUDA code | Fast implementation of histogram in CUDA
- CUDA complete | Complete reference on CUDA

SHARE THIS











SHARED MEMORY AND SYNCHRONIZATION IN CUDA **PROGRAMMING**

POSTED BY NITIN GUPTA AT 07:58 | 3 COMMENTS

This article lets u know what is shared memory and synchronization with detail and complete working example.

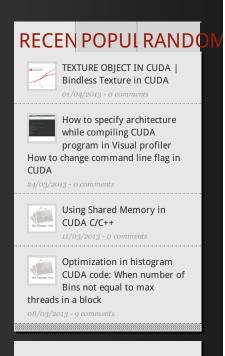
Let's start our discussion. We start with this question; What is Shared Memory and Synchronization in CUDA Programming?

Motivation

The motivation for splitting blocks into threads was simply one of working around hardware limitations to the number of blocks we can have in flight. This is fairly weak motivation, because this could easily be done behind the scenes by the CUDA runtime. Fortunately, there are other reasons one might want to split a block into threads.

Shared Memory in CUDA

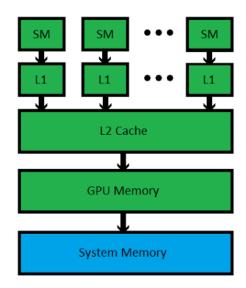
CUDA C makes available a region of memory that we call shared memory. This region of memory brings along with it another extension to the C language akin to __device__ and __global__. As a programmer, we can modify our variable declarations with the CUDA C keyword __shared__ to make this variable resident in shared memory. But what's the point?



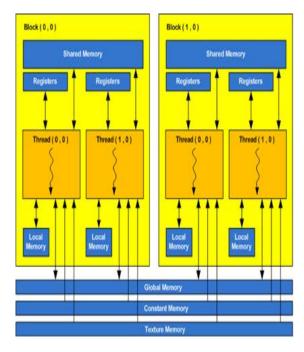
GOOGLE+

Add to circles

FOLLOWERS



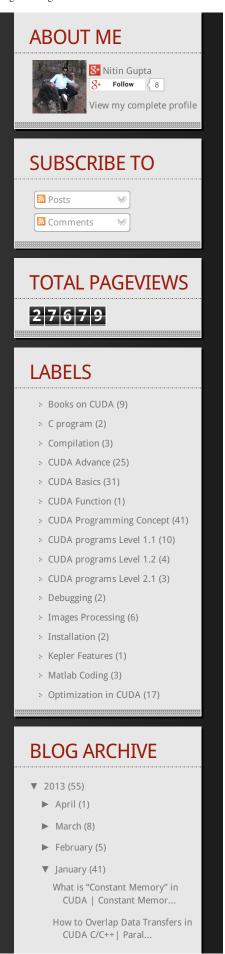
We're glad you asked. The CUDA C compiler treats variables in shared memory differently than typical variables. It creates a copy of the variable for each block that you launch on the GPU. Every thread in that block shares the memory, but threads cannot see or modify the copy of this variable that is seen within other blocks. This provides an excellent means by which threads within a block can communicate and collaborate on computations. Furthermore, shared memory buffers reside physically on the GPU as opposed to residing in off-chip DRAM. Because of this, the latency to access shared memory tends to be far lower than typical buffers, making shared memory effective as a per-block, software managed cache or scratchpad. Fig shows you the memory hierarchy diagram in CUDA Arch. With Shared Memory



Motivation of Synchronization

Race Condition

The prospect of communication between threads should excite you.



It excites me, too. But nothing in life is free, and interthread communication is no exception. If we expect to communicate between threads, we also need a mechanism for synchronizing between threads. For example, if thread A writes a value to shared memory and we want thread B to do something with this value, we can't have thread B start its work until we know the write from thread A is complete. Without synchronization, we have created a race condition where the correctness of the execution results depends on the nondeterministic details of the hardware.

Shared Memory and Global Memory

Shared memory

Threads within the same block have two main ways to communicate data with each other. The fastest way would be to use shared memory. When a block of threads starts executing, it runs on an SM, a multiprocessor unit inside the GPU. Each SM has a fairly small amount of shared memory associated with it, usually 16KB of memory. To make matters more difficult, often times, multiple thread blocks can run simultaneously on the same SM. For example, if each SM has 16KB of shared memory and there are 4 thread blocks running simultaneously on an SM, then the maximum amount of shared memory available to each thread block would be 16KB/4, or 4KB. So as you can see, if you only need the threads to share a small amount of data at any given time, using shared memory is by far the fastest and most convenient way to do it.

Global memory

However, if your program is using too much shared memory to store data, or your threads simply need to share too much data at once, then it is possible that the shared memory is not big enough to accommodate all the data that needs to be shared among the threads. In such a situation, threads always have the option of writing to and reading from global memory. Global memory is much slower than accessing shared memory; however, **global memory is much larger**. For most video cards sold today, there is at least 128MB of memory the GPU can access.

Looking for the example? Declaring shared arrays

For CUDA kernels, there is a special keyword, __shared__, which places a variable into shared memory for each respective thread block. The __shared__ keyword works on any type of variable or array. In the case for this tutorial, we will be declaring three arrays in shared memory.

```
// Declare arrays to be in shared memory.
// 256 elements * (4 bytes / element) * 3 = 3KB.
__shared__float min[256];
__shared__float max[256];
__shared__float avg[256];
```

If you are not clear with idea of thread and block architecture and how to decide. please go through this link

For descriptive example; Vector Dot Product
For Simple example with more description; Simple and explained

Summary of the Article

In summing up this article, it is possible, and many times necessary, for threads within the same block to communicate with each other through either shared memory, or global memory. Shared memory is by far the fastest way, however due to it's size limitations, some problems will be forced to use global memory for thread communication. Using __syncthreads is sometimes necessary to ensure that all data from all threads is valid before threads read from shared memory which is written to by other threads. Below is a graph of execution time it took my CPU against the amount of time it took my graphics card. the CPU is a 2.66 Core

- How to Optimize Data Transfers in CUDA C/C++ | Uti...
- How to Query Device Properties and Handle Errors i...
- How to Implement Performance Metrics in CUDA C/C++...
- Implementation Sobel operator in CUDA C on YUV vid...
- Sobel in C; Sobel operator on YUV video in C
- Matlab code for Sobel operator, Implementation Sob...
- Installing NVidia Nsight Visual studio plugin for ...
- Handling CUDA error messages
- Performance of sqrt in CUDA
- What is a warp in CUDA?
- Threads and Blocks in Detail in CUDA
- Implementation Sobel operator in Matlab on YUV vid...
- Implementation Sobel operator in Matlab on YUV ima...
- DYNAMIC PARALLELISM IN CUDA
- CUDA Streams (What is CUDA Streams?)
- Complete syntax of CUDA Kernels
- THREAD AND BLOCK HEURISTICS in CUDA Programming
- Vector Dot product in CUDA C; CUDA C Program for V...
- Shared Memory and Synchronization in CUDA Programm...
- CUDA program for Vector Addition for Long Vector
- Sobel Filter implementation in C
- CUDA C code for Addition of Two Array elements
- Vector Addition in CUDA (CUDA C/C++ program for Ve...
- How to Pass Parameters in CUDA Kernel?
- How to Query to Devices in CUDA C/C++?
- What is CUDA Driver API and CUDA Runtime API and D...
- Vector Dot product in CUDA C; CUDA C Program for V...
- How to Reverse Multi Block in an Array using Share...
- Programming Massively Parallel Processors: A Hands...

2 Duo, while the graphics card is a GTX 280, slightly **underclocked**. As you can see, the GPU is faster when there are at least a million elements, and the spread between the GPU and CPU continues to widen with more elements. However, main system memory may be a significant bottleneck which is preventing the GPU from achieving more than 1.5x the processor performance.

Got Questions?

Feel free to ask me any question because I'd be happy to walk you through step by step!

References and External Links Wikipedia hyperphysic algebralab CUDA C Programming Guide CUDA; Nvidia

For Contact us..... Click on Contact us Tab

GPU Computing Gems Emerald Edition

GPU Computing GEMs - Jade Edition

CUDA Application Design and Development

CUDA BY EXAMPLE: AN
INTRODUCTION TO GENERALPURPOS...

How to Reverse Multi Block in an Array; CUDA C/C++...

Installation Process; How to install CUDA in Ubunt...

Installation Process; How to install CUDA in Wind...

CUDA C program for matrix Multiplication using Sha...

Compile and Run CUDA C/C++
Programs

What is Compute Capability in CUDA | Details of Co...

2012 (15)

3 comments:



Anonymous 12 March 2013 09:33

guys the program that i'm working on is for matrix multiplication using non shared and shared memory, and it shows the same calculation time, if possible could you have a look at the code below thanks.

#include

#include

#include

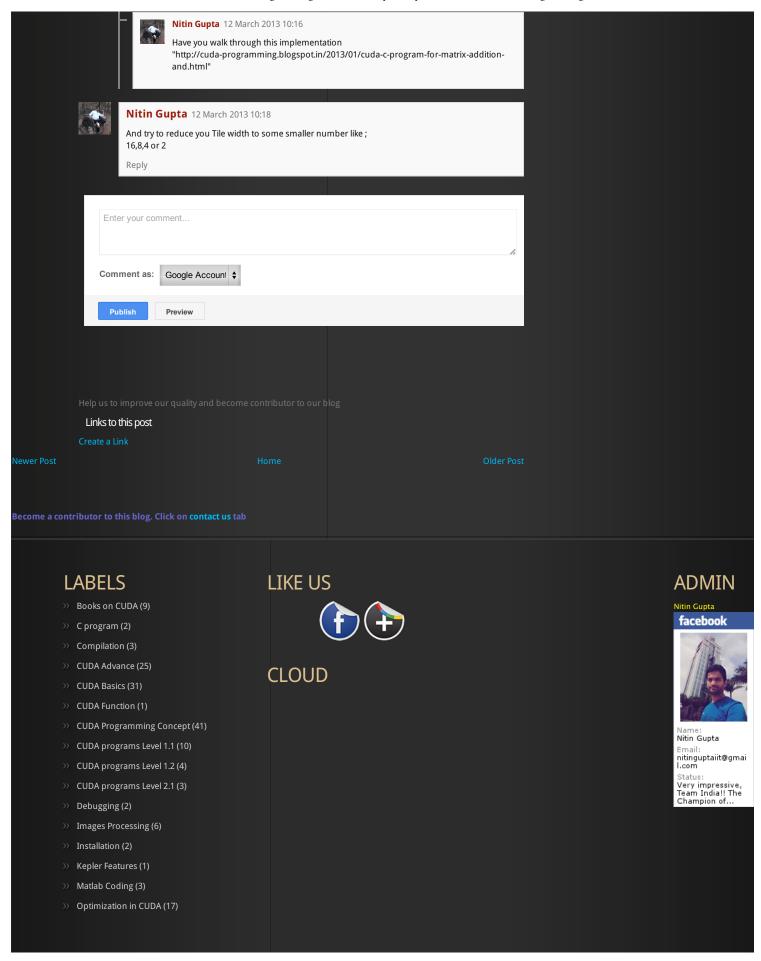
define TILE_WIDTH 32

```
_global__void gpu_matrixmult (int *Md, int *Nd, int *Pd, int Width)
_shared_ int Mds[TILE_WIDTH][TILE_WIDTH];
_shared_ int Nds[TILE_WIDTH][TILE_WIDTH];
int bx = blockIdx.x; // tile (block) indices
int by = blockIdx.y;
int tx = threadIdx.x; //thread indices
int ty = threadIdx.y;
int Row = by * TILE_WIDTH + ty; // global indices
int Col = bx * TILE_WIDTH + tx;
int Pvalue = 0;
for (int m = 0; m < Width/TILE_WIDTH; m++)
Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)]; // load Md, Nd tiles into sh. mem
Nds[ty][tx] = Nd[(m*TILE_WIDTH + ty)*Width + Col];
_syncthreads();
for ( int k = 0; k < TILE_WIDTH; k++)
Pvalue += Mds[ty][k] * Nds[k][tx];
Pd[Row * Width + Col] = Pvalue;
int main ()
int *A, *B, *C;
```

@cudaprogramming. Powered by Blogger.

int N=10;

```
int i,j; //loop counters
int size;
char key;
int* Ad;
int* Bd;
int* Cd;
cudaEvent_t start, stop; // using cuda events to measure time
float\ elapsed\_time\_ms; \textit{//}\ which\ is\ applicable\ for\ asynchronous\ code\ also
//keyboard input
do
printf("Enter size of array in one dimension (square array), currently %d\n",N);
scanf("%d",&N);
dim3 Block(TILE WIDTH, TILE WIDTH);
dim3 Grid(N / TILE_WIDTH, N / TILE_WIDTH);
size = N* N * sizeof(int);
A = (int*) malloc(size);
B = (int*) malloc(size);
C = (int*) malloc(size);
for(i=0;i < N;i++) { // load arrays with some numbers
for(j=0;j < N;j++) {
A[i * N + j] = i;
B[i * N + j] = i;
cudaMalloc((void**)&Ad, size);
cudaMalloc((void**)&Bd, size);
cudaMalloc((void**)&Cd, size);
cudaMemcpy(Ad, A, size, cudaMemcpyHostToDevice);
cudaMemcpy(Bd, B, size, cudaMemcpyHostToDevice);
cudaMemcpy(Cd, C, size, cudaMemcpyDeviceToHost);
cudaEventCreate(&start); // instrument code to measure start time
cudaEventCreate(&stop);
cudaEventRecord(start, 0); // here start time, after memcpy
// Launch the device computation
gpu_matrixmult<<>>(Ad, Bd, Cd, N);
// Read C from the device
cudaMemcpy(C, Cd, size, cudaMemcpyDeviceToHost);
cudaEventRecord(stop, 0); // measuse end time
cudaEventSynchronize(stop);
cudaEventElapsedTime(&elapsed_time_ms, start, stop );
printf("Time to calculate results on GPU: %f ms.\n", elapsed_time_ms);
printf("\nEnter c to repeat, return to terminate\n");
scanf("%c",&key);
scanf("%c",&key);
} while (key == 'c');
// Free device memory
cudaFree(Ad);
cudaFree(Bd);
cudaFree(Cd);
cudaEventDestroy(start);
cudaEventDestroy(stop);
system ("pause");
Reply
```



08:30:06 am

Copyright © 2012 CUDA Programming Whisky & Rum bestellen