CUDA Programming

Introduction
Writing a CUDA Kernel
Compiling for CUDA
Writing Kernels for *CUDALink*
Porting OpenCL to CUDA
Symbolic Code Generation

CUDA is a general C-like programming developed by NVIDIA to program Graphical Processing Units (GPUs). *CUDALink* provides an easy interface to program the GPU by removing many of the steps required. Compilation, linking, data transfer, etc. are all handled by *Mathematica*'s *CUDALink*. This allows the user to write the algorithm rather than the interface and code.

This section describes how to start programming CUDA in *Mathematica*.

CUDAFunctionLoad	loads a CUDA function into *Mathematica*

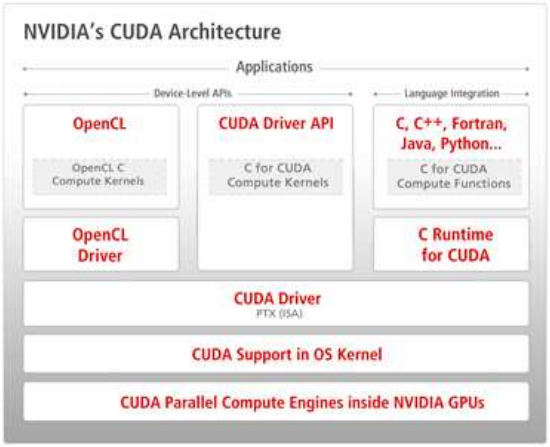
CUDA programming in *Mathematica*.

This document describes the GPU architecture and how to write a CUDA kernel. In the end, many applications written using *CUDALink* are demonstrated.

Introduction

The Common Unified Device Architecture (CUDA) was developed by NVIDIA in late 2007 as a way to make the GPU more general. While programming the GPU has been around for many years, difficulty in programming it had made adoption limited. *CUDALink* aims at making GPU programming easy and accelerating the adoption.

When using *Mathematica*, you need not worry about many of the steps. With *Mathematica*, you only need to write CUDA kernels. This is done by utilizing all levels of the NVIDIA architecture stack.



CUDALink is an application of the NVIDIA architecture stack.

CUDA Architecture

CUDA's programming is based on the data parallel model. From a high-level standpoint, the problem is first partitioned onto hundreds or thousands of threads for computation. If the following is your computation:

```
OutputData = Table[fun[InputData[[i, j]]], {i, 10000}, {j, 10000}]
```

then in the CUDA programming paradigm, this computation is equivalent to:

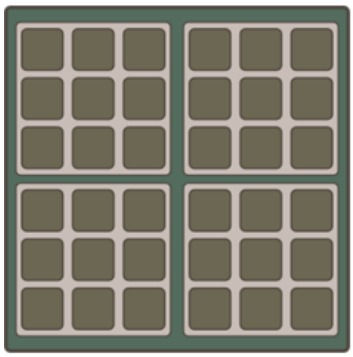
```
CUDALaunch[fun, InputData, OutputData, {10000, 10000}]
```

where `fun` is a computation function. The above launches 10000×10000 threads, passes their indices to each thread, applying the function to `InputData`, and places the results in `OutputData`. *CUDALink*'s equivalence to `CUDALaunch` is `CUDAFunction`.

The reason CUDA can launch thousands of threads all lies in its hardware architecture. The following sections will discuss this, along with how threads are partitioned for execution.

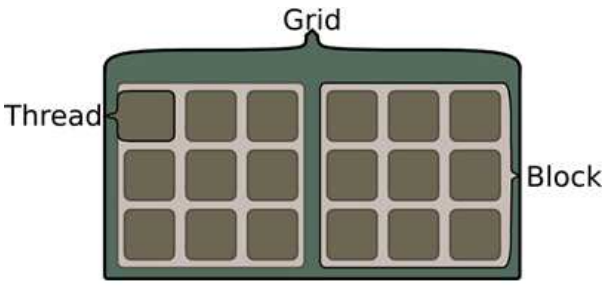
CUDA Grid and Blocks

Unlike the message-passing or thread-based parallel programming models, CUDA programming maps problems on a one-, two-, or three-dimensional grid. The following shows a typical two-dimensional CUDA thread configuration.



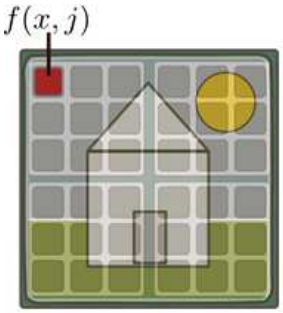
All CUDA programs are mapped on a one-, two-, or three-dimensional grid.

Each grid contains multiple blocks, and each block contains multiple threads. In terms of the above image, a grid, block, and thread are as follows.



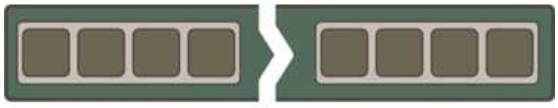
A pictorial definition of grid, block, and thread.

Choosing whether to have a one-, two-, or three-dimensional thread configuration is dependent on the problem. In the case of image processing, for example, you map the image onto the threads as shown in the following figure and apply a function to each pixel.



Thread configuration for two-dimensional image processing problems.

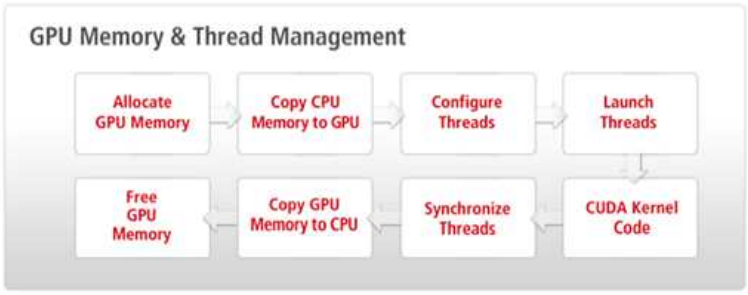
The one-dimensional cellular automaton can map onto a one-dimensional grid.



Thread configuration for one-dimensional problems.

CUDA Program Cycle

The gist of CUDA programming is to copy data from the launch of many threads (typically in the thousands), wait until the GPU execution finishes (or perform CPU calculation while waiting), and finally, copy the result from the device to the host.

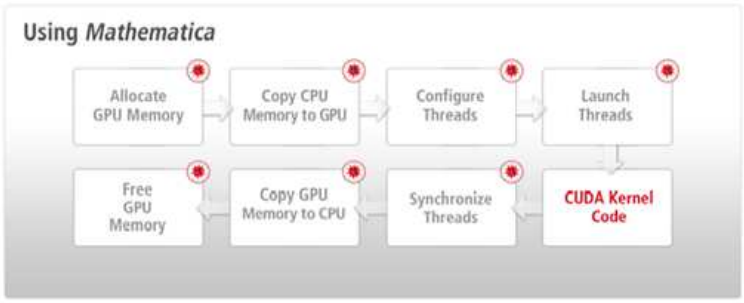


Typical CUDA program cycle.

The above figure details the typical cycle of a CUDA program.

1. Allocate memory of the GPU. GPU and CPU memory are physically separate, and the programmer must manage the allocation copies.
2. Copy the memory from the CPU to the GPU.
3. Configure the thread configuration: choose the correct block and grid dimension for the problem.
4. Launch the threads configured.
5. Synchronize the CUDA threads to ensure that the device has completed all its tasks before doing further operations on the GPU memory.
6. Once the threads have completed, memory is copied back from the GPU to the CPU.
7. The GPU memory is freed.

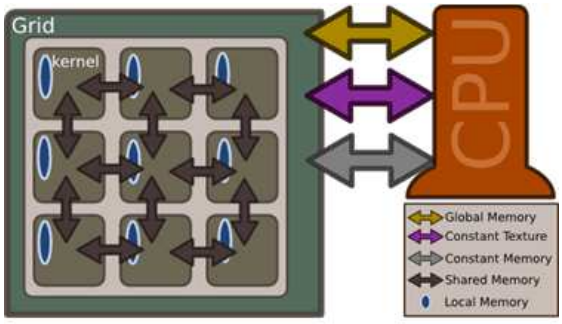
When using *Mathematica*, you need not worry about many of the steps. With *Mathematica*, you only need to write CUDA kernels.



You only need to write CUDA kernels in *Mathematica*.

Memory Hierarchy

CUDA memory is divided into different levels, each with its own advantages and limitations. The following figure depicts all types of memory available to CUDA.



Different levels of memory available for CUDA.

Global Memory

The most abundant (but slowest) memory available on the GPU. This is the memory advertised on the packaging—128, 256, or 512 MB. All threads can access elements in global memory, although for performance reasons these accesses tend to be kept to a minimum and have further constrictions on them.

The performance constrictions on global memory have been relaxed on recent hardware and will likely be relaxed even further. The general rule is that performance is deteriorated if global memory is accessed more than once.

Texture Memory

Texture memory resides in the same location as global memory, but it is read-only. Texture memory does not suffer for the performance deterioration found in global memory. On the flip side, only `char`, `int`, and `float` are supported types.

Constant Memory

Fast constant memory that is accessible from any thread in the grid. The memory is cached, but limited to 64 KB globally.

Shared Memory

Fast memory that is local to a specific block. On current hardware, the amount of shared memory is limited to 16 KB per block.

Local Memory

Local memory is local to each thread, but resides in global memory unless the compiler places the variables in registers. While a general performance consideration is to keep local memories to a minimum since the memory accesses are slow, they do not have the same problems as global memory.

Compute Capability

The compute capabilities determine what operations the device is capable of. Currently, only compute capabilities 1.1, 1.2, 1.3, and 2.0 exist, with the main differences listed below.

Compute Capability	Extra Features
1.0	base implementation
1.1	atomic operations
1.2	shared atomic operations and warp vote functions
1.3	support for double-precision operations
2.0	double-precision, L2 cache, and concurrent kernels

Information about the compute capability on the current system can be retrieved using `CUDAInformation`.

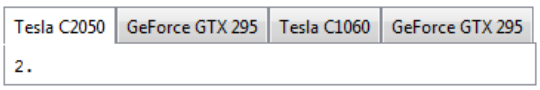
If you have not done so already, import *CUDALink*.

```
In[1]:= Needs["CUDALink`"]
```

This displays the names of all CUDA devices on the system along with their `"Compute Capabilities"`.

```
In[2]:= TabView[Table[CUDAInformation[ii, "Name"] →
          CUDAInformation[ii, "Compute Capabilities"], {ii, $CUDADeviceCount}]]
```

Out[2]=



Multiple CUDA Devices

If the system hardware supports it, CUDA allows you to select which device computation is performed on. By default, the fastest is chosen, but this can be overridden by the user. Once a device is set (whether chosen automatically or by the user) the device cannot be changed in the kernel session.

Writing a CUDA Kernel

CUDA kernels are atomic functions that are called many times. Usually these are a few lines inside the program's `For` loop. The following adds two vectors together.

First Kernel

A CUDA kernel is a small piece of code that performs a computation on each element of an input list. Your first kernel will add 2 to each element.

```
__global__ void addTwo_kernel(mint * arry, mint len) {

    int index = threadIdx.x + blockIdx * blockDim.x;

    if (index >= len) return;

    arry[index] += 2;
}
```

`__global__ void addTwo_kernel (mint * arry, len)`

`__global__` is a function qualifier that instructs the compiler that the function should be run on the GPU. `__global__` functions can be called from C. The other function qualifier is `__device__`, which

denotes functions that can be called from other `__global__` or `__device__` functions, but cannot be called from C.

A CUDA kernel must have void output, so to get that result you must pass in pointer inputs and overwrite them. In this case, you pass `arry` and overwrite the elements (you can think of `arry` as an input/output parameter).

```
int index = threadIdx.x + blockIdx * blockDim.x;
```

This gets the index. The CUDA kernel provides the following variables that are set depending on the launch grid and block size:

`threadIdx` — index of current thread; the thread index is between 0 and `blockDim - 1`

`blockIdx` — the index of current block; the block index is between 0 and `gridDim - 1`

`blockDim` — the block size dimensions

`gridDim` — the grid size dimensions

These parameters are set by CUDA automatically, based on the kernel launch parameters (the block and grid dimensions). The higher dimensions are automatically set to 1 when launching lower-dimension computation, so when launching a 1D grid the `.y` and `.z` are set to 1.

In most common cases in a 1D grid, you use `threadIdx.x + blockIdx.x * blockDim.x` to find the global offset, and you use `threadIdx.x + blockIdx.x * blockDim.x + (threadIdx.y + blockIdx.y * blockDim.y) * width` to find the global position in 2D.

```
if (index >= len) return;
```

Since threads are launched in multiples of the block dimensions, the user needs to make sure not to overwrite the boundaries if the dimension of the input is not a multiple of the block dimension. This assures that.

```
in[index] += 2;
```

This is the function applied to each element in the list, adding 2 to the input in this case.

Second Kernel

The second kernel implements a finite difference method (forward difference).

```
__device__ float f(float x) {
    return tanf(x);
}

__global__ void secondKernel(float * diff, float h, mint listSize) {
    mint index = threadIdx.x + blockIdx.x * blockDim.x;
    float f_n = f(((float) index) / h);
    float f_n1 = f((index + 1.0) / h);
    if( index < listSize) {
        diff[index] = (f_n1 - f_n) / h;
    }
}
```

```
__device__ float f(float x) {
```

This is a device function. `__device__` functions can be called from the `__global__` function, but cannot be called from *Mathematica* directly.

```
return tanf(x);
```

Perform the `Tan` of the floating-point input.

```
__global__ void secondKernel(float * diff, float h, mint listSize) {
```

Function that returns the list `diff`, and takes two scalar inputs `h` and `listSize`.

```
mint index = threadIdx.x + blockIdx.x * blockDim.x;
```

Get the global thread offset.

```
float f_n = f(((float) index) / h);
```

Evaluate the function at `index / h`. Since `index` and `h` are integers, you need to cast one to a floating-point number to avoid truncation. Call the device function `f`.

```
float f_n1 = f((index + 1.0) / h);
```

Evaluate the function at `(index + 1) / h`.

```
if (index < listSize) {
```

Make sure not to overwrite the output buffer.

```
diff[index] = (f_n1 - f_n) / h;
```

Calculate the forward difference and store the result in `diff`.

The next section shows how to load this CUDA program into *Mathematica*.

Loading a CUDA Kernel into *Mathematica*

If you have not done so already, import *CUDALink*.

```
In[1]:= Needs["CUDALink`"]
```

Place the code in the previous section into a string.

```
In[2]:= secondKernelCode = "
        __device__ float f(float x) {
            return tanf(x);
        }

        __global__ void secondKernel(float * diff, float h, mint listSize) {
            int index = threadIdx.x + blockIdx.x * blockDim.x;
            float f_n = f(((float) index) / h);
            float f_n1 = f((index + 1.0) / h);
            if( index < listSize) {
                diff[index] = (f_n1 - f_n) / h;
            }
        }";
```

This loads the `CUDAFunction`. Pass the kernel code as a first argument, the kernel name to be executed (`"secondKernel"`) as a second argument, the function parameters as a third argument, and the block size as the fourth argument. The result is stored in `secondKernel`.

```
In[3]:= secondKernel = CUDAFunctionLoad[secondKernelCode,
          "secondKernel", {{"Float"}, "Float", _Integer}, 16]

Out[3]= CUDAFunction[<>, secondKernel, {{Float}, Float, _Integer}]
```

Mathematica automatically compiles CUDA code, making the development process streamlined.

Behind the scenes a few things are happening:

CUDA availability of the system is checked.

The CUDA code is being compiled to a binary file optimized for the GPU select.

The compiled code is being cached to avoid future compilation.

A check is performed as to whether the kernel exists in the compiled code.

Once loaded, a `CUDAFunction` can be used like any *Mathematica* function. Before executing it, a buffer is needed to store the result. This creates the buffer of size 1000.

```
In[4]:= buffer = CUDAMemoryAllocate["Float", 1024]

Out[4]= CUDAMemory[<30143>, Float]
```

Here, you execute `secondKernel`.

```
In[5]:= secondKernel[buffer, 100.0, 1024]

Out[5]= {CUDAMemory[<30143>, Float]}
```

This gets the first 30 elements of the output buffer.

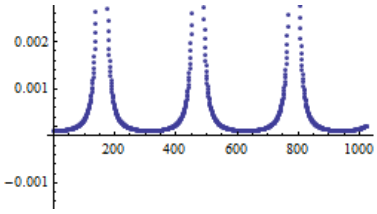
```
In[6]:= CUDAMemoryGet[buffer][[ ;; 30]]

Out[6]= {0.000100003, 0.000100023, 0.000100063, 0.000100123, 0.000100204, 0.000100304,
         0.000100425, 0.000100565, 0.000100727, 0.000100909, 0.000101112, 0.000101335,
         0.00010158, 0.000101846, 0.000102133, 0.000102442, 0.000102774, 0.000103127,
         0.000103503, 0.000103902, 0.000104324, 0.00010477, 0.000105239, 0.000105733,
         0.000106252, 0.000106796, 0.000107366, 0.000107962, 0.000108585, 0.000109235}
```

This plots the output buffer.

```
In[7]:= ListPlot@CUDAMemoryGet[buffer]
```

Out[7]=



The buffer must be manually freed by the user.

```
In[28]:= CUDAMemoryUnload[buffer];
```

C Sequential to CUDA Programming

The following details the progression of a program from the serial CPU version to a CUDA version.

The program implements the moving average with radius 3, calculating the average value of an array based on its neighboring pixels.

Generally, you start with the serial implementation. This allows you to gauge the problem and find possible avenues of parallelization. The serial implementation can also be used as the reference implementation as well as determining whether CUDA is fit for the task.

In this case, the serial implementation is as follows.

```
void xAverage_cpu (mint * in, mint * out, mint width, mint height, mint pitch) {
      int xIndex, yIndex, idx;
      mint left, curr, right;

      for (yIndex = 0; yIndex < height; yIndex++) {
            for (xIndex = 0; xIndex < width; xIndex++) {
                  idx = x + y*pitch;

                  left = idx > 0 ? in[idx - 1] : in[yIndex*pitch];
                  curr = in[idx];
                  right = idx < width - 1 ? in[idx + 1] : in[width + yIndex*pitch];

                  out[x + y*pitch] = (left + curr + right)/3;
              }
        }
  }
```

It is a good idea to find possible areas of optimization. In this case you remove the two "if" statements, one to check if the element is the rightmost, and the other to check if it is the leftmost.

```
void xAverage_cpu(mint * in, mint * out, mint width, mint height, mint pitch) {
    int xIndex, yIndex, idx;

    for (yIndex = 0; yIndex < height; yIndex++) {
        out[yIndex*pitch] = (2*in[yIndex*pitch] + in[yIndex*pitch + 1])/3;

        for (xIndex = 1; xIndex < width-1; xIndex++) {
            idx = x + y*pitch;
            out[idx] = (in[idx-1] + in[idx] + in[idx+1])/3;
        }
        out[width - 1 + yIndex*pitch] = (in[width - 2 + yIndex*pitch] +
                                         2*in[width - 1 + yIndex*pitch])/3;
    }
}
```

Another thing to consider is avoiding code that depends on adjacent pixels.

```
void xAverage_cpu(mint * in, mint * out, mint width, mint height, mint pitch) {
    mint accum;
    mint left, curr, right;

    for (yIndex = 0; yIndex < height; yIndex++) {
         accum = 2*in[yIndex*pitch] + in[yIndex*pitch + 1]
        out[yIndex*pitch] = accum/3;

        accum -= in[yIndex*pitch];

        for (xIndex = 0; xIndex < width-1; xIndex++) {
            idx = x + y*pitch;

            accum += in[index+1];
            out[idx] = accum/3;
            accum -= in[idx-1];
        }
        accum += in[width - 2 + yIndex*pitch];
        out[width - 1 + yIndex*pitch] = accum/3;
```

```
    }
}
```

Finally, write a program that is based on the most optimized CPU implementation.

```
__global__ void xAverage_kernel(mint * in, mint * out, mint width, mint height, mint pitch)
    int xIndex = blockDim.x*blockIdx.x + threadIdx.x;
    int yIndex = blockDim.y*blockIdx.y + threadIdx.y;
    int index = xIndex + yIndex*pitch;

    if (xIndex >= width || yIndex >= height) return;

    if (xIndex > 0) {
        out[index] = (2*in[index] + in[index + 1])/3;
    } else if (xIndex < width) {
        out[index] = (in[index - 1] + in[index] + in[index + 1])/3;
    } else {
        out[index] = (in[index - 1] + 2*in[index])/3;
    }
}
```

Notice that global memory copies are done three times for the same data. This can be avoided by placing the data temporarily in shared memory.

```
__global__ void xAverage_improved_kernel(mint * in, mint * out, mint width, mint height, min
    extern __shared__ smem[];

    int tx = threadIdx.x, dx = blockDim.x;
    int xIndex = dx*blockIdx.x + tx;
    int yIndex = blockDim.y*blockIdx.y + threadIdx.y;
    int index = xIndex + yIndex*pitch;

    if (yIndex >= height) return;

    smem[threadIdx.x+1] = index < width ? in[index] : in[yIndex*pitch + width - 1];

    if (tx == 0) {
        smem[0] = index > 0 ? in[index-1] : in[yIndex * pitch];
        smem[dx+1] = index+bx < width ? in[index+dx] : in[yIndex*pitch + width - 1];
    }

    __syncthreads();

    if (xIndex < width)
        out[index] = (smem[tx] + smem[tx+1] + smem[tx+2])/3;
}
```

This CUDA program can then be saved and loaded via `CUDAFunctionLoad`.

Compiling for CUDA

CUDALink provides a portable compiling mechanism for CUDA code. This is done through the `NVCCCompiler`, which registers the NVCC compiler found on the system with the `CCompilers` to compile DLLs and executables.

Before loading the `NVCCCompiler` in *CUDALink*, notice the available compilers on the system.

```
In[1]:= Needs["CCompilerDriver`"]
        CCompilers[]

Out[1]= {{Name → Visual Studio,
          Compiler → CCompilerDriver`VisualStudioCompiler`VisualStudioCompiler,
          CompilerInstallation → C:\Program Files (x86)\Microsoft Visual Studio 10.0,
          CompilerName → Automatic}, {Name → Visual Studio,
          Compiler → CCompilerDriver`VisualStudioCompiler`VisualStudioCompiler,
          CompilerInstallation → C:\Program Files (x86)\Microsoft Visual Studio 9.0,
          CompilerName → Automatic}, {Name → Intel Compiler, Compiler →
           CCompilerDriver`IntelCompiler`IntelCompiler, CompilerInstallation →
           C:\Program Files (x86)\Intel\Parallel Studio\Composer\,
          CompilerName → Automatic}}
```

The output above is only seen if you have not loaded the `NVCCCompiler`. If that is the case, then load the *CUDALink* application.

```
In[2]:= Needs["CUDALink`"]
```

Now check the compilers again.

```
In[3]:= CCompilers[]

Out[3]=
```

```
{{Name → Visual Studio,
  Compiler → CCompilerDriver`VisualStudioCompiler`VisualStudioCompiler,
  CompilerInstallation → C:\Program Files (x86)\Microsoft Visual Studio 10.0,
  CompilerName → Automatic}, {Name → Visual Studio,
  Compiler → CCompilerDriver`VisualStudioCompiler`VisualStudioCompiler,
  CompilerInstallation → C:\Program Files (x86)\Microsoft Visual Studio 9.0,
  CompilerName → Automatic}, {Name → Intel Compiler, Compiler →
   CCompilerDriver`IntelCompiler`IntelCompiler, CompilerInstallation →
   C:\Program Files (x86)\Intel\Parallel Studio\Composer\,
  CompilerName → Automatic}, {Name → NVIDIA CUDA Compiler,
  Compiler → NVCCCompiler, CompilerInstallation →
   C:\Users\abduld.WRI\AppData\Roaming\Mathematica\Paclets\Repository\
     CUDAResources-Win64-8.0.0.6\CUDAToolkit\bin64\,
  CompilerName → Automatic}}
```

The `NVCCCompiler` can now be used.

Load an example test file.

```
In[4]:= testFileName = FileNameJoin[{$CUDALinkPath, "SupportFiles", "cudaDLL.cu"}]

Out[4]= C:\Users\abduld.WRI\WolframWorkspaces\Base\CUDALink8\CUDALink\SupportFiles\
        cudaDLL.cu
```

You can see the contents of the file.

```
In[5]:= FilePrint[testFileName]
```

```
extern "C" {

#include "WolframLibrary.h"

__global__ void vecAdd(mint * in, mint * out, mint width) {
    int index = threadIdx.x + blockIdx.x*blockDim.x;
    if (index < width)
        out[index] += in[index];
}

DLLEXPORT mint WolframLibrary_getVersion( ) {
    return WolframLibraryVersion;
}


DLLEXPORT int WolframLibrary_initialize(WolframLibraryData libData) {
    return LIBRARY_NO_ERROR;
}

DLLEXPORT void WolframLibrary_uninitialize(WolframLibraryData libData) {
    return ;
}

DLLEXPORT int oTest(WolframLibraryData libData, mint Argc, MArgument * Args, MArgument Re
    MTensor inTensor, outTensor;
    int * in, * out;
    int * d_in, * d_out;
    int width;

    inTensor  = MArgument_getMTensor(Args[0]);
    outTensor = MArgument_getMTensor(Args[1]);
    width = libData->MTensor_getDimensions(inTensor)[0];

    in = libData->MTensor_getIntegerData(inTensor);
    out = libData->MTensor_getIntegerData(outTensor);

    cudaMalloc((void **) &d_in, width*sizeof(int));
    cudaMalloc((void **) &d_out, width*sizeof(int));

    cudaMemcpy(d_in, in, width * sizeof(int), cudaMemcpyHostToDevice);
    cudaMemcpy(d_out, out, width * sizeof(int), cudaMemcpyHostToDevice);

    dim3 blockDim(2);
    dim3 gridDim(width/2);

    vecAdd<<<blockDim, gridDim>>>(d_in, d_out, width);

    cudaMemcpy(out, d_out, width * sizeof(int), cudaMemcpyDeviceToHost);

    MArgument_setMTensor(Res, outTensor);
    return LIBRARY_NO_ERROR;
}
}
```

Compile the code into a library.

```
In[6]:= CreateLibrary[{testFileName}, "testDLL", "Compiler" → NVCCCompiler]
```

```
Out[6]= C:\Users\abduld.WRI\AppData\Roaming\Mathematica\SystemFiles\LibraryResources\
          Windows-x86-64\testDLL.dll
```

The library is now placed in the above location.

Generating PTX Files

PTX is CUDA bytecode that is able to run on different CUDA cards. The bytecode is then compiled on the fly (using a JIT mechanism).

This defines a simple CUDA kernel.

```
In[1]:= src = "
        __global__ void addTwo(int * in, int * out, int length) {
            int index = threadIdx.x + blockIdx.x*blockDim.x;
            if (index < length)
                out[index] = in[index] + 2;
        }";
```

Setting "CreatePTX"->True when creating the executable will compile to PTX.

```
In[2]:= ptxFile =
         CreateExecutable[src, "test", "Compiler" → NVCCCompiler, "CreatePTX" → True]

Out[2]= C:\Users\abduld.WRI\AppData\Roaming\Mathematica\SystemFiles\LibraryResources\
          Windows-x86-64\test.ptx
```

Here, you print the first 500 characters of the compiled code.

```
In[3]:= StringTake[Import[ptxFile, "Text"], 500]

Out[3]=     .version 1.4
            .target sm_10, map_f64_to_f32
            // compiled with
          C:\Users\abduld.WRI\AppData\Roaming\Mathematica\Paclets\Repository\
          CUDAResources-Win64-8.0.0.6\CUDAToolkit\bin64/../open64/lib//be.exe
            // nvopencc 3.1 built on 2010-06-08

            //-----------------------------------------------------------
            // Compiling
          C:/Users/abduld.WRI/AppData/Local/Temp/tmpxft_00000700_00000000-9_test.cpp3
          .i (C:/Users/abduld.WRI/AppData/Local/Temp/ccBI#.a05668)
            //-----------------------------------------------------
```

Generating CUBIN Files

CUBIN files are CUDA binary files that are compiled for a specific CUDA architecture. CUDAFunctionLoad, for example, will compile the input code to a CUBIN file.

This defines a simple CUDA function.

```
In[4]:= src = "
        __global__ void addTwo(int * in, int * out, int length) {
            int index = threadIdx.x + blockIdx.x*blockDim.x;
            if (index < length)
                out[index] = in[index] + 2;
        }";
```

Setting "CreateCUBIN"->True when creating the executable will compile to CUBIN.

```
In[5]:= cubinFile =
         CreateExecutable[src, "test", "Compiler" → NVCCCompiler, "CreateCUBIN" → True]

Out[5]= C:\Users\abduld.WRI\AppData\Roaming\Mathematica\SystemFiles\LibraryResources\
          Windows-x86-64\test.cubin
```

Here, you print the first 100 characters of the compiled code.

```
In[6]:= StringTake[Import[cubinFile, "Text"], 100]

Out[6]= ELF┐3┐        ┐ ¾             ô└       @

        @ 8 └ @ •
```

Note that, unlike a PTX file that contained ASCII instruction sets, a CUBIN file is an ELF binary.

Printing Debug and Register Information

When debugging or optimizing CUDA code, it is useful to find out what the compiler output is. It is customary, for example, to find the number of registers used up by a CUDA function.

This defines a simple CUDA function.

```
In[7]:= src = "
        __global__ void addTwo(int * in, int * out, int length) {
            int index = threadIdx.x + blockIdx.x*blockDim.x;
            if (index < length)
                out[index] = in[index] + 2;
        }";
```

Setting "Debug"->True and "CompileOptions" -> "--ptxas-options=-v" will instruct the compiler to print debug information and be verbose when generating the binary.

```
In[8]:= CreateExecutable[src, "test", "Compiler" → NVCCCompiler, "CreateCUBIN" → True,
         "Debug" → True, "CompileOptions" → "--ptxas-options=-v"]


C:\Users\abduld.WRI\AppData\Roaming\Mathematica\SystemFiles\LibraryResources\
  Windows-x86-64\Working-abduld1win-5216-6092-4>call "C:\Program
  Files (x86)\Microsoft Visual Studio 9.0\VC\vcvarsall.bat" amd64
Setting environment for using Microsoft Visual Studio 2008 Beta2 x64 tools.
test.cu
tmpxft_00000594_00000000-3_test.cudafe1.gpu
tmpxft_00000594_00000000-8_test.cudafe2.gpu
ptxas info    : Compiling entry function '_Z6addTwoPiS_i' for 'sm_10'
ptxas info    : Used 2 registers, 20+16 bytes smem

Out[8]= C:\Users\abduld.WRI\AppData\Roaming\Mathematica\SystemFiles\LibraryResources\
          Windows-x86-64\test.cubin
```

This simple kernel uses 2 registers, as indicated above.

Writing Kernels for *CUDALink*

Users familiar with CUDA programming might consider the following strategies when programming for *CUDALink*. The strategies help in making the CUDA code more portable, correct, easier to debug, and efficient.

Using Real Types

Because of the lack of double-precision support on most CUDA cards, a CUDA C programmer is forced to use floats to represent floating-point numbers. With *CUDALink*, you can use the `Real_t` type to define a floating-point number that uses the maximum precision found on the CUDA card.

Therefore, users are advised to use code like that below.

```
__device__ Real_t f(Real_t x) {
    return tanf(x);
}

__global__ void secondKernel(Real_t * diff, Real_t h, mint listSize) {
    int index = threadIdx.x + blockIdx.x * blockDim.x;
    Real_t f_n = f(index) / h);
    Real_t f_n1 = f((index + 1.0) / h);
    if( index < listSize) {
        diff[index] = (f_n1 - f_n) / h;
    }
}
```

Instead of code like this.

```
__device__ float f(float x) {
    return tanf(x);
}

__global__ void secondKernel(float * diff, float h, mint listSize) {
    int index = threadIdx.x + blockIdx.x * blockDim.x;
    float f_n = f(((double) index) / h);
    float f_n1 = f((index + 1.0) / h);
    if( index < listSize) {
        diff[index] = (f_n1 - f_n) / h;
    }
}
```

This would ensure maximum compatibility and use the maximum precision available.

Optimization

The compiler can optimize some loops if the user makes the loop parameters a constant. The following is a slightly more optimized version over passing channels as a variable, since the compiler can perform more code optimization.

```
__global__ void colorNegate(unsigned char * img, mint width, mint height) {
```

```
    int xIndex = threadIdx.x + blockIdx.x * blockDim.x;
    int yIndex = threadIdx.y + blockIdx.y * blockDim.y;
    int index = (xIndex + yIndex*width)*CHANNELS;
    if (xIndex < width && yIndex < height) {
#pragma unroll
        for (mint ii = 0; ii < CHANNELS; ii++)
            img[index + ii] = 255 - img[index + ii];
    }
}
```

Rather than make CHANNELS constant in the code, the user can pass it as a "Defines" using CUDAFunctionLoad.

```
CUDAFunctionLoad[...,"Defines"→{"CHANNELS"→3}]
```

Generate C Code and Load It as a Library

Once prototyped, and if code is used very often, the C code representation of the code can be exported using CUDACodeStringGenerate. The resulting C code can be compiled and loaded into CUDAFunctionLoad. Doing so will result in CUDAFunctionLoad taking a different execution path that does less error checking.

Off-Line Compilation

When passing source code into CUDAFunctionLoad, the code is compiled behind the scenes. To avoid the performance hit each time, the user can use CreateExecutable with the NVCCCompiler to compile the CUDA code into a binary and load the CUDAFunction from CUDA binary.

Porting OpenCL to CUDA

Since both *CUDALink* and *OpenCLLink* handle all the underlying bookkeeping for CUDA and OpenCL, the user need only concentrate on the kernel code. This section covers a CUDA-to-OpenCL translation. It is assumed that the user has used *OpenCLLink* to develop the function.

The following table summarizes some of the common changes in the kernel code needed to port OpenCL programs to CUDA.

CUDA	OpenCL
__device__ ...	...
__global__ ...	__kernel ...
... (mint * f, ...)	... (__global mint *, ...)
threadIdx.x	get_local_id(0)
blockIdx	get_group_id
blockDim	get_local_size
threadIdx + blockIdx * blockDim	get_global_id
__shared__	__local

This is a simple OpenCL function that takes input image and color negates it.

```
In[1]:= src = "
        __kernel void imageColorNegate(__global
            mint * img, mint width, mint height, mint channels) {
            mint ii;
            int xIndex = get_global_id(0);
            int yIndex = get_global_id(1);
            int index = channels*(xIndex + yIndex*width);
            if (xIndex < width && yIndex < height) {
                for (ii = 0; ii < channels; ii++)
                    img[index+ii] = 255 - img[index+ii];
            }
        }
        ";
```

Recall that to launch the OpenCL function you perform the following.

```
In[2]:= Needs["OpenCLLink`"]
        colorNegate = OpenCLFunctionLoad[src, "imageColorNegate",
           {{_Integer, _, "InputOutput"}, _Integer, _Integer, _Integer}, {16, 16}];
        {height, width, channels} = ImageDimensions[ ]~
           Join~{ImageChannels[ ]};
        colorNegate[ , width, height, channels]
```



```
Out[5]=
```

The following is changed in order to port to CUDA.

The `__kernel` was changed to `__global__`.

The `__global mint * img` was changed to `mint * img`.

The `get_global_id(0)` was changed to `threadIdx.x + blockIdx.x * blockDim.x`, and the same for `.y`.

In many cases, the above are the only required changes for OpenCL-to-CUDA porting in *Mathematica*. There are a handful of other one-to-one function translations that are readily accessible in an OpenCL or CUDA programming guide.

This is the ported CUDA code.

```
In[6]:= src = "
        __global__ void imageColorNegate(mint
            * img, mint width, mint height, mint channels) {
            mint ii;
            int xIndex = threadIdx.x + blockIdx.x*blockDim.x;
            int yIndex = threadIdx.y + blockIdx.y*blockDim.y;
            int index = channels*(xIndex + yIndex*width);
            if (xIndex < width && yIndex < height) {
                for (ii = 0; ii < channels; ii++)
                    img[index+ii] = 255 - img[index+ii];
            }
        }
        ";
```

This is the exact *Mathematica* functions done for OpenCL, but replacing `OpenCLFunctionLoad` load with `CUDAFunctionLoad`.

```
In[7]:= Needs["CUDALink`"]
        colorNegate = CUDAFunctionLoad[src, "imageColorNegate",
           {{_Integer, _, "InputOutput"}, _Integer, _Integer, _Integer}, {16, 16}];
        {height, width, channels} = ImageDimensions[ ]~
           Join~{ImageChannels[ ]};
        colorNegate[ , width, height, channels]
```

Out[10]=

An alternative to find and replace the mechanism shown above is to generate the kernel code symbolically and manipulate it in *Mathematica*. The following section covers that approach.

Symbolic Code Generation

Mathematica provides SymbolicC, which permits a hierarchical view of C code as *Mathematica*'s own language. This makes it well suited to creating, manipulating, and optimizing C code.

In conjunction with this capability, users can generate CUDA kernel code for several different targets, allowing greater portability, less platform dependency, and better code optimization.

An advantage of using SymbolicC is that you can ensure that the C code contains no syntactical errors, you can generate CUDA programs using SymbolicC and run them using `CUDAFunctionLoad`, and you can ease the porting of CUDA to OpenCL (or vice versa).

This section uses *CUDALink*'s symbolic code-generation capabilities to write an "RGB"-to-"HSV" and "RGB"-to-"HSB" color converter. This conversion is a fairly common operation for image and video processing.

For this tutorial, the *CUDALink* application must first be loaded.

```
In[1]:= Needs["CUDALink`"]
```

Introduction

CUDALink includes symbolic tools that help in writing kernels using SymbolicC.

SymbolicCUDAFunction	symbolic representation of a CUDA function
SymbolicCUDABlockIndex	symbolic representation of a block index CUDA call
SymbolicCUDAThreadIndex	symbolic representation of a thread index CUDA call
SymbolicCUDABlockDimension	symbolic representation of a block dimension CUDA call
SymbolicCUDACalculateKernelIndex	symbolic representation of a CUDA index calculation
SymbolicCUDADeclareIndexBlock	symbolic representation of a CUDA index declaration

Symbolic representations of CUDA programs.

The following is an example kernel written symbolically.

```
In[2]:= symb = SymbolicCUDAFunction["kernelFunctionName",
          {{CPointerType["mint"], "arg1"}, {"mint", "arg2"}},
          CBlock[{
            SymbolicCUDADeclareIndexBlock[2],
            CIf[COperator[Less, {"index", "arg2"}],
             CAssign[CArray["arg1", "index"], 33]
            ]
           }]
         ]

Out[2]= CFunction[{__global__, void}, kernelFunctionName,
         {{CPointerType[mint], arg1}, {mint, arg2}},
         CBlock[{{CDeclare[int, CAssign[xIndex, COperator[Plus, {CMember[threadIdx, x],
                 COperator[Times, {CMember[blockIdx, x], CMember[blockDim, x]}]}]]],
            CDeclare[int, CAssign[yIndex, COperator[Plus, {CMember[threadIdx, y],
                 COperator[Times, {CMember[blockIdx, y], CMember[blockDim, y]}]}]]],
            CDeclare[int, CAssign[index, COperator[Plus,
               {xIndex, COperator[Times, {width, yIndex}]}]]]},
           CIf[COperator[Less, {index, arg2}], CAssign[CArray[arg1, index], 33]]]]
```

This displays the C code generated using ToCCodeString.

```
In[3]:= ToCCodeString[symb]

Out[3]= __global__ void kernelFunctionName(mint* arg1, mint arg2)
        {
        int xIndex = threadIdx.x + blockIdx.x * blockDim.x;
        int yIndex = threadIdx.y + blockIdx.y * blockDim.y;
        int index = xIndex + width * yIndex;
        if( index < arg2)
        {
        arg1[index] = 33;
        }
        }
```

Another reason for writing code symbolically is that you can rewrite the above kernel to OpenCL form by just changing the "CUDA" instances to "OpenCL".

```
In[4]:= Needs["OpenCLLink`"]

In[5]:= symb = SymbolicOpenCLFunction["kernelFunctionName",
          {{CPointerType["mint"], "arg1"}, {"mint", "arg2"}},
          CBlock[{
            SymbolicOpenCLDeclareIndexBlock[2],
            CIf[COperator[Less, {"index", "arg2"}],
             CAssign[CArray["arg1", "index"], 33]
            ]
           }]
         ]
```

```
Out[5]= CFunction[{__kernel, void}, kernelFunctionName,
         {{CPointerType[mint], arg1}, {mint, arg2}},
         CBlock[{{CDeclare[int, CAssign[xIndex, CCall[get_global_id, {0}]]], CDeclare[
             int, CAssign[yIndex, CCall[get_global_id, {1}]]], CDeclare[int, CAssign[
              index, COperator[Plus, {xIndex, COperator[Times, {width, yIndex}]}]]]},
           CIf[COperator[Less, {index, arg2}], CAssign[CArray[arg1, index], 33]]}]]
```

Again, you display the C code using `ToCCodeString`.

```
In[6]:= ToCCodeString[symb]

Out[6]= __kernel void kernelFunctionName(mint* arg1, mint arg2)
        {
        int xIndex = get_global_id(0);
        int yIndex = get_global_id(1);
        int index = xIndex + width * yIndex;
        if( index < arg2)
        {
        arg1[index] = 33;
        }
        }
```

Simple Kernel

CUDALink provides utility functions that perform common GPU kernel programming tasks as discussed above. With them, you will write your first kernel function.

First, load the *CUDALink* application.

```
In[1]:= Needs["CUDALink`"]
```

Your first function will take an integer array and set all its elements to 0. You first need to define your function prototype. The function will be called "`firstKernel`", accepting an input list and the list size. Use the utility functions as follows.

```
In[2]:= SymbolicCUDAFunction["firstKernel",
          {{CPointerType["mint"], "list"}, {"mint", "listSize"}}, CBlock[{
        }]] // ToCCodeString

Out[2]= __global__ void firstKernel(mint* list, mint listSize)
        {
        }
```

Since you will be building this example incremental, and to avoid writing the above each time, you can define a helper function for this example.

```
In[3]:= FirstKernel[api_, body___] := ToCCodeString[
        If[api === "CUDA", SymbolicCUDAFunction, SymbolicOpenCLFunction][
           "firstKernel",
           {{CPointerType["mint"], "list"}, {"mint", "listSize"}}, CBlock[{
        body
        }]]]
```

Test it.

```
In[4]:= FirstKernel["CUDA"]

Out[4]= __global__ void firstKernel(mint* list, mint listSize)
        {
        }
```

Getting the Index

Using the `SymbolicCUDADeclareIndexBlock`, you can find the index of the list element based on the thread index, block index, and block dimensions.

```
In[5]:= FirstKernel["CUDA",
         SymbolicCUDADeclareIndexBlock[1]
        ]

Out[5]= __global__ void firstKernel(mint* list, mint listSize)
        {
        int index = threadIdx.x + blockIdx.x * blockDim.x;
        }
```

Declaring the Body

Since you can launch more threads than you actually have elements, you need to place the function body inside an "if" guard. Not doing so might make your program unpredictable.

```
In[6]:= FirstKernel["CUDA",
         SymbolicCUDADeclareIndexBlock[1],
         CIf[COperator[Less, {"index", "listSize"}], CBlock[{
           }]]
        ]

Out[6]= __global__ void firstKernel(mint* list, mint listSize)
        {
        int index = threadIdx.x + blockIdx.x * blockDim.x;
        if( index < listSize)
        {
        }
        }
```

You can now define the body of the kernel. The body is trivial, setting each element in the list to 0.

```
In[7]:= FirstKernel["CUDA",
         SymbolicCUDADeclareIndexBlock[1],
         CIf[COperator[Less, {"index", "listSize"}], CBlock[{
            CAssign[CArray["list", "index"], 0]
           }]]
        ]

Out[7]= __global__ void firstKernel(mint* list, mint listSize)
        {
        int index = threadIdx.x + blockIdx.x * blockDim.x;
        if( index < listSize)
        {
        list[index] = 0;
        }
        }
```

Testing the First Kernel

Import the *CUDALink* package, if you have not already done so.

```
In[1]:= Needs["CUDALink`"]
```

This defines the inputs.

```
In[2]:= listSize = 100;
        list = ConstantArray[6, listSize];
```

This generates the source code.

```
In[4]:= src = FirstKernel["CUDA",
          SymbolicCUDADeclareIndexBlock[1],
          CIf[COperator[Less, {"index", "listSize"}], CBlock[{
             CAssign[CArray["list", "index"], 0]
            }]]
         ]

Out[4]= __global__ void firstKernel(mint* list, mint listSize)
        {
        int index = threadIdx.x + blockIdx.x * blockDim.x;
        if( index < listSize)
        {
        list[index] = 0;
        }
        }
```

This loads the function.

```
In[5]:= zero = CUDAFunctionLoad[src, "firstKernel", {{_Integer}, _Integer}, 16]

Out[5]= CUDAFunction[<>, firstKernel, {{_Integer}, _Integer}]
```

This runs the function.

```
In[6]:= zero[list, listSize]

Out[6]=
```

```
{{0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0}}
```

Advanced Kernels

In this section you are shown how to write an RGB-to-HSV and RGB-to-HSB converter. These are common conversions in image and video processing.

Helper Functions

SymbolicC only includes C constructs. To make your code more *Mathematica*-like, define the following.

```
In[7]:= CWhich[x_, y_] := CIf[x, y];
        CWhich[x_, y_, tail__] :=
          CIf[x,
           {y},
           If[TrueQ[First[{tail}]],
            Rest[{tail}],
            CWhich[tail]
           ]
          ];
```

`CWhich` rewrites your expression using `CIf`.

```
In[9]:= CWhich[
         COperator[Equal, {x, 1}],
             CAssign[x, 4],
         COperator[Equal, {x, 4}],
             CAssign[x, 7],
         COperator[And, {COperator[Equal, {y, 6}], COperator[Unequal, {j, 5}]}],
             CAssign[x, 9],
         True,
             CAssign[x, 11]
        ]

Out[9]= CIf[COperator[Equal, {x, 1}], {CAssign[x, 4]},
         CIf[COperator[Equal, {x, 4}], {CAssign[x, 7]},
          CIf[COperator[And, {COperator[Equal, {y, 6}], COperator[Unequal, {j, 5}]}],
           {CAssign[x, 9]}, {CAssign[x, 11]}]]]
```

This converts the above expression into C code.

```
In[10]:= ToCCodeString[%]

Out[10]= if( x == 1)
         {
         x = 4;
         }
         else if( x == 4)
         {
         x = 7;
         }
         else if( y == 6 && j != 5)
         {
         x = 9;
         }
         else
         {
         x = 11;
         }
```

Use this to reimplement the code found in `FileNameJoin[{$CUDALinkPath, "SupportFiles", "colorConvert.cu"}]`.

Color Convert

Break up the problem into its components. First, define the RGB-to-Hue function. This function is common between RBG-to-HSV and RGB-to-HSB.

The following writes the RGB-to-H convert function.

```
In[11]:= RGB2H = {
           CWhich[
            COperator[Equal, {maxPixel, minPixel}], CAssign[x, 0],
            COperator[Equal, {maxPixel, r}], {
             CAssign[x, COperator[Plus,
               {COperator[Times, {60.0, COperator[Divide, {COperator[Subtract, {g, b}],
                     COperator[Subtract, {maxPixel, minPixel}]}]}], 360.0}]],
             CIf[COperator[GreaterEqual, {x, 360.0}],
              CAssign[x, COperator[Subtract, {x, 360.0}]]
             ]},
            COperator[Equal, {maxPixel, g}], CAssign[x, COperator[Plus,
              {COperator[Times, {60.0, COperator[Divide, {COperator[Subtract, {b, r}],
                    COperator[Subtract, {maxPixel, minPixel}]}]}], 120.0}]],
            COperator[Equal, {maxPixel, b}], CAssign[x, COperator[Plus,
              {COperator[Times, {60.0, COperator[Divide, {COperator[Subtract, {r, g}],
                    COperator[Subtract, {maxPixel, minPixel}]}]}], 240.0}]],
           CAssign[x, COperator[Divide, {x, 360.0}]]
          };
```

This transforms the expression into C.

```
In[12]:= ToCCodeString[RGB2H, "Indent" → Automatic]

Out[12]= if( maxPixel == minPixel)
         {
             x = 0;
         }
         else if( maxPixel == r)
         {
             x = 60. * ((g - b) / (maxPixel - minPixel)) + 360.;
             if( x >= 360.)
             {
                 x = x - 360.;
             }
         }
         else if( maxPixel == g)
         {
             x = 60. * ((b - r) / (maxPixel - minPixel)) + 120.;
         }
         else if( maxPixel == b)
         {
             x = 60. * ((r - g) / (maxPixel - minPixel)) + 240.;
         }
         x = x / 360.;
```

This writes the saturation in case of HSB.

```
In[13]:= ToCCodeString[RGB2HSBS = CIf[COperator[Equal, {maxPixel, 0}],
           CAssign[y, 0],
           CAssign[y,
            COperator[Divide, {COperator[Subtract, {maxPixel, minPixel}], maxPixel}]]],
          "Indent" → Automatic]

Out[13]= if( maxPixel == 0)
         {
             y = 0;
         }
         else
         {
             y = (maxPixel - minPixel) / maxPixel;
         }
```

This defines the formula to find the brightness.

```
In[14]:= RGB2HSBB =
          CAssign[z, COperator[Times, {0.5, COperator[Plus, {maxPixel, minPixel}]}]]

Out[14]= CAssign[z, COperator[Times, {0.5, COperator[Plus, {maxPixel, minPixel}]}]]
```

The same is done for RGB2HSV.

```
In[15]:=
```

```
ToCCodeString[RGB2HSVS = CIf[COperator[Equal, {maxPixel, minPixel}],
   CAssign[y, 0],
   {CIf[COperator[GreaterEqual, {COperator[Plus, {maxPixel, minPixel}], 1}],
     CAssign[y, COperator[Divide, {COperator[Subtract, {maxPixel, minPixel}],
        COperator[Plus, {maxPixel, minPixel}]}]],
     CAssign[y, COperator[Divide, {COperator[Subtract, {maxPixel, minPixel}],
        COperator[Plus, {-1, maxPixel, minPixel}]}]]]}], "Indent" → Automatic]
```

Out[15]=
```
if( maxPixel == minPixel)
{
    y = 0;
}
else
{
    if( maxPixel + minPixel >= 1)
    {
        y = (maxPixel - minPixel) / (maxPixel + minPixel);
    }
    else
    {
        y = (maxPixel - minPixel) / (-1 + maxPixel + minPixel);
    }
}
```

In[16]:=
```
RGB2HSVV = CAssign[z, maxPixel]
```

Out[16]=
```
CAssign[z, maxPixel]
```

Notice that you need to define what `max` and `min` are.

In[17]:=
```
CMax[x_, y_] := CCall[max, {x, y}]
```

In[18]:=
```
CMax[{x_, y_, tail___}] := CMax[x, CMax[y, tail]]
```

In[19]:=
```
CMin[x_, y_] := CCall[min, {x, y}]
```

In[20]:=
```
CMin[{x_, y_, tail___}] := CMin[x, CMin[y, tail]]
```

Putting everything together, `RGB2HSV` is defined as follows.

In[21]:=
```
ToCCodeString[RGB2HSV = {
    CAssign[maxPixel, CMax[{r, g, b}]],
    CAssign[minPixel, CMin[{r, g, b}]],
    RGB2H,
    RGB2HSVS,
    RGB2HSVV
   }, "Indent" → Automatic]
```

Out[21]=

```
maxPixel = max(r, max(g, b));
minPixel = min(r, min(g, b));
if( maxPixel == minPixel)
{
    x = 0;
}
else if( maxPixel == r)
{
    x = 60. * ((g - b) / (maxPixel - minPixel)) + 360.;
    if( x >= 360.)
    {
        x = x - 360.;
    }
}
else if( maxPixel == g)
{
    x = 60. * ((b - r) / (maxPixel - minPixel)) + 120.;
}
else if( maxPixel == b)
{
    x = 60. * ((r - g) / (maxPixel - minPixel)) + 240.;
}
x = x / 360.;
if( maxPixel == minPixel)
{
    y = 0;
}
else
{
    if( maxPixel + minPixel >= 1)
    {
        y = (maxPixel - minPixel) / (maxPixel + minPixel);
    }
    else
    {
        y = (maxPixel - minPixel) / (-1 + maxPixel + minPixel);
    }
}
z = maxPixel;
```

Similarly, RGB2HSB is defined as follows.

```
In[22]:= ToCCodeString[RGB2HSB = {
           CAssign[maxPixel, CMax[{r, g, b}]],
           CAssign[minPixel, CMin[{r, g, b}]],
           RGB2H,
           RGB2HSBS,
           RGB2HSBB
         }, "Indent" → Automatic]

Out[22]=
```

```
maxPixel = max(r, max(g, b));
minPixel = min(r, min(g, b));
if( maxPixel == minPixel)
{
    x = 0;
}
else if( maxPixel == r)
{
    x = 60. * ((g - b) / (maxPixel - minPixel)) + 360.;
    if( x >= 360.)
    {
        x = x - 360.;
    }
}
else if( maxPixel == g)
{
    x = 60. * ((b - r) / (maxPixel - minPixel)) + 120.;
}
else if( maxPixel == b)
{
    x = 60. * ((r - g) / (maxPixel - minPixel)) + 240.;
}
x = x / 360.;
if( maxPixel == 0)
{
    y = 0;
}
else
{
    y = (maxPixel - minPixel) / maxPixel;
}
z = 0.5 * (maxPixel + minPixel);
```

To generate the kernel function, you use *Mathematica*'s functional capabilities. This defines a helper function.

```
In[27]:= ToGPUKernelFunction[funName_, fun_, targetPrecision_] :=
 With[{realType = If[targetPrecision === "Single", "float", "double"]},
  SymbolicCUDAFunction[funName,
   {{CPointerType[realType], "input"}, {CPointerType[realType], "output"},
    {"mint", "width"}, {"mint", "height"}}, CBlock[{
    SymbolicCUDADeclareIndexBlock[2, "width"],
    CAssign[TimesBy, "index", 3],
    CDeclare[realType, {x, y, z, maxPixel, minPixel}],
    CIf[COperator[And, {COperator[Less, {"xIndex", "width"}],
       COperator[Less, {"yIndex", "height"}]}], {
      MapThread[CDeclare[realType, CAssign[#1, CArray["input",
           COperator[Plus, {"index", #2}]]]] &, {{"r", "g", "b"}, {0, 1, 2}}],
      fun,
      MapThread[CAssign[CArray["output", COperator[Plus, {"index", #1}]],
        #2] &, {{0, 1, 2}, {"x", "y", "z"}}]
     }]
    }]]
 ]
```

Using the above function, you can define the RGB-to-HSB operation to use single-precision arithmetic.

```
In[28]:= ToCCodeString[
 ToGPUKernelFunction["rgb2hsb", RGB2HSB, "Single"], "Indent" → Automatic]

Out[28]= __global__ void rgb2hsb(float* input, float* output, mint width, mint height)
{
    int xIndex = threadIdx.x + blockIdx.x * blockDim.x;
    int yIndex = threadIdx.y + blockIdx.y * blockDim.y;
    int index = xIndex + width * yIndex;
    index *= 3;
    float x, y, z, maxPixel, minPixel;
    if( xIndex < width && yIndex < height)
    {
        float r = input[index + 0];
        float g = input[index + 1];
        float b = input[index + 2];
        RGB2HSB;
        output[index + 0] = x;
        output[index + 1] = y;
        output[index + 2] = z;
    }
}
```

This generates the code for double precision.

```
In[29]:= ToCCodeString[
          ToGPUKernelFunction["rgb2hsb", RGB2HSB, "Double"], "Indent" → Automatic]

Out[29]= __global__ void rgb2hsb(double*
           input, double* output, mint width, mint height)
         {
             int xIndex = threadIdx.x + blockIdx.x * blockDim.x;
             int yIndex = threadIdx.y + blockIdx.y * blockDim.y;
             int index = xIndex + width * yIndex;
             index *= 3;
             double x, y, z, maxPixel, minPixel;
             if( xIndex < width && yIndex < height)
             {
                 double r = input[index + 0];
                 double g = input[index + 1];
                 double b = input[index + 2];
                 RGB2HSB;
                 output[index + 0] = x;
                 output[index + 1] = y;
                 output[index + 2] = z;
             }
         }
```

The same can be done for the RGB-to-HSV operation.

```
In[30]:= ToCCodeString[
          ToGPUKernelFunction["rgb2hsv", RGB2HSV, "Single"], "Indent" → Automatic]

Out[30]= __global__ void rgb2hsv(float* input, float* output, mint width, mint height)
         {
             int xIndex = threadIdx.x + blockIdx.x * blockDim.x;
             int yIndex = threadIdx.y + blockIdx.y * blockDim.y;
             int index = xIndex + width * yIndex;
             index *= 3;
             float x, y, z, maxPixel, minPixel;
             if( xIndex < width && yIndex < height)
             {
                 float r = input[index + 0];
                 float g = input[index + 1];
                 float b = input[index + 2];
                 RGB2HSV;
                 output[index + 0] = x;
                 output[index + 1] = y;
                 output[index + 2] = z;
             }
         }
```

Running the Program

The above code can be run using `CUDAFunctionLoad`. First, generate the source in single precision.

```
In[27]:= src = ToCCodeString[ToGPUKernelFunction["rgb2hsb", RGB2HSB, "Single"]];
```

Before running the code on the GPU, you need to define some parameters that are required. This defines the input and output image. Notice that the output is of type `Real`, since HSV and HSB are real valued.

```
In[28]:= img =
```

```
;
InputImage = ImageData[img];
OutputImage = ConstantArray[1.0, Dimensions[InputImage]];
{height, width} = ImageDimensions[img];
```

This loads the function into *Mathematica*.

```
In[29]:= rgb2hsb = CUDAFunctionLoad[src, "rgb2hsb",
           {{"Float", "Input"}, {"Float", "Output"}, _Integer, _Integer}, {16, 16}]

Out[29]= CUDAFunction[<>, rgb2hsb, {{Float, Input}, {Float, Output}, _Integer, _Integer}]
```

This runs the function.

```
In[30]:= res = rgb2hsb[InputImage, OutputImage, width, height];
```

This displays the result.

```
In[31]:= Image[First[res], ColorSpace → "HSB"]
```

Out[31]=

Related Guides

- Running Computations on GPU Using CUDA
- Running Computations on GPU Using OpenCL
- C/C++ Language Interface
- Calling C Compilers from *Mathematica*

Related Tutorials

- *CUDALink* User Guide
- Introduction
- Setup and Operations
- Functions
- Memory
- Applications
- Multiple Devices
- Reference

Give Feedback