Parallel programming in OpenCL

Part 1/3 – OpenCL framework

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Single Program Multiple Data (SPMD)

Consider the following vector addition example

Serial program: one program completes the entire task

SPMD program: multiple copies of the same program run on different chunks of the data

Multiple copies of the same program execute on different data in parallel
Parallel Software – SPMD

- In the vector addition example, each chunk of data could be executed as an independent thread.
- On modern CPUs, the overhead of creating threads is so high that the chunks need to be large.
  - In practice, usually a few threads (about as many as the number of CPU cores) and each is given a large amount of work to do.
- For GPU programming, there is low overhead for thread creation, so we can create one thread per loop iteration.
Parallel Software – SPMD

**Single-threaded (CPU)**

// there are N elements
for(i = 0; i < N; i++)
  C[i] = A[i] + B[i]

**Multi-threaded (CPU)**

// tid is the thread id
// P is the number of cores
for(i = 0; i < tid*N/P; i++)
  C[i] = A[i] + B[i]

**Massively Multi-threaded (GPU)**

// tid is the thread id

Time

<table>
<thead>
<tr>
<th></th>
<th>T0</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
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<th>T11</th>
<th>T12</th>
<th>T13</th>
<th>T14</th>
<th>T15</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>1</td>
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<td>14</td>
<td>15</td>
</tr>
</tbody>
</table>

From: OpenCL 1.2 University Kit - [http://developer.amd.com/partners/university-programs/](http://developer.amd.com/partners/university-programs/)
Parallel programming frameworks

- These are some of more relevant frameworks for creating parallelized code.

- **CPU**
  - OpenMP
  - OpenACC

- **GPU**
  - CUDA
  - Metal
OpenCL

- OpenCL is a framework for writing parallelized code for CPUs, GPUs, DSPs, FPGAs and other processors
- Initially developed by Apple, now supported by AMD, IBM, Qualcomm, Intel and Nvidia

Version

- Latest: OpenCL 3.0
  - OpenCL C++ kernel language
  - SPIR-V as intermediate representation for kernels
    - Vulcan uses the same Standard Portable Intermediate Representation
  - AMD, Intel, Nvidia
- Mostly supported: OpenCL 1.2
  - OSX, older GPUs
OpenCL platforms and drivers

To run OpenCL code you need:
- Generic ICD loader
  - Included in the OS
- Installable Client Driver
  - From Nvidia, Intel, etc.
- This applies to Windows and Linux, only one platform on Mac

To develop OpenCL code you need:
- OpenCL headers/libraries
  - Included in the SDKs
    - Nvidia – CUDA Toolkit
    - Intel OpenCL SDK
  - But lightweight options are also available
Programming OpenCL

- OpenCL natively offers C99 API
- But there is also a standard OpenCL C++ API wrapper
  - Strongly recommended – reduces the amount of code
- Programming OpenCL is similar to programming shaders in OpenGL
  - Host code runs on CPU and invokes kernels
  - Kernels are written in C-like programming language
    - In many respects similar to GLSL
  - Kernels are passed to API as strings and compiled at runtime
    - Kernels are usually stored in text files
    - Kernels can be precompiled into SPIR from OpenCL 2.1
Example: Step 1 - Select device

```cpp
// get all platforms (drivers)
std::vector<cl::Platform> all_platforms;
cl::Platform::get(&all_platforms);
if (all_platforms.size() == 0){
    std::cout << "No platforms found. Check OpenCL installation!\n";
    exit(1);
}
cl::Platform default_platform = all_platforms[0];
std::cout << "Using platform: " << default_platform.getInfo<CL_PLATFORM_NAME>() << "\n";

// get default device of the default platform
std::vector<cl::Device> all_devices;
default_platform.getDevices(CL_DEVICE_TYPE_ALL, &all_devices);
if (all_devices.size() == 0){
    std::cout << "No devices found. Check OpenCL installation!\n";
    exit(1);
}
cl::Device default_device = all_devices[0];
std::cout << "Using device: " << default_device.getInfo<CL_DEVICE_NAME>() << "\n";
```
Example: Step 2 - Build program

Create context -> Load sources (usually from files) -> Create Program -> Build Program

c::Context context({ default_device });

c::Program::Sources sources;
// kernel calculates for each element C=A+B
std::string kernel_code =
  "__kernel void simple_add(__global const int* A, __global const int* B, __global int* C) {
  int index = get_global_id(0);
};",
sources.push_back({ kernel_code.c_str(), kernel_code.length() });

c::Program program(context, sources);
try {
  program.build({ default_device });
}
catch (cl::Error err) {
  std::cout << "Error building: " <<
    program.getBuildInfo<CL_PROGRAM_BUILD_LOG>(default_device) << "\n";
  exit(1);
}
Example: Step 3 - Create Buffers and copy memory

// create buffers on the device
cl::Buffer buffer_A(context, CL_MEM_READ_WRITE, sizeof(int) * 10);
cl::Buffer buffer_B(context, CL_MEM_READ_WRITE, sizeof(int) * 10);
cl::Buffer buffer_C(context, CL_MEM_READ_WRITE, sizeof(int) * 10);

int A[] = { 0, 1, 2, 3, 4, 5, 6, 7, 8, 9 };
int B[] = { 0, 1, 2, 0, 1, 2, 0, 1, 2, 0 };

// create queue to which we will push commands for the device.
cl::CommandQueue queue(context, default_device);

// write arrays A and B to the device
queue.enqueueWriteBuffer(buffer_A, CL_TRUE, 0, sizeof(int) * 10, A);
queue.enqueueWriteBuffer(buffer_B, CL_TRUE, 0, sizeof(int) * 10, B);
Example: Step 4 - Execute Kernel and retrieve the results

cl::Kernel kernel(program, "simple_add");

kernel.setArg(0, buffer_A);
kernl.setArg(1, buffer_B);
kernl.setArg(2, buffer_C);
queue.enqueueNDRangeKernel(kernel, cl::NullRange, cl::NDRange(10), cl::NullRange);

int C[10];
//read result C from the device to array C
queue.enqueueReadBuffer(buffer_C, CL_TRUE, 0, sizeof(int) * 10, C);
queue.finish();

std::cout << " result: \n"
for (int i = 0; i < 10; i++){
    std::cout << C[i] << " "
}
std::cout << std::endl;

Our Kernel was

__kernel void simple_add(__read_only const int* A,
__read_only const int* B,
__write_only int* C) {

    int index = get_global_id(0);
};
OpenCL API Class Diagram

- **Platform** – Nvidia CUDA
- **Device** – GeForce 1080
- **Program** – collection of kernels
- **Buffer or Image** – device memory
- **Sampler** – how to interpolate values for Image
- **Command Queue** – put a sequence of operations there
- **Event** – to notify that something has been done

From: OpenCL API 1.2 Reference Card
Platform model

- The host is whatever the OpenCL library runs on
  - Usually x86 CPUs for both NVIDIA and AMD
- Devices are processors that the library can talk to
  - CPUs, GPUs, DSPs and generic accelerators
- For AMD
  - All CPUs are combined into a single device (each core is a compute unit and processing element)
  - Each GPU is a separate device
Execution model

- Each kernel executes on 1D, 2D or 3D array (NDRange)
- The array is split into work-groups
- Work items (threads) in each work-group share some local memory
- Kernel can query
  - `get_global_id(dim)`
  - `get_group_id(dim)`
  - `get_local_id(dim)`
- Work items are not bound to any memory entity (unlike GLSL shaders)
Memory model

- **Host memory**
  - Usually CPU memory, device does not have access to that memory

- **Global memory** [__global__]
  - Device memory, for storing large data

- **Constant memory** [__constant__]

- **Local memory** [__local__]
  - Fast, accessible to all work-items (threads) within a workgroup

- **Private memory** [__private__]
  - Accessible to a single work-item (thread)
Memory objects

- **Buffer**
  - ArrayBuffer in OpenGL
  - Accessed directly via C pointers

- **Image**
  - Texture in OpenGL
  - Access via texture look-up function
  - Can interpolate values, clamp, etc.

This diagram is incomplete – there are more memory objects
Programming model

- Data parallel programming
  - Each NDRange element is assigned to a work-item (thread)
  - Each kernel can use vector-types of the device (float4, etc.)

- Task-parallel programming
  - Multiple different kernels can be executed in parallel

- Command queue

  clCreateCommandQueue(
    cl_context context,
    cl_device_id device,
    cl_command_queue_properties properties,
    cl_int* errcode_ret)

  CL_QUEUE_OUT_OF_ORDER_EXEC_MODE_ENABLE
  Execute out-of-order if specified, in order otherwise

  Provides means to both synchronize kernels and execute them in parallel
Parallel programming in OpenCL
Part 2/3 – Thread mapping

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Thread Mapping

- By using different mappings, the same thread can be assigned to access different data elements
- The examples below show three different possible mappings of threads to data (assuming the thread id is used to access an element)

Mapping

<table>
<thead>
<tr>
<th>Mapping</th>
<th>Thread IDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>int tid = get_global_id(1) * get_global_size(0) + get_global_id(0);</td>
<td>0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15</td>
</tr>
<tr>
<td>int tid = get_global_id(0) * get_global_size(1) + get_global_id(1);</td>
<td>0 4 8 12 1 5 9 13 2 6 10 14 3 7 11 15</td>
</tr>
<tr>
<td>int tid = get_group_id(1) * get_num_groups(0) * group_size + get_group_id(0) * group_size + get_local_id(1) * get_local_size(0) + get_local_id(0);</td>
<td>0 1 4 5 2 3 6 7 8 9 12 13 10 11 14 15</td>
</tr>
</tbody>
</table>

*assuming 2x2 groups

From: OpenCL 1.2 University Kit - http://developer.amd.com/partners/university-programs/
Thread Mapping

- Consider a serial matrix multiplication algorithm

```c
for (i1=0; i1 < M; i1++)
    for (i2=0; i2 < N; i2++)
        for (i3=0; i3 < P; i3++)
            C[i1][i2] += A[i1][i3]*B[i3][i2];
```

- This algorithm is suited for output data decomposition
  - We will create $N \times M$ threads
    - Effectively removing the outer two loops
  - Each thread will perform $P$ calculations
    - The inner loop will remain as part of the kernel

- Should the index space be $M \times N$ or $N \times M$?
Thread Mapping

- Thread mapping 1: with an MxN index space, the kernel would be:

  ```
  int tx = get_global_id(0);
  int ty = get_global_id(1);
  for (i3=0; i3<P; i3++)
    C[tx][ty] += A[tx][i3]*B[i3][ty];
  ```

- Thread mapping 2: with an NxM index space, the kernel would be:

  ```
  int tx = get_global_id(0);
  int ty = get_global_id(1);
  for (i3=0; i3<P; i3++)
    C[ty][tx] += A[ty][i3]*B[i3][tx];
  ```

- Both mappings produce functionally equivalent versions of the program
Thread Mapping

- This figure shows the execution of the two thread mappings on NVIDIA GeForce 285 and 8800 GPUs

- Notice that mapping 2 is far superior in performance for both GPUs
Thread Mapping

- The discrepancy in execution times between the mappings is due to data accesses on the global memory bus
  - Assuming row-major data, data in a row (i.e., elements in adjacent columns) are stored sequentially in memory
  - To ensure coalesced accesses, consecutive threads in the same wavefront should be mapped to columns (the second dimension) of the matrices
    - This will give coalesced accesses in Matrices B and C
    - For Matrix A, the iterator i3 determines the access pattern for row-major data, so thread mapping does not affect it
Parallel programming in OpenCL

Part 3/3 – Reduction

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Reduction

- GPU offers very good performance for tasks in which the results are stored independently
  - Process N data items and store in N memory location

- But many common operations require reducing N values into 1 or few values
  - sum, min, max, prod, min, histogram, …

- Those operations require an efficient implementation of reduction

```c
float reduce_sum(float* input, int length) {
    float accumulator = input[0];
    for(int i = 1; i < length; i++)
        accumulator += input[i];
    return accumulator;
}
```

- The following slides are based on AMD’s OpenCL™ Optimization Case Study: Simple Reductions
Reduction tree for the min operation

```c
__kernel
void reduce_min(__global float* buffer,
    __local float* scratch,
    __const int length,
    __global float* result) {

    int global_index = get_global_id(0);
    int local_index = get_local_id(0);
    // Load data into local memory
    if (global_index < length) {
        scratch[local_index] = buffer[global_index];
    } else {
        scratch[local_index] = INFINITY;
    }
    barrier(CLK_LOCAL_MEM_FENCE);
    for(int offset = get_local_size(0) / 2;
        offset > 0; offset >>= 1) {
        if (local_index < offset) {
            float other = scratch[local_index + offset];
            float mine = scratch[local_index];
            scratch[local_index] = (mine < other) ? mine : other;
        }
        barrier(CLK_LOCAL_MEM_FENCE);
    }
    if (local_index == 0) {
        result[get_group_id(0)] = scratch[0];
    }
}
```

- barrier ensures that all threads (work units) in the local group reach that point before execution continue
- Each iteration of the for loop computes next level of the reduction pyramid

Parallel Reduction Tree for Commutative Operator

SIMD Utilization for Reduction Tree
Multistage reduction

- The local memory is usually limited (e.g. 50kB), which restricts the maximum size of the array that can be processed.
- Therefore, for large arrays need to be processed in multiple stages.
  - The result of a local memory reduction is stored in the array and then this array is reduced.
Two-stage reduction

First stage: serial reduction by N concurrent threads
- Number of threads < data items

Second stage: parallel reduction in local memory

```
__kernel
void reduce(__global float* buffer,
            __local float* scratch,
            __const int length,
            __global float* result) {

    int global_index = get_global_id(0);
    float accumulator = INFINITY;
    // Loop sequentially over chunks of input vector
    while (global_index < length) {
        float element = buffer[global_index];
        accumulator = (accumulator < element) ?
                       accumulator : element;
        global_index += get_global_size(0);
    }

    // Perform parallel reduction
    [The same code as in the previous example]
}
```
Reduction execution times on CPU/GPU

- Different reduction algorithm may be optimal for CPU and GPU
- This can also vary from one GPU to another

Better way?

- **Halide** - a language for image processing and computational photography
  - Code written in a high-level language, then translated to x86/SSE, ARM, CUDA, OpenCL
  - The optimization strategy defined separately as a *schedule*
  - Auto-tune software can test thousands of schedules and choose the one that is the best for a particular platform
  - (Semi-)automatically find the best trade-offs for a particular platform
  - Designed for image processing but similar languages created for other purposes
OpenCL resources

- https://www.khronos.org/registry/OpenCL/
- Reference cards
  - Google: “OpenCL API Reference Card”
- AMD OpenCL Programming Guide
  - http://developer.amd.com/wordpress/media/2013/07/AMD_Accelerated_Parallel_Processing_OC