Writing Optimal OpenCL™ Code with Intel® OpenCL SDK

Performance Guide

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Contents

1 About This Document

This document highlights general principles of efficient programming for modern Intel® architectures using OpenCL™. It focuses on CPU-specific optimization fundamentals without explaining higher level tool chain. For this information, please see the documents referred in the Related Documents section of this guide.

1.1 Prerequisites

This document assumes background knowledge of OpenCL. You should also be familiar with the basic concepts of Single Instruction Multiple Data (SIMD) vector instruction sets.

To get started, you can see the OpenCL specification [2] or the Overview presentation of OpenCL at http://www.khronos.org.

1.2 Related Documents

The following is a list of documents referenced in this Guide:

[1] Intel(R) OpenCL SDK User Guide

This document is located in the Intel® OpenCL SDK installation directory: `<install-dir>\doc\`

[2] OpenCL Specification Version 1.1

http://www.khronos.org/registry/cl/specs/opencl-1.1.pdf

2 Introduction

Basically, you can achieve parallelism via concurrent work-items execution. This guide explains how you can benefit from the automatic vectorization using OpenCL on Intel CPUs. Another option to consider is using vector data types within a work-item. This approach is sometimes referred to as *explicit vectorization*.

OpenCL permits you to use both Data Parallel and Task Parallel Programming Models [2]. The following sections of this guide introduce a few OpenCL concepts, provide an overview of these programming models, and give optimization tips for each model.

2.1 Basic OpenCL™ Concepts

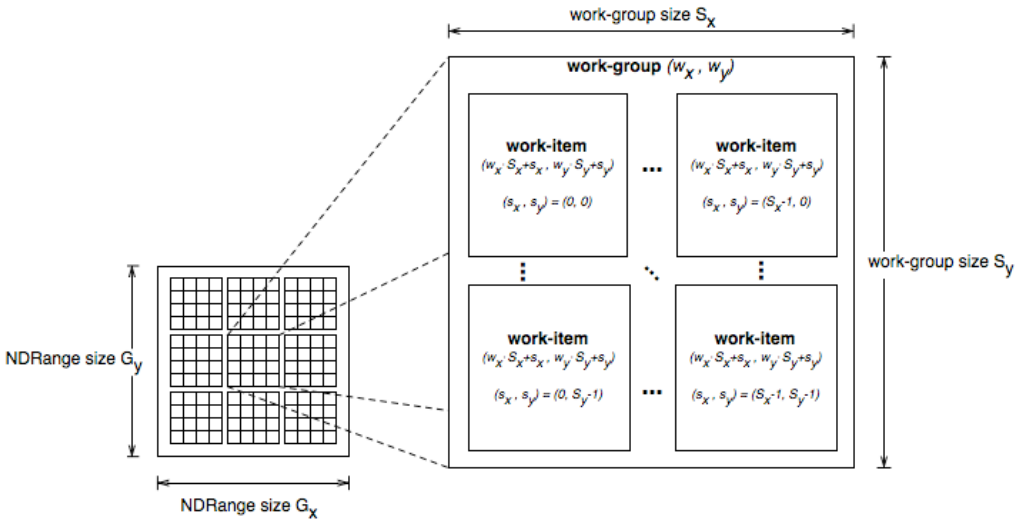
One of the main concepts in OpenCL is a *kernel* – a function declared in an OpenCL program. A running instance of a kernel code is called a *work-item*.

Each kernel is compiled for the specific *device(s)* that consist of *compute units*. Work-items are executed on the compute units by *work-groups*. Each work-group has the following properties:

- Data sharing between work-items via local memory
- Synchronization between work-items via barriers and memory fences
- Special work-group level built-in functions, such as `work_group_copy`.

A multi-core CPU constitutes a single OpenCL device. Multiple CPUs also appear a single OpenCL device. According to this logic, separate cores are compute units. The “device fission” extension (introduced with Beta release of SDK) relaxes this model; refer to the [1] for description.

The main difference between the traditional C execution model and OpenCL execution model is that kernel instances are executed concurrently over a virtual grid defined by the *host code*. Consider the following figure [2]:



When launching the kernel for execution, the host code defines the grid dimensions, or the global work size. The host code can also define the partitioning to work-groups, or leave it to the implementation. During the execution, the implementation runs a single work-item for each point on the grid. It also groups the execution on compute units according to the work-group size.

The order of execution of work-items within a work-group, as well as the order of work-groups, is implementation-specific.

NOTE: Task-Parallel OpenCL programming model is also mapped to this model. The task parallel execution runs a single work-group, with a single work-item in it.

2.2 Using Data Parallelism

OpenCL basic data parallelism uses Single Program Multiple Data (SPMD) coding style. SPMD resembles fragment processing with pixel shaders in the context of graphics.

In this programming model, a kernel is executed concurrently on multiple elements. Each element has its own data and its own program counter. If elements are vectors of any kind (for example, 4-way pixel values for RGBA image), using vector types is a natural choice.

This section describes how to convert regular C code to an OpenCL program using a simple "hello world" style example. Consider the following C function:

```
void scalar_mul(int n, const float *a, const float *b, float *result)
{
  int i;
  for (i = 0; i < n; ++i)
    result[i] = a[i] * b[i];
}
```

This function performs element-wise multiplication of two arrays, `a` and `b`. Each element in `result` stores the product of the matching elements from arrays `a` and `b`.

Note the following:

- The `for` loop contains two parts: the range of operation (a single dimension containing `n` elements), and the internal parallel operation.
- The basic operation is done on scalars (floats).
- Loop iterations are independent.

In OpenCL, the same function looks as follows:

```
__kernel void scalar_mul(__global const float *a,
                         __global const float *b,
                         __global float *result)
{
  size_t id = get_global_id(0);
  result[id] = a[id] * b[id];
}
```

The kernel function performs the same basic element-wise multiplication of two scalars. The index is provided by using a built-in function that gives the *global ID*, a unique number for each work-item within the grid (`NDRange`).

Note that the code itself does not imply any parallelism. Only the combination of the code with the execution over a global grid exploits the parallelism of the device.

This parallelization method abstracts the details of the underlying hardware. You can write your code according to the native data types of the algorithm, leaving the actual mapping to specific hardware to the implementation.

Section 2.4 discusses another way of writing OpenCL kernels, in which you tailor your code to the underlying hardware. This might sacrifice *performance portability* but also provides maximum performance gain on the specific platform.

2.3 Methods in Coding for Intel Architecture

Modern Intel processors provide acceleration using Single Instruction Multiple Data (SIMD) instruction sets that include a wide range of Intel® Streaming SIMD Extensions (Intel® SSE) instructions.

Today CPUs support SIMD parallelism on relatively short vectors. By processing multiple data elements in a lock-step, these ISA extensions enable data parallelism usage in scientific, engineering, or graphic applications.

On Intel SIMD architecture, vector registers can store a group of data elements of the same data type, such as float or char. The number of data elements packed depends on the vector width and the base data type width. For example, the vector width for processors based on the Intel® microarchitecture code-named Nehalem is 128 bits. Each vector (XMM) register can store four floats, four 32-bit integers, eight shorts, 16 chars, and so on.

When dealing with code written in SPMD style, the OpenCL implementation can map the work-items to the hardware in one of the following ways:

- Mapping work-items to be executed via scalar code. Work-items are executed one-by-one.
- Mapping work-items to SIMD elements, as explained above. In this case, several work-items are packed together to run simultaneously.

Intel® OpenCL SDK contains an implicit CPU vectorization module that implements the second scheme. Depending on the kernel code, this operation may have some limitations. If the vectorization module optimization is disabled, SDK uses the first scheme.

2.4 Using Vector Data Types

You can maximize utilization of the CPU vector units by using vector data types directly through the kernel code. In this style, you map vector data types directly to the vector registers. Thus, the data types used should match the width of the underlying SIMD. For example, on processors based on the Intel® microarchitecture code-named Nehalem you should use float4, int4, short8 and so on, as explained in the section above.

Notice that this way a code is tied to the specific underlying hardware (e.g. SIMD width). This might somewhat sacrifice the performance portability but gain the maximum performance on the specific platform.

You might want to use even wider data types, such as int8 or float16, to transparently benefit from upcoming 8- or 16-way SIMD. However, using types wider than the underlying SIMD is somewhat similar to loop-unrolling. This might be performance advantageous in some cases, but also increases register pressure, so some experimenting is required.

With vector data types, each work-item now processes N elements. You should reduce the size of the grid (number of work-items required to process the same dataset) accordingly by N.

In this coding style, you plan the vector-level parallelism yourself (instead of relying on the implicit vectorization module described in the following chapter). This approach can be beneficial in these scenarios:

- You are porting the code that originally used Intel® SSE/AVX instructions.
- You want to benefit from hand-tuned vectorization of your code.

The following example shows the same multiplication kernel written to target the 128-bit vector units of Intel® Core™ i7 processor:

```
__kernel __attribute__((vec_type_hint(float4)))
void edp_mul(__global const float4 *a,
                     __global const float4 *b,
                     __global float4 *result)
{
  size_t id = get_global_id(0);
  result[id] = a[id]* b[id];
}
```

In this example, the data passed to the kernel represents buffers of float4. The calculations are performed on four elements together.

The attribute added before the kernel signals the compiler or implementation that this kernel is written in an optimized vectorized form, so the implicit CPU vectorization module does not operate on it. You must use *vec_type_hint* to disable vectorization if you kernel already processes data using mostly vector types. For more details on this attribute, see section 6.7.2 of the OpenCL Specification [2].

2.5 Benefitting from Implicit Vectorization

Intel® OpenCL SDK includes an implicit CPU vectorization module as part of the program build process. When enabled, this module packs several work-items to be executed in a lock-step via SIMD instructions. This allows you to benefit from the vector units in Intel hardware without writing explicit vector code to specifically target them.

Vectorization module transforms scalar operations on adjacent work-items into an equivalent vector operation. When vector operations already exist in the kernel source code, they are scalarized (broken down into component operations) and re-vectored. This provides additional performance gain by transforming the memory access pattern of the kernel into structure of arrays (SOA), which is often more cache-friendly than the array of structures (AOS).

2.6 Writing Kernels to Benefit From Implicit CPU Vectorization

The implicit CPU vectorization module works best for kernels that operate on elements of 4-byte width, such as float or int. In OpenCL, you can define the computational width of a kernel using the `vec_type_hint` attribute.

By default, kernels are always vectorized, since the default computation width is 4-byte. Specifying `__attribute__((vec_type_hint(<typen>)))` with typen of any vector type (e.g. float3 or char4) disables the vectorization module optimization for this kernel.

A performance benefit from the CPU vectorization module might be lower for kernels that include complex control flow which depends on the work-item ID.

To benefit from vectorization, you do not need to necessarily use `for` loops within kernels. In other words, you don't need to loop over several data elements inside a kernel. It is better to have the kernel dealing with a single data element, and let the vectorization module take care of the rest. The more straightforward your OpenCL code is, the more optimization you may get from vectorization.

2.7 Work-Group Size Considerations

We always recommend letting the OpenCL implementation to automatically determine the optimal work-group size (sometimes referred as “local work size”) for a given kernel. Simply pass NULL for a pointer to the local work size when calling clEnqueueNDRangeKernel.

If you want to experiment with workgroup sizes please take into account the following:

- To benefit from the auto-vectorization optimization (section 2.5), the work-group size must be a multiple of 4 for Nehalem micro-architecture, and 8 for SandyBridge respectively. You can use multiple of 8 to target both.
- The best way to fit multiple architectures is querying device for the `CL_KERNEL_PREFERRED_WORK_GROUP_SIZE_MULTIPLE` parameter via call to clGetKernelWorkGroupInfo and using the value to set work-group size accordingly.
- If the kernel code contains the barrier instruction, issuing it causes a lightweight context switch. It forces the framework to save the state of all the work-items in the work-group prior to the barrier instruction. In this case, the issue of work-group size becomes a tradeoff - the more local and private memory each work-item in the work-group requires, the smaller the work-group size should be. The reason is that a barrier also issues copying for the total amount of private and local memory used by all work-items in the work-group.

Generally, the recommended work-group size for kernels without a barrier instruction is 64-128. For kernels with a barrier instruction, the recommended work-group size is 32-64. However, some experimentation is advised.

3 Writing Kernels to Target the Intel Architecture Vector Units

3.1 Using Vector Data Types

Usage of the OpenCL vector data types permits utilization of the Intel vector instruction set. For instance, consider the following OpenCL snippet:

```
float4 a, b;
float4 c = a + b;
```

After compilation, it resembles the following C snippet:

```
__m128 a, b;
__m128 c = _mm_add_ps(a, b);
```

Or in assembly:

```
movaps xmm0, [a]
addps  xmm0, [b]
movaps [c], xmm0
```

As the width of vector units is 128 bits, it is recommended to choose vector data types that are 128 bits in length, such as (u)int4, float4, or (u)short8.

If the native size for your kernel requires less than 128 bits and you want to use explicit vectorization, the best solution is to manually pack work-items together.

For instance, suppose your kernel receives an (x, y) float coordinates and shifts it by (dx, dy):

```
__kernel __attribute__((vec_type_hint(float2)))
void shift_by(__global float2* coords, __global float2* deltas)
{
  size_t tid = get_global_id(0);
  coords[tid] += deltas[tid];
}
```

This kernel uses the float2 vector type. This might cause a performance degradation compared to manually packing pairs of work-items-together:

```
__kernel __attribute__((vec_type_hint(float4)))
void shift_by(__global float2* coords, __global float2* deltas)
{
  size_t tid = get_global_id(0);
  float4 my_coords = (float4)(coords[tid], coords[tid + 1]);
  float4 my_deltas = (float4)(deltas[tid], deltas[tid + 1]);
  my_coords += my_deltas;
  vstore4(my_coords, tid, (__global float*)coords);
}
```

Every work-item in this kernel does twice as much work as a work-item executing the previous kernel. Consequently, only half of invocations is required (and run-time overheads are better amortized), so you need to change the host code accordingly.

The best performance can be gained when using vectors of 32-bit data types, e.g. `int4` and `float4` data types. Other types may cause a behind-the-scenes upcast of the input data that has negative impact on performance.

3.2 Work-Group Level Parallelism

Consider the following loop:

```
for (int i = 0; i < 1024; ++i)
{
  data[i]++;
}
```

In OpenCL, the equivalent is to launch the following kernel as a one-dimensional NDRange of size 1024:

```
__kernel void inc(__global int* data)
{
  data[get_global_id(0)]++;
}
```

As the amount of work done in the loop body is small, a conventional native C compiler would unroll the loop above by a certain factor for better performance:

```
for (int i = 0; i < 256; ++i)
{
  //unrolling 4 times
  data[4 * i + 0]++;
  data[4 * i + 1]++;
  data[4 * i + 2]++;
```

```
  data[4 * i + 3]++;
}
```

This also has an OpenCL equivalent, as a kernel invocation can perform more than one work-item referred by global ID. It can iterate on several indices in the index space:

```
__kernel void inc_unrolled(__global int* data)
{
  size_t tid = get_global_id(0);
  data[4 * tid + 0]++;
  data[4 * tid + 1]++;
  data[4 * tid + 2]++;
  data[4 * tid + 3]++;
}
```

This method is a useful optimization for lightweight kernels. Besides, given a constant work-group size and an index space whose size cannot be controlled, it enables the host code to effectively control the number of work-groups created.

As work-groups are independent, they can be executed concurrently on different hardware threads. So, the number of work-groups should not be less than the number of logical cores (as reported by the OS). A larger number of work-groups results in more flexibility in scheduling at the cost of more task switching overhead.

To get the largest performance gain from parallelism between work-groups or different tasks, you should ensure that the execution of a work-group or a task takes around 10,000 – 100,000 instructions. A smaller value increases the proportion of switching overhead compared to actual work. However, this is a rule of thumb, so you should experiment.

4 Optimizing OpenCL Usage

4.1 Using Memory Objects

As the host code shares the physical memory with the OpenCL framework, you can either request the framework to allocate memory for the host and use that, or allocate memory yourself and share the pointer with the framework. In either case, unneeded copies are avoided.

To take advantage of this, use calls to `clEnqueueMapBuffer` and `clEnqueueUnmapBuffer` instead of calls to `clEnqueueReadBuffer` or `clEnqueueWriteBuffer`. The former are lightweight (locking and unlocking the memory objects) whereas the latter affect an actual memory copy. You can apply the same optimization for mapping/un-mapping of other memory objects, such as images.

If your application uses a specific memory management algorithm, or if you want more control over memory allocation, you can allocate a buffer and then pass the pointer at `clCreateBuffer` time with the `CL_MEM_USE_HOST_PTR` flag. However, the pointer must be aligned to a 128-byte boundary. Otherwise, the framework may perform memory copies. It is recommended to query the required memory alignment using `clGetDeviceInfo` with `CL_DEVICE_MEM_BASE_ADDR_ALIGN` token.

4.2 Avoiding Needless Synchronization

To achieve the optimal usage of the OpenCL framework, try to avoid explicit command synchronization primitives, such as `clEnqueueMarker/Barrier`. Explicit synchronization commands and event tracking result in cross-module round trips that decrease performance.

The less explicit synchronization commands you issue, the better CPU load and performance you can get. For example, consider a scenario when you need to wait for kernel to complete execution before reading the resulting buffer. Instead of blocking after issuing the kernel with `clFinish`, you can continue execution until you really

need the first buffer with results. For this purpose, use implicit synchronization via call to blocking buffer-mapping (`clEnqueueMapBuffer` with blocking set to `CL_TRUE`).

Another way to ensure that results are ready and you can proceed is using *in-order* command queues. In this execution model, the commands in a command-queue are executed in order of submission, with each command running to completion before the next one begins. This is a typical case for straightforward processing pipeline.

You can also call `clFlush` to get things rolling, and do something useful in the host thread rather than immediately block on `clFinish` and wait for results. This approach is more effective than using `clWaitForEvents`, because `clWaitForEvents` really blocks the underlying thread, whereas `clFinish` allows the thread to participate in kernels execution. Besides, using events to control execution might be error-prone.

Finally, using blocking OpenCL API is still more effective than explicit synchronization schemes based on OS sync primitives.

Also if you are optimizing kernels pipeline first measure kernels *separately* to find the most-time consuming one. In the final pipeline version though, it is recommended to avoid calling `clFinish` or `clWaitForEvents` frequently (e.g. after each kernel invocation). Rather prefer to submit the whole sequence (to the in-order queue) and issue `clFinish` (or wait on the event) once. This would reduce host-device round-trips.

4.3 Image Support

Intel® OpenCL SDK supports image objects. Sampler calls are performed via software emulation. So if your legacy code uses images or depends on image-specific formats, use the fastest interpolation mode that suffices your needs. For example, many (interpolating) kernels work fine with nearest-neighbor filtering. Linear filtering causes software emulation of samplers and decreases performance.

If your algorithm does not require linear data interpolation, consider using buffers instead of images.

4.4 Re-using Compilation Results with `clCreateProgramWithBinary`

To retrieve binaries generated from calls to `clCreateProgramWithSource` and `clBuildProgram`, you can call `clGetProgramInfo` with the `CL_PROGRAM_BINARIES` parameter. For performance-critical applications that typically pre-compile kernel code, you can cache the resulting binaries after the first OpenCL compilation and reuse them on subsequent executions via `clCreateProgramWithBinary`. Another way to save intermediate binaries is using Intel® OpenCL Offline Compiler tool, as described in section 4.7.4 of [1].

5 Performance Debugging Intro

There are many ways to measure performance of applications; in particular for OpenCL™ kernels. For example there are host-side timing mechanisms like `QueryPerformanceCounter` or `rdtsc`. Still those "wall-clock" measurements might not provide any insights into the actual cost breakdown. We start this section with discussion of OpenCL™ profiling events.

5.1 Host-side timing

We wouldn't discuss `QueryPerformanceCounter` API, or other host-side timing mechanisms here. Refer to the "OpenCL Optimizations Tutorial" sample from the SDK for `QueryPerformanceFrequency` code examples. The sample is located in `<install-dir>\samples\SimpleOptimizations`.

Below is trivial host-side timing routine around kernel call (error handling is omitted for simplicity):

```
float start = …;//getting the first time-stamp
        clEnqueueNDRangeKernel(g_cmd_queue, …);
        clFinish(g_cmd_queue);// to make sure the kernel completed
float end = …;//getting the last time-stamp
float time = (end-start);
```

Couple of things to pay attention to:

- `clEnqueueNDRangeKernel` only puts a kernel to a queue and immediately returns
- Thus to measure kernel execution time you need to explicitly sync on kernel completion via call to `clFinish` or `clWaitForEvents`.

5.2 Wrapping the right set of operations

When using any host-side routine for evaluating the performance of your kernel, please ensure you wrapped the proper set of operations.

For example avoid including various printf calls, file i/o operations and other potentially costly and/or serializing routine.

5.3 Profiling Operations using OpenCL Profiling Events

Next piece of code measures the kernel execution via profiling events, again error handling is omitted:

```
g_cmd_queue = clCreateCommandQueue(…CL_QUEUE_PROFILING_ENABLE, NULL);
clEnqueueNDRangeKernel(g_cmd_queue,…, &perf_event);
clWaitForEvents(1, &perf_event);
cl_ulong start = 0, end = 0;

clGetEventProfilingInfo(perf_event, CL_PROFILING_COMMAND_START,
sizeof(cl_ulong), &start, NULL);
clGetEventProfilingInfo(perf_event, CL_PROFILING_COMMAND_END,
sizeof(cl_ulong), &end, NULL);

//END-START gives you hints on kind of “pure HW execution time”
//the resolution of the events is 1e-06
g_NDRangePureExecTime = (cl_double)(end - start)*(cl_double)(1e-06);
```

Important caveats:

- The queue should be enabled for profiling (CL_QUEUE_PROFILING_ENABLE property) in creation time
- You need to explicitly sync via `clWaitForEvents`. The reason is that device time counters (for the command being profiled) are associated with the specified event.

This way you can profile operations on both Memory Objects and Kernels. Refer to section 5.12 of the OpenCL 1.1 standard for the detailed description of profiling events, [2]. Notice that host-side wall-clock time might return different results. For CPU the difference is typically negligible though.

5.4 Comparing OpenCL Kernel Performance with Performance of Native Code

When comparing the OpenCL *kernel* performance with native code (e.g. C or SSE), make sure that you wrapped exactly the same set of operations. For example:

- Don't include program build time in the kernel execution time
  - This build step can be amortized well via program pre-compilation (refer to `clCreateProgramFromBinary`)
- Track data transfers costs separately
  - Also prefer data-mapping, section 4.1, this is closer to the way a data is passed in a native code (i.e. by pointers).

Also ensure the working set is identical for native/OpenCL code. Similarly, for correct performance comparison, access patterns should be the same (e.g. rows vs. columns).

Finally make sure you're demanding the same accuracy. For example `rsqrt(x)` built-in is inherently of the higher accuracy than `__mm_rsqrt_ps` SSE intrinsic. There are 2 options for more fair performance in this particular case:

- Either equip `__mm_rsqrt_ps` in your native code with couple of additional Newton-Raphson iterations, to match the precision of OpenCL's rsqrt
- Alternatively you can use `native_rsqrt` in your kernel which would map exactly to `rsqrtps` instruction in the final assembly
  - Yet another way to enable similar optimization for the *whole* program is using relaxed-math compilation flag, refer to section 6.8.

Similarly to `rsqrt`, there are relaxed versions for `rcp`, `sqrt`, etc, refer to section 6.2 "Working with the `-cl-fast-relaxed-math` Flag" of [1] for the full list.

5.5 Getting Credible Performance Numbers

In the world of computing, performance conclusions are typically deduced from sufficiently large number of invocations of the same routine. Since the first iteration is almost exclusively slower than later iterations, minimum (or average, geomean, etc) value for the execution time is usually used for final projections. A simple alternative to

having loop that calls your kernel zillion times is having single “warming” run as explained in this section.

“Warming” run is especially helpful for small/lightweight kernels for which one-time overheads (like some “lazy” object creations, delayed initializations and other costs potentially incurred by the OpenCL run-time) might really cost something. “Warming” run also brings data in the cache. Thus for bandwidth-limited kernels operating on the data that doesn’t fit last-level cache, the “warming” run is unlikely to help.

If your kernel is just a small number of instructions executed over small data set, then even infinitely-precise measurements mechanism is very unlikely to yield a reliable result. This is due to OS, cache, threading, etc influence. Having kernel run for at least 20 milliseconds is strongly recommended.

The bottom-line is that you need to build your performance conclusions on reproducible data. If “warming” run doesn’t help and/or execution time still varies, you can try to run large number of iterations and then average the results (for time values that range too much, geomean is preferable).

Remember that kernels that are too lightweight wouldn’t give you reliable data, so making them artificially heavier could give you important insights into the hotspots. Examples are adding loop *into* the kernel, or replicating its heavy pieces.

5.6 Using tools

Once you get the stable/reproducible performance numbers, the next question would be about what to optimize first.

Unless you suspect some specific parts of the kernel (e.g. heavy math built-ins), we strongly recommend using VTune to determine hot-spots as described in section 7.1 “Working with the Intel® VTune™ Amplifier XE 2011” of the User Guide, [1]

Remember that tuning the kernel itself might in turn require tweaking the run-time parameters as well, e.g. increasing size work-group once you kernel getting faster (larger work-groups would help to amortize run-time overheads). That is why the best practice is letting the run-time to decide on optimal local size as described above.

You can also check the overall CPU utilization and job distribution with GPA as detailed in section 7.3 “Tracing OpenCL Commands with the Intel® Graphics Performance Analyzers” of [1].

Use Offline Compiler to inspect resulting assembly as described in section 7.2 “Using the Intel® OpenCL SDK Offline Compiler” of the [1]. Check whether your kernel is vectorized as you expect it to be, especially if you’re trying to compare to your hand-tuned SSE.

6 Tips and Tricks for Kernel Development

6.1 Why Optimizing Kernel Code Is Important?

Probably the most important optimization advice is to keep thinking about kernel code as being inside (the innermost) for-loop. Indeed, issuing kernel means it is called many times by the OpenCL run-time. Every little waste is going to be costly. If you'd move something out of the loop, move it from the kernel. Examples:

- Edge detection
- Constant branches
- Variable initialization
- Variable casts.

The following sections explain the optimizations in details.

6.2 Avoiding Spurious Operations with IDs in Kernel Code

As every line in the kernel code is executed many times, make sure you have no spurious instructions in the kernel code.

Spurious instructions are not always evident. Consider the following kernel:

```
__kernel void inc(__global int* data)
{
  uint tid = get_global_id(0);
  data[tid]++;
}
```

Every work-item executing this kernel stores the global ID in a `uint` variable. If running in 64-bit mode, the thread ID is stored as a 64-bit value. Thus, every work-item downcasts the value to 32 bits, resulting in overhead larger than the execution time for the actual kernel code might be.

There is a group of built-in functions used to query the work-item parameters for the given dimension (section 6.11.1 of the spec [2]). For better performance it is recommended that the input-dimension parameter for these built-ins is constant:

```
__kernel void inc(__global int* data)
{
  //dimension is just 0, 1, or 2, so avoid using variables here
 //using variables (even const) results in range-checking for the input
 //which might add an overhead to the lightweight kernels
  size_t x  = get_global_size(0);
  //…
}
```

Another common error leading to spurious code is the following pattern:

```
__kernel void unrolled(const __global int* data, const uint dataSize)
{
  size_t tid = get_global_id(0);
  size_t gridSize = get_global_size(0);
  size_t workPerItem = dataSize / gridSize;
  size_t myStart = tid * workPerItem;
  for (size_t i = myStart; i < myStart + workPerItem; ++i)
  {
    //actual work
  }
}
```

In this kernel, the `for` loop is used to reduce the number of work-items and the overhead of keeping them. However, in this example every work-item recalculates the amount of indices to iterate on, while this number is identical for all work-items. As both the size of the dataset and the `NDRange` dimensions are known before kernel launch, it is preferable to calculate the amount of work per item on the host once and then pass the result as a constant parameter.

6.3 Performing Initialization in a Separate Task

You may sometimes be tempted to write the following sort of code:

```
__kernel void something(const __global int* data)
{
  size_t tid = get_global_id(0);
  if (0 == tid)
  {
    //Do some one-shot work, like initializing a lookup table
  }
  barrier(CLK_GLOBAL_MEM_FENCE);
  //Regular kernel code
}
```

In this example, the first branch is encountered by all the work-items although it is only relevant to one. A better solution is moving the initialization phase outside the kernel code, either to a separate kernel, or to the host code.

6.4 Avoiding Handling Edge Conditions in Kernels

Consider this simple smoothing filter:

```
__kernel void smooth(const __global float* input,
                     uint image_width, uint image_height,
                     __global float* output)
{
  size_t myX = get_global_id(0);
  size_t myY = get_global_id(1);
  uint neighbors = 1;
  float sum = 0.0f;
  if (myX + 2 < width)
  {
    sum += input[myY * image_width + (myX + 1)];
    ++neighbors;
  }
  if (myX > 0)
  {
    sum += input[myY * image_width + (myX - 1)];
    ++neighbors;
  }
  if (myY + 2 < image_height)
  {
    sum += input[(myY + 1) * image_width + myX];
    ++neighbors;
  }
  if (myY > 0)
  {
    sum += input[(myY – 1) * image_width + myX];
    ++neighbors;
  }
  sum += input[myY * image_width + myX];
  output[myY * image_width + myX] = sum / (float)neighbors;
}
```

Assume you have a full HD image of 1920x1080. The four edge `if` conditions are executed for every pixel, that is, roughly 2 million times. However, they are only relevant for the 6000 pixels on the image edges that make 0.2% of all the pixels. For the remaining 99.8% work-items, the edge condition check would be a waste of time.

The kernel below is much more effective:

```
__kernel void smooth(const __global float* input,
                     uint image_width, uint image_height,
                     __global float* output)
{
  size_t myX = get_global_id(0);
  size_t myY = get_global_id(1);
  float sum = 0.0f;
  sum += input[myY * image_width + (myX + 1)];
  sum += input[myY * image_width + (myX - 1)];
  sum += input[(myY + 1) * image_width + myX];
  sum += input[(myY – 1) * image_width + myX];
  sum += input[myY * image_width + myX];
  output[myY * image_width + myX] = sum / 5.0f;
}
```

Additionally, you can either pad the image appropriately (by using larger input, for example, 1922x1082) or simply ignore the pixels on the edge (by executing the kernel on a 1918x1078 sub-region within the buffer). The current version of OpenCL also permits you to use `global_work_offset` parameter with `clEnqueueNDRangeKernel` to get a similar behavior.

NOTE: Using image types along with the appropriate sampler (`CL_ADDRESS_REPEAT` or `CLAMP`) also automates edge condition checks for data reads. However, due to samplers being emulated on CPU, this approach is also inefficient and results in poor performance. Refer to the Image Support section for details.

6.5 Using the Preprocessor for Constants

Consider the following kernel:

```
__kernel void exponentor(__global int* data, const uint exponent)
{
  size_t tid = get_global_id(0);
  int base = data[tid];
  for (int i = 1; i < exponent; ++i)
  {
    data[tid] *= base;
  }
}
```

The number of iterations for the inner `for` loop is determined at run time, after the kernel is issued for execution. However, you can use OpenCL dynamic compilation feature to ensure the `exponent` is known at the kernel compile time (that is still host run time). In this case, the kernel looks as follows:

```
__kernel void exponentor(__global int* data)
{
  size_t tid = get_global_id(0);
  int base = data[tid];
  for (int i = 1; i < EXPONENT; ++i)
  {
    data[tid] *= base;
  }
}
```

Capitalization indicates that `exponent` became a preprocessor macro.

The original version of the host code passes `exponent_val` through kernel arguments as follows:

```
clSetKernelArg(kernel, 1, exponent_val);
```

The updated version uses a compilation step:

```
sprintf(buildOptions, “-DEXPONENT=%u”, exponent_val);

clBuildProgram(program, <…>, buildOptions, <…>);
```

Thus, the value of `exponent` is passed during preprocessing of the kernel code. Beside saving stack space used by the kernel, this also permits the compiler to perform optimizations, such as loop unrolling or elimination.

NOTE: This approach requires recompiling the program every time the value of `exponent_val` changes. If you expect to change this value often, the former approach is preferable. However, this technique is often useful for transferring parameters like image dimensions to video-processing kernels, where the value is only known at host run time, but does not change once it is defined.

6.6 Prefer Signed Integer Data Types Over Unsigned

Many image-processing kernels operate on uchar input. To avoid overflow those 8-bit input values are typically converted and processed as 16- or 32-bit integer values. In both cases it is strongly recommended to use signed data types (shorts and ints), especially in case of further conversion to floating point and back.

6.7 Using One-Dimensional Range

OpenCL enables you to submit kernels on one-, two- or three-dimensional index space. Given the choice, one-dimensional ranges are preferable, for reasons of cache locality and saving index computations.

If two- or three-dimensional range is unavoidable or more convenient, try to keep work-items scanning along rows, not columns. For example:

```
__kernel void smooth(const __global float* input,
                     uint image_width, uint image_height,
                     __global float* output)
{
  size_t myX = get_global_id(0);
  size_t myY = get_global_id(1);
  size_t myPixel = myY * image_width + myX;
  …
}
```

In the example above, the first dimension is the image width and the second is the image height. The following code would be less effective:

```
__kernel void smooth(const __global float* input,
                     uint image_width, uint image_height,
                     __global float* output)
{
  size_t myY = get_global_id(0);
  size_t myX = get_global_id(1);
  size_t myPixel = myY * image_width + myX;
  …
}
```

In the second code example, the image height is the first dimension and the image width is the second dimension. The inefficiency comes from the fact that the framework iterates over the first dimension of the index space before the second.

The same rule applies if each work-item calculates several elements. For best performance, make sure work-items read from consecutive memory addresses.

6.8 Trading off Accuracy and Speed of Calculations

OpenCL offers two basic ways to trade precision for speed:

- `native_*` and `half_*` math built-ins, that have lower precision but are faster than their un-prefixed variants
- compiler optimization options like `-cl-fast-relaxed-math` flag that allows optimizations for floating-point arithmetic for the whole OpenCL program.

For the list of other compiler options and their description please refer to [1]. In general, while the `-cl-fast-relaxed-math` flag is a quick way to get potentially large performance gains for kernels with many math operations, it does not permit fine numeric accuracy control. That is why it is also recommended to experiment with native_* equivalents separately for each specific case, keeping track of the resulting accuracy.

The list of functions that have optimized versions support is provided in "Working with `cl-fast-relaxed-math` Flag" section of [1].

6.9 Local Memory Usage

One typical GPU-targeted optimization is using local memory for caching of intermediate results. For CPU all OpenCL memory objects are cached by HW, so explicit caching via local memory just introduces unnecessary (moderate) overhead.

6.10 Built-In Functions

OpenCL offers a library of built-in functions, including vector variants. For details, please see [2].

Using the built-in functions is typically more efficient than their manual implementation in OpenCL code. For example, consider this code example:

```
__kernel void Pythagorean(const __global float* a,
                          const __global float* b,
                          __global float* c)
{
  size_t tid = get_global_id(0);
  c[tid] = sqrt(a[tid] * a[tid] + b[tid] * b[tid]);
}
```

The following code is more effective than the previous example:

```
__kernel void Pythagorean(const __global float* a,
                          const __global float* b,
                          __global float* c)
{
  size_t tid = get_global_id(0);
  c[tid] = hypot(a[tid], b[tid]);
}
```

In general, math, integer, and geometric built-in functions are faster than their manually-computed counterparts. Built-in functions that do not belong to these three categories should be used carefully. For example, avoid using `mul24`:

```
int iSize = x*y;//not mul24(x,y);
```

6.11 Avoid Extracting Vector Components

Consider a more complicated inverter kernel:

```
__constant float4 oneVec = (float4)(1.0f, 1.0f, 1.0f, 1.0f);
__kernel void inverter(__global float4* input, __global float4* output)
{
  size_t tid = get_global_id(0);
  output[tid] = oneVec – input[tid];
  output[tid].w = input[tid].w;
}
```

In this case, you actually want to invert only a 3-vector, leaving the `w` component unmodified. However, extracting a vector component is costly, especially in the middle of a sequence of operations. The above example would not be too bad in practice, since the compiler stores the vector value back to memory, and then performs a single write to update the `w` component in memory. However, the following kernel implementation is less successful:

```
__constant float4 oneVec = (float4)(1.0f, 1.0f, 1.0f, 1.0f);
```

```
__kernel void inverter2(__global float4* input, __global float4* output)
{
  size_t tid = get_global_id(0);
  output[tid] = oneVec – input[tid];
  output[tid].w = input[tid].w;
  output[tid] = sqrt(output[tid]);
}
```

Extraction of the w component is very costly in this case, as the subsequent vector operation forces re-loading the same vector from memory. It is preferable to load a vector once and perform all changes, even to a single component, via vector operations.

In this specific case, two changes are required:

1. Modify the oneVec so that its w component is zero, causing only a sign flip in the w component of the input vector.
2. Use float representation to manually flip the sign bit of the w component back.

As a result, the kernel looks as follows:

```
__constant float4 oneVec = (float4)(1.0f, 1.0f, 1.0f, 0.0f);
__constant int4 signChanger = (int4)(0, 0, 0, 0x80000000);
__kernel void inverter3(__global float4* input, __global float4* output)
{
  size_t tid  = get_global_id(0);
  output[tid] = oneVec – input[tid];
  output[tid] = as_float4(as_int4(output[tid]) ^ signChanger);
  output[tid] = sqrt(output[tid]);
}
```

At the cost of another constant vector this implementation performs all the required operations addressing only full vectors.

7 A Real-Life Vectorization Case-Study

Below is a simple C implementation of the Black-Scholes pricing model.

```
// The cumulative normal distribution function
float CND( float X )
{
  float L, K, w ;
  const float a1 = 0.31938153f, a2 = -0.356563782f, a3 = 1.781477937f;
  const float a4 = -1.821255978f, a5 = 1.330274429f;
  L = fabs(X);
  K = 1.0 / (1.0 + 0.2316419 * L);
  w = 1.0 - 1.0 / sqrt(2 * Pi) * exp(-L *L / 2) *
      (a1 * K + a2 * K * K +   a3 * K * K * K * + a4 * K * K * K * K +
      a5 * K * K * K * K * K;
  if (X < 0 )
  {
    w = 1.0 - w;
  }
  return w;
}

// The Black and Scholes (1973) Stock option formula
float BlackScholes(char CallPutFlag, float S, float X, float T,
                   float r, float v)
{
  float d1, d2;

  d1=(log(S/X)+(r+v*v/2)*T)/(v*sqrt(T));
  d2=d1-v*sqrt(T);

  if(CallPutFlag == 'c')
  {
    return S *CND(d1)-X * exp(-r*T)*CND(d2);
  }
  else if(CallPutFlag == 'p')
  {
    return X * exp(-r * T) * CND(-d2) - S * CND(-d1);
  }
}
```

The CND implementation would be more efficient with the sign bit extracted from X and the last branch eliminated. However, focus on the second function that is the actual pricing model. In OpenCL, this function looks as follows:

```
__kernel void BlackScholes (const __global float* S,
                            const __global float* K,
                            const __global float* T,
                            const __global float r,
                            const __global float v,
                            const __global char* CallPutFlag,
                            __global float* output)
{
  ulong tid = get_global_id(0);
  float  d1 = 0.0f;
  float  d2 = 0.0f;

  d1 = (log(S[tid] / K[tid]) + (r + v * v / 2) * T[tid]) /
       (v * sqrt(T[tid]));
  d2 = d1 - v * sqrt(T[tid]);

  if (CallPutFlag[tid] == 'c')
  {
    output[tid] = S[tid] * CND(d1)- K[tid] * exp(-r * T[tid]) * CND(d2);
  }
  else if (CallPutFlag[tid] == 'p')
  {
    output[tid] = K[tid] * exp(-r * T) * CND(-d2) – S[tid] * CND(-d1);
  }
}
```

Notice the following minor issues to be corrected:

- As r and v are constant parameters for all work-items it is always better to pass them via the preprocessor.
- Thread ID should be stored in size_t, not in a 64-bit type.

```
__kernel void BlackScholes (const __global float* S,
                            const __global float* K,
                            const __global float* T,
                            const __global char* CallPutFlag,
                            __global float* output)
{
  size_t tid = get_global_id(0);
  float  d1 = 0.0f;
  float  d2 = 0.0f;
  d1 = (log(S[tid] / K[tid]) + (r + v * v / 2) * T[tid]) /
```

```
      (v * sqrt(T[tid]));
  d2 = d1 - v * sqrt(T[tid]);
  if (CallPutFlag[tid] == 'c')
  {
    output[tid] = S[tid] * CND(d1)- K[tid] * exp(-r * T[tid]) * CND(d2);
  }
  else if (CallPutFlag[tid] == 'p')
  {
    output[tid] = K[tid] * exp(-r * T) * CND(-d2) – S[tid] * CND(-d1);
  }
}
```

The next target should be the if-condition checking for call/put options. A possible solution for this issue is manual use of vector types. The example below calculates both the call and put options for quartets of options (four floats make 128 bits), and merges the results according to the actual value of the flag. The kernel looks as follows:

```
__kernel __attribute__((vec_type_hint(float4)))
void BlackScholes (const __global float4* S,
                   const __global float4* K,
                   const __global float4* T,
                   const __global int4* callPutFlag,
                   __global float4* output)
{
  size_t tid = get_global_id(0);
  float4  d1 = 0.0f;
  float4  d2 = 0.0f;
  float4  callResult, putResult;
  int4  calls = (int4)’c’;

  d1 = (log(S[tid] / K[tid]) + (r + v * v / 2) * T[tid]) /
       (v * sqrt(T[tid]));
  d2 = d1 - v * sqrt(T[tid]);

  callResult = S[tid] * CND(d1)- K[tid] * exp(-r * T[tid]) * CND(d2);
  putResult  = K[tid] * exp(-r * T) * CND(-d2) – S[tid] * CND(-d1);
  int4 callMask = CallPutFlag[tid] == calls;
  output[tid] = select(putResult, callResult, callMask);
}
```

Note the use of the relational operator for vector comparisons and the subsequent use of select. This is a common solution for branches in code that uses vector types.

8 Task-Parallel Programming Model Hints

Task-parallel programming model is general-purpose. It permits you to express parallelism by enqueuing multiple tasks. You can apply this model in the following usage scenarios:

- Performing different tasks concurrently by multiple threads.
  If you use this scenario, choose sufficient granularity of the tasks to have good load balancing.
- Adding an extra queue (beside conventional data-parallel pipeline) for tasks that occur less frequently and in asynchronous manner, for example, some scheduled events.