

Performance Evaluation of IPMACC: Open Source OpenACC to CUDA Translator

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1 Background

1.1 CUDA Model

In CUDA [17], an application is composed of host and device codes. The host code executes on CPU and the device code executes on system's accelerator. The host controls the operations of the device through procedure calls to CUDA API. CUDA allows programmers to explicitly allocate memory on device and transfer data between the host and the device. The device obtains the device code from kernel and executes it by thousands of light-weight threads, in SIMT style [14]. All threads share common off-chip DRAM memory or global memory. In software, threads are grouped into coarser scheduling elements, referred to as the thread block. Threads within the same block execute concurrently and communicate through a fast, per-block, on-chip software-managed cache, referred to as shared memory. Shared memory is much faster than global memory; e.g. under GTX 280, the latency of global memory and shared memory are 440 and 38 core cycles, respectively [26].

1.2 OpenACC Model

OpenACC API introduces a set of compiler directives, library routines, and environment variables to offload a region of code from the CPU to the system's accelerator [4]. We refer to this region as the accelerator region. OpenACC has two classes of directives: i) data management and ii) parallelism control. Each directive has clauses providing finer-grain control. Data management directives perform data allocation on the accelerator, data transfer between the host and the accelerator, and passing pointers to the accelerator. Parallelism control directives allow the programmer to mark regions of code, usually work-sharing

Listing 1: OpenACC and CUDA matrix-matrix multiplications.

```

#pragma acc data copy(a[0:LEN*LEN],b[0:LEN*LEN],c[0:LEN*LEN])
#pragma acc kernels
#pragma acc loop independent
for(i=0; i<LEN; ++i){
#pragma acc loop independent
  for(j=0; j<LEN; ++j){
    float sum=0;
    for(l=0; l<LEN; ++l) sum += a[i*LEN+l]*b[l*LEN+j];
    c[i*LEN+j]=sum;
  }
}

```

(a) OpenACC.

```

__global__
void matrixMul(int *a, int *b, int *c, int len){
  int i=threadIdx.x+blockIdx.x*blockDim.x;
  int j=threadIdx.y+blockIdx.y*blockDim.y;
  for(int l=0; l<len; ++l) sum=a[i*len+l]*b[l*len+j];
  c[i*len+j]=sum;
}
int main(){
  ...
  bytes=LEN*LEN*sizeof(int);
  cudaMalloc(&a_d, bytes);
  cudaMalloc(&b_d, bytes);
  cudaMalloc(&c_d, bytes);
  cudaMemcpy(a_d, a, bytes, cudaMemcpyHostToDevice);
  cudaMemcpy(b_d, b, bytes, cudaMemcpyHostToDevice);
  dim3 gridSize(LEN/16,LEN/16), blockSize(16,16);
  matrixMul<<<gridSize,blockSize>>>>(a_d,b_d,c_d,LEN);
  cudaMemcpy(c, c_d, bytes, cudaMemcpyDeviceToHost);
  ...
}

```

(b) CUDA.

loops, intended to run in parallel on the accelerator. They also control parallelism granularity, variable sharing/privatization, and variable reduction. OpenACC introduces four levels of parallelism: gang, worker, vector, and thread. In CUDA terminology, these terms best map to kernel, thread block, warp, and thread, respectively.

1.3 Matrix-Matrix Multiplication Example

Listing 1a and 1b illustrate a simple matrix-matrix multiplication in OpenACC and CUDA, respectively. Ignoring the directive lines, Listing 1a shows the baseline serial multiplication of a and b , storing the result in c . Each matrix is $LEN \times LEN$ in size. The outer loops iterated by i and j variables can be executed in parallel. Listing 1a shows how these loops can be parallelized using OpenACC. In this code, *kernels* directive marks a region intended to be executed on the accelerator. *loop* directive guides the compiler to consider the loop as a parallel work-sharing loop. Programmers can control the parallelism using kernels and loop directives. As an example of parallelism control, the independent clause is used to force the compiler to parallelize the loop. This clause

overwrites the compiler’s auto-vectorization and loop dependency checking. In Listing 1a, data clauses hint the compiler to copy a, b, and c arrays from the host to the accelerator, and copy them out from the accelerator to the host. For each array, the [start:n] pair indicates that n elements should be copied from the start element of array.). Listing 1b shows how the parallelization can be exploited in CUDA. global indicates the declaration of kernel code. Parallel threads execute the kernel and operate on different matrix elements, based on their unique indexes (i and j). Inside the host code, device memory is allocated for a, b, and c, keeping the pointer in a_d, b_d, and c_d, respectively. Then, input matrices are copied into device memory. Then, a total of LEN*LEN light-weight accelerator threads are launched on the device to execute matrix-Mul kernel. After kernel completion, the resulting matrix c d is copied back to the host memory. As presented in Listing 1, OpenACC significantly reduces the accelerator programming effort in comparison to CUDA. OpenACC hides low-level accelerator-related code from the programmer and provides a unified view over both host and accelerator code.

2 Motivation

In this section, we compare a set of OpenACC applications to their highly optimized CUDA version. Our goal is to identify OpenACC’s programming limitations resulting in the performance gap between OpenACC and CUDA performance. See Methodology section for applications, compilers, and hardware setup.

2.1 Performance Comparison

Figure 1 reports the execution time for OpenACC applications, compared to their CUDA version. The figure reports the breakdown of time spent on the accelerator; kernel launch (launch), kernel execution (kernel), or memory transfer between host and accelerator (memory). Kernel launch time includes the time spent on setting kernel arguments and launching the kernel on the accelerator. In most cases, CUDA’s kernel launch/execution portion is shorter than OpenACC. Also, memory transfer times are comparable on both CUDA and OpenACC. There are exceptions where OpenACC memory transfers are faster (e.g. Backpro.) or kernel time of CUDA and OpenACC are equal (e.g. Nearest.). We investigate the differences between CUDA and OpenACC in the following sections.

2.2 Investigating Performance Gap

In this section, we discuss applications separately providing insight into why CUDA and OpenACC implementations presented in Figure 1 have different kernel launch, kernel execution, and memory transfer times.

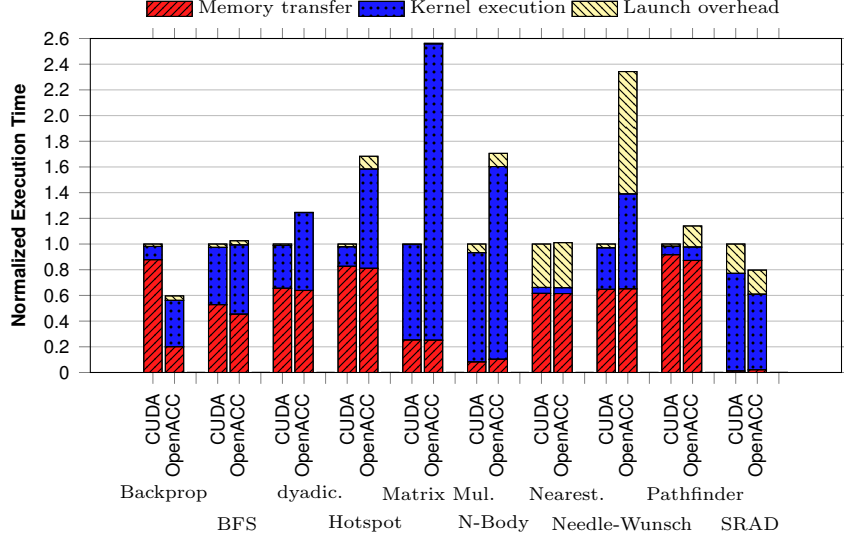


Figure 1: Comparing the execution time of OpenACC to highly-optimized CUDA implementations. Each bar shows the duration of time that the application spends on memory transfer, kernel execution, and kernel launch overhead.

Back Propagation. Back Propagation (Backpro.) is a machine-learning algorithm used to train the weights in a three-layer neural network. In both OpenACC and CUDA versions, there are six back-to-back serial operations where the output of each stage is fed to the immediate next stage as input. Each stage can be performed in parallel on the accelerator.

OpenACC implementation performs faster memory transfers and slower kernel launch/execution, compared to CUDA. This is explained by the fact that the OpenACC version executes all six stages on GPU, while the CUDA version alternates between CPU and GPU for execution. Alternating between CPU and GPU imposes extra memory transfer overhead.

BFS. BFS visits all the nodes in the graph and computes the visiting cost of each node. Each node is visited only once. Parallel threads of a kernel visit the nodes belonging to the same graph depth concurrently and the algorithm traverses through the depth iteratively. The operation stops once there is no child to visit.

Compared to the CUDA version, the OpenACC version of BFS spends less time on memory transfers. This can be explained by the fact that the OpenACC version performs data initializations on the GPU. However, the CUDA version initializes the inputs on the host and transfers the inputs to GPU. Compared to the CUDA version, OpenACC spends more time on kernel execution, since it forces a debilitating reduction on a global variable. The global variable is a boolean indicating whether there remains more nodes to visit or not. CUDA avoids global reduction by initializing the variable to FALSE on the host and

imposing a control-flow divergent in the kernel to guard the global variable from FALSE writes (allowing TRUE writes).

Dyadic Convolution. Dyadic Convolution (dyadic.) is an algebra operation calculating the XOR-convolution of two sequences. The OpenACC implementation parallelizes output calculations, where each thread calculates one output element. Although this implementation is fast to develop, it exhibits a high number of irregular memory accesses. To mitigate irregular memory accesses, the CUDA version uses Fast Walsch-Hadamard Transformation (FWHT) for implementing dyadic convolution (as described in [2]).

As reported in Figure 1, both OpenACC and CUDA versions spend almost the same amount of time on memory transfers. While the CUDA version launches several kernels, OpenACC launches only one kernel. This explains why the CUDA version imposes higher kernel launch overhead. In CUDA the kernels’ execution time is 82% faster than OpenACC. This is due to the fact that the CUDA version uses FWHT to mitigate irregular memory accesses. Although OpenACC can implement dyadic convolution using FWHT, the same FWHT algorithm used in CUDA cannot be implemented in OpenACC. CUDA FWHT uses shared memory to share intermediate writes locally between neighbor threads, which is not possible under OpenACC standard.

Hotspot. Hotspot simulates chip characteristics to model the temperature of individual units. At every iteration, the algorithm reads the temperature and power consumption of each unit and calculates new temperatures. Although both OpenACC and CUDA spend the same amount of time on memory transfers, CUDA kernel is much faster.

In Hotspot, the temperature of each unit depends on its power consumption and neighbors’ temperatures. CUDA kernel exploits this behavior to localize the communication and reduce global memory accesses as follows. In CUDA, threads of the same thread block calculate the temperature of neighbor units. The CUDA version locally updates the new temperature of neighbor units using the threads of the same thread block. This local communication reduces the number of kernel launches used to synchronize the temperature across all thread blocks, explaining why the CUDA version performs faster kernel launches and comes with shorter execution time. In OpenACC, unlike CUDA, the software-managed cache cannot be exploited for local communication. Hence, In OpenACC there are higher number of global synchronizations and kernel launches, which in turn harms performance.

Matrix Multiplication. Matrix Multiplication (Matrix Mul.) performs multiplication of two 1024x1024 matrices. Both CUDA and OpenACC implementations use output parallelization, calculating each element of the output matrix in parallel. CUDA version is different from OpenACC as it processes input matrices tile-by-tile. By processing in tiles, CUDA version fetches the input tiles in few well-coalesced accesses into software-managed cache and shares the tiles among the threads of the same thread block.

While kernel launch and memory transfer times are nearly the same across CUDA and OpenACC, CUDA kernel time is much lower than OpenACC. CUDA version takes advantage of software-managed cache in two ways. First, CUDA

version merges the required data of the thread block and fetches them once, minimizing redundant memory accesses across thread of the same thread block. Second, software-managed cache removes cache conflict misses, since the replacement policy is controlled by the programmer. Under OpenACC, although the threads have very high spatial locality, parsing the matrix row-by-row at a time highly pollutes the cache, returning high number of conflict misses. Also having multiple thread blocks per SM exacerbates this effect.

N-Body simulation. N-Body models a system of particles under the influence of gravity force. In each timestep, operations of $O(N^2)$ complexity are performed (for a system of N particles) to calculate forces between all pairs of particles. Inherently, there are many redundant memory reads, since the mass and position information of each particle is fetched by other particles $N-1$ times to calculate its interaction with other particles.

While both CUDA and OpenACC memory transfers take about the same time, CUDA kernels are much faster. The CUDA version tiles the computations to reduce redundant memory reads [12]. CUDA exploits shared memory to share the particles among all threads of a thread block. In OpenACC, however, the redundant memory accesses are not filtered out by the software-managed cache. As reported, redundant memory accesses can degrade performance significantly.

Nearest Neighbor. Nearest Neighbor (Nearest.) finds the five closest points to a target position. The Euclidean distance between the target position and each of the points is calculated and the top five points with the lowest distance are returned. OpenACC and CUDA versions both calculate Euclidean distances for each point in parallel. OpenACC and CUDA versions spend about the same time on kernel launch, kernel execution, and memory transfer. This is explained by the similarity of parallelization methods applied in both OpenACC and CUDA.

Needleman-Wunsch. Needleman-Wunsch (Needle.) is a sequence alignment algorithm used in bioinformatics. In either CUDA or OpenACC, traverses a 2D matrix and updates the costs. Upon updating a new cost, four memory locations are read and one location is written.

Although both CUDA and OpenACC versions spend the same amount of time on memory transfers, CUDA kernel launch/executions are much faster than OpenACC kernels. The CUDA version fetches a data chunk of *costs* matrix into shared memory and traverses the matrix at the shared memory bandwidth. This mechanism comes with three advantages: i) filtering redundant global memory accesses by shared memory, ii) minimizing global communication by sharing intermediate results stored in the shared memory, iii) reducing the number of kernel launches and global communications. The fewer number of kernel launches explains why the launch time of CUDA is much less than OpenACC.

Pathfinder. In Pathfinder (Pathfin.) kernel, every working element iteratively finds the minimum of three consequent elements in an array. The CUDA version of Pathfinder performs two optimizations: i) finding the minimum by accessing the data from shared memory, and ii) sharing the updated minimum locally among neighbor threads for certain iterations and then reflecting the

changes globally to other threads. Such local communications reduce the number of global synchronizations and kernel launches.

However, OpenACC’s API is not flexible enough to allow the programmer exploit the shared memory in a similar way. Therefore neighbor threads in the OpenACC version do not communicate via shared memory. Therefore, each thread fetches the same data multiple times and threads communicate only through global memory. Communication through global memory is implemented through consequent kernel launches. This explains why OpenACC imposes higher kernel launch overhead.

Speckle reducing anisotropic diffusion. Speckle reducing anisotropic diffusion (SRAD) is an image processing benchmark performing noise reduction through partial differential equations iteratively. Compared to CUDA, the kernel time of OpenACC version is less. Three code blocks construct the computation iterative body of this benchmark: one reduction region and two data parallel computations. Our evaluation shows OpenACC version performs 5% slower than CUDA, upon executing two data parallel computations. However, OpenACC outperforms CUDA in executing the reduction portion. This is explained by the difference in reduction implementations. Our OpenACC framework performs the reduction in two levels: reducing along threads of thread block on GPU and reducing along thread block on CPU. In the CUDA version, however, reduction is performed by multiple serial kernel launches, all on the GPU. The OpenACC version spends less time on executing the kernel as part of the computation is carried on host. Meanwhile, performing two levels of reduction imposes the overhead of copying intermediate data from GPU to CPU. This explains why the OpenACC version spends slightly more time on memory transfers and less time on kernel launch/execution.

3 Methodology

Benchmarks. We use benchmarks from NVIDIA CUDA SDK [19] and Rodinia benchmark suit [7]. NVIDIA CUDA SDK includes a large set of CUDA test-cases, each implementing a massively-parallel body of an application in CUDA very efficiently. Each test-case also includes a serial C/C++ implementation. We developed an OpenACC version of these benchmarks over the serial C/C++ code. Rodinia is a GPGPU benchmark suite composed of a wide set of workloads implemented in C/C++. Originally, each of these benchmarks was implemented in CUDA and OpenCL parallel models. Recently, OpenACC implementation of the benchmarks has been added by a third-party [3]. We include Dyadic Convolution and N-Body simulation from CUDA SDK and the remaining benchmarks from Rodinia.

OpenACC Compiler. We use our in-house framework, IPMACC, for compiling OpenACC applications. IPMACC translates OpenACC to either CUDA or OpenCL and executes OpenACC application over CUDA or OpenCL runtime (e.g. NVIDIA GPUs or AMD GPUs). We validated the correctness of our framework by comparing the results of OpenACC benchmarks against the serial

and CUDA version.

Performance evaluations. We compile the OpenACC version of benchmarks by our framework and run it over CUDA runtime. We compare these to CUDA implementations available in CUDA SDK and Rodinia. In order to evaluate performance, we report the total time of kernel execution, kernel launch, and memory transfer between host and accelerator. We use *nvprof* for measuring these times [20]. For kernel execution and memory transfers time, we report the time that *nvprof* reports after kernels/transfers completion. For kernel launch time, we report the time measured by *nvprof* in calling *cudaLaunch*, *cudaSetupArgument*, and *cudaConfigureCall* API procedures. Every reported number is the harmonic mean of 30 independent runs.

Platforms. We perform the evaluations under a CUDA-capable accelerator. We use NVIDIA Tesla K20c as the accelerator. This system uses NVIDIA CUDA 6.0 [19] as the CUDA implementation backend. The other specifications of this system are as follows: CPU: Intel Xeon CPU E5-2620, RAM: 16 GB, and operating system: Scientific Linux release 6.5 (Carbon) x86_64. We use GNU GCC 4.4.7 for compiling C/C++ files.

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