Adapting SYCL's SIMT Programming Paradigm for Accelerators via Program Reconstruction

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ABSTRACT

We present an IR-to-IR Converter that is capable of converting from LLVM IR to Halide IR and MLIR's Affine Dialect to support generation of high performance SYCL kernel code [10] targeting accelerators with explicit memory hierarchy design. The converter performs *program reconstruction* to raise abstraction of the IR. Once the IR is raised to the level of Halide IR, AKG [2] can be leveraged to generate performant DaVinci code [2]. Alternatively, when the IR is raised to MLIR's Affine Dialect, existing MLIR Affine passes with minor modifications can be readily used. Subsequently, the IR is lowered back to LLVM IR through progressive lowering. LLVM's LLC is used to create the final binary for both cases. We extend upon SYCL's buffer, accessor and `parallel_for` abstractions to facilitate the IR raising process.

CCS CONCEPTS

• **Software and its engineering** → **Source code generation**; • **Computer systems organization** → **Single instruction, multiple data**.

KEYWORDS

SYCL, Program Reconstruction, Parallel Computing, Tiling, MLIR, LLVM

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1 INTRODUCTION

SYCL is a cross-platform abstraction layer from Khronos Group that enables code for heterogeneous processors to be written using standard ISO C++ with host and kernel code for an application contained in the same source file. There are many SYCL implementations in development with possibly Intel's DPC++ being the most active one with hundreds of commits per week [6].

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Since SYCL has its lineage from OpenCL, it inherits the SIMT based programming model for programming the device kernel. While the SIMT model has gained its vast popularity from GPU programming, generating performant code targeting many-core processors or accelerators with traditional SIMD vector units, or *SPMD-on-SIMD*, remains a widely researched topic for compilers. Whole-Function Vectorization (WV) [1, 9, 14] and Intel's ISPC compiler [18] are both well-known efforts of SPMD-on-SIMD.

While the WV technique proves to be effective for CPU, it does not address the unique challenge of adapting SIMT for accelerators with traditional SIMD units and requiring explicit memory hierarchy management [4, 15]. For CPU, as the memory subsystem brings data through the different levels of caches automatically, a *single SIMD lane or SIMT thread* style of optimization such as WV suffices. On the other hand, the DaVinci architecture as shown in Figure 1, has the L1 Buffer and Unified Buffer serving as on-chip lower-level caches [19]. The exchange of data between the L1 Buffer and the Unified Buffer with external memory needs to be efficiently orchestrated. A traditional loop style vectorization working concertedly with a memory tiling [19] optimization to ensure data locality is a superior approach.

To be able to effectively apply the traditional loop style optimizations such as tiling, vectorization or parallelization, the converter thus shoulders the key task of making explicit, in other words, *sinking* the surrounding SYCL `parallel_for` loop construct into the kernel code. In summary, we make the following new contributions:

- We introduce an IR-to-IR converter to raise the abstraction of the LLVM IR to the level of the Halide IR and MLIR's Affine Dialect to effectively leverage existing loop level optimizations offered by AKG and Affine Dialect.
- We extend upon SYCL's abstraction with constructs that preserve host side and runtime side information in the LLVM IR to facilitate in the process of program reconstruction.
- We demonstrate our approach is viable with performance results.

Figure 1: Overview of the DaVinci Architecture

Since SYCL buffers are created on the host code and kernel code, outlining happens early in the compilation process. Buffer and accessor ranges are passed as `sycl::range` function arguments into the kernel code as shown in Figure 2. While `sycl::buffer` creation on the host code leverages a C++ template for the dimensionality of `range<2>(32, 32)` in line 6 of Figure 3, the static *shape* information unfortunately becomes runtime constants when passed in via function arguments.

```

1  define weak_odr dso_local spir_kernel void @"_main"(
2      float addrspace(1)* %data_pointer,
3      "%cl::sycl::range*" byval("%cl::sycl::range") align 8 %accessor_range,
4      "%cl::sycl::range*" byval("%cl::sycl::range") align 8 %memory_range,
5      "%cl::sycl::id*" byval("%cl::sycl::id") align 8 %offset)
6      local_unnamed_addr #0 comdat {
7          ; omitted text
8      }

```

```

1  constexpr access::mode sycl_read = access::mode::read;
2  constexpr access::mode sycl_write = access::mode::write;
3  queue deviceQueue(default_selector{});
4  {
5      // buffer creation: existing sycl::buffer abstraction
6      // buffer<float,2> OUT_buf(OUT_ten.data(), range<2>(32,32));
7
8      // buffer creation: our extension
9      ndbuffer<float, 32, 32> A_buf(A_ten.data());
10     ndbuffer<float, 32, 32> B_buf(B_ten.data());
11     ndbuffer<float, 32, 32> OUT_buf(OUT_ten.data());
12
13     deviceQueue.submit([&](handler& cgh) {
14         auto A_acc.get_access<sycl_read>(A_buf, cgh);
15         auto B_acc.get_access<sycl_read>(B_buf, cgh);
16         auto OUT_acc.get_access<sycl_write>(OUT_buf, cgh);
17
18         auto kern = [=](cl::sycl::id<2> ids) {
19             int m = ids[0];
20             int n = ids[1];
21             float sum = 0.0f;
22             for(int k = 0; k < 32; k++)
23                 sum += A_acc[m][k] * B_acc[k][n];
24             OUT_acc[m][n] = sum;
25         };
26         static_parallel_for<class matmul, 32, 32>(cgh, kern);
27     });
28 }

```

To retain this information from the host code where a `sycl::buffer` is first created, we create a `sycl::ndbuffer` abstraction. The `ndbuffer` abstraction also addresses the 3D limitation inherent in `sycl::buffer`.

To obtain the iteration space of the `parallel_for` construct, we need to obtain the number of work items and work groups from the SYCL runtime. When the iteration space information is statically present, we use our templated `static_parallel_for` or `nd_parallel_for` abstractions. As C++ templates embeds the template parameters into the mangled names of the spir kernel function in the LLVM IR, we can obtain the iteration space information from the kernel code's LLVM IR via demangling. The `nd_parallel_for` abstraction allows the user to specify parallelism in n dimensions rather than the limited maximum of 3D. We acknowledge that this technique currently only works if the iteration space is available during compile time.

3 IR-TO-IR CONVERTER OVERVIEW

The IR-to-IR converter is an LLVM OPT pass as shown in Figure 4. The SYCL language abstractions are built using heavy C++ features, particularly operator/function overloading. As such, our converter requires LLVM OPT’s inlining pass to run first, in order to remove the many function calls and present clean loop and array access patterns to our converter. A direct conversion approach from the Clang AST becomes infeasible. The IR-to-IR converter has two backends: Halide IR and MLIR Affine. The DaVinci code generation currently may take either route by going through the TVM/AKG route, or MLIR’s progressive lowering route. Both routes

can be viewed as *another* LLVM OPT pass as the LLVM IR continues through LLC to produce the final binary.

4 PROGRAM RECONSTRUCTION

4.1 Shape Reconstruction

As described in section 2, the `ndbuffer` and `usmbuffer` abstraction embed the shape information into a chain of types in the kernel code's LLVM IR. The converter then extracts the shape information from the IR and presents it in a form that AKG can consume.

4.2 Induction and Reduction PhiNode Identification

LLVM IR is written in SSA form, with instructions arranged into Basic Blocks. In order to perform raising of the IR to Halide or MLIR's Affine Dialect, we must first perform various program analyses to understand the control flow and data flow of the code. Then, by traversing through the LLVM IR, we can reconstruct the high level IR constructs such as `affine.for` correctly.

A few analyses that are done are loop structure identification, phi node conversion, and delinearization of global indices. Rather than having Basic Blocks to deal with loops, Halide and MLIR's affine dialect both have an intrinsic for loop constructs. Halide IR is in a high-level AST form, but LLVM IR introduce the phi instructions to keep the static single assignment form (SSA). Thus we must convert phi instructions of the LLVM IR into a proper recognizable form.

Firstly, we need to identify phi instructions as the induction variables. This information is obtained by Scalar Evolution given the loop. For each induction phi variable, we introduce a scalar variable as a loop variable representing the loop index value.

Additionally, we verify that all loops are normalized. Normalized loops are loops in which the induction variable starts at 0 (or any constant) and gets incremented by one in each iteration until the exit condition is met. This means that there are no break/continues/exceptions in the loop. As such, we are able to easily extract the iteration count, and ensure that there is a single induction variable for this loop.

We also need to identify phi reduction variables. Usually, to represent a reduction, LLVM IR uses a series of phi instructions. We perform pattern matching to identify the following reduction pattern:

```

1  store init_value, ptr_addr
2  phi_head_1 = phi [ init_value, ... ], [ phi_tail_1, ... ]
3  phi_head_2 = phi [ phi_head_1, ... ], [ phi_tail_2, ... ]
4  ...
5  phi_head_n = phi [ phi_head_{n-1}, ... ], [ phi_tail_n, ... ]
6  phi_head_{n+1} = phi [ phi_head_n, ... ], [ reduction_val, ... ]
7  reduction_val = func(phi_head_{n+1}, reduction_update)
8  phi_tail_n = phi [ reduction_val, ... ]
9  phi_tail_{n-1} = phi [ phi_tail_n, ... ]
10 ...
11 phi_tail_1 = phi [ phi_tail_2, ... ]
12 store phi_tail_1, ptr_addr

```

which gets recognized as the following:

```

13 ptr_addr = init_value
14 for(...)
15   ptr_addr = func(ptr_addr, reduction_update)

```

Later in code generation, we skip all of the `phi_head_i` and `phi_tail_i` instructions, as well as the final store instruction

```

1  func @func(%A: memref<32x32xf32, 1>, %B: memref<32x32xf32, 1>,
2      %OUT: memref<32x32xf32, 1>) {
3      %zero = constant 0.000000e+00 : f32
4      %tmp = memref.alloca() : memref<1xf32>
5      affine.for %m = 0 to 32 {
6          affine.for %n = 0 to 32 {
7              affine.store %zero, %OUT[%m, %n] : memref<32x32xf32, 1>
8              affine.store %zero, %tmp[0] : memref<1xf32>
9              affine.for %k = 0 to 32 {
10                 %orig = affine.load %tmp[0] : memref<1xf32>
11                 %_A = affine.load %A[%m, %k] : memref<32x32xf32, 1>
12                 %_B = affine.load %B[%k, %n] : memref<32x32xf32, 1>
13                 %prod = mulf %_A, %_B : f32
14                 %res = addf %orig, %prod : f32
15                 affine.store %res, %tmp[0] : memref<1xf32>
16             }
17             %result = affine.load %tmp[0] : memref<1xf32>
18             affine.store %result, %OUT[%m, %n] : memref<32x32xf32, 1>
19         }
20     }
21     return
22 }

```

Figure 5: Output of MLIR Affine backend for `matmul`

on line 12. We then generate `ptr_addr` on line 15 in place of `reduction_value` on line 7.

Lastly, we assign a 1D tensor variable of size one to each of the non-reduction, non-induction phi variable. This results in the statement, `vi[0] = incoming_value`, at the end of the corresponding block. Here, `vi` is the tensor variable assigned to represent the phi variable.

We also perform pattern matching on delinearized global indices to accommodate our loop reconstruction pass, mapping global indices to proper variables. Once we have completed our analyses, we can generate the main body of our kernel to be embedded into our reconstructed loops.

4.3 Iteration Space Reconstruction

With the `static_parallel_for` and `nd_parallel_for` abstractions, the converter uses a custom demangler to extract the iteration space information. In the case of the MLIR affine backend, the converter outputs `affine.for` loops as shown in Figure 5 for the kernel shown in Figure 3.

During the process of *sinking* the `parallel_for` construct into the kernel code, the semantic of the code is changed from parallel execution to sequential execution. This means that if there are synchronization primitives inside the kernel body, deadlocks may occur. As such, we must activate a `SemaChecker` to ensure the reconstructed loops do not change the semantics of the kernel code. Data dependencies do not need to be checked but the converter issues a warning for `A[i] = A[i+1]`. Such a statement inside a `parallel_for` construct is an implementation error from the programmer so the converter issues a warning for the possible data race condition.

Once the converter has identified the iteration space and reconstructed the loops along with the buffer shapes, a high level form of *loopy* IR with attributes is given to AKG for optimization. The *loopy* IR enters AKG through our custom C++ Halide IR Builder API.

5 MLIR PROGRESSIVE LOWERING FOR ACCELERATORS WITH AN EXPLICIT MEMORY HIERARCHY ARCHITECTURE

5.1 Overview: MLIR Framework

Multi-level IR (MLIR) [7] supports different levels of abstractions of representations namely Dialects, and various transformations. It allows users to customize ops, rewrite patterns, and create Dialects targeting specific backends with extreme flexibility. Progressively lowering is needed between the different Dialects.

Figure 6: Passes in the mlir-llvm-compile tool

For accelerators with an explicit memory hierarchy [4, 15, 17] architecture, software is responsible for managing data transfers between the external memory and the small on-chip buffers. Since no memory subsystem is provided by the hardware to guarantee coherency, large loops have to be broken down into smaller tiles so that data can be copied from the external memory to on-chip buffers (OnChipBuf) and vice versa, through DMA calls. In other words, tiling is no longer an optional performance optimization but an essential pass to generate functional code. As shown in Figure 6, we take advantage of the existing LoopTiling and DataCopyGeneration passes in the MLIR Affine Dialect which allow us to tile perfectly nested loops and insert DMA calls at a suitable depth level. We then progressively lower Affine Dialect to LLVM Dialect and translate LLVM Dialect into LLVM IR. An LLVM OPT pass assigns addresses to the allocated memory on the OnChipBuf. Before the OnChipBuf Mem-Alloc pass, an InstructionCombine pass is called to simplify the IR. Finally, the LLVM IR file is given to LLC of the CCE compiler to generate the final AICORE binary [12]. All the intermediate passes, from the Affine Loop Tiling and DMA generation pass in MLIR to the OnChipBuf Mem-Alloc pass in LLVM, are integrated in a single tool called *mlir-llvm-compile*. This tool takes in an Affine Dialect IR text as input and outputs LLVM IR which is consumed by LLC of the backend compiler.

5.2 Affine Passes

LoopTiling. The IR-to-IR converter described in section 3 produces a text file with the kernel code in Affine Dialect. Since the size of the OnChipBuf is a hard constraint as the data we bring into the OnChipBuf cannot exceed its capacity, the LoopTiling pass is initialized with `cacheSizeBytes` set to the OnChipBuf size. Our work incidentally uncovers a limitation with the existing tile size

formula which takes the n^{th} root of the memory footprint divided by the `cacheSizeBytes`. When `cacheSizeBytes` increases, the formula erroneous results in smaller tile sizes. After LoopTiling, the inner loop may be naturally SuperVectorized. However, we defer the exploitation of vectorization as future work.

DataCopyGeneration. The current DataCopyGeneration pass in Affine Dialect performs explicit data copying. We utilize this pass to generate the necessary DMA calls. The external memory setting is the `slowMemorySpace` and OnChipBuf is the `fastMemorySpace`. By using the OnChipBuf capacity as the `fastMemCapacityBytes` and the `cacheSizeBytes` in the LoopTiling pass, we guarantee that a safe tiling strategy can be found and OnChipBuf's capacity would not be exceeded. We also customize `Affine.DMA_start_cce` and `Affine.DMA_wait_cce` to store the necessary pipe and event information needed for lowering into synchronization intrinsics later on. Corresponding ops are introduced into the Standard Dialect to support lowering.

5.3 Lowering from Standard Dialect to LLVM Dialect

Lowering of DMA intrinsics. There are no DMA intrinsics defined in the LLVM Dialect so direct lowering from Standard to LLVM Dialect fails. We introduce two DMA intrinsics into the LLVM Dialect which has the exact API as the CCE DMA intrinsics. To support MLIR-to-LLVM IR translation, we define the corresponding intrinsics in LLVM as well. The LLVM intrinsic signature matches that of the CCE intrinsics and new types such as void pointers to external memory space are introduced. Synchronization intrinsics are also introduced into the LLVM Dialect as the semantics of DMA calls are asynchronous. They map to the synchronization intrinsics in the LLVM IR of the CCE compiler. The synchronization instructions are placed next to the DMA instructions.

Lowering of Alloc on OnChipBuf. The DataCopyGeneration pass in the Affine Dialect generates memory allocation and free calls in the OnChipBuf address space. Since the system or software stack of the accelerator does not provide memory management tool such as `libmalloc`, our tool needs to insert IR into the kernel code to manually manage the memory allocation by manipulating the address pointer for the OnChipBuf. In the Standard To LLVM conversion, we temporarily lower alloc in OnChipBuf address space to a C-like function call which is later processed by the LLVM OnChipBuf Mem-Alloc OPT pass.

5.4 LLVM Passes

OnChipBufMemoryAllocation. After obtaining the LLVM IR from `translateModuleToLLVMIR`, we run the InstructionCombine pass and then the OnChipBufMem-Alloc pass to clean up the IR. A C-like function which is used to represent memory allocation in the OnChipBuf address space, created in the Standard To LLVM conversion pass, are searched and turned into an `IntToPtr` instruction. A simple memory allocation mechanism is implemented where memory allocation corresponds to a pointer increment and memory free corresponds to a pointer decrement.

5.5 Integrity of the Original MLIR Lowering Pipeline

Our custom lowering pipeline with modifications to LoopTiling, DataCopyGeneration passes and Standard To LLVM conversion are currently guarded using the module target triple attribute as the flag. This helps to preserve the original MLIR lowering pipeline for other platforms.

6 EXPERIMENTS

To verify that our IR-to-IR Converter with the MLIR backend, shown in Figure 4, can work for a CPU backend, we use MLIR's original lowering pipeline to generate the LLVM IR. The LLVM IR is then compiled with `-O3 -ffast-math -std=c++17` to produce an ARM64 executable and ran on Huawei's Kunpeng 920 server. Our SYCL implementation is based on `sycl-nightly/20210514` [6], with LLVM 13.

The clock speed of the server is 2.6GHz with 64 KB L1 data cache, 512 KB L2 cache and 24M L3 cache. We measure the speed of double precision Matrix Multiplication kernels where $M=N=K$ in GFlops. We take an average of 10 runs with max and min values removed. We compare our MLIR path with that of Eigen3.3 [5] with and without OpenBLAS [8], with `OPENBLAS_NUM_THREADS=1`. We run the experiments with different matrix sizes ranging from 40 to 3100. The compiler options for Eigen is `-O3 -ffast-math -std=c++17 -march=armv8-a -mfpu=vfpv3`. As shown in Figure 7, Eigen with OpenBLAS has the best performance reaching 10GFlops which is almost the single core theoretical peak. Our MLIR path only achieves 1 to 2 GFlops with `cacheSizeBytes` set to 1K or 64K. The reason is that only Affine LoopTiling pass with the default tiling strategy is utilized to tile the M,N,K loops equally. Performance critical optimizations such as packing, register tiling and data prefetching for the micro-kernel are not performed.

Figure 7: MLIR Code Generation: Performance Comparison with Eigen3.3 and OpenBLAS

We also compare performance on DaVinci using our customized AICORE MLIR lowering pipeline with that of using AKG via the Halide IR backend. We measure using Huawei's Ascend 910 Server with 32 AICORES but we focus on measuring a single core performance using hardware performance counters. Both paths do

not make use of the cube unit. We set the `cacheSizeBytes` and `fastMemorySpace` to be 256K, matching the size of the Unified Buffer.

We show speedup comparison using five kernels: ReLU 16x32, ReLU 32x32, MatMul 16x16x16, MatMul 32x32x32, and MatMul 64x64x64. As shown in Figure 8, 3.02 to 20.58 times speedups are achieved by AKG's code generation.

Distribution of cycles spent in executing scalar, vector and memory instructions are gathered through hardware performance counters and presented in Figure 9. Since AICORE's scalar unit is significantly slower than its vector unit, the ability to use vector instructions in AKG contributes to its performance advantage. The speedup can also be attributed to AKG's usage of a polyhedral analysis for tiling in combination with an auto-search strategy. AKG also performs double buffering to overlap DMA transfers with computation as well as inserting the required DMA and synchronization instructions based on dependency analysis. Thus, AKG is a much more mature optimizer than our current MLIR lowering pipeline. The ReLU kernels are less computationally intensive as compared to matrix multiplication kernels and therefore, higher percentage of memory instructions are observed.

Figure 8: Performance Speedup using AKG

Figure 9: Distribution of Execution Cycles

7 RELATED WORK

Moses and Chelini’s work [11, 16] raises the IR abstraction using the MLIR Extraction (MET) tool for C code and enters the Affine Dialect directly from Clang’s AST. There is also the CIL project which compiles C++/C into the CIL [3] Dialect directly from Clang.

8 CONCLUSION

We have implemented an IR-to-IR converter which raises the LLVM IR to a higher abstraction level for the purpose of generating efficient SYCL kernel code written with the SIMT programming style. We would like to explore more MLIR passes to close the performance gap between MLIR and AKG in the future.

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