Auto-re-vectorization into RISCV Vector Code, from Vector/SIMD Intrinsics Code Written for Other Architectures like x86 AVX or ARM Vector/Neon, Using LLVM

Infrastructure

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Abstract

Coming up with a new RISCV Vector processor demands efficient workload execution. Conventional approaches include: (1) compiling high-level C/C++ code using auto-vectorizing compilers (e.g., LLVM or GCC), (2) hand-optimizing performance-critical kernels using intrinsics or assembly, or (3) a hybrid of both—yielding the best binaries but requiring significant manual effort. Although auto-vectorization is fast, it often produces suboptimal code compared to what hand optimization can achieve. We propose an alternative: leverage existing hand-optimized kernels (originally developed for x86 AVX, ARM Neon, and RISCV Vector - with differing micro - archs) by generating compiler IR (e.g., LLVM IR) from these vector codes and then revectorizing it for the target processor using a tool like LLVM. This approach produces more optimal machine code than compiling high-level language code and yields structures that are easier to further hand-optimize. This also makes quick enablement of existing code bases in other ISA intrinsics on RISCV Vector Processors possible. In this paper, we detail our auto-re-vectorization method, its implementation, and present cycle-based performance comparisons against vector code generated from high-level language compilations and other existing approaches.

Introduction

When a new processor is released, optimizing workloads to minimize latency, maximize throughput, reduce memory footprint, and lower power consumption is critical. A small number of kernels—frequently executed code blocks—often dominate execution time, so optimizing these (usually via hand-tuned intrinsics or assembly) is essential to fully exploit the processor's ISA. Many domains use libraries (e.g., BLIS [1], OpenBLAS [2], Eigen [3]) that include such kernels, but manually optimizing them for a new processor can take many human-months, and compiling high-level C/C++ often yields suboptimal performance, as evidenced by Alireza et al. (Sep 2023) [4].

We propose leveraging existing hand-optimized kernels from other ISAs by auto-re-vectorizing them to the new processor's ISA using compiler infrastructure. These kernels already have efficient, vector-friendly patterns compared to generic code. Prior work by Charith et al. (Feb 2019) [5] demonstrated that LLVM IR passes can re-vectorize code for newer vector ISA versions (e.g., AVX \rightarrow AVX2/AVX512). We have implemented a tool that transforms vector intrinsic code from x86 AVX and ARM Neon into RISC-V Vector code via LLVM IR transformations. We also compare our approach to header-based translations [6, 7] and a proprietary tool from a RISC-V vendor [8]. Our contribution is the disclosure of our LLVM pass–based method, with the tool and source code released to the RISC-V community.

Methodologies

Auto-re-vectorization Method / Algorithm

The methodology was designed to systematically transform other vector ISA (x86 AVX, ARM Vector/Neon, etc) intrinsic code into RISC-V Vector assembly and analyse its performance metrics. The procedure consists of first converting the input intrinsic code (other vector ISA) to LLVM Vector IR, then modifying the input ISA attributes to RISC-V Vector attributes, applying LLVM vector optimization passes (for a specific RISC-V Vector Processor) and finally lowering the optimized LLVM Vector IR to the target RISC-V Vector assembly code. The details are described in the following steps using the example of converting x86 AVX code to RISC-V Vector code:

Conversion of AVX Intrinsic Code to LLVM Vector IR

The C/C++ AVX intrinsic code was complied to the LLVM intermediate representation (IR) using the clang compiler. Example command:

clang -target x86_64-unknown-linux-gnu -S -emit-llvm - mfma <source_file>.c -o <llvm_ir_file>.ll

Modification of x86 Attributes to RISC-V Vector Attributes

The generated LLVM IR file is modified to replace x86specific attributes with RISC-V Vector-specific attributes. Specifically, attributes such as "target triple" "target-cpu" "target-features" "tune-cpu" were changed to RISC-V Specific attributes, that align with Risc-V Vector architecture.

Application of LLVM Optimizer Passes

The next step is to apply LLVM Optimizer (opt) passes on the modified IR File. Before applying the optimizer passes the "optnone" Attribute was removed from the modified IR File as the optnone attribute suppresses essentially all optimizations on a function or method.

The optimizer passes applied are:

- default<O2>
- loop-vectorize
- slp-vectorizer
- load-store-vectorizer
- Example command:

opt -S -debug-pass-manager -passes="default<O2>,loop-vectorize,slp-vectorizer,load-store-vectorizer"

<modified_llvm_ir_file>.ll -o <optimized_llvm_ir>.ll mtriple=riscv64 -mcpu=<target CPU for riscv64 architecture>

Generation of RISC-V Vector Assembly

The optimized LLVM IR was lowered into RISC-V Vector Assembly using the LLVM backend. Example command:

llc -march=riscv64 -mattr=<target-features> mcpu=<target CPU for riscv64 architecture> -o <output_rvv_asm_file>.s <optimized_llvm_ir>.ll

Discussion

LLVM provides the llvm-mca tool [9] to analyze machine code using LLVM's processor scheduling models. It retrieves instruction timing, latencies, and throughput for a given CPU. We used llvm-mca to analyze generated RISC-V Vector assembly code, measuring cycle counts and performance estimates for specific target processors. Example command:

llvm-mca -mtriple=riscv64 -mcpu=<target-cpu> iterations=1 < rvv_asm.s > <output.txt>

Results

We compared the performance of a matrix multiplication kernel, written in reference C code as well as in C intrinsics of x86 AVX. The reference C code was autovectorized to RVV using LLVM (Generic Flow), and the intrinsic code was converted to RVV using our Auto-revectorization tool (for targets SiFive X280 and P670). We compared the performance of these two RVV assemblies using the llvm-mca tool. The results are given below:

Table 1: Matmul	performance	comparison.
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	Generic Flow	Auto Re- Vectorization	Performance Gain
Target	(cycles)	Flow	
Processor		(cycles)	
SiFive	548	315	1.74 x
X280			
SiFive	91	52	1.75 x
P670			

We see that the performance of the code generated by our Auto-re-vectorization tool is better than the autovectorized code generated from reference C code. We intend to do similar comparison of more kernel types, which is expected to give even better results, since matrix multiplication is well optimized in compilers compared to other compute kernels.

Comparison with Alternative Approaches

There are couple of open-source tools available for converting x86 SSE code and ARM Neon code to RVV code [6, 7]. They use an alternative approach for this conversion. They replace the intrinsic headers with the corresponding implementation using RVV or C code wherever there is no one-to-one RVV replacement for the SSE/Neon instructions. The disadvantage of this approach is that a separate implementation of the header is required for each different version of the ISA, while our approach leverages the LLVM infrastructure itself. Also, the header replacement approach generates one-to-one replacement of the input code, which might not be the optimal RVV code for a given Vector microarch. Our approach leverages LLVM infrastructure to do optimizations suitable for the given target Vector microarchitecture.

References

[1] <u>https://github.com/flame/blis</u>

- [2] http://www.openmathlib.org/OpenBLAS/
- [3] <u>https://eigen.tuxfamily.org/</u>

[4] Alireza Khadem, Daichi Fujiki, Nishil Talati, Scott Mahlke,Reetuparna Das, "Vector-Processing for Mobile Devices: Benchmark and Analysis", In Proceedings of the IEEE International Symposium on Workload Characterization (IISWC), Oct. 2023

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- [6] https://github.com/pattonkan/sse2rvv
- [7] https://github.com/howjmay/neon2rvv
- [8] SiFive Recode: https://www.sifive.com/software
- [9] https://llvm.org/docs/CommandGuide/llvm-mca.html