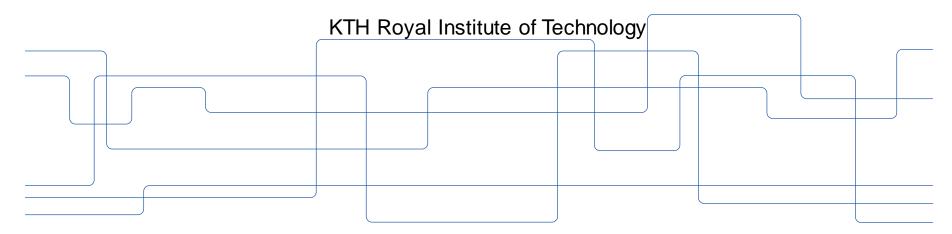


FFTc: An MLIR Dialect for Developing HPC Fast Fourier Transform Libraries

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Outline

- Motivation
- Methodology
- Evaluation
- Conclusion & Future work

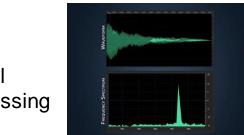


Motivation



Motivation: Importance of FFT

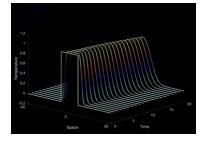
Applications



Signal processing



Partial Differential Equations(PDE)



• Libraries for FFT:

FFTE FFTPACK **FFTW**

Intel oneAPI Math Kernel Library





The Problems with FFT libraries like FFTW

- Lack of support for modern hardware
 - Newly introduced SIMD/tensor instructions in CPU, GPU, etc
- Lack of portability over heterogeneous hardware
 - Different code generation routines for different backends, cost is high
- Cannot utilize the evolving compiler community
 - MLIR/LLVM is more adaptive to search/learn based methods
- Emit C code, lack of control on low level compilation



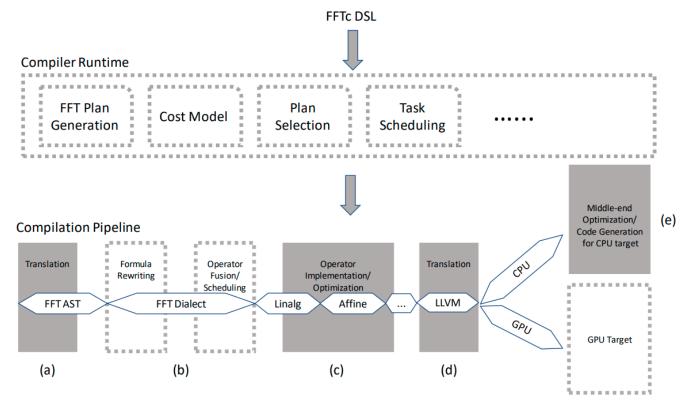
FFT Algorithm in matrix-formalism



Methodology



FFTC: A Domain Specific Compilation for Automatic Generation of FFT Algorithms





FFTc language: Declarative representation of FFT tensor Algorithm

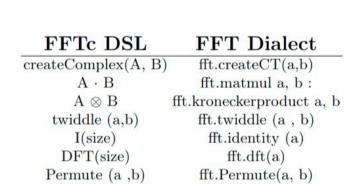
Fourier transform Diagonal matrix (twiddles)

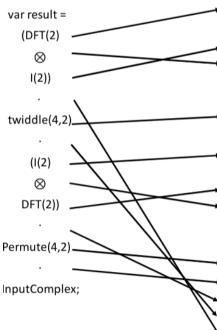
$$DFT_4 = (DFT_2 \otimes I_2) D_4^2 (I_2 \otimes DFT_2) \Pi_4^2$$
Kronecker product Identity Permutation

```
var InputReal <4, 1> = [[1], [2], [3], [4]];
var InputImg <4, 1> = [[1], [2], [3], [4]];
var InputComplex = createComplex(InputReal, InputImg);
var result = (DFT(2) & I(2)) · twiddle(4,2) ·
[1(2) & DFT(2)) · Permute(4,2) · InputComplex;
```



FFT Dialect (IR): Operations in FFT Dialect





%5 = fft.arithconstant 2.000000e+00: f64 %6 = "fft.dft"(%5) : (f64) -> tensor<*xcomplex<f64>> %7 = fft.arithconstant 2.000000e+00: f64 %8 = "fft.identity"(%7): (f64) -> tensor<*xcomplex<f64>> %9 = fft.kroneckerproduct%6,%8 : tensor<*xcomplex<f64>> %10 = fft.arithconstant 4.000000e+00 : f64 %11 = fft.arithconstant 2.000000e+00 : f64 %12 = "fft.twiddle"(%10, %11) : (f64, f64) -> tensor<*xcomplex<f64>> %13 = fft.arithconstant 2.000000e+00 : f64 %14 = "fft.identity"(%13): (f64) -> tensor<*xcomplex<f64>> %15 = fft.arithconstant 2.000000e+00 : f64 %16 = "fft.dft"(%15): (f64) -> tensor<*xcomplex<f64>> %17 = fft.kroneckerproduct %14, %16 : tensor<*xcomplex<f64>> %18 = fft.arithconstant 4.000000e+00 : f64 %19 = fft.arithconstant 2.000000e+00 : f64 %20 = "fft.Permute"(%18, %19): (f64, f64) -> tensor<*xcomplex<f64>> %21 = fft.matmul %20, %4 : tensor<*xcomplex<f64>> %22 = fft.matmul %17, %21 : tensor<*xcomplex<f64>> %23 = fft.matmul %12, %22 : tensor<*xcomplex<f64>> %24 = fft.matmul %9, %23 : tensor<*xcomplex<f64>>

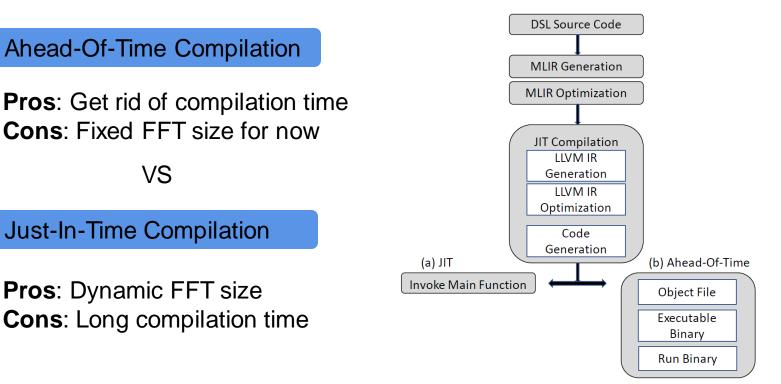


Progressive Lowering To Affine Dialect

```
From:
    %10 = fft.matmul \%9, \%3 : (tensor < 4x4xcomplex < f64 >>,
    tensor <4x1xcomplex <f64>>) ->
    tensor <4x1xcomplex <f64>>
To:
    affine.for %arg0 = 0 to 4 {
      affine.for %arg1 = 0 to 1 {
        affine.for %arg2 = 0 to 4 {
          %18 = affine.load %9[%arg0, %arg2] :
          memref <4x4xcomplex <f64>>
          %19 = affine.load %3[%arg2, %arg1] :
          memref <4x1xcomplex <f64>>
          %20 = complex.mul %18, %19 : complex<f64>
```



Different Code Generation Modes





Evaluation



Benchmark:

FFT from input size 32 to 128 Double complex input data Single thread Ahead-of-Time compilation mode



Evaluation:

Run for 1000 times, calculate standard deviation for 30 rounds

Hardware:

Dual-socket Intel Xeon Gold 6132 CPU, 192 GB of RAM



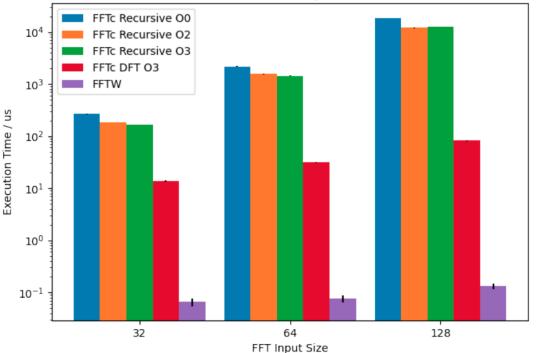
FFT Size 32 Compile & Run: 6.8903s Frontend: 0.0% MLIR Compilation: 90.4% LLVM Middle-end optimization & Code Generation & Run: 8.9%

Execution Time Report in JIT Mode

Wall Time / Seconds	Name
0.0034 (0.0%)	Parser & MLIRGen
0.0003 (0.0%)	Inliner
0.0000 (0.0%)	(A) CallGraph
0.0000 (0.0%)	'builtin.func' Pipeline
0.0002 (0.0%)	Canonicalizer
6.2268 (90.4%)	builtin.func' Pipeline
0.0001 (0.0%)	{anonymous}::ShapeInference
0.0001 (0.0%)	Canonicalizer
0.0000 (0.0%)	CSE
0.0000 (0.0%)	(A) DominanceInfo
0.0116 (0.2%)	{anonymous}::AffineToLLVMLoweringPass
0.0226 (0.4%)	Canonicalizer
0.0014 (0.0%)	CSE
0.0000 (0.0%)	(A) DominanceInfo
0.6238 (9.1%)	AffineLoopFusion
5.5622 (80.7%)	AffineScalarReplacement
0.0000 (0.0%)	(A) PostDominanceInfo
0.0000 (0.0%)	(A) DominanceInfo
0.0009 (0.0%)	AffineLoopInvariantCodeMotion
0.0384 (0.6%)	{anonymous}::FFTToLLVMLoweringPass
0.0000 (0.0%)	output
0.6154 (8.9%)	Jit
0.0057 (0.1%)	Rest
6.8903 (100%)	Total



- 02
 - Inliner, Canonicalizer, CSE
 - Affine: LoopFusion, LoopInvariantCodeMotion
 - LLVM O3 passes
- 03
 - MLIR O2 passes
 - Affine: ScalarReplacement
 - LLVM O3 passes



Execution Time by FFT Size



- Reasons contribute to the performance gap with FFTW
 - The FFTs are computed through dense matrix-matrix multiplication
 - Not fully optimized MLIR/LLVM compilation flow
 - No automatic FFT decomposition planner yet



Conclusion & Future Work





- Tensor-based FFT DSL and FFT Dialect in MLIR
 - DSL: Declarative representation of FFT tensor algorithm
 - FFT Dialect: Operations in FFT dialect to represent FFT algorithm
- Code generation pipeline through MLIR and LLVM infrastructure
 - Progressive lowering in MLIR for optimization & transformation at multiple abstraction level
 - Invoke LLVM JIT compilation for lower optimization on LLVM IR & code-generation



Future Work

- Fully Optimized Compilation:
 - FFT formula rewriting(decomposition): Pattern matching & Rewriting in MLIR
 - Loop tiling, vectorization
- Support various hardware backends:
 - CPU tensor unit, GPU, FPGA, etc
- Reduce Compilation Time
 - Multi-threading compilation & remove unnecessary MLIR passes
- Dynamic FFT Size at Compilation Time
 - Take advantage of MLIR bufferization process





This work is supported by IO-SEA under the European High-Performance Computing Joint Undertaking (JU)







- <u>https://www.inf.ed.ac.uk/teaching/courses/ct/18-19/slides/llvm-1-intro.pdf</u>
- https://llvm-hpc-2020-workshop.github.io/presentations/llvmhpc2020-amini.pdf