

SPIRAL-Generated Modular FFTs*

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Outline

SPIRAL Overview

- Challenge of Obtaining Efficient Code
- Transforms and Rules
- SPIRAL Architecture
- SPIRAL Abstraction Levels
- Example
- Performance

Modular DFT in SPIRAL

Addition of Modular DFT Transform and Modular FFT Rules

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- Code Generation for Modular FFT
- Performance
- Future Work



Challenge of Obtaining Efficient Code



Performance [Gflop/s]



High performance library development has become a nightmare

Spiral Overview

Research Goal: *"Teach" computers to write fast libraries*

- Complete automation of implementation and optimization
- Including vectorization, parallelization

Functionality:

- Linear transforms (discrete Fourier transform, filters, wavelets)
- BLAS
- SAR imaging
- En/decoding (Viterbi, Ebcot in JPEG2000)
- ... more

Platforms:

Desktop (vector, SMP), FPGAs, GPUs, distributed, hybrid

Collaboration with Intel (Kuck, Tang, Sabanin)

- Parts of MKL/IPP generated with Spiral
- IPP 6.0: ippg domain for Spiral generated code

DSP Algorithms: Transforms & Breakdown Rules

$$\begin{split} & \mathrm{DFT}_n \to P_{k/2,2m}^{\mathsf{T}} \left(\mathrm{DFT}_{2m} \oplus \left(I_{k/2-1} \otimes_i C_{2m} \mathrm{rDFT}_{2m}(i/k) \right) \right) \left(\mathrm{RDFT}_k \otimes I_m \right), \quad k \text{ even}, \\ & \begin{bmatrix} \mathrm{RDFT}_n \\ \mathrm{DHT}_n \\ \mathrm{DHT}_n \\ \mathrm{DHT}_n \\ \mathrm{DHT}_n' \end{bmatrix} \to \left(P_{k/2,m}^{\mathsf{T}} \otimes I_2 \right) \left(\begin{bmatrix} \mathrm{RDFT}_{2m} \\ \mathrm{RDFT}_{2m} \\ \mathrm{RDFT}_{2m}' \\ \mathrm{RDF}_{2m}' \\ \mathrm{RDF}_{$$

Combining these rules yields many algorithms for every given transform

SPIRAL: Architecture



SPIRAL: Abstraction Levels



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SPIRA

www.spiral.net



DSP Algorithms: E.G. 4-point DFT





Dynamic Programming (DP) searches over different applications of CT Rule using best transform found for recursive calls

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SPL to Shared Memory Code: Basic Idea [SC 06]

Governing construct: tensor product

$$y = (\mathbf{I}_p \otimes A) x$$



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p-way embarrassingly parallel, load-balanced

Problematic construct: permutations produce false sharing



Task: Rewrite formulas to extract tensor product + keep contiguous blocks



Parallelization by Rewriting



Load-balanced No false sharing

Same Approach for Other Parallel Paradigms

Message Passing [ISPA 06]



Vectorization [VECPAR 06]

 $\begin{array}{lcl} \overline{mn} & \rightarrow & \underbrace{\left((\mathbf{DFT}_{m} \otimes \mathbf{I}_{n}) \mathsf{T}_{n}^{mn} (\mathbf{I}_{m} \otimes \mathbf{DFT}_{n}) \mathsf{L}_{m}^{mn} \right)}_{\mathrm{vec}(\nu)} \\ & \cdots \\ & \rightarrow & \underbrace{\left(\overline{\mathbf{DFT}_{m} \otimes \mathbf{I}_{n}} \right)^{\nu} (\underbrace{\mathsf{T}_{n}^{mn}}_{\mathrm{vec}(\nu)})^{\nu} \underbrace{\left(\mathbf{I}_{m} \otimes \mathbf{DFT}_{n} \right) \mathsf{L}_{m}^{mn}}_{\mathrm{vec}(\nu)} \\ & \cdots \\ & \rightarrow & \underbrace{\left(\mathbf{I}_{mn/\nu} \otimes \underline{\mathsf{L}}_{\nu}^{2\nu} \right)}_{\mathrm{SSe}} (\overline{\mathbf{DFT}_{n} \otimes \mathbf{I}_{n/\nu}} \vec{\otimes} \mathbf{I}_{\nu}) \underbrace{\left(\underline{\mathsf{T}}_{m}^{mn} \right)^{\nu}}_{\mathrm{SSe}} \\ & & \left(\mathbf{I}_{m/\nu} \otimes (\underline{\mathsf{L}}_{\nu}^{m} \vec{\otimes} \mathbf{I}_{\nu}) (\mathbf{DFT}_{m} \otimes \underline{\mathsf{L}}_{\nu}^{2\nu} \vec{\otimes} \mathbf{I}_{\nu}) (\mathbf{I}_{2} \otimes \underbrace{\mathsf{L}}_{\nu}^{\nu^{2}}) (\mathbf{DFT}_{n} \vec{\otimes} \mathbf{I}_{\nu}) \right) \\ & & & \left((\mathsf{L}_{m}^{mn} \otimes \mathbf{I}_{2}) \vec{\otimes} \mathbf{I}_{\nu} \right) (\mathbf{I}_{mn/\nu} \otimes \underbrace{\mathsf{L}}_{2}^{2\nu} \vec{\otimes} \mathbf{Sse} \right)$

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Cg/OpenGL for GPUs

Verilog for FPGAs [DAC 08]

$$\underbrace{\left(\operatorname{DFT}_{rk}\right)}_{\operatorname{gpu}(t,c)} \rightarrow \underbrace{\left(\prod_{i=0}^{k-1} \operatorname{L}_{r}^{r^{k}} \left(\operatorname{I}_{r^{k-1}} \otimes \operatorname{DFT}_{r}\right) \left(\operatorname{L}_{r^{k-i-1}}^{r^{k}} (\operatorname{I}_{r^{i}} \otimes \operatorname{T}_{r^{k-i-1}}^{r^{k-i}}) \operatorname{L}_{r^{i}}^{r^{k-i}} \right) \right)}_{\operatorname{gpu}(t,c)} \xrightarrow{\operatorname{gpu}(t,c)} \rightarrow \underbrace{\left(\prod_{i=0}^{k-1} \operatorname{L}_{r}^{r^{k}} \left(\operatorname{I}_{r^{k-1}} \otimes \operatorname{DFT}_{r}\right) \left(\operatorname{L}_{r^{k-i-1}}^{r^{k-i}} (\operatorname{I}_{r^{i}} \otimes \operatorname{T}_{r^{k+1}}^{r^{k-i}}) \operatorname{L}_{r^{i}}^{r^{k}}\right) \right]}_{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \rightarrow \underbrace{\left(\prod_{i=0}^{k-1} \operatorname{L}_{r}^{r^{k}} \left(\operatorname{I}_{r^{k-1}} \otimes \operatorname{DFT}_{r}\right) \left(\operatorname{L}_{r^{k-i-1}}^{r^{k-i}} (\operatorname{I}_{r^{i}} \otimes \operatorname{T}_{r^{k+i-1}}^{r^{k-i}}) \operatorname{L}_{r^{i}}^{r^{k}}\right) \right]}_{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \cdots \xrightarrow{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \underbrace{\left(\prod_{i=0}^{k-1} \operatorname{L}_{r}^{r^{k}} \left(\operatorname{I}_{r^{k-1}} \otimes \operatorname{DFT}_{r}\right) \left(\operatorname{L}_{r^{k-i-1}}^{r^{k-i}} (\operatorname{I}_{r^{i}} \otimes \operatorname{T}_{r^{k+i}}^{r^{k-i}}) \operatorname{L}_{r^{i+1}}^{r^{k}}\right) \right]}_{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \underbrace{\left(\prod_{i=0}^{k-1} \operatorname{L}_{r}^{r^{k}} \left(\operatorname{I}_{r^{k-1}} \otimes \operatorname{DFT}_{r}\right) \left(\operatorname{L}_{r^{k-i-1}}^{r^{k-i}} (\operatorname{L}_{r^{k-i}} \otimes \operatorname{L}_{r^{k-i}}^{r^{k-i}}) \operatorname{L}_{r^{k+i}}^{r^{k-i}}\right) \operatorname{L}_{r^{k+i}}} \right)}_{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \underbrace{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \operatorname{stream}(r^{s})} \xrightarrow{\operatorname{stream}(r^{s})} \xrightarrow{\operatorname{st$$

Example Results

Multicore [SC 06]



DFT (single precision): on 3 GHz 2 x Core 2 Extreme performance [Gflop/s]

Code written by the computer is faster (for many sizes) than any human-written code

Modular DFT in SPIRAL

New Transform: ModDFT(n, p, w, i)

- **n**, the size of the transform
- *p* , the prime modulus
- \boldsymbol{w} , primitive n^{th} root of unity
- *i* , forward/inverse flag
- Same as DFT except must store p and w

Breakdown Rule for ModDFT: Cooley-Tukey in Z_p

Same as complex DFT except different roots of unity are computed

• CUnparser for ModDFT: Generate Z_p C code

- C code generated for modular arithmetic operations
- Alternative approaches explored







Modular FFTs: Cooley-Tukey in ${\mathbb Z}_p$

Cooley-Tukey algorithm

A transform of size mn breaks down into smaller transforms of size m and n

 $\begin{array}{c} DFT(m \cdot n) \longrightarrow DFT(m), DFT(n) \\ \longrightarrow Tensor(DFT(m), I(n)) \cdot T_m^{mn} \\ Tensor(I(n), DFT(m)) \cdot L_n^{mn} \end{array}$

• Cooley-Tukey algorithm in Z_p

Primitive root of P used in twiddle factors instead of complex root of unity

$$\begin{split} ModDFT(m \cdot n, p, \omega) &\longrightarrow ModDFT(m, p, \omega^m), ModDFT(n, p, \omega^n) \\ &\longrightarrow Tensor(ModDFT(m, p, \omega^m), I(n)) \cdot T_m^{mn}(\omega^m) \\ &\quad Tensor(I(m), ModDFT(n, p, \omega^n)) \cdot L_n^{mn} \end{split}$$

Modular FFTs: Unparser

- Unparser: translate symbolic arithmetic operations to corresponding C code
- Unparser for Modular FFTs
 - add (a, b) → (a + b) % p
 - sub (a, b) → (a b) % p
 - All elements are positive and smaller than p
 - $0 < a + b < 2p \rightarrow (a + b) \% p = (a + b < p)? (a + b) : (a + b p)$
 - -p < a b < p → (a b) % p = (a b < 0)? (a b + p) : (a b)
 - Faster than division though may introduce branches
 - Can use Conditional Move instead of branch (avoid pipeline stalls)
 - mul (a, b) → a * b % p

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Experiments

Platform

- AMD Phenom II X4 940 quad-core processor
 - Operating Frequency: 3.0 GHz
 - L1 Cache: 4 X 128 KB (64KB Instruction + 64KB Data)
 - L2 Cache: 4 X 512 KB
 - L3 Cache: 6 MB

Experiments

- Compare SPIRAL performance of modular FFT and complex floating point FFT
 - Optimal algorithms found may be different
- Compare SPIRAL modular FFT to numeric recipes (NR) code modified to perform modular DFT [NR uses iterative FFT]
- Compare optimal SPIRAL modular FFT found by DP to radix 2 recursive FFT

SPRIAL Code Performance

Best Code found by DP Modular DFT vs. Complex DFT



Expensive modular operations slow down ModDFT within the cache boundary

• Memory accesses dominate performance when input size crosses cache boundary ($\ge 2^{13}$)

Cache boundary reached one size earlier for complex DFT

SPRIAL Code Performance

Complex DFT Code Best SPIRAL code (DP) vs. Radix 2 Recursive Code & NR



SPIRAL best code about twice faster than its right recursive code

- Better algorithm found by the search engine
- SPIRAL best code averagely 4.8 times faster the numerical recipes code.
 - Better cache/memory utilization by SPIRAL
- Performance grouped into 3 regions (unrolled, in-cache, outside L1 cache)

SPRIAL Code Performance

Modular FFT Best SPIRAL code (DP) vs. Radix 2 Recursive Code & NR



- Best SPIRAL code twice as fast as right recursive code
 - Better algorithm found by the search engine
- Best SPIRAL code on average 3 times faster than NR code.
 Better cache/memory utilization by SPIRAL
- Similar performance trends for modular and complex DFTs
 - Larger jumps across unrolling and cache boundaries

Experimental Data

Input Size	Radix-2 Right Recursive		Dynamic Programming		Numerical Recipes	
	ModDFT	DFT	ModDFT	DFT	ModDFT	DFT
2 ³	*107	73	106	68	1852	5202
2 ⁴	271	183	271	165	3002	6073
2 ⁵	701	559	684	465	5402	7636
2 ⁶	2146	1950	2033	1130	10130	11713
27	7183	5113	5054	2528	19194	20382
2 ⁸	19491	12769	11290	5909	39687	38049
2 ⁹	46169	30097	23490	15214	81820	75729
2 ¹⁰	109924	71651	52297	34368	164575	163198
2 ¹¹	256097	170499	132688	83046	363737	345289
2 ¹²	611067	424499	284737	217446	800674	748075
2 ¹³	1440588	1316808	613370	778572	5555759	1628003
2 ¹⁴	3814025	3648241	1737673	1979379	13952347	5782618
2 ¹⁵	9987370	9698445	4866960	5301481	34076665	14269816
2 ¹⁶	24608317	22981890	11386662	13381989	86195220	36172945

* Number of cycles on AMD Phenom II 940 3.0 GHz Quad-core processor

Standard FFT Ruletrees

- Radix-2 Right Recursive Rule
 Iterative Tree in Numerical Tree
- **Recipes**





Optimal Modular FFT Ruletree

Best Rule Tree found by Dynamic Programming



Conditional Move

Conditional Moves



- CMOVcc theoretically reduces pipeline penalty by converting branches to branchless codes in ternary operations of add/sub
- Experiments show improvement only for large sizes
 - Short branches of ternary operations optimized by CPU's multi-instruction fetch and conditional execution
 - Branch prediction table entries overwritten in large-sized programs
 - Instructions fetches insufficient for conditional execution of larger programs

Future Work



Montgomery Algorithm [MATHCOMP 85]

- Modular multiplication without division
- Enable vectorization when vector division not available

Vectorization

Extend SPIRAL vectorization to support modular DFT

Multicore Parallelization

Extend SPIRAL parallelization to support modular DFT

Conclusion

Minor modifications to SPIRAL to support generation of efficient modular FFT code

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- SPIRAL generated code 2-5 times faster than standard implementations
 - Better memory utilization
 - Reduced loop/recursion overhead
- Modular code 1.38 times slower than floating point code
 - Beyond cache boundary modular code becomes faster
- SPIRAL machinery can be used to obtain vectorized/parallel code

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