AUTOTUNING HLS FOR FPGAS USING OPENTUNER AND LEGUP

Pedro Bruel (phrb@ime.usp.br)

Alfredo Goldman (gold@ime.usp.br)

Sai Rahul Chalamalasetti (sairahul.chalamalasetti@hpe.com)

Dejan Milojicic (dejan.milojicic@hpe.com)

ReConFig. December 5, 2017



Institute of Mathematics and Statistics University of São Paulo







OUTLINE

- 1. FPGAs, HLS & Autotuning
- 2. Background
- 3. Experiments & Results
- 4. Conclusion



The slides and all source code are hosted at GitHub:

- Code & Data: github.com/phrb/legup-tuner
- Slides: github.com/phrb/slides-reconfig-2017-autotuning

FPGAs:

- Logic Blocks and Interconnections
- Reconfigurable

Tradeoff:

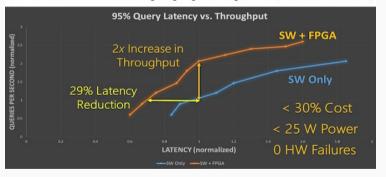
- Energy Efficiency and Performance
- Programmability



FPGAs

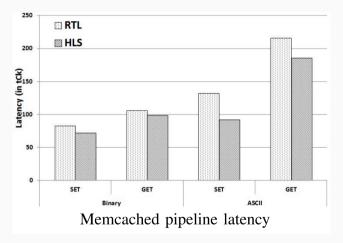
Using FPGAs in Bing:

1,632 Servers with FPGAs Running Bing Page Ranking Service (~30,000 lines of C++)



 $Image: \verb|enterprise| tech.com/2014/09/03/microsoft-using-fpgas-speed-bing-search/| [Accessed in 27/11/17] | tech.com/2014/09/03/microsoft-using-search/| [Accessed in 27/11/17]$

HLS can generate lower-latency applications:



Qualitatively, with less effort:

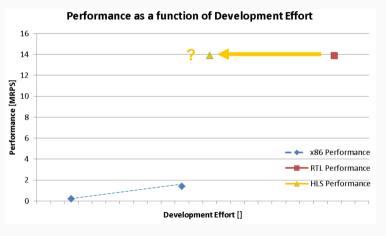


Image: Blott, Michaela, et al. "Achieving 10Gbps line-rate key-value stores with FPGAs." Presented as part of the 5th USENIX Workshop on Hot Topics in Cloud Computing. 2013.

This is an old issue:

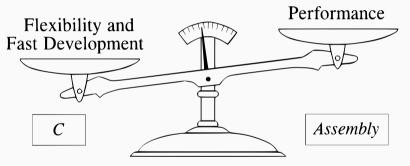
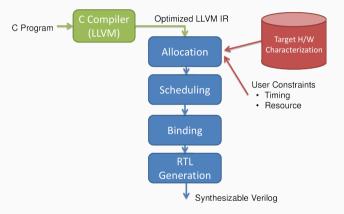


Image: Smith, Steven W. "The scientist and engineer's guide to digital signal processing." 1997

Schkufza et al., "Stochastic program optimization." Communications of the ACM 59.2 (2016):

- Optimizing assembly instructions
- Using stochastic methods to explore the design space

LegUp HLS flow:

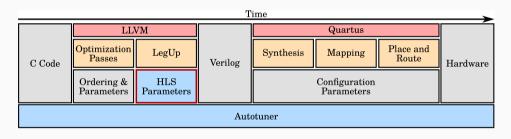


 $Image: Canis, Andrew \ Christopher. \ Leg Up: Open-Source \ High-Level \ Synthesis \ Research \ Framework. \ Diss. \ University of \ Toronto, 2015.$

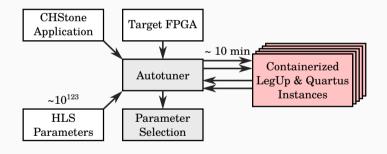
Why use autotuning for HLS?

- HLS aims to ease FPGA programming for software engineers
- But configuring HLS requires FPGA programming knowledge
- Autotuning can help software engineers use HLS

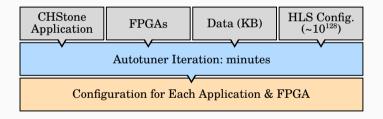
Our HLS compilation flow:



Our autotuner setup:



Our HLS autotuning workflow:



RELATED WORK: AUTOTUNING LLVM PASSES FOR HLS

Huang, Qijing, et al., "The effect of compiler optimizations on high-level synthesis-generated hardware." ACM Transactions on Reconfigurable Technology and Systems (2015):

- Optimizes parameters & ordering of a subset of LLVM passes
- Uses LegUp as an HLS tool
- Targets the Cyclone II device family
- Uses the CHStone benchmark
- Performs Exhaustive Search

RELATED WORK: AUTOTUNING INDUSTRY DESIGNS FOR VTR

Xu et al., "A Parallel Bandit-Based Approach for Autotuning FPGA Compilation." FPGA (2017):

- Does not optimize HLS
- Optimizes parameters of the Verilog-to-Routing (VTR) FPGA compilation tool
- Uses distributed OpenTuner instances

HIGH-LEVEL SYNTHESIS BENCHMARK

C-based High-Level Synthesis benchmark (CHStone):

Table 1: Autotuned CHStone Applications

Application	Short Description
blowfish	Symmetric-key block cypher
aes	Advanced Encryption Algorithm (AES)
adpcm	Adaptive Differential Pulse Code Modulation dec. and enc.
sha	Secure Hash Algorithm (SHA)
motion	Motion vector decoding from MPEG-2
mips	Simplified MIPS processor
gsm	Predictive coding analysis of systems for mobile comms.
dfsin	Sine function for double-precision floating-point numbers
dfmul	Double-precision floating-point multiplication
dfdiv	Double-precision floating-point division
dfadd	Double-precision floating-point addition

HARDWARE METRICS

Metric composition problem:

- 8 hardware metrics obtained from Quartus
- But the autotuner optimizes a single value

Our solution so far:

- Normalize metrics using initial values
- Optimize the normalized sum of the 8 metrics

HARDWARE METRICS

Normalized sum of metrics:

$$f(M, W) = \frac{\displaystyle\sum_{\substack{m_i \in M \\ w_i \in W}} w_i \left(\frac{m_i}{m_i^0}\right)}{\displaystyle\sum_{\substack{w_i \in W}} w_i}$$

Where M is the set of hardware metrics and W is the set of weights

WEIGHTED OPTIMIZATION SCENARIOS

An Optimization Scenario consists of:

- An optimization objective: performance, area, . . .
- Weights for hardware metrics

Our scenarios:

- 3 specific scenarios & 1 balanced scenario
- Weights: powers of two from 1: irrelevant to 8: high

WEIGHTED OPTIMIZATION SCENARIOS

Table 2: Weights for Optimization Scenarios (High = 8, Medium = 4, Low = 2)

Metric	Area	Perf. & Lat	Performance	Balanced
LUT	High	Low	Low	Medium
Registers	High	High	Medium	Medium
BRAMs	High	Low	Low	Medium
DSPs	High	Low	Low	Medium
FMax	Low	High	High	Medium
Cycles	Low	High	Low	Medium

EXPERIMENTS

Experiments

- We performed 10 autotuning runs for each scenario
- Each run took 1.5 hours
- We kept track of how each hardware metric changed over time
- We used the Weighted Normalized Sum (WNS) as autotuning objective

RESULTS

Presentation of results for each scenario:

- Mean of the relative changes, over 10 tuning runs
- For each hardware metric, and for WNS
- For each CHStone application
- Bluer is always better than Redder

RESULTS: COMPARING DEFAULT & RANDOM STARTS

Comparing Default & Random starts:

- A Default start already provides a sensible optimization
- A Random start might favor the exploration of new, unintuitive solutions
- In our case, the Default start was provided to the StratixV FPGA by LegUp

RESULTS: COMPARING DEFAULT & RANDOM STARTS

aes:	0.79	0.91	1.00	0.56	1.00	0.47	1.00	1.12
adpcm	0.68	1.13	1.00	0.54	1.00	0.56	0.60	0.98
sha	1.00	1.03	1.00	0.82	1.00	0.55	1.00	0.89
motion	1.02	1.00	0.60	0.85	1.00	0.57	1.00	0.94
mips	1.00	0.93	1.00	0.44	1.00	0.45	0.98	1.24
gsm	0.83	1.17	1.00	0.48	1.00	0.56	0.52	0.99
dfsin	0.79	0.97	1.00	0.61	1.00	0.60	1.49	1.53
dfmul	1.00	1.06	0.90	0.47	0.90	0.47	1.31	1.10
dfdiv	0.83	1.07	0.80	0.73	0.80	0.65	1.32	1.49
$dfadd\cdot$	1.00	0.94	1.00	0.82	1.00	0.71	1.00	0.93
blowfish-	_	_	_	_	_	_	_	_
	$L\dot{U}Ts$	Pins	BRAM	Regs	Blocks	Cycles	DSP	FMax

Figure 1: Comparison of the absolute values for Random and Default starting points in the Balanced scenario

RESULTS: COMPARING DEFAULT & RANDOM STARTS

Comparing Default & Random starts:

- The Default start achieves better absolute values than the Random start, on most cases
- The next results were obtained using the Default start

RESULTS: THE BALANCED SCENARIO

Metric	Balanced
LUT	Medium
itRegisters	Medium
BRAMs	Medium
DSPs	Medium
FMax	Medium
Cycles	Medium

aes	0.94	0.90	1.00	1.00	0.97	1.00	0.98	1.00	0.76
adpcm:	0.84	0.73	1.13	1.00	0.91	1.00	1.05	0.63	0.49
sha	0.98	1.00	1.03	1.00	0.96	1.00	0.86	1.00	0.97
motion	0.98	0.97	1.00	1.00	0.99	1.00	0.95	1.00	0.95
mips	0.95	1.00	1.07	1.00	0.90	1.00	1.01	0.80	0.89
gsm	0.95	0.95	1.17	1.00	0.99	1.00	0.95	0.49	1.08
dfsin	0.93	1.03	1.03	1.00	1.05	1.00	1.07	0.65	0.73
dfmul	0.85	1.00	1.13	0.90	0.88	0.90	1.06	0.31	0.76
dfdiv	0.84	1.00	1.07	0.80	1.15	0.80	1.34	0.41	0.57
dfadd	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97
blowfish	0.99	1.00	1.00	1.00	0.98	1.00	0.98	1.00	0.99
	WNS	$L\dot{U}Ts$	Pins	\overrightarrow{BRAM}	Regs	Blocks	Cycles	DSP	FMax

 $\textbf{Figure 2:} \ \ \textbf{Relative improvement for all metrics in the } \textit{Balanced } \textbf{scenario}$

RESULTS: THE AREA SCENARIO

Metric	Area
LUT	High
Registers	High
BRAMs	High
DSPs	High
FMax	Low
Cycles	Low

aes	0.96	0.92	1.00	1.00	0.93	1.00	0.97	1.00	0.86
adpcm	0.83	0.78	1.11	1.00	0.96	1.00	1.04	0.63	0.52
sha	0.96	1.00	1.06	1.00	0.84	1.00	0.83	1.00	1.08
motion	0.97	0.94	1.00	1.00	0.97	1.00	0.92	1.00	0.95
mips	0.91	1.00	1.06	1.00	0.89	1.00	1.00	0.72	0.84
gsm	0.89	0.83	1.06	1.00	0.86	1.00	0.89	0.82	1.14
dfsin	0.94	1.00	1.06	1.00	1.00	1.00	1.02	0.76	0.80
dfmul	0.82	1.00	1.06	1.00	0.90	1.00	1.21	0.27	0.86
dfdiv	0.77	1.00	1.22	0.67	1.03	0.67	1.62	0.28	0.77
dfadd	0.99	1.00	1.11	1.00	0.94	1.00	1.00	1.00	1.04
blow fish	0.99	1.00	1.00	1.00	0.97	1.00	0.91	1.00	1.01
	$_{ m WNS}$	$L\dot{U}Ts$	Pins	\overrightarrow{BRAM}	Regs	Blocks	Cycles	DSP	FMax

Figure 3: Relative improvement for all metrics in the \emph{Area} scenario

RESULTS: THE PERFORMANCE SCENARIO

Metric	Performance
LUT	Low
Registers	Medium
BRAMs	Low
DSPs	Low
FMax	High
Cycles	Low

aes	0.82	0.75	1.00	1.00	0.92	1.00	1.05	1.00	0.63
adpcm	0.84	0.94	1.17	1.00	0.96	1.00	0.94	0.69	0.74
sha	0.92	1.00	1.06	1.00	0.92	1.00	0.88	1.00	0.96
motion	0.99	1.00	1.00	1.00	1.01	1.00	1.00	1.00	0.98
mips	0.90	1.00	1.06	1.00	0.93	1.00	1.03	0.83	0.80
gsm	0.95	0.92	1.00	1.00	0.95	1.00	0.90	1.00	1.02
dfsin	0.87	1.11	1.06	1.00	1.27	1.00	1.25	0.53	0.56
dfmul	0.77	1.00	1.17	0.83	0.85	0.83	1.04	0.21	0.70
dfdiv	0.81	1.00	1.06	1.00	1.03	1.00	1.25	0.50	0.59
dfadd	0.97	1.00	1.00	1.00	0.97	1.00	1.00	1.00	0.94
blow fish	0.94	1.00	1.00	1.00	0.98	1.00	0.91	1.00	0.95
	WNS	$L\dot{U}Ts$	Pins	\overrightarrow{BRAM}	Regs	Blocks	Cycles	DSP	$F\dot{M}ax$

Figure 4: Relative improvement for all metrics in the *Performance* scenario

RESULTS: THE PERFORMANCE & LATENCY SCENARIO

Metric	Perf. & Lat
LUT	Low
Registers	High
BRAMs	Low
DSPs	Low
FMax	High
Cycles	High

aes	0.83	0.83	1.00	1.00	0.88	1.00	0.89	1.00	0.73
adpcm	0.76	0.78	1.11	1.00	0.95	1.00	0.98	0.62	0.47
sha	0.88	1.00	1.06	1.00	0.85	1.00	0.77	1.00	1.00
motion	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95
mips	0.95	1.00	1.11	1.00	0.91	1.00	0.99	0.89	0.96
gsm	0.92	0.92	1.11	1.00	0.87	1.00	0.90	0.67	1.11
dfsin	0.97	1.00	1.17	1.00	0.99	1.00	0.99	0.61	1.00
dfmul	0.86	1.00	1.22	1.00	0.89	1.00	1.01	0.33	0.84
dfdiv	0.82	1.00	1.11	1.00	0.84	1.00	0.96	0.34	0.83
dfadd	0.98	1.00	1.17	1.00	0.94	1.00	0.98	1.00	1.01
blow fish	0.96	1.00	1.00	1.00	0.97	1.00	0.93	1.00	0.97
	WNS	$L\dot{U}Ts$	Pins	BRAM	Regs	Blocks	Cycles	DSP	FMax

 $\textbf{Figure 5:} \ \ \textbf{Relative improvement for all metrics in the} \ \textit{Performance \& Latency } \ \textbf{scenario}$

RESULTS: COMPARING THE WEIGHTED NORMALIZED SUM (WNS)

aes:	0.94	0.96	0.82	0.83
adpcm	0.84	0.83	0.84	0.76
sha-	0.98	0.96	0.92	0.88
motion	0.98	0.97	0.99	0.98
mips	0.95	0.91	0.90	0.95
gsm-	0.95	0.89	0.95	0.92
dfsin	0.93	0.94	0.87	0.97
dfmul	0.85	0.82	0.77	0.86
dfdiv	0.84	0.77	0.81	0.82
$dfadd\cdot$	1.00	0.99	0.97	0.98
blowfish-	0.99	0.99	0.94	0.96
Average	0.93	0.91	0.89	0.90
	Balanced	Area	Performance	Perf. & Lat.

Figure 6: Relative improvement for WNS in all scenarios

RESULTS: CONCLUSION

In all scenarios:

- Heavily weighted metrics improved the most
- Lightly weighted or irrelevant metrics did not worsen greatly

Autotuning starting point:

- A random start might achieve more relative improvement
- But a sensible start achieves better absolute values

LIMITATIONS OF THIS WORK

Issues with the Weighted Normalized Sum:

- The WNS is a very naive metric combination strategy
- The multi-objective optimization domain provides better approaches

FUTURE WORK

Bigger designs:

- CHStone designs are very simple
- We will use our autotuning approach for bigger FPGA designs

Compiler configuration:

- HLS usually includes a C/C++ compiler step
- We will include compiler parameters or passes in our autotuner

Other HLS tools:

- Other HLS tools provide different search spaces
- We will use our autotuning approach for more proprietary and open HLS tools
- We want to use cost models that predict hardware metrics before synthesis

CONCLUSION

Autotuning HLS for FPGAs:

- Designers can select optimization objectives using weights
- Good WNS improvements after 1.5 hours of autotuning
- Improvements for targeted metrics without worsening other metrics
- A sensible starting point impacts autotuning results positively

AUTOTUNING HLS FOR FPGAS USING OPENTUNER AND LEGUP

Pedro Bruel (phrb@ime.usp.br)

Alfredo Goldman (gold@ime.usp.br)

Sai Rahul Chalamalasetti (sairahul.chalamalasetti@hpe.com)

Dejan Milojicic (dejan.milojicic@hpe.com)

ReConFig. December 5, 2017



Institute of Mathematics and Statistics University of São Paulo





