Work-in-Progress: Automatic Generation of Application-Specific FPGA Overlays

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ABSTRACT

This work proposes a generic flow for designing application-specific FPGA overlays that can achieve bare metal performance while improving productivity, resulting in increased adoption of FPGAs by software developers. The proposed approach relies on automatic extraction of kernels in high-level language applications. Extracted Kernels are then systematically translated into optimized hardware circuits using RapidWright, which allows bypassing HDL design flows. Initial results show up to 19× productivity improvement over regular overlays, and higher Fmax compared to bare metal in several cases.

KEYWORDS

FPGA, Overlay, LLVM, RapidWright

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1 INTRODUCTION

FPGA overlays have been developed to increase the programmability and adoption of FPGAs while achieving high-performance. They generally use coarse-grained processors in a communication infrastructure allowing parallel processing and data exchange. Unfortunately, the programmability gains of FPGA overlays are more than offset by massive performance loss, and increased power and resource consumption, mainly because they most often embed more features than what is actually needed to run applications. Current FPGA overlays mostly present architectures tailored for specific applications that relies on homogeneous processing units not adaptable to different use cases [1, 6]. Further, some research discuss the automatic generation of hardware accelerators. But, they either require expertise on domain-specific languages, imposing a learning burden on developers [5], or they necessitate specific types of inputs, not reflecting how developers would typically implement applications [2], all that without necessarily achieving high performance. Tools such as Vivado HLS allow to write high-level codes

for FPGAs, but still necessitate hardware skills and long compilation time. In this paper, we propose an application-specific FPGA overlay (AS-Overlay) design flow for productivity and performance improvement. At first, the flow leverages Level Virtual Machine (LLVM) [3], a compilation and code instrumentation framework, for automatic extraction of kernels within applications. Then, hardware is systematically produced with no HDL generation using RapidWright [4], an open source framework for custom netlist manipulation from Xilinx Research Labs.

2 PROPOSED APPROACH

2.1 Design Flow

Figure 1: Design Flow, Utilization Flow and Architecture

We aim to build FPGA overlays that can compete with bare metal implementations. Figure 1 summarizes the design flow, the architecture supporting the application-specific overlay generation, and the utilization flow. The design flow starts by inspecting the intermediate representation (IR) of applications at compile time with LLVM to extract compute-intensive sections that we call kernels. Next, we manually pre-synthesize basic operations from the IR using vendor tools: this step is done exactly once, and the synthesized netlists are reusable in several applications. Finally, we use RapidWright to combine the pre-synthesized basic operations into hardware kernels. Hardware kernels thus generated are embedded within processing units of an arbitrary overlay architecture in place of general-purpose ALUs, and Vivado is used for placement and routing. Users only call high-level functions described in a custom API with the data to process, removing the need for hardware expertise.

2.2 Hardware Generation

An LLVM transform pass is implemented to extract kernel from applications based on the gspan algorithm [7]. Code sections are identified as kernels if their frequency of appearance is greater than a threshold. Kernels are then pruned to select only operations that can actually be mapped on FPGAs: applications are written

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for Von Newman CPUs, which incurs the insertion of load/store, and casting instructions that are not actually needed on FPGAs.

Figure 2: Generation Example

Initially, the function implemented by a PE in the overlay layout is defined as a black-box. We leverage the pre-implemented design flow of RapidWright [4] to produce netlists from kernels previously identified with LLVM. The first step consists in synthesizing basic operations from LLVM IR out-of-context (OOC) with Vivado to create a *library of Modules*. This stage implies a manual implementation (through HDL or HLS) of operations to combine into kernels by an engineer, with the advantage that this step is done once. In the following stage, an application built on top of RapidWright assembles pre-implemented modules according to the kernel descriptions. The hardware kernels thus generated are returned as design checkpoint files (DCP) and define the functions executed by PEs. A custom Vivado Tcl script reads-in kernel DCPs into PE black-boxes. Finally, placement and routing are run with Vivado. Figure 2 summarizes the steps for the automatic generation of an FPGA overlay.

3 EXPERIMENTAL RESULTS

Designs are implemented on a Xilinx Kintex UltraScale+ FPGA (xcvu5p-ffvd900-2-i). Hardware generation is conducted with Vivado HLx Editions v2018.2, and RapidWright v2018.2.5-beta allows assembling hardware kernels. We ran Vivado, RapidWright, and the LLVM kernel mining on a computer with an Intel Corei3-8130U CPU@2.20GHz×4 and 8Gb of RAM. We compare manual implementation (Bare Metal), a regular overlay with an ALU in each PE, and AS-Overlays for each application, with 3 × 3 PEs. For Fmax and productivity studies summarized in Table 1, we introduced a Phase-Locked Loop generating a 300MHz clock on each testing architecture. The idea was to observe the maximum frequency and how long would the compilation take. AS-Overlays achieved up to 1.47× improved Fmax compared to regular overlays. This is caused by the muxes in general-purpose ALUs, introducing substantial delays on datapaths. On the other hand, bare metal implementations achieved higher Fmax compared to AS-Overlays on outer product and Robert cross filter. It is because vendor tools such as Vivado often produce high performance results for small modules [4]. In this case of figure, outer product and Robert cross are respectively a set of independent multiplications and subtractions followed by comparisons, simple enough give to bare metal a 1.09× Fmax advantage over AS-Overlays. That advantage is nevertheless lost on more complex functions such as image smoothing, highlighting the benefits of using the RapidWright pre-implemented flow as smaller modules can be pre-implemented to achieve maximum frequency, and later be assembled with minimal QoR loss. Reported compilation times show that Kernel netlist generation with RapidWright and loading with Vivado *read_checkpoint* command, outperforms by about 5× Vivado synthesis both in Regular overlays and bare metal implementations. Table 1 finally demonstrates that the proposed

AS-overlay generation flow can provide up to 19× productivity improvement over regular overlays on tested benchmarks.

Ma et al. [5] reported a productivity improvement between 170× and 214×, which only accounts synthesis. Further, they used benchmarks and FPGA different from ours. Similar observations can be made on other related work, making it challenging to establish fair comparisons.

Table 1: Productivity Analysis & Maximum Frequency

3×3 Overlay Generation Flow		Applications			
		Matrix Mult	Outer Product	Robert Cross	Smoothing
Bare Metal	Synthesis	26	17	35	35
	Optimization	5	2	6	34
	Placement	28	23	44	85
	Routing	68	59	55	1064
	Total (Seconds)	127	101	140	1218
	Fmax (MHz)	365	488	348	231
Regular	Vivado Flow →	Synth. 40	Opt. 27	Place. 111	Routing 1457
	Total (Seconds)	1635 (27 minutes 15 seconds)			
	Fmax (MHz)	304			
AS-Overlay	Kernel Gen.	3.89	3.48	3.55	4.34
	Kernel Load.	8.12	5.83	4.12	7.8
	Optimization	5	4	3	33
	Placement	46	19	24	83
	Routing	65	54	117	646
	Total (Seconds)	128.01	86.31	154.67	774.14
	Fmax (MHz)	435	447	318	308

4 CONCLUSION

We presented an approach for automatic generation of Application-Specific FPGA Overlays capable of providing bare metal performances. The approach extracts kernel from applications, and automatically builds a tailored accelerator. Experimental evaluations demonstrated the viability of our approach with significant productivity and Fmax improvement over regular FPGA overlays. Future works will investigate the possibility of generating hardware capable of reaching higher Fmax. We also intend to study how the power consumption scales in AS-Overlays compared to bare metal implementations and regular overlays.

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