Axl: Accelerating Approximations via Slack Recycling

Gokul Subramanian Ravi
gravi@wisc.edu

Mikko Lipasti
mikko@engr.wisc.edu

Abstract

We extend the notion of clock cycle slack into approximate computation. In prior work, we performed slack recycling for accurate computing to improve clock period utilization. Now, we propose Axl: disciplined but increased aggressiveness in slack estimates at an operation granularity - accounting for slack from PVT, data, as well as approximation tolerance. This results in improved performance/efficiency within application-specific tolerable error rates.

1 Introduction

In order to operate reliably and produce expected outputs, modern processors set timing margins conservatively at design time to support extreme variations in workload (data) and environment (PVT) [4, 6]. In the common non-critical cases, this creates clock cycle *slack* - the fraction of the clock cycle performing no useful work. In prior works, we proposed LAGS and ReDSOC (both under submission; based on [11]) which use transparent latching techniques to effectively recycle multiple forms of slack and improve performance while maintaining required reliability constraints. These mechanisms focused on timing slack reduction for accurate computing - we believe there is significant potential to extend these proposals into the realm of approximate computing.

Our proposal Axl, is motivated by limitations in current approximate hardware, with specific focus on timing approximation, further elaborated in Sec.3. Axl is effective in avoiding prior limitations, by piggy-backing approximation atop our prior work on slack recycling (Sec.2). **Converting tolerable approximation into a component of a computation's clock cycle slack** allows the use of LAGS/ReDSOC slack recycling techniques to accelerate sequences of computations.

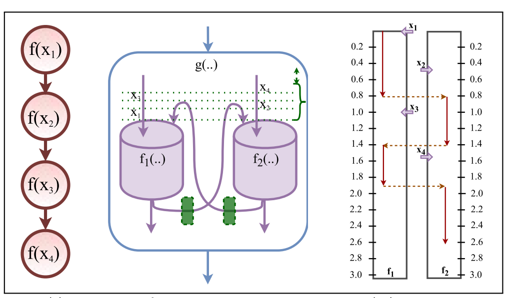

Figure 1. (i) "Asynchronous" Sequence, (ii) Execution units with transparent latching, (iii) Slack recycling

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2 Recycling Slack in Accurate Computing

In this section we summarize our prior proposals for identifying PVT slack from PVT variations, data slack from operation type, and operand data widths/types (examples in Table.1) and recycling them by employing a transparent latching mechanism which targets accurate computing. The mechanism is illustrated in Fig.1

① Simple asynchronous execution engines are integrated seamlessly into synchronous pipelines. ② Asynchronous engines are implemented as transparent (latched) pipelines with synchronous control, resulting in low design complexity. ③ Multiple asynchronously executable operations, bounded by synchronous boundaries, are grouped together into a transparent multi-cycle execution flow, allowing slack to accumulate along the sequences. ④ Transparent latches with slack-aware control are employed between execution units to recycle the slack from a producer operation; by starting the execution of dependent consumer operations at the exact instant of completion of the producer operation. ⑤ PVT Slack is identified via CPMs [8] (supported by feedback mechanisms and multi-operation statistical modeling) while data slack is identified by analyzing opcodes and operand bit-widths. ⑥ Speedup in executing any naive sequence is obtained by recycling accumulated slack: by clocking synchronous boundaries (to sequences) on early cycles, rather than altering voltage/frequency. This neither requires adjacent operations to fit into single cycles nor any rearrangement of operations. ⑦ Our proposals target both spatial architectures and out-of-order cores.

3 Extending to Approximate Computing

Axl, our proposed design for timing approximation is an extension of the slack recycling mechanism discussed in Sec.2.

① Application-level approximability is translated into operation-level approximability, to allow fine-grained control of approximation (as explored in prior works [1, 2, 5, 14]). Examples of approximate slack are seen in the "Approx" column in Table.1. ② Potential slack for each executing operation is identified - accounting for PVT/Data Slack and Approximate Slack (from the approximation a computation can handle, if any). Timing slack vs error-rates have been analyzed to some degree by prior work [4, 12, 13] ③ The total cumulative slack is tracked across sequences of operations. ④ The sequences are then accelerated by recycling the total slack via the transparent latch based data-flow and early clocking mechanisms as shown in Fig.1.

S#	D#	Instruction	PVT	Data	Approx	Tot. Slack
1	1	add.a r3, r1, r2, 95	10%	5%	15%	20%
2	1	or r6, r4, r5	10%	30%	0%	40%
3	1	add.a r9, r7, r8, 99	10%	8%	10%	28%
1	2	add.a r3, r1, r2, 95	10%	10%	15%	35%

Table 1. Example slack breakdown of dynamic instances of multiple accurate/approximate operations.

Limitations in current approximate hardware (with specific focus on timing approximation) and benefits of our proposed design are discussed in detail below.

Fine grained performance speedup:

Challenge: Prior proposals on functional-unit-level approximation have completely focused on power savings (via power gating or low-voltage rails) [3, 5, 7, 9, 14]. While saving power is an important goal, so is performance speedup - accelerating approximate computations can, for instance, help meet QoS requirements.

Proposal: Our slack recycling proposals can accelerate sequences of operations via early clocking when sufficient slack accumulates (Sec.2). There is potential for performance speedup as and when sufficient slack exists. The fraction of approximate slack varies depending on each computation's approximation tolerance. The greater the slack, the more potential for speedup.

Approximate vs. accurate compute resources:

Challenge: Most applications amenable to energy-accuracy trade-offs have a fine grained inter-mingling of approximate and precise components [5]. To support this, prior general-purpose solutions employ duplicate hardware compute units (separate sets for accurate and approximate), eg. Truffle [5].They incur significant design overheads - extra resources, multiple voltage rails, scheduling logic overheads and further suffer from high potential for under-utilization.

Proposal: In our proposal, each functional unit can work as accurate compute or as approximate compute. In the former scenario, the FU only exploits PVT/Data slack but in the latter, it can estimate slack more aggressively - estimating for the required level of approximation as well (Instructions 1 vs. 2 in Table.1). This allows flexible execution of both compute forms without additional type constraints.

Temporal control at fine granularities:

Challenge: Dynamically tuned approximate hardware often employ a feedback mechanism [14] to correct the amount of approximation. Timing approximation hardware use voltage/frequency (V/F) scaling, and the time period of this feedback loop can be limited by granularity at which V/F can change. This can result in poor temporal adaptability of feedback based timing approximation hardware.

Proposal: Our proposal can perform timing approximation at very fine temporal granularities, due to the absence of V/F scaling. This feedback makes aggressive or conservative corrections to the slack estimation, and is immediately reflected in the approximate computation.

Inherent precision and environmental effects:

Challenge: Traditional timing approximation solutions lack the ability to adapt to local characteristics such as random PVT variations and inherent operation precision/datatype/data-width. In prior work, when voltage scaling is applied, the voltage is set according to average error rates across phases of execution. Setting a constant low voltage for all approximate computations has limitations, because the actual effect of the timing approximation becomes dependent on the PVT/data slack experienced by the computation. This leads to undisciplined approximation across the approximate operations.

Proposal: In our work, approximate slack is applied atop other forms of slack. Slack is modeled separately for separate compute units and for each operation. Once PVT and data slack is computed, the approximate slack for that operation (depending on the level of approximation) is added. Thus, for instance, multiple operations on the same compute unit, with the same level of approximation, might have different total slack depending on their operand values (Instructions 1 vs. 4 in Table.1).

Support for multiple approximation levels:

Challenge: Approximate programs often consist of multiple approximate variables with each tolerating different levels of approximation. In this regard, recent quantitative approximability proposals, both at application [1, 2] and ISA [14] levels, allow for fluid precision reliability control and show the benefits of multiple approximate levels among operations within standard approximate applications. However, current approximate hardware proposals are unable to efficiently design for fluid precision - especially in the case of timing approximate hardware.

Proposal: In our work, multiple levels of approximation can be integrated seamlessly. In the presence of software and ISA support, each instruction carries information on the level of approximation that it requires. This is interpreted at the time of slack estimation for the operation. Similar to the assignment of data slack based on opcode etc, approximation slack is assigned based on this approximation level (Instructions 1 vs. 3 in Table.1).

A comprehensive summary of our prior works and more details motivating this proposal can be found in [10]

4 Future Steps

We are currently studying Axl's benefits across error-tolerant applications (eg. Axbench [15]) over standard OOO and spatial substrates. We expect to explore specialized architectures such as neural network accelerators.

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