QASM-to-HLS: A Framework for Accelerating Quantum Circuit Emulation on High-Performance Reconfigurable Computers



Introduction Motivation

- Existing FPGA-based quantum circuit emulation methods [1][2] exhibit limited flexibility in emulating a variety of quantum algorithms
- They have fixed, algorithm-specific hardware architectures.
- Additionally, the computational load of generating transformation matrices generally fall on the CPU, thereby restricting the extent to which FPGAs can be leveraged for accelerating quantum algorithms.
- Mapping a quantum algorithm to its corresponding FPGA architecture for emulation is challenging, particularly for algorithm developers with limited FPGA design experience.

Objectives and Approach

- Provide an interface between front-end quantum algorithm design and backend FPGA-based emulation.
- Develop a methodology for converting quantum circuits represented in Quantum Assembly Language (QASM) into their corresponding architectures for emulation on FPGA backends.
- Automatically derive quantum emulation architectures for High-Level Synthesis (HLS) on FPGAs. Investigate variations of hardware architectures with trade-offs between area and speed. Derived architectures support 64-bit FP precision and complex number arithmetic.

Background

• QASM

- Quantum assembly languages [3] are machine-independent languages that traditionally describe quantum computation in the circuit model.
- Open quantum assembly language (Open QASM 2) was proposed as an imperative programming language for quantum circuits based on earlier QASM dialects.
- In principle, any quantum computation could be described using Open QASM 2.

High-level Synthesis

- High-level synthesis (HLS) [4] automates hardware design by converting high-level programming languages into optimized hardware code.
- Let's hardware designers efficiently build and verify hardware, by allowing them to describe the design at a higher level of abstraction.

In our methodology, we start with the QASM description of the quantum circuit. An efficient QASM parsing method (QASM-to-HLS) is developed that generates high-level hardware codes for HLS. Layering:

37 (38 $L2 \downarrow 39$ h 40 L3 [41 **L4** { 42 43 x L5 < 44 h 45 h 46 h q[0];

<u>Ex:</u>

L1: [h, h,

Generate an i of size 2^n

Ex.:

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QASM Processing

- To emulate quantum operation, each layer of the quantum circuit is considered, and the corresponding matrix operation is generated.
- o To conserve resources, layers with CNOT gates only are segregated.

q[0]; q[1];	q[0] – H	Ð		H	D		
q[3];	q[1] — H	н	D H	н	ÐHG	н 🕂 н	
q[0]; q[1];	q[2] — H		<u> </u>	Н	D		
q[3];	q[3] – H	н	🕀 н	н	Ð H G	н 🕂 н	
< q[0], q[1];	Ľ	1 L2	L3 L5	L6 I	.7 L8 L9	Ð	1.
q[0]; q[1];							5
q[3];							

- o Multiplying the matrices of two adjacent layers can yield a consolidated single-layer matrix, leveraging this insight can effectively mitigate data transfer latency and accelerate the computation of results across multiple layers.
- Controlled gates [5] will be processed differently without forming the pairs.

Matrix Generation

- Each layer's matrix is computed using the developed python based QASM-to-HLS package.
- The package contains functions for layer identification and classification from the QASM code.
- o Layer matrices are generated by tensor operations between individual gate matrices.

$$[\mathbf{l}, \mathbf{x}] = \begin{bmatrix} 0.707 & 0.707 \\ 0.707 & -0.707 \end{bmatrix} \otimes \begin{bmatrix} 0.707 & 0.707 \\ 0.707 & -0.707 \end{bmatrix} \otimes \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \otimes \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

entity matrix
$$\begin{bmatrix} \mathbf{n} - \text{digit} & \mathbf{n} - \text{digit} \\ \mathbf{0} - \mathbf{0} & \mathbf{1} \end{bmatrix}$$

Based on control bit, flip the target bit and at corresponding place of new binary string, update with 1

- QASM-to-HLS processes the QASM and produces the HLS application code, consisting of host (PC) code and kernel (FPGA) code
- For fixed number of qubits, only the host code changes for different algorithms and gate parameters. Kernel architecture remains same.

FPGA Architectures

- complex matrix-vector computation.







ASM-to-HLS can generate 3 design variants kernel architecture for quantum emulation

ype-1 Design: This design performs a equence of matrix-vector multiplications to determine a final output quantum state. This is performed by a single kernel that takes a layer matrix and state vector as inputs and performs

Type-2 Design: A parallelized version of Type-1 design which uses concurrent input streams and reduces the data transfer time. This design is optimal for emulation of small circuits and utilizes the FPGA resources more efficiently.

3. <u>Type-3 Design</u>: This design offers th throughput and acceleration; however, it con cost of increased memory utilization. The involves passing k matrices into the buffer, w pair of matrix computation results is stored in buffers. These intermediate results are then later to produce the resultant matrix comprising passed m matrices in a dataflow design. The matrix is multiplied by the initial statevector.



Type-1 Design:

<u>Time Complexity</u>: $(t_{avg} + t_{avg}^c) \times D$; D, depth of circ Space Complexity: $2^{n+5} + 2^{2n+4}$ Average Computation time $(t_{avg}^c) \rightarrow$ $O(N^2)$; N, number of elements in matrix $t_{avg}^{c} = Avg time for data transfer$

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Type-2 Design:
<u>Time Complexity</u> : $r t_{avg} + D t_{avg}^c$; $r = \frac{D}{K}$
Space Complexity: $2^{n+5} + K \cdot 2^{2n+4}$
Average Computation time $(t_{avg}^{c}) \rightarrow$
$O(N^2)$; N, number of elements in matrix
$t_{avg}^{c} = Avg$ time for data transfer

Type-3 Design:

<u>Time Complexity</u>: $(t_{avg}^c \cdot \log_2 K + t_{avg}) \times r + t^{c'}; r = \frac{D}{K}; K = 2,$ 4, 8, 16 - - - -Space Complexity for max parallelism: $K\left[\frac{K}{2}+1\right]$. 2^{2n+4}

Matrix-Matrix Multiplication $time(t^c_{avg}) \rightarrow O(N^3)$ Matrix – Vector Multiplication time $(t^{c'}) \rightarrow O(N^2)$ N, number of elements in matrix $t_{avg}^{c} = Avg$ time for data transfer

t Statevector]	Experimental Results						
	Number of Qubits	FPGA Kernel Execution Time (ms)	LUT%	Register%	BRAM%	DSP%	Software Simulation Time
	3	0.012	0.52	0.46	1.06	0.16	7.16
^{to PS} ► M _{Total}	5	0.131	0.51	0.47	1.25	0.16	12
	7	1.923	0.52	0.46	3.89	0.16	37.1
			Cor	ıclus	ions		
:o PS ► S _{o/p}	 FPGAs can be used for efficient emulation of quantum algorithm however mapping quantum circuits to FPGA emulation architectures is challenging The proposed automation framework facilitates the mapping quantum circuits to FPGA emulation architectures. Experimental results include implementation on Xilinx Alveo V 200 FPGA [7]. Compared to state-of-the-art software simulator[7]. 						
	speed	up of almost	up to \times	(100.	ntationa	and ontine	Totiona

ruture work includes more implementations and optimizations.

References

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