



FPGAs in HPC applications and methods

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What are FPGAs

• Field Programmable Gate Arrays

- Adaptable computing resources
- Reconfigurable at any time
- Devices for processing digital data streams



Arrays of Configurable Logic Blocks



Basic Configurable Logic Block





R. Kastner, J. Matai, S. Neuendorffer "Parallel Programming for FPGAs"



CPU vs GPU vs FPGA

Instr 1

Instr 2

Data N

Data M

Clock cycle

Instr 1 Data 1 Instr 2 Data 2 Instr 3 Data 3 Instr 4 Data 4

- CPU
 - Single Instruction Single
 Data per core
 - Fixed instruction set
 - Multiple cores
 - High clock freq.
 - Operating system

□ GPU

Data 1

Data 3

Clock cycle

- Single Instruction Multiple Data
- Fixed instruction set
- High clock freq.
- Memory access
- Accelerates CPU

- 12 11 Instr 13 lnstr 1M Instr Instr Data 1 Instr 23 21 22 lnstr 2M Instr Instr Data 2 32 31 Instr 33 Instr NM Instr Instr Data N
 - FPGA
 - Flexible architecture
 - Massive parallelism
 - Streamlined processing
 - Low clock freq.
 - Instant memory access
 - Standalone platforms



Devices

• First FPGA introduced by Xilinx in 1985

- 64 Configurable Logic Blocks with programmable interconnect
- Addition of two integers consumes ~30 CLB
- Design built manually by connecting logic gates

• Typical applications

- Interfacing with digitization devices (TDCs, ADCs)
- Sensor Fusion
- True real-time device control e.g. servo-motors,
- Network streams processing

In experimental physics

- Digitization of analog signals
- Preprocessing of digitial data streams (e.g. filters, zero-reduction, feature extraction)
- Control and monitoring of electronics
- High-speed data transmission
- Low-level, fast data selection (trigger)



















FPGAs and GPUs

• FPGAs after 40 years

- Market value from 10\$ bilion in 2020 to estimated 30\$ bilion in 2030
- GPU market value from 25\$ billion in 2020 to estimated 300\$ bilion in 2030

• GPU breakthrough into mainstream computing

- Generic PCIe interface
- Superior performance in specific applications
- Programming environment CUDA introduced in 2007, Tensorflow in 2017

Current FPGA situation

- PCIe accelerator cards since 2018
- Largest device over 2 millions CLBs
- First mainstream C++ to HDL compiler released in 2015
- First complete system builder released in 2018
- Altera acquired by Intel in 2015, Xilinx acquired by AMD in 2022

Development methods

• Hardware Description Language (HDL)

- Natural development flow (VHDL, Verilog, SystemVerilog)
- Bit- and clock-cycle- level operations
- Difficult, nonintuitive for software developers
- Output product of any other design development method

• High-Level Synthesis

- C++ compiler into HDL
- Enables implementation of complex algorithmics
- Enables development of acceleration kernels
- Requires basic understanding of FPGA architecture

• System builder

- Development suite for accelerator cards with PCIe
- Host kernel architecture
- OpenCL or native XRT abstractions
- Complete flow in C++
- Compiler automatically generates host memory kernels interconnect



FPGA Accelerators

- High-capacity FPGA variants
 - 500k CLB U280 for 8k EUR, equivalent VU35P 40k EUR
- PCIe 4.0x8
- Integrated 8 GB HBM
- External 32 GB DDR4
- 2x QSFP28
- Similar products from various manufacturers







- Delegation of some algorithmic parts to FPGA resources
 - Complete development flow in C/C++
 - FPGA design generated based on configuration files
 - Kernel compiled with High-Level Synthesis
 - Link automatically generated based on configuration
 - FPGA configuration bitfile produced for execution





Optimizations

- Kernel level (HLS pragmas)
 - Loop unrolling
 - Pipelining computations
 - Memory layout
 - Data types
 - Balance between resource usage and performance
- System level (System Builder config. file)
 - Types of kernels
 - Instances of kernels
 - Memory layout
 - Kernels interconnections







- Compilation and debugging
 - System builder produces FPGA configuration bitfile
 - Bitfile can be uploaded to the device at any time
 - Configured device can be used by various host executables
 - Unless they use the same kernels and memory layout
- Producing a bitfile is highly time consuming
- Development flow:
 - Emulation C (fastest)
 - Compilation and execution the entire sourcebase as standard g++ on CPU
 - Consistency check of the algorithm
 - Hardware Emulation (slow)
 - Link with kernels compiled into HDL
 - Execution as simulation of the HDL clock cycle after cock cycle
 - Verification of optimizations, memory layout
 - Hardware (extremly slow)
 - Final bitfile produced
 - Execution on hardware
- Each step produces series of reports to analyze (execution profiles, resource consumption, etc.)



- Execution
 - Host has to configure the device, transfer data, call the kernel and retrieve the results
 - OpenCL abstractions
 - cl::Device, cl::Context, cl::Program
 - cl::Buffer, cl::CommandQueue, cl::Kernel
 - Xilinx Runtime (XRT) abstractions
 - xrt::device, device.load_xclbin
 - xrt::bo, xrt::bo.sync, xrt::kernel
 - pyxrt bidings for Python

from xrt binding import * import pyxrt
<pre>d = pyxrt.device(opt.index) xbin = pyxrt.xclbin(opt.bitstreamFile) uuid = d.load_xclbin(xbin)</pre>
<pre>simple = pyxrt.kernel(d, uuid, "simple")</pre>
<pre>boHandle1 = pyxrt.bo(d, 10, pyxrt.bo.normal, simple.group_id(0)) boHandle2 = pyxrt.bo(d, 10, pyxrt.bo.normal, simple.group_id(1))</pre>
<pre>boHandle1.sync(pyxrt.xclB0SyncDirection.XCL_B0_SYNC_B0_T0_DEVICE, 10, 0) boHandle2.sync(pyxrt.xclB0SyncDirection.XCL_B0_SYNC_B0_T0_DEVICE, 10, 0)</pre>
run = simple(boHandle1, boHandle2, 0x10) state = run.wait()
<pre>boHandle1.sync(pyxrt.xclB0SyncDirection.XCL_B0_SYNC_B0_FROM_DEVICE, 10, 0)</pre>





- How to construct a kernel?
 - Implement plain C++
 - Search accelerated libraries catalog for subfunctions
 - Configurable and optimised implementations of typical functions
 - Github examples of all FPGA features and optimizations
 - External tools e.g.:
 - HLS-4-ML
 - Keras, PyTorch to C++ and HLS project
 - Direct model inference conversion from Python to FPGA kernel





Al on FPGA accelerators

- Inference only
 - Inference is feed-forward, simple arithmetics, layer-by-layer pipelined, natural for FPGA
- Optimizations on data types
 - Custom data types are natural for FPGA
 - (int<8>, int<3>, ap_fixed(14, 5), ...)
- Control over each clock cycle
 - Low and deterministic latency in true real-time





- CMS experiment trigger system
- Sustained collision rate 40 MHz
- Fast decision on data quality
- Implemented with HLS-4-ML



Figure 2: Compared to alternative devices such as GPUs and ASICs, FPGAs are the only viable choice for the event trigger processing because they provide extremely low latency. While the large numerical processing capability of GPUs is attractive, these technologies are optimized for high throughput, not low latency.

https://www.xilinx.com/publications/powered-by-xilinx/cerncasestudy-final.pdf



Data sources

- Sources of data for kernels:
 - Buffers allocated and migrated to local resources ٠
 - Migrate to, compute, migrate from scheme
 - Buffer streamed to the kernel through PCIe •
 - Dataflow and streamlined computations ٠
 - 100G Ethernet QSFP28 sockets •
 - Dataflow and streamlined computations ٠
 - Lowest and deterministic network latency ٠
 - 150ns from electric signals to decoded bytes ready ٠ to process











Ethernet solutions

- OpenNIC
 - Acts as a regular network card
 - Protocol stack on CPU and OS
 - Two regions for low-level processing
 - Network security, encryption, encoding...



https://github.com/Xilinx/open-nic?tab=readme-ov-file

- VNx
 - ARP, ICMP, UDP implemented in the FPGA
 - UDP transmitter and receiver as a kernel
 - No driver, kernel access from the host via OpenCL or XRT
 - Custom, ultra-low latency applications, ...



https://github.com/Xilinx/xup_vitis_network_example



- Packet processing kernels as HLS
 - Single loop iteration single clock cycle

Higher-level abstractions

Programming models for heterogeneous systems

- Single codebase compiled to any platform
- Any C++ callable as kernel
- Reused OpenCL concepts
- Implicit host-kernel link
- Deep optimization requires tech. specific constructs
- Target platform selected in a Makefile
- Compilers chain run underneath
- Interesting solution for data analysis in physics



```
#include <iostream>
class vector addition;
int main(int, char**) {
   cl::sycl::float4 a = { 1.0, 2.0, 3.0, 4.0 };
   cl::sycl::float4 b = { 4.0, 3.0, 2.0, 1.0 };
   cl::sycl::float4 c = { 0.0, 0.0, 0.0, 0.0 };
   cl::sycl::default selector device selector;
   cl::sycl::queue queue(device selector);
      cl::sycl::buffer<cl::sycl::float4, 1> a sycl(&a, cl::sycl::range<1>(1));
      cl::sycl::buffer<cl::sycl::float4, 1> b sycl(&b, cl::sycl::range<1>(1));
      cl::sycl::buffer<cl::sycl::float4, 1> c sycl(&c, cl::sycl::range<1>(1));
     queue.submit([&] (cl::sycl::handler& cgh) {
         auto a acc = a sycl.get access<cl::sycl::access::mode::read>(cgh);
         auto b acc = b sycl.get access<cl::sycl::access::mode::read>(cgh);
         auto c acc = c sycl.get access<cl::sycl::access::mode::discard write>(cgh);
         cgh.single task<class vector addition>([=] () {
         c acc[0] = a acc[0] + b acc[0];
   return 0:
```



FPGAs in HPC

- FPGAs have a unique set of features:
 - Naturally parallel and pipelined processing
 - Ultra-low latency, true real-time processing
 - Adaptable resources, dynamic reconfiguration
- Devices have sufficient amount of resources
 - Capable of accelerating complex algorithms
 - Problematic for the compilers
- Difficulty in transition from sequential programming to HDL
 - High-level abstractions, compilers and tools introduced
- Software maturity required for another technology breaktrough
- Hardware Acceleration Cluster at UJ
 - 4x nodes
 - 7x AMD Alveo acceleration cards (U280, U50)
 - 4x Nvidia GPUs (RTX 4090, 2080)
 - 100G Ethernet network







T. Boku, "Japanese Supercomputer

development and hybrid accelerated supercomputing"