ESE532: System-on-a-Chip Architecture

Day 6: September 18, 2019
Data-Level Parallelism

Today

Data-level Parallelism

- For Parallel Decomposition
- Architectures
- Concepts
- NEON

Message

- Data Parallelism easy basis for decomposition
- Data Parallel architectures can be compact
  - pack more computations onto a fixed-size IC die
  - *OR* perform computation in less area

Preclass 1

- 400 news articles
- Count total occurrences of a string
- How can we exploit data-level parallelism on task?
- How much parallelism can we exploit?

Parallel Decomposition

Data Parallel

- Data-level parallelism can serve as an organizing principle for parallel task decomposition
- Run computation on independent data in parallel

Exploit

- Can exploit with
  - Threads
  - Pipeline Parallelism
  - Instruction-level Parallelism
  - Fine-grained Data-Level Parallelism

Performance Benefit

- Ideally linear in number of processors (resources)
- Resource Bound:
  - $T_{dp} = (T_{single} \times N_{data}) / P$
- T_{single} = Latency on single data item
- $T_{dp} = \max(T_{single}, N_{data} / P)$

SPMD

Single Program Multiple Data

- Only need to write code once
- Get to use many times

Preclass 2 Common Examples

- What are common examples of DLP?
  - Simulation
  - Numerical Linear Algebra
  - Signal or Image Processing
  - Image Processing
  - Optimization

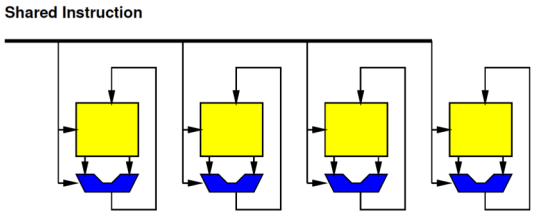
Hardware Architectures

Idea

- If we're going to perform the same operations on different data, exploit that to reduce area, energy
- Reduced area means can have more computation on a fixed-size die.

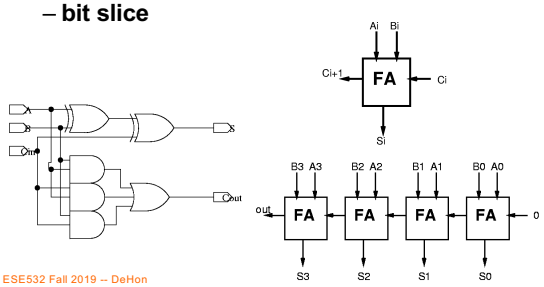
SIMD

- Single Instruction Multiple Data



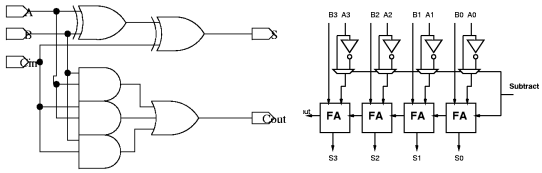
Ripple Carry Addition

- Can define logic for each bit, then assemble:
  - **bit slice**

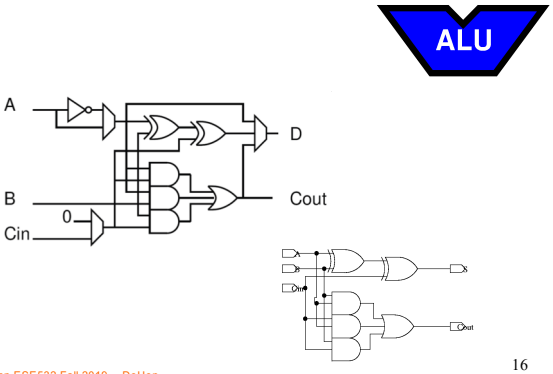


Arithmetic Logic Unit (ALU)

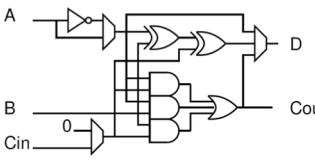
- Observe:
  - with small tweaks can get many functions with basic adder components



Arithmetic and Logic Unit



ALU Functions

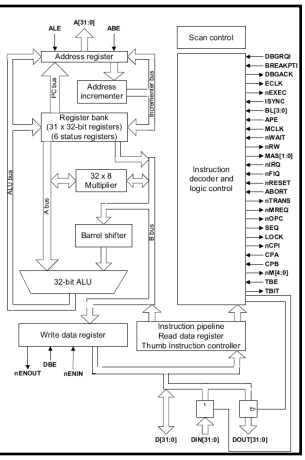


- A+B w/ Carry
- B-A
- A xor B (squash carry)
- A*B (squash carry)
- /A

Key observation: every ALU bit does the same thing on different bits of the data word(s).

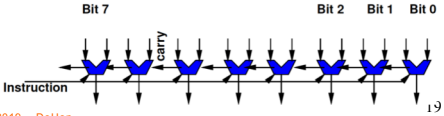
ARM v7 Core

- ALU is Key compute operator in a processor

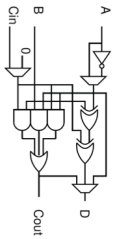


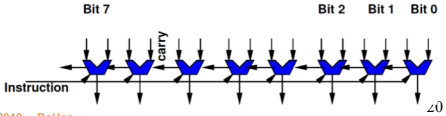
W-bit ALU as SIMD

- Familiar idea
- A W-bit ALU (W=8, 16, 32, 64, …) is SIMD
- Each bit of ALU works on separate bits
  - Performing the same operation on it
    - Trivial to see bitwise AND, OR, XOR
    - Also true for ADD (each bit performing Full Adder)
- Share one instruction across all ALU bits



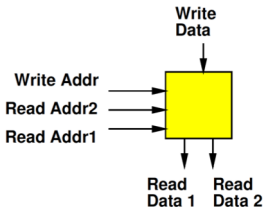
ALU Bit Slice





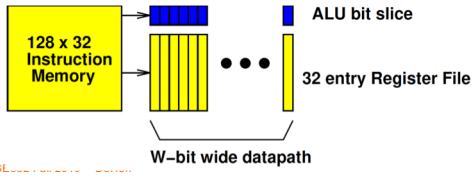
Register File

- Small Memory
- Usually with multiple ports
  - Ability to perform multiple reads and writes simultaneously
- Small
  - To make it fast (small memories fast)
  - Multiple ports are expensive

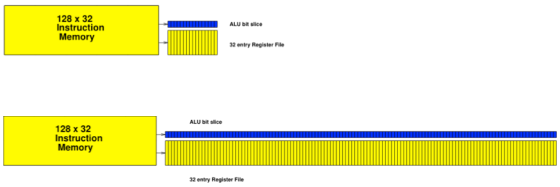


Preclass 4

- Area W=16?
- Area W=128?
- Number in 10^8
  - W=16
  - W=128
- Perfect Pack Ratio?
- Why?

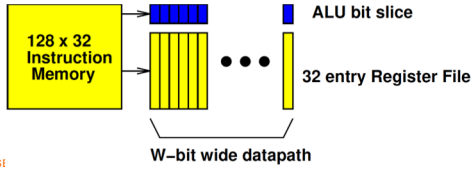


To Scale Comparison

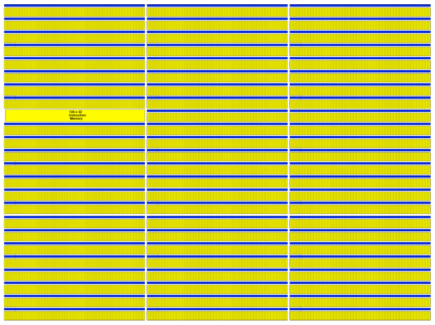


Preclass 4

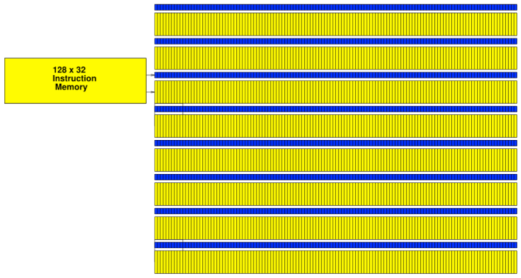
- W for single datapath in 10^8?
- Perfect 16b pack ratio?
- Compare W=128 perfect pack ratio?



To Scale W=9088



To Scale W=1024



Preclass 6

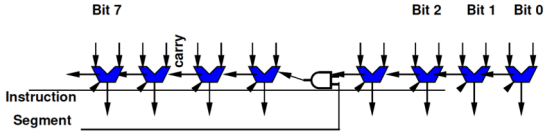
- What do we get when add 65280 to 257
  - 32b unsigned add?
  - 16b unsigned add?

ALU vs. SIMD ?

- What's different between
  - 128b wide ALU
  - SIMD datapath supporting eight 16b ALU operations

Segmented Datapath

- Relatively easy (few additional gates) to convert a wide datapath into one supporting a set of smaller operations
  - Just need to squash the carry at points

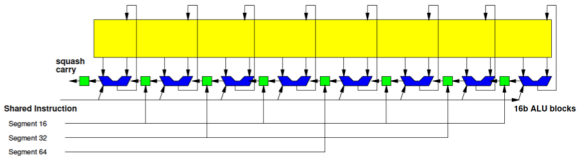


Segmented Datapath

- Relatively easy (few additional gates) to convert a wide datapath into one supporting a set of smaller operations
  - Just need to squash the carry at points
- But need to keep instructions (description) small
  - So typically have limited, homogeneous widths supported

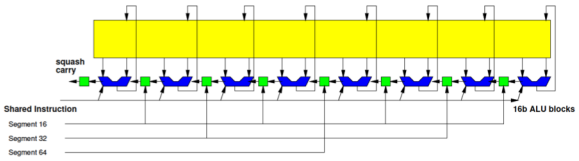
Segmented 128b Datapath

- 1x128b, 2x64b, 4x32b, 8x16b



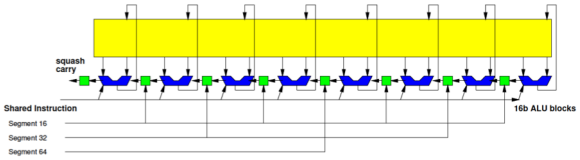
Terminology: Vector Lane

- Each of the separate segments called a **Vector Lane**
- For 16b data, this provides 8 vector lanes



Performance

- Ideally, pack into vector lanes
- Resource Bound: $T_{vector} = N_{op}/VL$



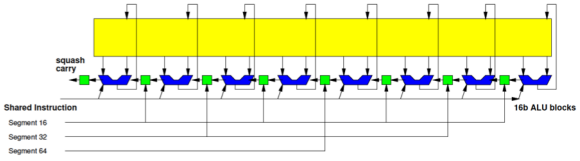
Preclass 5: Vector Length

- May not match physical hardware length
- What happens when
  - Vector length > Vector Lanes?
  - Vector length < Vector Lanes?
  - Vector length % (Vector Lanes) !=0
    - E.g. vector length 20, for 8 hdw operators

Performance

- Resource Bound

  $T_{vector} = ceil(N_{op}/VL)*T_{cycle}$



Preclass 3: Opportunity

- Don't need 64b variables for lots of things
- Natural data sizes?
  - Audio samples?
  - Input from A/D?
  - Video Pixels?
  - X, Y coordinates for 4K x 4K image?

Vector Computation

- Easy to map to SIMD flow if can express computation as operation on vectors
  - Vector Add
  - Vector Multiply
  - Dot Product

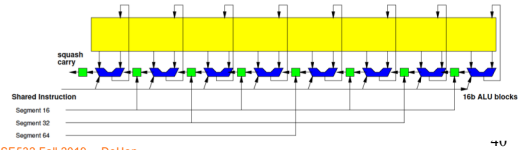
Concepts

Terminology: Scalar

- Simple: non-vector
- When we have a vector unit controlled by a normal (non-vector) processor core often need to distinguish:
  - Vector operations that are performed on the vector unit
  - Normal=non-vector=scalar operations performed on the base processor core

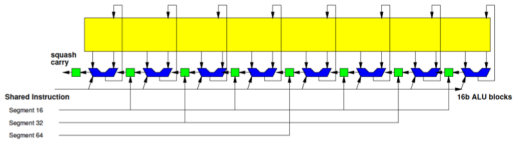
Vector Register File

- Need to be able to feed the SIMD compute units
  - Not be bottlenecked on data movement to the SIMD ALU
- Wide RF to supply
- With wide path to memory



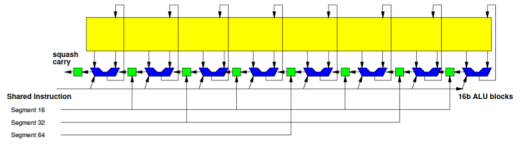
Point-wise Vector Operations

- Easy – just like wide-word operations (now with segmentation)



Point-wise Vector Operations

- …but alignment matters.
- If not aligned, need to perform data movement operations to get aligned



Ideal

- for (i=0;i<64;i=i++)
  - c[i]=a[i]+b[i]
- No data dependencies
- Access every element
- Number of operations is a multiple of number of vector lanes

Skipping Elements?

- How does this work with datapath?
  - Assume loaded a[0], a[1], …a[63] and b[0], b[1], …b[63] into vector register file
- for (i=0;i<64;i=i+2)
  - c[i/2]=a[i]+b[i]

Stride

- Stride: the distance between vector elements used
- for (i=0;i<64;i=i+2)
  - c[i/2]=a[i]+b[i]
- Accessing data with stride=2

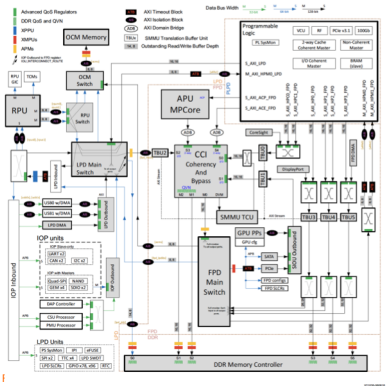
Load/Store

- Strided load/stores
  - Some architectures will provide strided memory access that compact when read into register file
- Scatter/gather
  - Some architectures will provide memory operations to grab data from different places to construct a dense vector

Neon

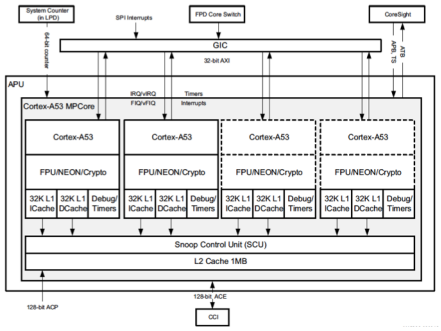
ARM Vector Accelerator on Zynq

Programmable SoC



UG1085
Xilinx
UltraScale
Zynq
TRM
(p27)

APU MPcore



UG1085 Xilinx UltraScale Zynq TRM (p53)

Neon Vector

- 128b wide register file, 16 registers
- Support
  - 2x64b
  - 4x32b (also Single-Precision Float)
  - 8x16b
  - 16x8b

Sample Instructions

- VADD – basic vector
- VCEQ – compare equal
  - Sets to all 0s or 1s, useful for masking
- VMIN – avoid using if's
- VMLA – accumulating multiply
- VPADAL – maybe useful for reduce
  - Vector pair-wise add
- VEXT – for "shifting" vector alignment
- VLDn – deinterleaving load

Neon Notes

- Didn't see
  - Vector-wide reduce operation
- Do need to think about operations being pipelined within lanes

ARM Cortex A53 (similar to A-7 Pipeline)

2-issue
In-order
8-stage pipe

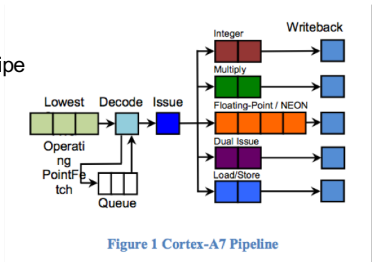


Figure 1 Cortex-A7 Pipeline

https://www.anandtech.com/show/8718/the-samsung-galaxy-note-4-exynos-review/3

https://arstechnica.com/gadgets/2011/10/arms-new-cortex-a7-is-tailor-made-for-android-superphones/

Big Ideas

- Data Parallelism easy basis for decomposition
- Data Parallel architectures can be compact – pack more computations onto a chip
  - SIMD, Pipelined
  - Benefit by sharing (instructions)
  - Performance can be brittle
    - Drop from peak as mismatch

Admin

- SDSoC available on Linux machines
  - See piazza
- Reading for Day 7 online
- HW3 due Friday
- HW4 out