

ESE532: System-on-a-Chip Architecture

Day 18: March 27, 2017
Representation and Precision



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Today

- Fixed Point
- Errors from Limited Precision
- Precision Analysis / Interval Arithmetic
- Floating Point

2

Message

- We must always calculate with limited precision
- Precision costs area (and energy)
 - Can economize area (and energy) by judiciously using just the precision we need
 - Precision-cost tradeoff
- Can perform analysis on precision

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3

Fixed Point

- Integer which interpret as a fraction
- Fixed-Point N.F
 - N bits
 - F bits below fraction (typically N<F)
 - Equivalently: meaning is Integer-value/ 2^F

$$A = \sum_{i=0}^{N-1} a_i 2^{i-F}$$

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4

Operator Sizes

Operator	LUTs	LUTs + DSPs
Double FP Add	712	681+3 DSPs
Single FP Add	370	219+2 DSPs
Fixed-Point Add (32)	16	
Fixed-Point Add (n)	n/2	
Double FP Multiply	2229	223+10 DSPs
Single FP Multiply	511	461+3 DSPs
Fixed Multiply (32x32)	1099	
Fixed Multiply (16x16)	283	1 DSP
Fixed Multiply (18x25)		1 DSP
Fixed Multiply (n)	~ n ²	

FP sizes from: https://www.xilinx.com/support/documentation/ip_documentation/ru_floating-point.html

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5

Observe

- Floating-Point operators are large compared to Fixed-Point
 - For similar precision
 - 712 vs. 32 for addition
- Double-precision Floating point operators are large
 - 2229 Multiply, 712 Add
 - Can quickly fill 50,000 LUT programmable logic

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6

Fixed-Point Economy

- Can fit more logic (more parallelism) using modest fixed-point
 - At 16b: Multiply 283, Add 16
 - Vs. Double: 2229, 712
- But
 - How much precision do we need?
 - How do we determine?

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7

Perfect Representation

- Start with Fixed-Point 16.8
- What do we need to
 - represent the result of an addition? (3a)
 - represent the result of a multiplication? (3b)

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Sequence

- Across a sequence of operations
 - A, B, C, D, E start Fixed-Point 16.8
- $Y=((A+B)*C+D)*E;$
- Perfect representation for partial results up to Y?

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9

Looping: Bound loop

```
res=0;  
for(i=0;i<4;i++)  
    res=res*x+a[i]
```

- Assume a[i], x start Fixed-Point 16.8
- Final precision needed for res?

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10

Looping: Unbound

```
res=0;  
for(i=0;i<len;i++)  
    res=res*x+a[i]
```

- Assume a[i], x start Fixed-Point 16.8,
- len starts Integer 16
- Final precision needed for res?

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Perfect Representation

- Start with Fixed-Point 16.8
- What do we need to
 - represent the result of a division? (3e)
 - E.g. 00000001.00000000/00000011.00000000

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12

Conclude

- Cannot generally keep perfect precision
- Will typically need to decide how much precision we need and where

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Errors from Limited Precision

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What error introduce?

- **Absolute Error** – what level of error do we have in approximated value or a result
 - 4.13742 – assume full
 - 4.1374 – 0.00002
 - 10^{-5}
 - 4.137 – 0.00042
 - 10^{-4}
 - 4.14 – 0.00256
 - 10^{-3}
 - 4.1 – 0.03742
 - 10^{-2}
- Might be all we care about
 - Get answer to 1mV accuracy
 - ...or 1 pixel accuracy

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15

What error introduce?

- **Relative Error** – error as percentage of intended result
 - 4.13742 – assume full
 - 4.1374 – 4.8E-6
 - 10^{-6}
 - 4.137 – 1.02E-4
 - 10^{-4}
 - 4.14 – 6.2E-4
 - 10^{-4}
 - 4.1 – 9.0E-3
 - 10^{-3}
- May be more relevant, particularly if trying to identify small values

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16

Preclass 1

- Complete Table

Reduced Precision Calculation	Y	Y_1	Error (2 significant figures)
			Absolute $ Y - Y_1 $
			Relative $ (Y - Y_1)/Y $
$Y_1 = A_1 + B_1$			
$Y_1 = A_1 \times B_1$			
$Y_1 = A_1/B_1$			
$Y_1 = A_1/C_1$			
$Y_1 = A_1/D_1$			

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17

Observe

- Add/Multiply relatively well behaved
- Must be very careful when
 - Division involved
 - Divisors can be small
 - Get approximated near zero

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18

Precision Allocation

- Full precision can be too expensive
 - Non-sensical
- Limited precision introduces errors
 - May be smaller than we care about
- Determine minimal precision needed
 - ...or where to spend precision...

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19

Empirical Analysis

- Make guess at precisions
- Set precisions in calculation
- Simulate on data
- Evaluate results (absolute, relative error) compared to gold standard
 - Unlimited precision...or, at least, higher precision
 - Often standard is double-precision float
 - ...but, as we'll, even that's a compromise
- Update precision guess and repeat

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20

Empirical Analysis

- Make guess at precisions
 - Set precisions in calculation
 - Simulate on data
 - Evaluate results compared to gold standard
- Care
- Adequate set of test data to trigger worst-case errors?
 - Requires some understanding of calculation
 - Shouldn't be entirely black box

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21

Vivado HLS Support

- Has libraries to support
 - Arbitrary precision integers
 - Arbitrary precision fixed point
- For
 - Simulation
 - Synthesis
- UG902 – Vivado HLS User Guide
 - Chapter 2: Arbitrary Precision Data Type Library

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22

Precision Analysis

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Precision Analysis

- Can analyze worst-case error impacts from limited precision
- Give results not sensitive to test set
- Give guidance on where to allocate precision
- ...can be automated

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24

Limit Precision Inputs

- Typically start with limited precision
 - A/D only sample to 12b
 - Real-world had more precise value, but didn't capture
 - Quantized data stored in representation
 - Sound samples, DCT frequency coefficients
- We start with error
 - What does that mean about values we calculate?

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25

Interval Analysis

- Treat every value as an interval arrange
- Model effects of operations on range of results
- $A = (A.H, A.L)$
- $A+B = (A.H+B.H, A.L+B.L)$
- Positive A, B and B interval not cross 0
 - $A*B = (A.H*B.H, A.L*B.L)$
 - $A/B = (A.H/B.L, A.L/B.H)$

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26

Interval Analysis

- $A*B = (\max(A.H*B.H, A.H*B.L, A.L*B.H, A.L*B.L), \min(A.H*B.H, A.H*B.L, A.L*B.H, A.L*B.L))$
- A/B ... more complicated
 - If B.H positive, B.L negative, can become infinity

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27

Limited Precision

- $A = (A.H, A.L) = (A + \epsilon, A - \epsilon) = A \pm \epsilon$
- E.g. if rounded to Fixed Point 16.8
 - ϵ may be 2^{-9}

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28

Preclass 2

- Complete Table

Calculation	Result Range (report like A)
$Y = 1 + A$	$A_8 + 1 \pm \epsilon$
$Y = A + B$	
$Y = 2A$	
$Y = A \times B$	

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Multiplication

- $(A \pm \epsilon)(B \pm \epsilon)$
- $A*B \pm ((A+B)\epsilon + \epsilon^2)$
- A and B can be MAXVAL, MINVAL
 - Assume symmetric ($\text{MAXVAL} = -\text{MINVAL}$)
- $A*B \pm (2*\text{MAXVAL}*\epsilon + \epsilon^2)$
 - Probably reasonable to drop ϵ^2
- $A*B \pm 2*\text{MAXVAL}*\epsilon$

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Preclass 3c

- Recall: Fixed-Point 16.8 multiply
 - Full precision result: 32.16
- What is error interval for result of 16.8 multiply?

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Preclass 3c

- For 16.8, $\epsilon_0=1/512$, maxval=256
- From answer multiply in preclass 2
 - $A \cdot B \pm 2 \cdot \text{MAXVAL} \cdot \epsilon$
 - So, get $A \cdot B \pm 2 \cdot 256 \cdot (1/512)$
 - Or $A \cdot B \pm 1$

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Observe

- Full precision may keep bits well below the error in the calculation

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Rounding

- Rounding introduces an error
- Round Nearest A to Fixed-Point N.8
 $\epsilon=2^{-9}$
- As does truncation, floor, ceil...
 - But asymmetric interval

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Preclass 3d

- Error range if round 32.16 result to 18.2?
 - (from 16.8 multiply)

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Preclass 3d

- Rounding 32.16 to 18.2 introduces a quantization error of 2^{-3}
- Our 32.16 multiply result was ± 1
 - Add an addition $\pm 1/8$
 - Total error: $\pm 9/8$

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Result

- Dropping (rounding) bits may not increase error range (much)

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Symbolic

- If work through computation symbolically, can generate equation for error
- Each rounding (precision drop) adds some ϵ_i precision

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Symbolic Example (start)

- Start A, B, C, D, E with maxval_0 , ϵ_0
- $Y=((A+B)*C+D)*E;$
- $A+B \quad \text{maxval}_1=2\text{maxval}_0, \epsilon_2=2\epsilon_0+\epsilon_1$
 - ϵ_1 for round after this operation
- $(A+B)*C$
 - $\text{maxval}_2=\text{maxval}_1*\text{maxval}_0$
 - $\epsilon_4=\epsilon_2*\text{maxval}_0+\epsilon_0*\text{maxval}_1+\epsilon_3$
 - ϵ_3 for round at this operation

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Result Precision

- After series of operations, may have expression like:
 - $Y \pm (3\epsilon_2+\epsilon_1+1024*\epsilon_0)$
- If looking for result with precision $\pm\epsilon_{\text{res}}$
$$\epsilon_{\text{res}} \geq (3\epsilon_2+\epsilon_1+1024*\epsilon_0)$$

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40

Result Precision

- Fixed Precision 12.0 = Round(val)
 - E.g. A/D output
 - Only need to know val to $\epsilon=1/2$
- Fixed Precision 12.0 = Round(val/4)
 - E.g. Quantized value stored in file
 - Only need to know val to $\epsilon=2$
 - $\epsilon_{\text{res}} \geq (3\epsilon_2+\epsilon_1+1024*\epsilon_0)$
 - Maybe: $\epsilon_0=1/1024, \epsilon_1=1/2, \epsilon_2=1/8$

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41

Optimize Precision Allocation

- $\epsilon_{\text{res}} \geq (3\epsilon_2+\epsilon_1+1024*\epsilon_0)$
 - Maybe: $\epsilon_0=1/1024, \epsilon_1=1/2, \epsilon_2=1/8$
- More generally
 - Combine with area model and look at expense of providing each ϵ_i
- Try pick ϵ_i to meet ϵ_{res} while minimizing area

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42

Tools

- Tools can automate interval calculations to verify precision
 - E.g. Gappa++
 - <https://bitbucket.org/mlinderm/gappa>

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Floating Point



Robert Tinney
(Byte circa 1980)

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44

Floating Point

- Leading 0s aren't that useful
- Can represent more compactly by counting them
 - Only need log bits to count
- Represent value as
 - Mantissa $value = 1 \text{ mantissa} \times 2^{\text{exp}-\text{offset}}$
 - Exponent
- Like Scientific Notation

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Floating Point

- Floating Point means
 - Move the datapath to the interesting/significant part of computation
 - Don't represent leading zeros
 - Don't represent less significant bits
 - Even if they are well above 1
 - In the integer portion

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Revisit Divisions Preclass 1

- C=0.14378 $\rightarrow 1.4 \times 2^{-1}$
- D=0.00192 $\rightarrow 1.9 \times 2^{-3}$
- Float A/C = 4.1/0.14
 - Absolute error 0.5
 - Relative error 0.018
- Float A/D = 4.1/0.0019
 - Absolute error 3.0
 - Relative error 0.0014

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47

Standard Floating Point

- Double Precision (64b)
 - 1 bit sign
 - 11 bit exponent
 - Offset 1023 represents 1023 to -1022
 - 53 bit mantissa (52b + implicit 1)
- Single Precision (32b)
 - 1 bit sign
 - 8 bit exponent (offset 127)
 - 24 bit mantissa (23b + implicit 1)

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48

Expensive Add

Recall Double=712, Single= 370

A=(A.m,A.e), B=(B.m,B.e)

- By e, sort to large, small
- Small.m>>(large.e-small.e)
- Perform mantissa addition
 - Large.m+small.m>>(large.e-small.e)
- Possibly shift to normalize result
 - Update exponent
 - Round

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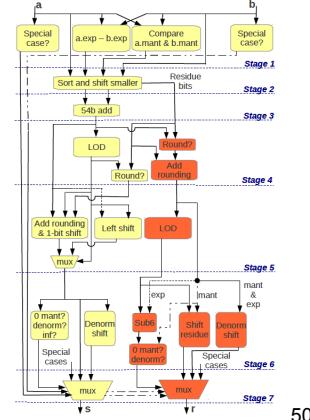
49

FP Add

- 54b add one stage of 7 in pipeline
- Done in 27 6-LUTs

[Kadric, Arith 2013]

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50

Floating Point Multiply

Double 2229, Single 461

- Don't need to sort, pre-shift
- m=A.m*B.m (53x53 multiply dominates)
- e=A.e+B.e
- Still have shifting, rounding at end

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51

Dynamic Range

- Floating Point has very wide dynamic range
- Can deal with significant piece being anywhere in 1023 to -1022
- For fixed-point to cover same range
 - Fixed Point 2046.1022
 - Add 1024 LUTs
 - Multiply ~ 4M LUTs
- When need dynamic range, FP economical

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52

Customization

- Can customize on FPGA or custom silicon
 - Mantissa bits
 - Exponent bits
- Fewer bits when need less precision or range to save area
- More bits if need greater precision or range

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53

Floating Point

Not free of precision problems

- $((1+2^{100})-2^{99})-2^{99}=0$
- $1+(2^{100}+(-2^{99}-2^{99}))=1$

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54

Floating-Point Analysis

- Can do similar analysis on floating point
 - ...and there are tools to help
 - Including Gappa++

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Floating-Point vs. Fixed-Point

- Floating-Point (esp. double-precision) is a **big hammer** solution
 - Trades hardware/energy for programmer attention to needs
 - Standards have been well thought out so works over wide range
 - Most cases it is more than needed
- Cost/energy sensitive designs will ask what's necessary and tune accordingly

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56

Economizing Precision

- FPGAs
 - Get fined-grained selection of precision
- GPUs
 - Often provide single-precision
 - Enough, allow pack more parallelism
- DSP
 - Fixed-Point DSPs cheaper, lower energy

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Big Ideas

- We must always calculate with limited precision
- Precision costs area (and energy)
 - Can economize area (and energy) by judiciously using just the precision we need
 - Precision-cost tradeoff
- Can perform analysis on precision

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58

Admin

- Project Design Space Milestone
 - Out
 - Due Friday

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59