Design of Integrated Circuits: Phase 2 Report

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October 29, 2022

Introduction

This phase starts to focus on the Verilog implementations for sub-modules of neural networks. A neural network-based classifier consists of adders, multipliers, and activation functions. In this phase, each student is required to implement the Verilog modules of adders, multipliers, the activation function (e.g., Sigmoid function and ReLU function), etc. You should implement all of these modules, simulate them, and validate their functionalities, separately. The default value representation is 16-bit fixed point value (8-bit integer and 8-bit fraction). According to your weights from neural network training (such as maximum values or precision), you can change the value representation to a wider-range value or floating-point value. The associated justification might be added into your report.

In this phase, all necessary modules in the neural network like adders and multipliers are required to be implemented. For example, 16-bit ripple-carry and the 16-bit bit-array multiplier are as shown in Figure 1 and 2 (also as shown in Chapter 11 of Textbook). Other more advanced adders and multipliers (e.g., carry-lookahead adder or Kogge-Stone adder) are welcome and will be graded with the consideration of extra credit. The simulation results should be included to validate the implemented adder/multiplier working well.

Adder Implementation

We implement a pipe-lined architecture of the adder to reperesent a 32-bit floating point number, but can be expanded with any N-bit using parameterization. After extensive research, this was chosen over a Kogge-Stone or Brent-Kung adder in order to have more accurate data representation. This design has some issues, and looking into the roadmap of the hardware implementation, some corrections need to be made to have a completely working adder. So far, the implementation will run through 3 clock cycles and compile correctly in DUT testbench, but the final output is incorrect.

2.1 Simulation

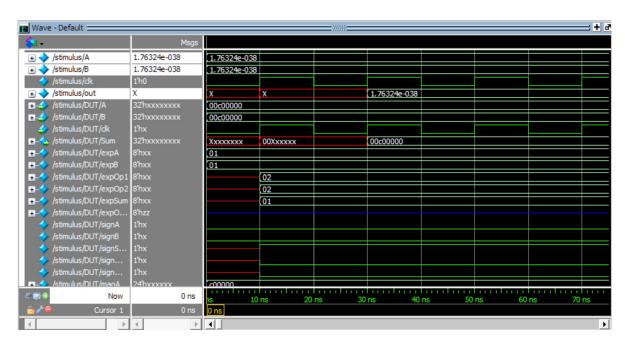


Figure 2.1: Waveform of Pipelined Adder Architecture

As seen in Figure 2.1, we can see that the architecture is very quick, but it appears to be only moving a copy of an operand into the summation. This will be discussed further during more thorough implementation. For now, we have the following code base to work with:

```
/*
Author: Christian Moser
Date: 10-28-2022
Description: Full-Precision (N-bit) floating point adder implementation
example of 32-bit single precision float:
1 11111111 1111111111111111111111
S E
S = 0 \mid 1 implies positive (0) or negative (1)
E = 1111 1111 equivalent to whole number component
M = 1111 \ 1111 \ 1111 \ 1111 \ 1111 \ 1111 \ equivalent to decimal component
*/
module adder
   #(parameter N=32)
   (input wire[N-1:0] A,
   input wire[N-1:0] B,
   input clk,
   output wire[N-1:0] Sum
```

```
);
   //def wires
   wire
         [(N/4)-1:0]
                         expA, expB, expOp1, expOp2, expSum, expOp1Hold;
   wire signA, signB, signSum, signOp1, signOp2;
         [N-(N/4)-1:0] magA, magB, magOp1, magOp2, magSum;
   wire
         [N-(N/4):0] magHold;
   wire
         rst;
   wire
   wire
          done1, done2;
   reg
          done3;
          [N-1:0] sum;
   reg
   //initial assignments
   assign signA = A[N-1];
   assign signB = B[N-1];
   assign expA = A[N-2:(N-1)-(N/4)];
   assign expB = B[N-2:(N-1)-(N/4)];
   assign magA[N-(N/4)-1] = 1'b1;
   assign magB[N-(N/4)-1] = 1'b1;
   assign magA[N-(N/4)-2:0] = A[N-(N/4)-1:0];
   assign magB[N-(N/4)-2:0] = B[N-(N/4)-1:0];
   shiftreg #(.N(32)) compare(expA, expB, expOp1, expOp2, clk, signA, signB, signSum,
       signOp1, signOp2, magA, magB, magOp1, magOp2, done1);
   FA #(.N(32)) additive(magA, magB, expOp1Hold, clk, rst, magHold, done2, expSum);
   normalizer #(.N(32)) form(magHold, signA, signB, signSum, signOp1, signOp2, clk, expA,
       expOp1, expSum, magOp1, magOp2, magSum);
   assign Sum = \{signA, expSum, magSum[(N-(N/4)-2):0]\};
endmodule
module shiftreg
#(parameter N=32)
( input [(N/4)-1:0] expA,
   input [(N/4)-1:0] expB,
   output reg [(N/4)-1:0] expOp1,
   output reg [(N/4)-1:0] exp0p2,
   input clk,
   input signA,
   input signB,
   output reg signSum,
   output reg signOp1,
   output reg signOp2,
   input [N-(N/4)-1:0] magA,
   input [N-(N/4)-1:0] magB,
   output reg [N-(N/4)-1:0] magOp1,
```

```
output reg [N-(N/4)-1:0] magOp2,
   output reg done1 = 0
);
   reg[(N-4)-1:0] diff;
   always @(posedge clk) begin
       signOp1 = signA;
       signOp2 = signB;
       if(expA == expB) begin
           expOp1 = expA + 8'b1;
           expOp2 = expB + 8'b1;
          magOp1 = magA;
          magOp2 = magB;
          signSum = 1'b1;
       end
       else if(expA > expB) begin
          diff = expA - expB;
           expOp1 = expA + 8'b1;
           expOp2 = expB + 8'b1;
          magOp1 = magA;
          magOp2 = magB >> diff;
           signSum = 1'b1;
       end
       else if(expB > expA) begin
          diff = expB - expA;
           expOp1 = expB + 8'b1;
           expOp2 = expA + 8'b1;
          magOp1 = magB;
          magOp2 = magA >> diff;
           signSum = 1'b0;
       end
       else begin
          diff = expB - expA;
           expOp1 = expB + 8'b1;
           expOp2 = expB + 8'b1;
          magOp1 = magB;
          magOp2 = magA >> diff;
```

```
done1 <= 1;
   end
endmodule
module normalizer#(parameter N=32)
   input
           [N-(N/4):0]
                         magHold,
   input
           signA,
   input
           signB,
   input signSum,
   input signOp1,
   input signOp2,
   input clk,
   input [(N/4)-1:0]
                        expA,
   input [(N/4)-1:0]
                        expOp1,
   output reg [(N/4)-1:0] expSum,
   output reg [N-(N/4)-1:0] magOp1,
   output reg [N-(N/4)-1:0] magOp2,
   );
   always @(posedge clk) begin
       magSum = magHold[N-(N/4):1];
       expSum = expA;
       repeat(N-(N/4)) begin
          if(magSum[N-(N/4)-1] == 1'b0) begin
             magSum = magSum << 1'b1;</pre>
             expSum = expSum - 8'b1;
          end
       end
   end
endmodule
module FA#(parameter N=32)
   input [N-(N/4)-1:0] magA,
   input [N-(N/4)-1:0] magB,
   input [(N/4)-1:0]
                        tmpExp,
   input clk,
   input rst,
   output reg [N-(N/4):0] magSum,
   output reg done2 = 0,
   output reg [(N/4)-1:0] tmpExpAdd
);
always @(posedge clk) begin
```

```
magSum <= magA + magB;
tmpExpAdd <= tmpExp;
if(magSum == (magA + magB)) begin
    done2 <= 1;
end
end
endmodule
```

Testbench:

Multiplier Implementation

Our multiplier also uses 32-bit floating point representation, but is not parameterized as the adder was due to time constraints. The multiplier has some issues that need to be fixed before hardware implementation.

3.1 Simulation

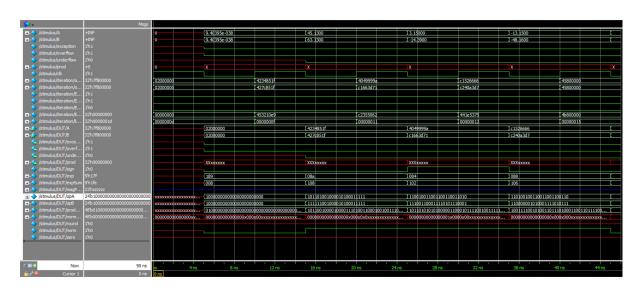


Figure 3.1: Multiplier Waveforms with 32-bit floating point data

We also used some CLI to test certain values. This can be seen in the attached testbench.

/*

Author: Christian Moser

Date: 10-28-2022

```
Project Description:
Create floating-point multiplier used for MLP neural network implementation.
module multiplier
( input [31:0] A,
   input [31:0] B,
   output exception,
   output overflow,
   output underflow,
   output [31:0] prod
);
//def wires
wire sign;
wire [8:0] exp, expSum;
wire [22:0] magProd;
wire [23:0] opA, opB;
wire [47:0] prodTmp, normalizedProd;
assign sign
                 = A[31] ^ B[31]; // get sign
assign exception = (&A[30:23]) | (&B[30:23]);
                  = (|A[30:23]) ? {1'b1, A[22:0]} : {1'b0, A[22:0]};
assign opA
assign opB
                 = (|A[30:23]) ? {1'b1, B[22:0]} : {1'b0, B[22:0]};
assign prodTmp
                   = opA * opB;
assign round
                   = |normalizedProd[22:0];
assign norm
                   = prodTmp[47] ? 1'b1 : 1'b0;
assign normalizedProd = norm ? prod : prod << 1;</pre>
assign zero
                  = exception ? 1'b0 : (magProd == 23'b0) ? 1'b1 : 1'b0;
                   = A[30:23] + B[30:23];
assign expSum
                   = \exp Sum - 8'd127 + norm;
assign exp
assign overflow = ((exp[8] & !exp[7]) & !zero);
assign underflow = ((exp[8] & exp[7]) & !zero) ? 1'b1 : 1'b0;
                  = exception ? 32'd0 : zero ? {sign, 31'd0} : overflow ? {sign, 8'hFF,
assign prod
    23'd0} : underflow ? {sign, 31'd0} : {sign, exp[7:0], magProd};
endmodule
   Testbench:
module stimulus();
   reg[31:0] A, B;
   wire exception, overflow, underflow;
   wire [31:0] prod;
```

```
reg clk = 1'b1;
   multiplier DUT(A, B, exception, overflow, underflow, prod);
   always clk = #5 ~clk;
   initial begin
       iteration (32'h0200_0000,32'h0200_0000,1'b0,1'b0,1'b0,32'h0000_0000,'__LINE__);
       iteration (32'h4234_851F,32'h427C_851F,1'b0,1'b0,1'b0,32'h4532_10E9,'__LINE__); //
           45.13 * 63.13 = 2849.0569;
       iteration (32'h4049_999A,32'hC166_3D71,1'b0,1'b0,1'b0,32'hC235_5062,'__LINE__);
           //3.15 * -14.39 = -45.3285
       iteration (32'hC152_6666,32'hC240_A3D7,1'b0,1'b0,1'b0,32'h441E_5375,'__LINE__);
           //-13.15 * -48.16 = 633.304
       iteration (32'h4580_0000,32'h4580_0000,1'b0,1'b0,1'b0,32'h4880_0000,'__LINE__);
           //4096 * 4096 = 16777216
       iteration (32'h3ACA_62C1,32'h3ACA_62C1,1'b0,1'b0,1'b0,32'h361F_FFE7,'__LINE__);
           //0.00154408081 * 0.00154408081 = 0.00000238418
       iteration (32'h0000_0000,32'h0000_0000,1'b0,1'b0,1'b0,32'h0000_0000,'__LINE__); //
           0 * 0 = 0;
       iteration (32'hC152_6666,32'h0000_0000,1'b0,1'b0,1'b0,32'h441E_5375,'__LINE__);
           //-13.15 * 0 = 0;
       iteration (32'h7F80_0000,32'h7F80_0000,1'b1,1'b1,1'b0,32'h0000_0000,'__LINE__);
       $stop;
   end
   task iteration(
input [31:0] op_a,op_b,
input Expected_Exception,Expected_Overflow,Expected_Underflow,
input [31:0] Expected_result,
input integer linenum
begin
@(negedge clk)
begin
  A = op_a;
  B = op_b;
end
@(posedge clk)
if ((Expected_result == prod) && (Expected_Exception == exception) && (Expected_Overflow
```

);

Activation Function Implementation

We will implement the tanh(x) (hyperbolic tangent) function as our activation function such to match the architecture of the neural network created in Phase I. This is still being developed but will be closely monitored after completing the adder and multiplier correctly.

References

- https://github.com/rez39/Floatingpointadder
- https://github.com/debtanu09/fmultiplier
- $\bullet \ https://github.com/sudhamshu091/32-Verilog-Mini-Projects$
- T. K. R. Arvind, M. Brand, C. Heidorn, S. Boppu, F. Hannig and J. Teich, "Hardware Implementation of Hyperbolic Tangent Activation Function for Floating Point Formats," 2020 24th International Symposium on VLSI Design and Test (VDAT), 2020, pp. 1-6, doi: 10.1109/V-DAT50263.2020.9190305.