

EE6470 Final Project Demo

Design and Implementation of LSTM Digital pre-distortion model inference on RISC V

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Abstract

- With the ever growing number of devices, the signals are getting more complex with dynamic behaviour, which causes non-linearity in the Power Amplifier (PA) output.
- Digital Pre-distortion (DPD) is considered an effective technique to reduce these effects and to make this system more real-time, scholars are now diving into deep learning methodologies like CNN and LSTM.
- To run these algorithms in devices with less capability of resource storage and computation, is a major challenge since these models are computational and memory escalated.
- We need a scalable and flexible implementation to meet requirements from IoT to high-end applications, supporting both inference and on-device learning for edge devices.
- In this work, we propose a step-by-step guide to build LSTM deep learning based DPD model inference accelerators using RISC V ISA.



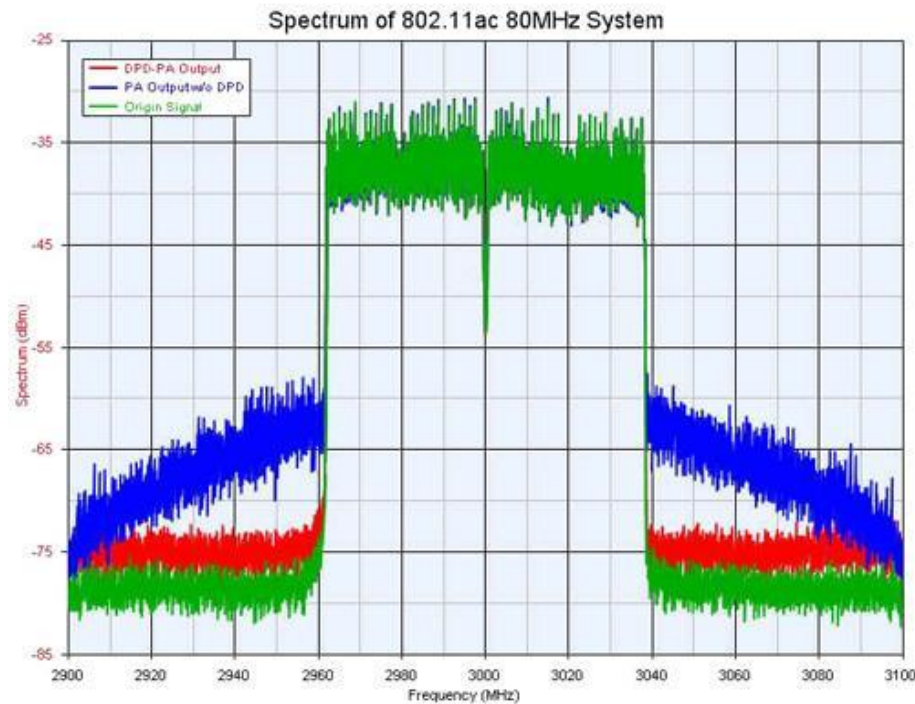
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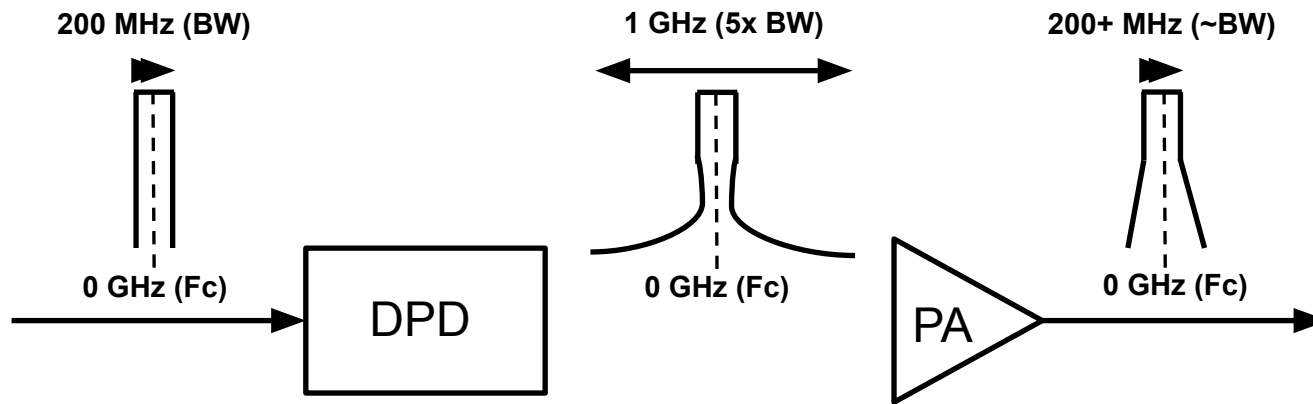
- Introduction to DPD
- Introduction to LSTM
- Software Implementation
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- RISC V Implementation
 - single core
 - Multi - core
- Comparative study
- Result
- Future work



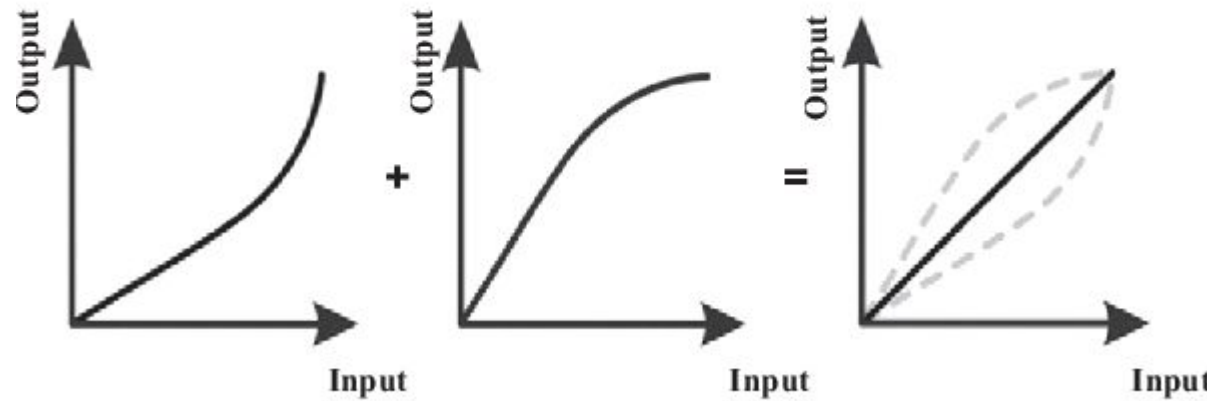
What is Digital Perdistortion (DPD)

- A technique for improving the linearity of power amplifiers
- Ideally the output signal of a PA is the input scaled up perfectly
- Instead the semiconductor physics causes distortions
 - Amplitude, frequency and phase errors
- If we can predict the errors, we can try to reverse them



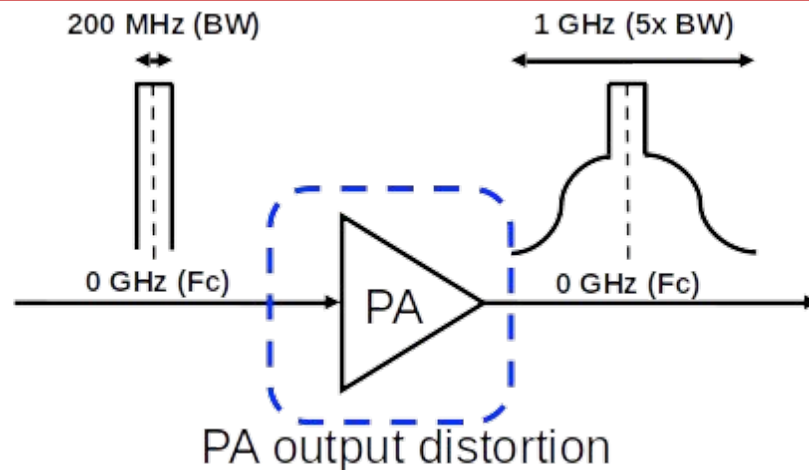


Mitigate PA output distortion through Pre-distortion

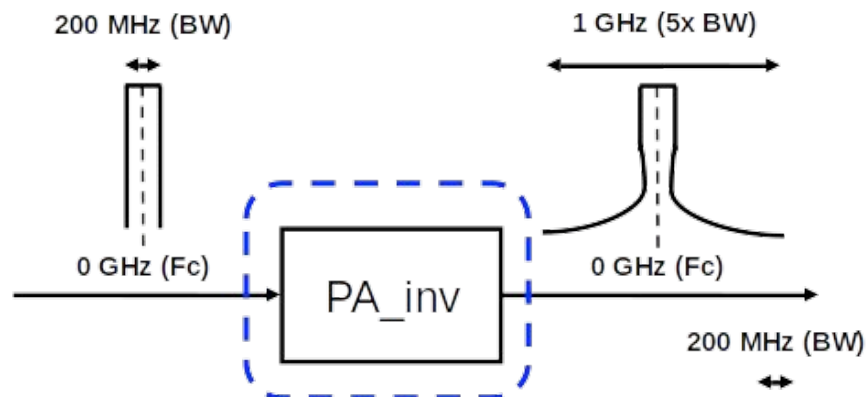


Implementation steps

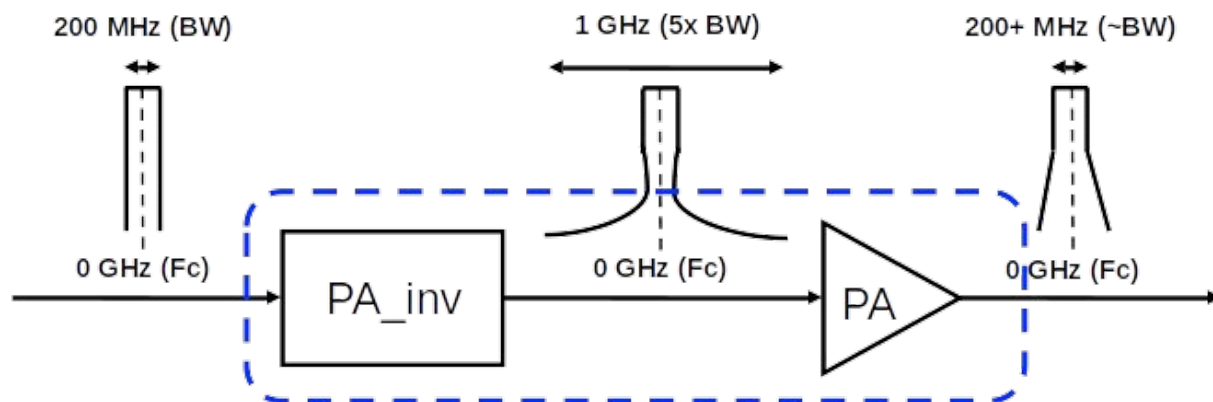
- Step - 1:



- Step - 2



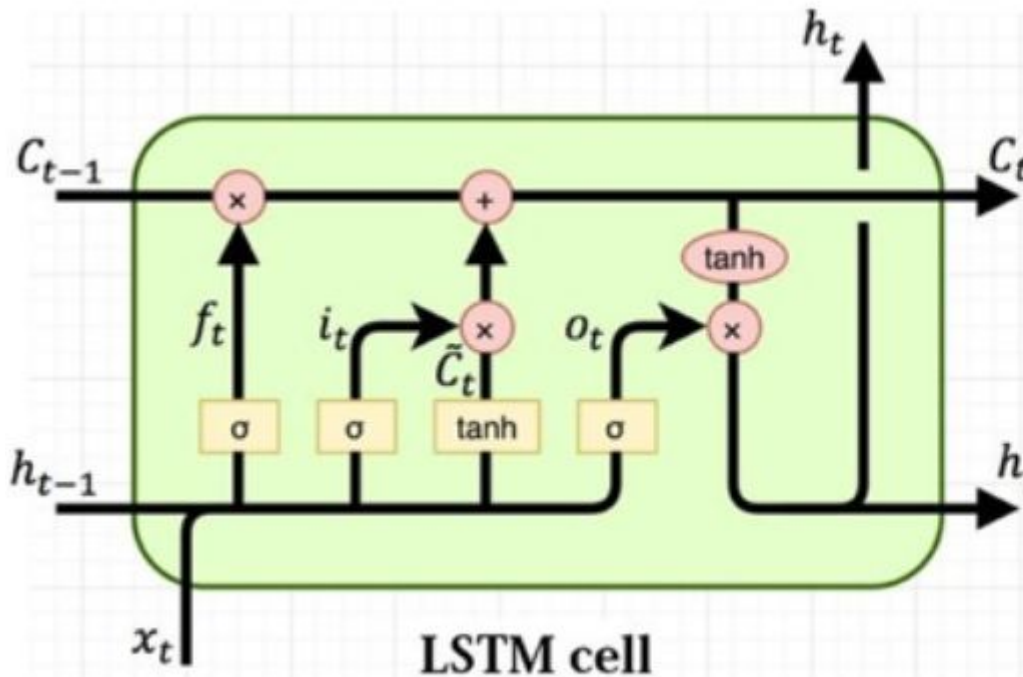
- Step - 3



Mitigate PA output distortion through Predistortion

Introduction to LSTM

- ❑ Long Short Term Memory networks - usually just called “LSTMs” - are a special kind of Recurrent Neural Network (RNN), capable of learning long-term dependencies.
- ❑ Unlike regular RNN networks, LSTMs also have this chain like structure but the repeating module has a different structure.



$$\begin{aligned} i_t &= \sigma(x_t U^i + h_{t-1} W^i) \\ f_t &= \sigma(x_t U^f + h_{t-1} W^f) \\ o_t &= \sigma(x_t U^o + h_{t-1} W^o) \\ \tilde{C}_t &= \tanh(x_t U^g + h_{t-1} W^g) \\ C_t &= \sigma(f_t * C_{t-1} + i_t * \tilde{C}_t) \\ h_t &= \tanh(C_t) * o_t \end{aligned}$$

LSTM Gates

- Input gate i :
 - Takes previous output h_{t-1} and current input x_t .
 - $i_t \in (0, 1)$
 - $i_t = \sigma(\theta_{xi}x_t + \theta_{hi}h_{t-1} + b_i)$
- Forget gate f :
 - Takes previous output h_{t-1} and current input x_t .
 - $f_t \in (0, 1)$
 - $f_t = \sigma(\theta_{xf}x_t + \theta_{hf}h_{t-1} + b_f)$
 - If $f_t = 0$: **Forget** previous state, otherwise pass through prev. state.
- Read gate g :
 - Takes previous output h_{t-1} and current input x_t .
 - $g_t \in (0, 1)$



LSTM Gates

- Cell gate c :
 - New value depends on f_t , its previous state c_{t-1} , and the read gate g_t .
 - Element-wise multiplication: $c_t = f_t \odot c_{t-1} + i_t \odot g_t$.
 - We can learn whether to **store** or **erase** the old cell value.
- Output gate o :
 - $o_t = \sigma(\theta_{xo}x_t + \theta_{ho}h_{t-1} + b_o)$
 - $o_t \in (0, 1)$
- New output gate h :
 - $h_t = o_t \odot \tanh(c_t)$
 - Will be fed as input into next block.



Software implementation

```
# In[] Load Data
```

```
data = sio.loadmat('../Data/outdatapa_1G.mat')  
data = sio.loadmat('../Data/indatapa_1G.mat')
```

```
# In[] Plot Data
```

```
plt.plot(np.reshape(indata_1G, (-1,1)), color='r')  
plt.plot(np.reshape(outdata_1G, (-1,1)), color='b')  
plt.show()
```

```
#spectrum_ = lambda x: np.fft.fftshift(np.fft.fft(x, fftLen)) / Fs * (len(u))
```

```
spectrum = lambda x: 5*np.log10(np.fft.fftshift(np.fft.fft(x, fftLen)) / Fs * (len(indata_1G)))
```

```
# In[] Prepare Training Model
```

```
out_real, out_img = np.reshape(outdata_1G.real,(-1,1)),np.reshape(outdata_1G.imag,(-1,1))
outp = [0]*4000
j = 0
for i in range(4000):
    if (i%2==0):
        outp[i]=out_real[j]

    else:
        outp[i]=out_img[j]
        j=j+1

oo = np.asarray(outp)
np.save("outp.npy",oo)
```



In[4] Network and Parameter

```
i_r = Input(batch_shape=(batch_size, timesteps, input_dim), name='main_input')
```

```
i_i = Input(batch_shape=(batch_size, timesteps, input_dim), name='aux_input')
```

```
x = concatenate([i_r, i_i])
```

```
o = LSTM(400, return_sequences=True, stateful=True)(i_r)
```

In[4] Training

```
history_r = m_r.fit({'main_input': train_x_r, 'aux_input': train_x_i}, {'main_output': train_y_r, 'aux_ou
```

In[4] Load Model

```
m_r.save_weights('./weight/LST.h5')
```

```
m_r.load_weights('./weight/LST.h5')
```

```
m_r.save_weights('./weight/LSTM.h5py')
```

```
m_r.load_weights('./weight/LSTM.h5py')
```



```
# In[4]: Prediction
```

```
predict_r = m_r.predict({'main_input': train_y_r})  
predict_r_ = np.reshape(predict_r, (-1, 1))
```

```
trainPredict_r = np.reshape(scaler_ur.inverse_transform(predict_r_), (-1,))
```

Results

- ❑ The time taken when performing LSTM in software is **113s**.

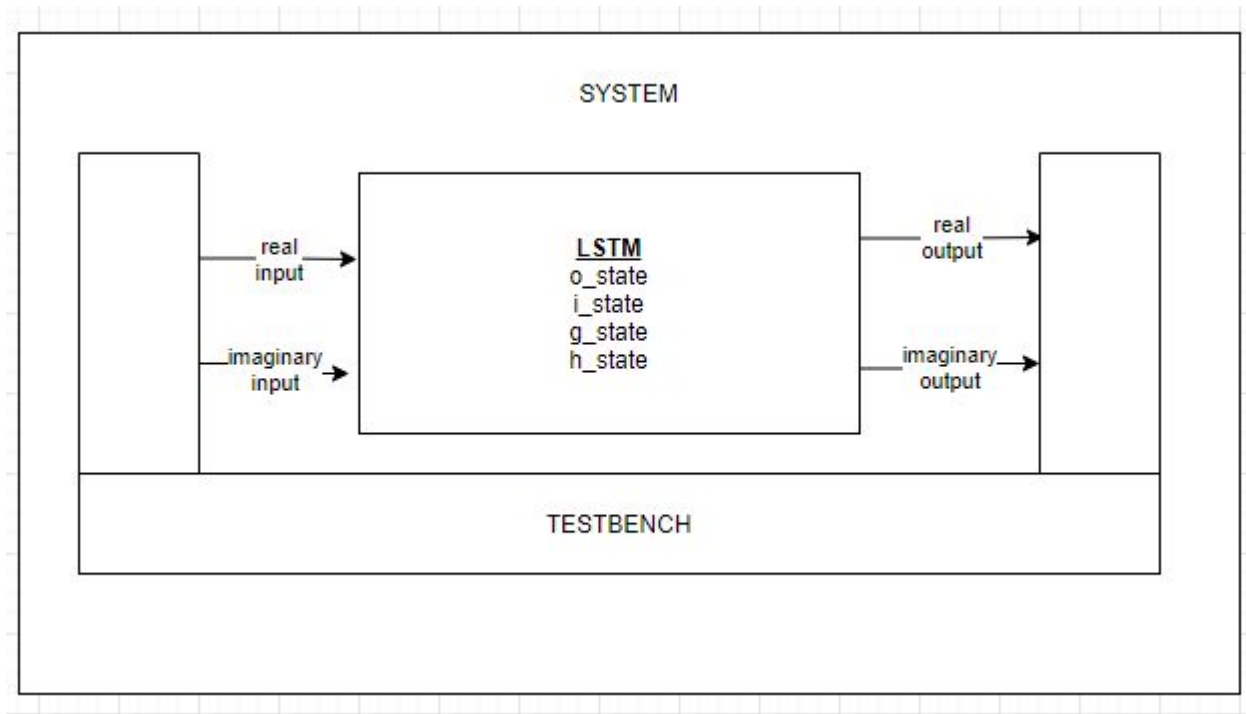
```
sw_ocr = lstm.PynqFrakturOCR(lstm.RUNTIME_SW)

sw_result = sw_ocr.inference(im)
sw_mops_per_s, sw_ms_inference_time, sw_recognized_text = sw_result

print("SW OCRed text: {}".format(sw_recognized_text))
print("SW MOps/s: {}".format(sw_mops_per_s))
print("SW inference time [ms]: {}".format(sw_ms_inference_time))
```

```
SW OCRed text: spruches nichts, daß eine leise Bitterkeit oder ein Wort der Resig-
SW MOps/s: 1.2346284082729002
SW inference time [ms]: 113142.3828125
```

Stratus HLS implementation



Results

```
i_state-0.122049
o_state0.0728104
g_state0.0726688
h_state0.126844
i_state-0.0239955
o_state0.05687
g_state0.0543943
h_state-0.132827
i_state-0.011761
o_state-0.0470634
g_state-0.00885692
h_state-0.15961
i_state-0.0511192
o_state-0.0818065
g_state-0.00753786
h_state-0.0989751
i_state-0.114914
o_state-0.028768
g_state0.0738344
h_state0.120309
i_state-0.0676995
o_state-0.0603062
g_state0.00581274
h_state-0.139757
i_state0.108128
o_state0.0125849
g_state0.0277029
h_state-0.118148
LSTM REAL AND IMAGINARY VALUES
Info: /OSCI/SystemC: Simulation stopped by user.
Total run time = 14417910 ns
Simulated time == 14417970 ns
```

Simulated time:
0.0144 sec



RISC V LSTM Implementation single core

LSTM in VP:

```
#main.cpp

addr_t lstm_start_addr = 0x77000000;
addr_t lstm_size = 0x01000000;
addr_t lstm_end_addr = lstm_start_addr + lstm_size - 1;
bool use_E_base_isa = false;

bus.ports[15] = new PortMapping(opt.lstm_start_addr, opt.lstm_end_addr);

bus.isocks[15].bind(lstm.tsock);

#lstm.h

struct lstm : public sc_module {
//lstm input_1 and input2
    sc_fifo<int> i_1;//since the total input is flatten so at every even position real
    sc_fifo<int> i_2;//after every real is its corresponding imaginary(odd pos)
//output_1 and output2
    sc_fifo<int> o_result1;
    sc_fifo<int> o_result2;
```



```
i_state = bias_lstm[v] + ker[v]*input1 + ker[N1+v]*input2;
    for(j =0;j<N1;j++){
        recur_ker_l[j] = recur_ker[first + j];
    }
    i_state = i_state + hidden_multiply(h_state,recur_ker_l);
    i_state = sigmoid(i_state);
f_state = bias_lstm[N1+v] + ker[2*N1+v]*input1 + ker[3*N1+v]*input2;
o_state = bias_lstm[2*N1+v] + ker[4*N1+v]*input1 + ker[5*N1+v]*input2;
g_state = bias_lstm[3*N1+v] + ker[6*N1+v]*input1 + ker[7*N1+v]*input2;

int result1 = (int)((output_main + main_bias)*precision);
int result2 = (int)((output_aux+ aux_bias)*precision);

o_result1.write(result1);
o_result2.write(result2);
```



LSTM in SW

```
#main.cpp

void write_data_to_ACC(char* ADDR, int buffer, int len){
    unsigned char buff[4];

    data.uint = buffer;
    buff[0] = data.uc[0];
    buff[1] = data.uc[1];
    buff[2] = data.uc[2];
    buff[3] = data.uc[3];

    if(_is_using_dma){
        // Using DMA
        *DMA_SRC_ADDR = (uint32_t)(buff);
        *DMA_DST_ADDR = (uint32_t)(ADDR);
        *DMA_LEN_ADDR = len;
        *DMA_OP_ADDR = DMA_OP_MEMCPY;
    }else{
        // Directly Send
        memcpy(ADDR, buff, sizeof(unsigned char)*len);
    }
}

#include "input_real.h"
#include "input_imag.h"

write_data_to_ACC(lstm_START_ADDR, buffer_r, 4);
write_data_to_ACC(lstm_START1_ADDR, buffer_i, 4);

read_data_from_ACC(lstm_READ_ADDR, buffer_r, 4);
read_data_from_ACC(lstm_READ1_ADDR, buffer_i, 4);
```



```
Info: /OSCI/SystemC: Simulation stopped by user.
=[ core : 0 ]=====
simulation time: 229953920 ns
zero (x0) = 0
ra (x1) = 104a2
sp (x2) = 1ffffec
gp (x3) = 24cb0
tp (x4) = 0
t0 (x5) = 0
t1 (x6) = 36c0
t2 (x7) = 1
s0/fp(x8) = 0
s1 (x9) = 0
a0 (x10) = 0
a1 (x11) = 0
a2 (x12) = 10f9
a3 (x13) = 0
a4 (x14) = 0
a5 (x15) = 0
a6 (x16) = 1
a7 (x17) = 5d
s2 (x18) = 0
s3 (x19) = 0
s4 (x20) = 0
s5 (x21) = 0
s6 (x22) = 0
s7 (x23) = 0
s8 (x24) = 0
s9 (x25) = 0
s10 (x26) = 0
s11 (x27) = 0
t3 (x28) = 0
t4 (x29) = 2
t5 (x30) = 8800
t6 (x31) = 5
pc = 1b422
num-instr = 7244726
```



RISC V LSTM Implementation multi - core

```
#main.cpp

//address
static char* const lstm_START_ADDR = reinterpret_cast<char* const>(0x45000000);
static char* const lstm_START1_ADDR = reinterpret_cast<char* const>(0x45000036);

// Gaussian Filter ACC 1
static char* const lstm1_START_ADDR = reinterpret_cast<char* const>(0x45000000);
static char* const lstm1_START1_ADDR = reinterpret_cast<char* const>(0x45000036);

//dma read
void read_data_from_ACC(char* ADDR, int buffer, int len){
    unsigned char buff[4];
    if(!_is_using_dma){
        // Using DMA
        *DMA_SRC_ADDR = (uint32_t)(ADDR);
        *DMA_DST_ADDR = (uint32_t)(buff);
        *DMA_LEN_ADDR = len;
        *DMA_OP_ADDR = DMA_OP_MEMCPY;
    }else{
        // Directly Send
        memcpy(buff, ADDR, sizeof(unsigned char)*len);
    }
    data1.uc[0] = buff[0];
    data1.uc[1] = buff[1];
    data1.uc[2] = buff[2];
    data1.uc[3] = buff[3];
    buffer = data1.uint;
}
```



```
//mutex lock
sem_wait(&lock);
    if (hart_id == 0) {
        write_data_to_ACC(lstm_START_ADDR, buffer_r, 4);
        write_data_to_ACC(lstm_START1_ADDR, buffer_i, 4);
    }
    else {
        write_data_to_ACC(lstm1_START_ADDR, buffer_m, 4);
        write_data_to_ACC(lstm1_START1_ADDR, buffer_n, 4);
    }
    sem_post(&lock);
```



SystemC 2.3.3-Accellera --- Jun 8 2021 14:00:49
Copyright (c) 1996-2018 by all Contributors,
ALL RIGHTS RESERVED

hart_id = 1

=====

Reading from array

=====

input_rgb_raw_data_offset = 8
width = 2000
length = 0
bytes_per_pixel = 32

=====

hart_id = 0

=====

Reading from array

=====

input_rgb_raw_data_offset = 8
width = 2000
length = 0
bytes_per_pixel = 32

=====

real : [1000 1000] -4816 -4816 -4816 -4816
imag : [1000 1000] -25385 -25385 -25385 -25385
real : [1001 1001] 18537 18537 18537 18537
imag : [1001 1001] -28641 -28641 -28641 -28641
real : [1002 1002] 33889 33889 33889 33889
imag : [1002 1002] -28295 -28295 -28295 -28295
real : [1003 1003] 36360 36360 36360 36360
imag : [1003 1003] -22631 -22631 -22631 -22631
real : [1004 1004] 25142 25142 25142 25142
imag : [1004 1004] -11178 -11178 -11178 -11178
real : [1005 1005] 3577 3577 3577 3577
imag : [1005 1005] 4330 4330 4330 4330
real : [1006 1006] -22176 -22176 -22176 -22176
imag : [1006 1006] 20058 20058 20058 20058
real : [1007 1007] -45059 -45059 -45059 -45059
imag : [1007 1007] 31151 31151 31151 31151
real : [1008 1008] -59125 -59125 -59125 -59125
imag : [1008 1008] 33700 33700 33700 33700
real : [1009 1009] -61016 -61016 -61016 -61016
imag : [1009 1009] 26624 26624 26624 26624
real : [0 0] -28790 -28790 -28790 -28790
imag : [0 0] 13390 13390 13390 13390
real : [1 1] -24153 -24153 -24153 -24153



Multi core LSTM (2 Processors)

```
Info: /OSCI/SystemC: Simulation stopped by user.
```

```
=[ core : 0 ]=====
```

```
simulation time: 27873540 ns
```

```
zero (x0) = 0
ra (x1) = 10c38
sp (x2) = 18d00
gp (x3) = 36020
tp (x4) = 0
t0 (x5) = 2010000
t1 (x6) = 1
t2 (x7) = 1
s0/fp(x8) = 0
s1 (x9) = 0
a0 (x10) = 0
a1 (x11) = 37b48
a2 (x12) = 1
a3 (x13) = 25
a4 (x14) = 1
a5 (x15) = 0
a6 (x16) = 0
a7 (x17) = 5d
s2 (x18) = 0
s3 (x19) = 0
s4 (x20) = 0
s5 (x21) = 0
s6 (x22) = 0
s7 (x23) = 0
s8 (x24) = 0
s9 (x25) = 0
s10 (x26) = 0
s11 (x27) = 0
t3 (x28) = 3
t4 (x29) = 2
t5 (x30) = 0
t6 (x31) = 0
```

```
pc = 10c64
num-instr = 922647
```

```
=[ core : 1 ]=====
```

```
=[ core : 1 ]=====
```

```
simulation time: 27873540 ns
```

```
zero (x0) = 0
ra (x1) = 10c38
sp (x2) = 20d00
gp (x3) = 36020
tp (x4) = 0
t0 (x5) = 20d00
t1 (x6) = 1
t2 (x7) = 1
s0/fp(x8) = 0
s1 (x9) = 0
a0 (x10) = 0
a1 (x11) = 37b48
a2 (x12) = 1
a3 (x13) = 2a
a4 (x14) = 2
a5 (x15) = 0
a6 (x16) = fefefeff
a7 (x17) = 40
s2 (x18) = 0
s3 (x19) = 0
s4 (x20) = 0
s5 (x21) = 0
s6 (x22) = 0
s7 (x23) = 0
s8 (x24) = 0
s9 (x25) = 0
s10 (x26) = 0
s11 (x27) = 0
t3 (x28) = 3
t4 (x29) = 2
t5 (x30) = 8800
t6 (x31) = 5
```

```
pc = 10c4c
```

```
num-instr = 952521
```

```
user@ubuntu:~/ee6470/riscv-vp/sw/lstm-multicore$
```


Comparative study

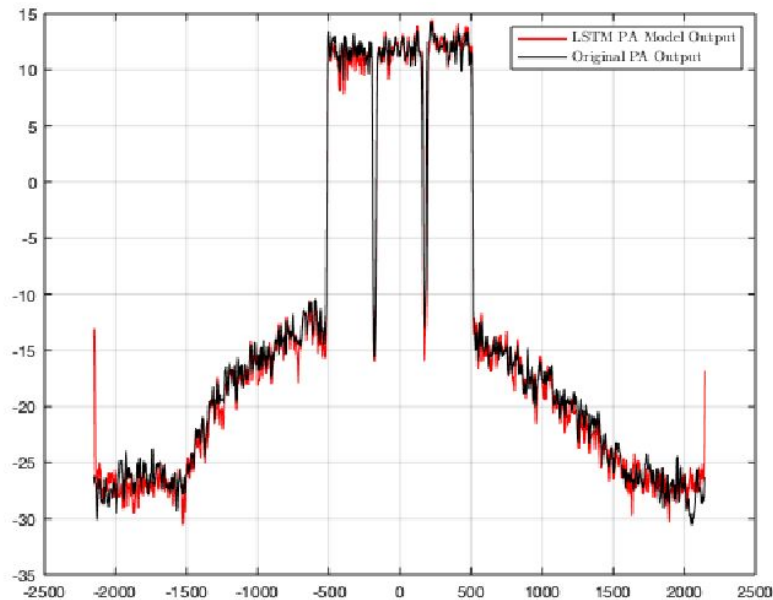
	Simulated Time
Single - Core	229953920 ns
Multi - Core (2 cores)	27873540 ns
DIFFERENCE	~8x reduced

	Simulated time
Software implementation	1131425656 ns
RISC V implementation	27873540 ns
DIFFERENCE	~40x reduced

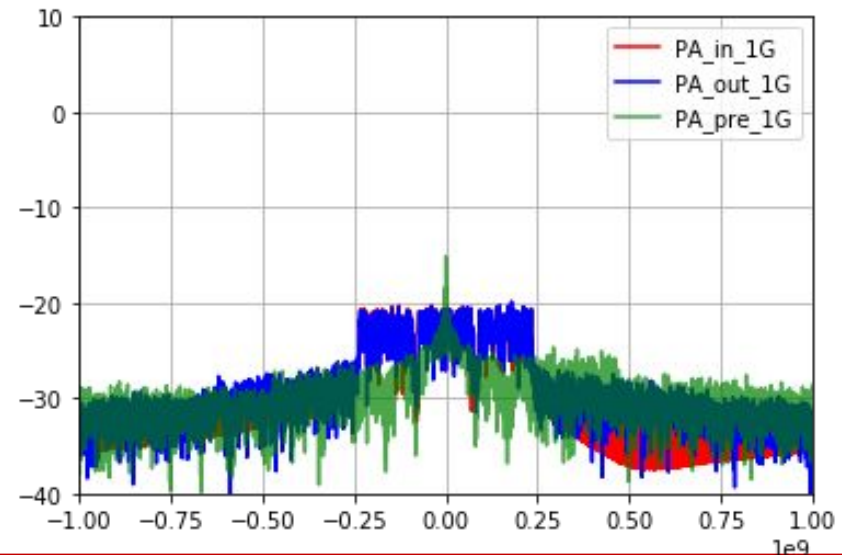
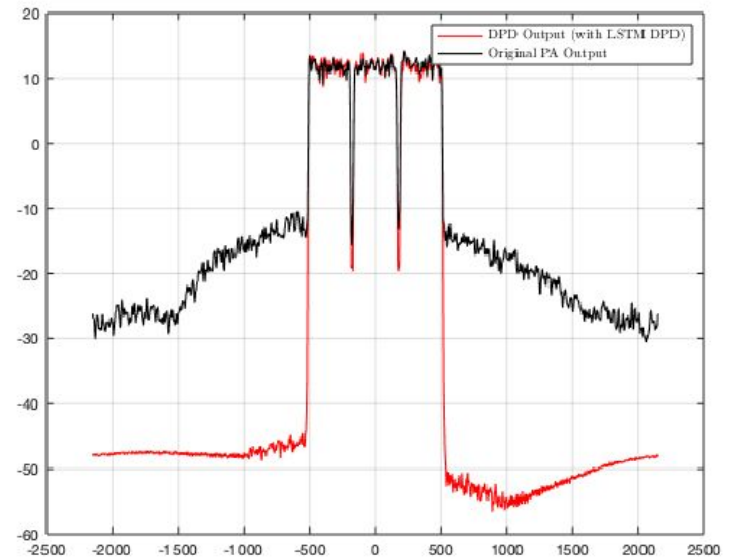


Results

LSTM PA Model Performance

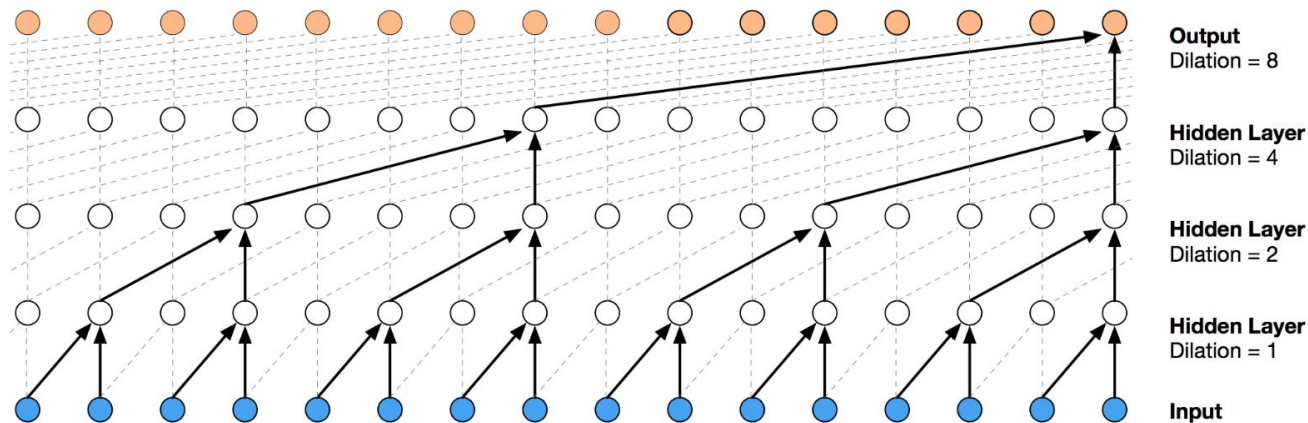


LSTM DPD Result



Future work

- Since the data from a power amplifier is 1-Dimensional, we will explore a different type of convolution called **Temporal convolution network** with dilation. Introducing dilation will help us take even smaller details in the put.



- As you can see it has a directional structure, which captures dependencies between the input (in our case words) and aggregates into a number of units. Similar to what LSTM and GRU does, however with less loops.

Thank You!

Questions??

