A Deep Learning Model for Gain Compensation in Adaptive Excitation Fluorescence Microscopy

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Introduction

In this report, we present results on a deep learning model for compensation of the gain transience in an adaptive excitation source (AES) [1] for multiphoton microscopy. The previously proposed AES amplifies the input pulse train before passing the amplified signal to the laser. However, this amplification causes an unwanted signal corruption known as a gain transience. Previously, an iterative algorithm was used to preshape the input pulse train before passing it into the amplifier, which is known as gain compensation. This algorithm is expensive and typically takes 20 to 30 iterations to converge. In this project, we seek to replace this algorithm with a neural network which learns to output the compensated signal. This significantly reduces computation time due to the efficiency of forward passes of a neural network.

Method

Our goal was to take in a 1d time-series signal and use a neural network to predict the compensated version of the input signal.

Independent variables in the Experiments:

- Signal length →[3000,6000,12000,15000]
- Initial learning rate → [1e-1, 1e-2, 1e-3, 1e-4, 1e-5]
- Loss → [MSE, MAE]

Dependent variables in the Experiments:

- Training loss
- Validation loss
- Training speed

Our dataset consists of 20 input signals and their corresponding compensated signal. These signals were further decomposed into chunks of smaller length, such that all data points were the same size chunks. We experimented with 4 different chunk lengths, [3000,6000,12000,15000].

We used a UNet structure with an encoder-decoder architecture. The architecture was:

- Encoder
    - Convolution layer, 64 channels
    - Batch Normalization layer
    - Relu Layer
    - Convolution layer, 128 channels
    - Batch Normalization layer
    - Relu Layer
    - Convolution layer, 256 channels
    - Batch Normalization layer
    - Relu Layer
- Decoder
    - Convolution layer, 128 channels
    - Batch Normalization layer
    - “Relu” Layer
    - Convolution layer, 64 channels
    - Batch Normalization layer
    - “Relu” Layer
- Regressor
    - 1x1 Convolutional layer

For training, we used an Adam optimizer with an exponential learning rate decay. The Adam optimizer uses gradient descent to find the second order machine learning function. We experimented with 5 different initial learning rate values, [1e-1, 1e-2, 1e-3, 1e-4, 1e-5], and recorded the training loss, validation loss, and training speed. We trained for 50 epochs, with early stopping.

Experiments

Experiment 1: Effect of different Signal Lengths

The neural network was trained keeping the initial learning rate constant at 1e-3 to determine the effect of signal length on Validation Loss, Training Loss, and Training Speed.

Table 1:

Signal Length	**Initial Learning Rate**	**Validation Loss**	**Training Loss**	**Training Speed**
3000	1e-3	0.0106	9.4456e-05	65 ms/step
6000	1e-3	0.0098	2.5721e-05	106 ms/step
12000	1e-3	0.0044	1.7196e-05	196 ms/step
15000	1e-3	0.0047	5.1159e-05	240 ms/step

Experiment 2: Effect of different Initial Learning Rates

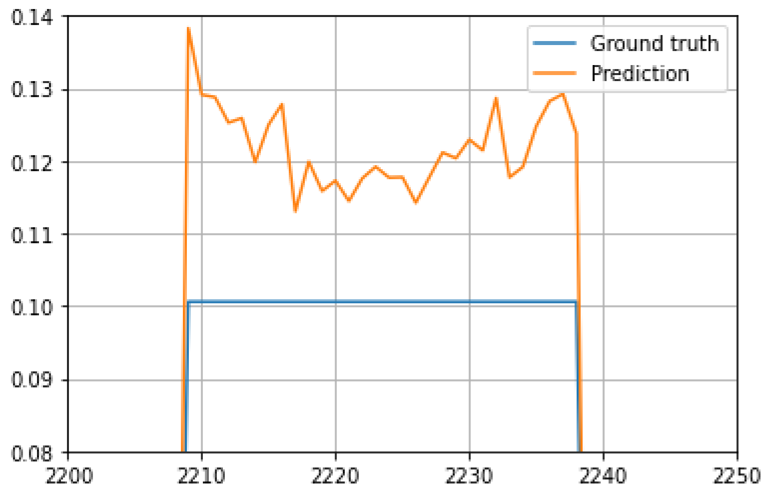
Table 2:

Initial Learning Rate	**Signal Length**	**Validation Loss**	**Mean Squared Error (Training Loss)**	**Training Speed**
1e-1	3000	0.0160	2.9e-03	64ms/step
1e-2	3000	0.0118	1.5612e-04	71ms/step
1e-3	3000	0.0111	9.8629e-05	66ms/step
1e-4	3000	0.0099	9.3554e-05	67ms/step
1e-5	3000	0.0096	7.2098e-05	66ms/step
1e-1	6000	0.0154	1.1e-03	107ms/step

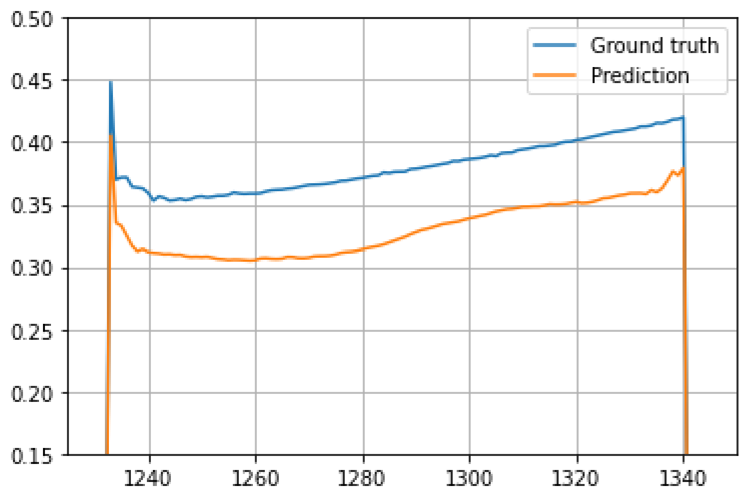
1e-2	6000	0.0154	1.1e-03	110ms/step
1e-3	6000	0.0080	3.0730e-05	109ms/step
1e-4	6000	0.0072	5.9369e-05	109ms/step
1e-5	6000	0.0087	4.2152e-04	110ms/step
1e-1	12000	0.0164	1.4e-03	184ms/step
1e-2	12000	0.0164	1.4e-03	195ms/step
1e-3	12000	0.0023	8.3315e-05	198ms/step
1e-4	12000	0.0032	7.0438e-05	197ms/step
1e-5	12000	0.0183	6.3e-03	198ms/step
1e-1	15000	0.0183	1.8e-03	235ms/step
1e-2	15000	0.0183	1.8e-03	247ms/step
1e-3	15000	0.0150	3.2626e-04	247ms/step
1e-4	15000	0.0050	1.3335e-04	255ms/step
1e-5	15000	0.0210	8.9e-03	247ms/step

Representative Test Predictions:

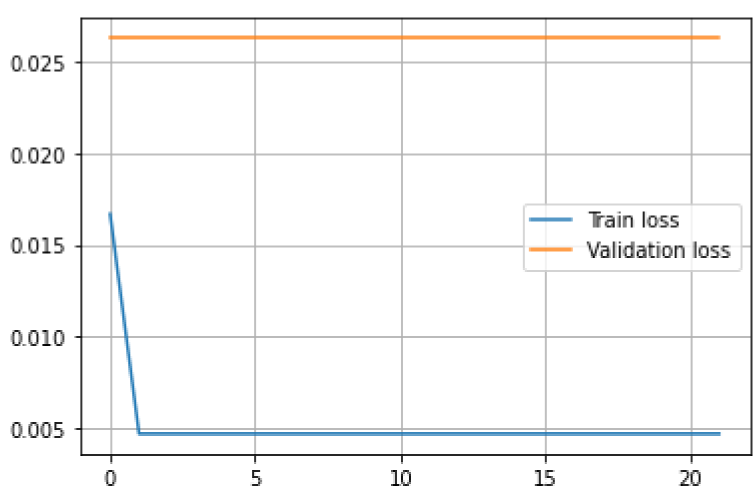
Signal length 12000, learning rate 1e-4



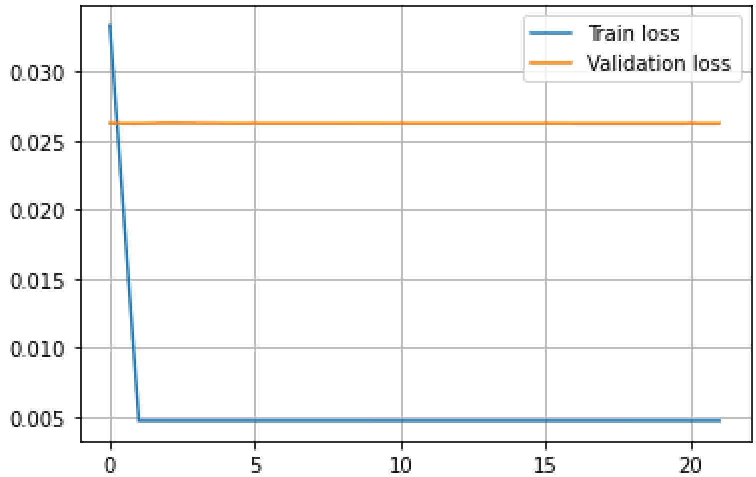
Signal length 6000, learning rate 1e-3



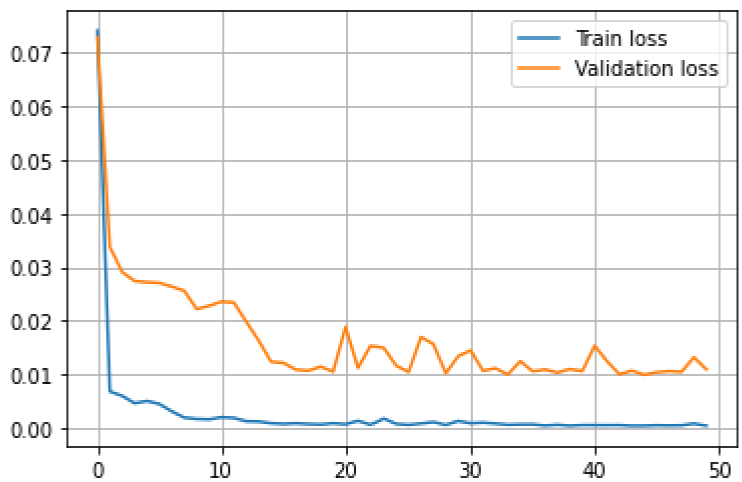
Learning Curves for Signal Length 12000 and Different Learning Rates:



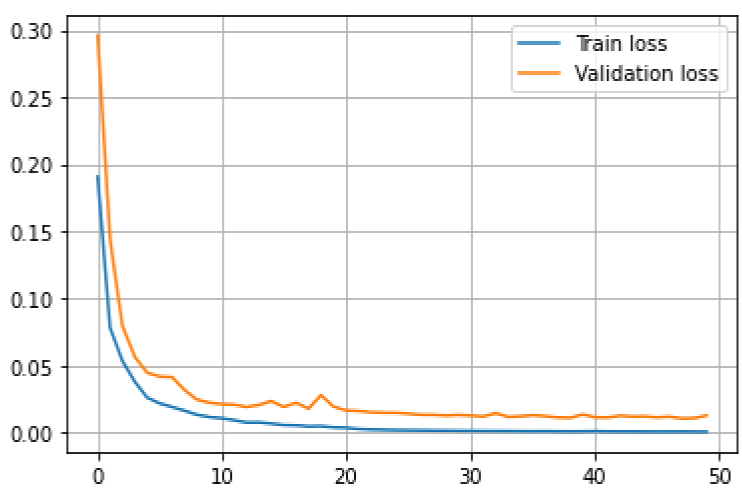
Learning rate 1e-1



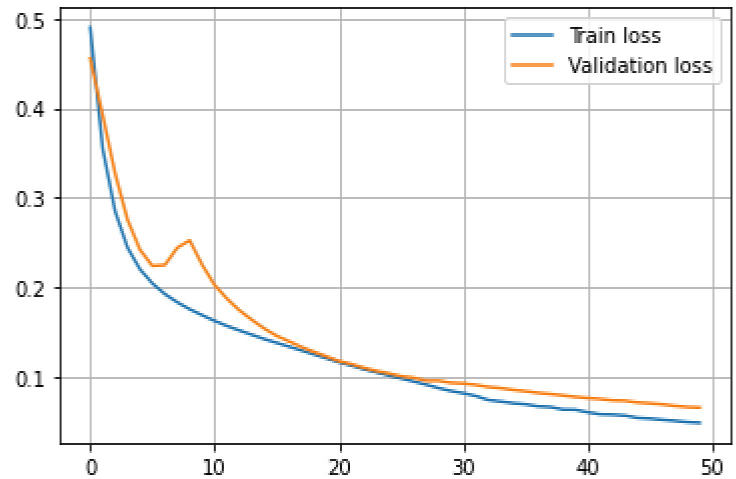
Learning rate 1e-2



Learning rate 1e-3



Learning rate 1e-4



Learning rate 1e-5

Conclusion

Experiment 1: The best signal length is 12000, as the training and validation loss are smallest for this value. This is expected, as a larger signal length typically creates a model with a better fit. Furthermore, the training speed of 12,000 is 196 ms/step, which is approximately 1.85 times the capacity of 6,000, which is 106 ms/step.

Experiment 2: The best initial learning rates for all different signal length values is 1e-3 and 1e-4, as that is when the mean squared error is the lowest. As shown in the learning curves, too high of a learning rate (such as 1e-2) causes poor convergence while too low of a learning rate (such as 1e-5) converges too slowly.

In addition to having more data samples, one point of improvement could be comparing MAE and MSE loss to see the results. Another point of improvement could be using a different type of learning algorithm such as an online gradient descent and comparing the results.

References:

[1] Li et al, An adaptive excitation source for high-speed multiphoton microscopy, 2019