# **UBC Okanagan/Medical Physics** A Deep Learning Approach to RF Pulse Design for MRI

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0.09

0.08

9 0.07

WSE 0.05

0.05

0.04

Training Parameters:

Dataset size: ~550k

· Learning rate: 1e-4

· Optimization: Adam

· Batch size: 32

· Dropout

**Methods** 

Band edges

## Background

### What is MRI?

- · Medical imaging tool that uses radiofrequency (RF) pulses to excite protons to acquire a signal [1]
- · RF pulses can be designed to acquire multiple slices simultaneously, without increasing the overall power deposition (SMS-PINS pulses) [2, 3]

### What are the challenges with designing RF pulses?

- Ill-defined
- Iterative

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- Time-consumina
- In order to achieve a custom slice profile, one must first design an RF pulse [2-4].

### What is the solution?

Use deep learning to reverse the process by training a model on a large dataset of RF pulse / slice profile pairs

#### Results Slice Profile Input Model Output: Pulse Generation Parameters (not scaled) · A 5 layer forward-feed neural network was 0.9 trained to classify an RF pulse given a 8.0 custom slice profile input [5] 0.6 Model outputs a combination of parameters 0.5 Deep Learning Model that are used to simulate the RF pulse with 0.4 the desired slice profile input: ÓÓ · Gradient duty cycle Band Edge 2 Duty Cycle Number of Lobes Band Edge 1 Pulse Duration Number of lobes 66000 Model Output: Pulse Generation Parameters (scaled) Pulse Duration Train and Validation Loss vs. Epoch — Train Loss Validation Loss Model Output Number of Lobes Band Edge 1 Band Edge 2 Pulse Duratio Number of Lobes Compare with Expected & Generated Slice Profiles & Their Residuals model input 1.0 Pulse Duration 0.0 -0.5 Pulse Generation -1.0 60 Epoch ž. SEAMS-PINS Algorithm 100 Generated RF Pulse Epochs: 125 (early stopping) 80.0 0.06 **RF Pulse Output** Simulate Slice Profile · Loss: Mean Squared Error 0.04 0.02 0.00 Compute RMSE 2500 2000 3000 Time [us]

## Discussion

- · RMSE was calculated over a smaller test set (computationally limited to n = 1000)
- Normalized Mean RMSE = 36.5%
- · Visual inspection of the slice profiles results reveal significant variation

In Conclusion, this model serves as a proof of concept for the deep learning based design of **RF** pulses for MRI

## **Future Steps**

· Investigate other deep learning models, expand dataset, introduce optimization loop following original prediction

## References

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- 5. Paszke, Pytorch, 2023

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