Deep Reinforcement Adaptive Computational Processors

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Background

When working with signals, the information is captured through a sequence of points sampled from the source. When performing operations between signals, we need to either very finely sample or reconstruct (through interpolation) the original signals. Reconstructing a signal from sampled values will introduce interpolation error.

In this project, we seek to:

- decrease the number of sampling operations to reduce energy consumption or extend battery life
- strategically select sample locations to minimize reconstruction error

Motivation

Our goal when strategically sampling is to minimize the absolute relative error in the product of the operation. We focus on multiplication in this project.

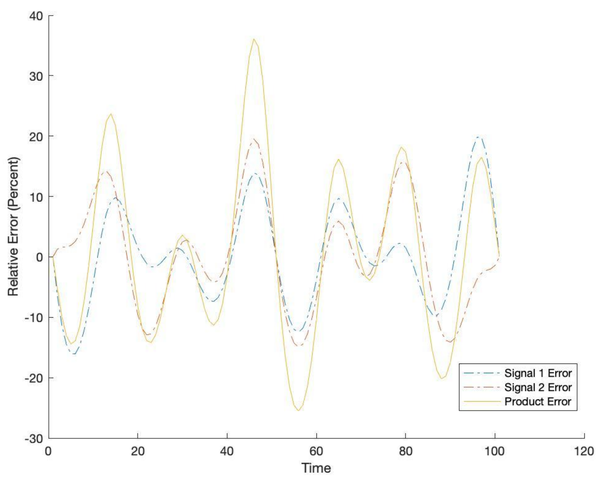
The multiplication error propagation equation gives a relationship between the signals' relative errors.

$$q = xy$$

$$\Delta x \Delta y \approx 0$$

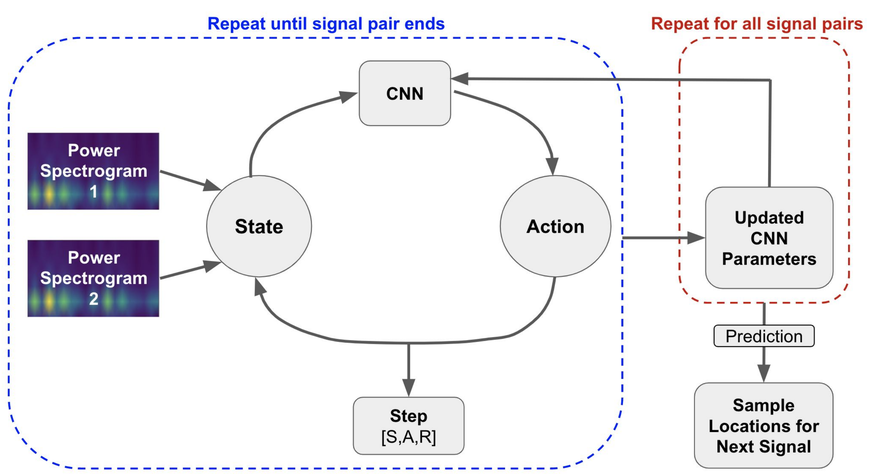
$$\Delta q = (x + \Delta x)(y + \Delta y) - xy \Rightarrow \frac{\Delta q}{q} \approx \frac{\Delta x}{x} + \frac{\Delta y}{y}$$

The equation suggests that errors in the original signals can "cancel" out if they have opposite signs i.e. Destructive Interference



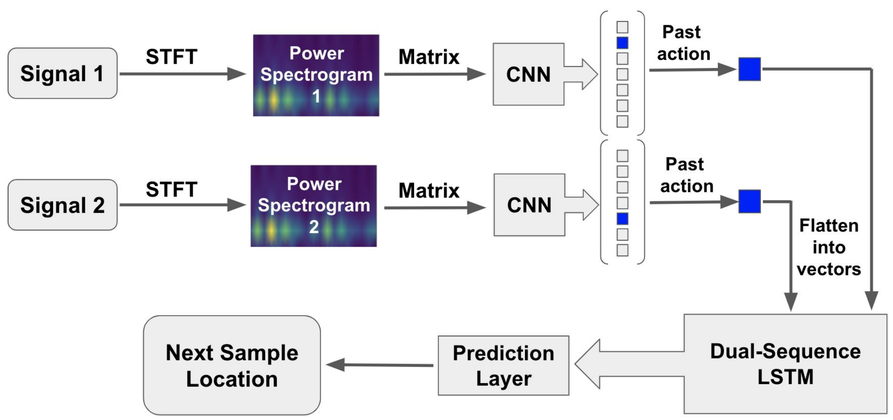
Proposed Models

Reinforcement Learning Model:



Learns state-specific sampling strategies through Monte Carlo simulation by optimizing CNN parameters.

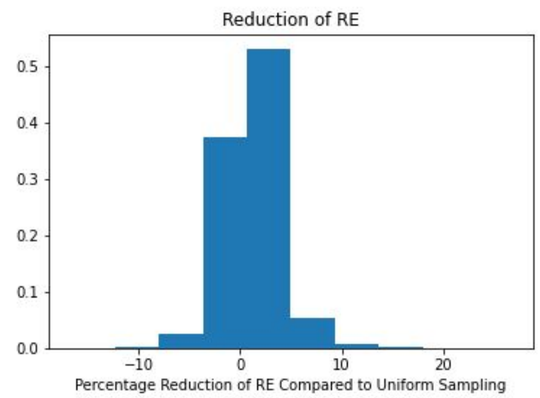
Deep Learning Model:



Leverages power spectrograms and a dual-sequence LSTM to predict sample locations.

Experimental Results

RL Monte Carlo Control Model:



Random Perturbation Search:

- 5000 signal pairs of 50Hz bandwidth
- 50000 random perturbation trials for each signal pair
- it is possible for certain pairs to achieve 40% reductions
- only 4% of the pairs had more than 10% reductions

Next Steps

Deep Reinforcement Learning Model:

- Optimize the current deep learning model
- Implement a model that combines Monte Carlo control with dual-sequence LSTM to further improve performance

TD(λ) Model:

- Explore TD(λ) reinforcement learning model
- Implement TD(λ) model by eligibility trace