The Implementation of Neural Networks for Phaseless Parametric Inversion

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Presentation overview

Introduction to the problem
- Grain bin imaging
- Measurement challenges

Neural network

Datasets
- Training data
- Testing data

Results
- Network performance
- Computational cost

Conclusion
Grain bin imaging

- Microwave imaging of the interior of a grain bin
- Voxel-wise reconstruction of permittivities using contrast source inversion requires calibration and a good initial guess
- Bulk parameters can be used to calibrate experimental data to synthetic models

Grain bin (with grain) is modeled in 3D using a finite element mesh, an example tetrahedral mesh on the grain is shown.
Measurement challenges

- Physical limitations prevent measurement on known calibration targets
- Bin measurements for inventory require climbing in the bin and are dangerous and impractical
  - i.e. we cannot obtain a large dataset to be used for neural network training.

Hopper-style bin at the University of Manitoba campus.
Objectives

- Obtain bulk parameters:
  - Height, cone angle, complex-valued bulk permittivity of grain
- Use supervised machine learning
  - Train only on *synthetic* data
  - Demonstrate performance on *experimental* data

Grain in bin (red) is characterized by bulk parameters.
Neural networks

- Three fully connected networks
  - Differ in number of hidden layers, and maximum number of accepted frequencies
- Trained solely on *synthetic* data

- Input shape: 552Nx1 column vector
  *where N is the number of frequencies*
- Output shape: 4 parameters
  *bulk parameters: [height, cone angle, permittivity (real part), permittivity (imaginary part)]*
Neural networks

**Introduction**

- **Neural Network**
- **Datasets**
- **Results**
- **Conclusion**

**Neural Networks Diagram**

- **NN-1**
  - Up to 1 frequency
- **NN-2**
  - Up to 3 frequencies
- **NN-3**
  - Up to 6 frequencies

*All activations are ReLU*
Training data

- Building an experimental training set is not practical:
  - Filling a grain bin with a known and controlled amount of grain is difficult
- Supervised learning requires **synthetic** training data
- Frequencies: 80MHz, 85MHz, 90MHz, 95MHz, 100MHz, 105MHz

- Synthetic data set:
  - Each dataset consists of 552 data points: Synthetic electromagnetic field estimate at each receiver point
  - 50,000+ datasets at each frequency
  - Generated by a finite element method forward solver
Testing (experimental) data

- Frequencies: 80MHz, 85MHz, 90MHz, 95MHz, 100MHz, 105MHz

- Experimental data set:
  - 14 labelled data sets at various heights and cone angles (no permittivity labels)
  - Measurements taken from Hopper-style bin on University of Manitoba campus
  - Each dataset at each frequency consists 552 data points: S-parameter data at each transceiver (proportional to phi component of magnetic field)
  - Raw, uncalibrated experimental data
Simplex inversion performance

- Our previous work uses an optimization method (simplex method) for obtaining the bulk parameters
  - Simplex inversion is performed on data from a single frequency
- We use the results from this simplex inversion (at two separate frequencies) as a baseline for neural network performance
Neural Network 3 (NN3) using all frequencies performed best on height predictions (bold dark red).

Comparison to Simplex Inversion (SI) at 90 MHz (bold red dash).
Angle prediction

- NN3 for 85-100 MHz performed best on angle predictions (bold blue)
- Comparison to SI at 90 MHz (bold red dash)
Permittivity predictions are reasonably close to both Simplex Inversion (SI) predictions, and theoretical model predictions.

Bulk permittivity: $\varepsilon = \varepsilon' + j\varepsilon''$

<table>
<thead>
<tr>
<th>Method</th>
<th>Avg. $\varepsilon'$</th>
<th>std.</th>
<th>Avg. $\varepsilon''$</th>
<th>std.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural Networks*</td>
<td>[4.17, 4.25]</td>
<td>0.219</td>
<td>[-0.502, -0.435]</td>
<td>0.0690</td>
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<tr>
<td>Simplex Inversion (70)</td>
<td>4.11</td>
<td>0.233</td>
<td>-0.572</td>
<td>0.303</td>
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<tr>
<td>Simplex Inversion (90)</td>
<td>4.07</td>
<td>0.141</td>
<td>-0.572</td>
<td>0.421</td>
</tr>
<tr>
<td>Composite model[1]</td>
<td>[3.90, 4.13]</td>
<td>--</td>
<td>[-0.42, -0.38]</td>
<td>--</td>
</tr>
</tbody>
</table>

*Average permittivity values are given as a range of averages across all networks tested.

Computational cost

- Simplex inversion:
  - Measurement analysis (per frequency): ~3 hours, per measurement

- Neural network:
  - Synthetic data generation: ~1 day per frequency, one time cost
  - Training data preparation and network training: < 30 minutes, one time cost
  - Measurement analysis: < 1 minute, per measurement
    - Analysis time is not significantly affected by additional frequencies once the synthetic training set is created.
Neural network trained solely on synthetic data can accurately obtain bulk parameters from experimental data.

- Bulk parameters can be obtained from raw, uncalibrated data.
- For continued field use, neural network method reduces computational cost of parametric inversion (as compared to optimization based simplex inversion).
Thank you

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