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The Implementation of Neural Networks for Phaseless Parametric Inversion

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Abstract

We present a machine learning work flow for the parametric inversion of grain bin measurements in which a neural network is trained solely on synthetic data for a unique bin geometry. This neural network can subsequently be used to rapidly obtain 4 inversion parameters (grain height, cone angle, and bulk real and imaginary permittivity of the grain) from uncalibrated, experimental data. We have previously shown that these 4 parameters can be used to calibrate experimental data and serve as prior information for full-data inversion. Our results show that a densely connected neural network that supports multifrequency data can better predict the cone angle of grain, and perform almost as well on grain height predictions, as the single-frequency simplex inversion method previously described. These findings suggest that neural networks trained on synthetic data may be a useful tool in the inversion of experimental data, providing prior information and a method for calibration.

1 Introduction

Grain is typically harvested and stored in large metal grain bins before being processed. The most important economic factor affecting grain price is simply the weight of grain in the bin, with the moisture content also having an effect on the value of the crop. Current methods for measuring grain levels and moisture content vary and can involve a person physically climbing inside the bin to obtain measurements, which is impractical and dangerous. Our group has previously presented an electromagnetic imaging system for monitoring grain bins [1] and has shown that phaseless parametric inversion can provide useful prior information and enable calibration to improve the results of full-data (magnitude and phase) inversion of grain in a grain bin [2]. Grain bin measurements are taken as often as once per day, and current parametric inversion methods are computationally expensive and time consuming, requiring a few hundred forward solver calls, over several hours, to produce a result.

The grain bin problem, which involves repeated calculation of the same parameters on a fixed region of interest, is an ideal application for neural networks. Neural networks are currently being studied for their applications to the inverse scattering problem and microwave imaging. Such networks have yielded promising results for both parametric synthetic [3] and pixel-based inversions for synthetic data and experimental data from the Institute Fresnel database [4].

Neural networks are computationally expensive to train, requiring large training sets to obtain accurate models. Once trained however, a neural network can perform complex computations on new data in a short amount of time. Each bin may have a unique geometry, but for applications such as inventory management, inversion must be performed regularly without changes to the bin geometry or transceiver locations. As each bin, and therefore each implementation of the proposed neural network, is unique, it is not practical to obtain large experimental data sets for training (in this work we analysed the performance on 14 experimental data sets). For this reason the neural network must be trained solely on synthetic data that models the various fill patterns of grain in the bin. Once trained, such a network could be used to quickly analyse the experimental data obtained at each measurement.

2 Neural Network

A densely connected neural network architecture, implemented with TensorFlow Keras [5], was chosen for this study for simplicity and for ease of implementation and training. We present results for a Hopper-style bin with 24 transceivers positioned at known locations on the bin wall, as shown in Figure 1. For this bin / transceiver set up, measurements are taken at frequencies ranging from 70 MHz to 110 MHz in 5-MHz steps. Our previous measurements have shown that data obtained in the 90-95 MHz range provides the most accurate reconstructions.

The described neural network accepts field measurements as inputs and computes 4 parameters: grain height, cone angle, bulk real permittivity, and bulk imaginary permittivity of the grain. More than 50,000 synthetic measurement sets were generated at each frequency, using an finite element method (FEM) forward solver as described by Zakaria et al [6], to create the training sets. Meshes were generated for various heights (-1.985 m to 1.920 m, in 0.195 m steps, where a height of 0 m corresponds to the vertical center of cylindrical portion of the bin (Figure 1)) and cone angles

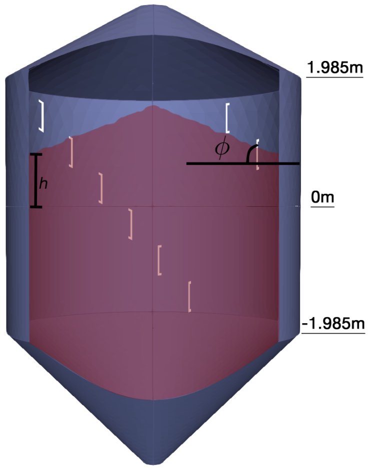

Figure 1. Hopper-style bin with antennas shown in white, and grain fill shown in red. The cone angle, ϕ, and the height, h, are shown, and the height reference of 0 m is identified.

($-30°$ to $30°$, in $3°$ steps). The FEM solver was called on each mesh for permittivities with real component ranging from 3.0 to 5.0 (in 0.18 steps) and imaginary component ranging from -0.6 to -0.2 (in 0.036 steps).

We trained and tested 3 different neural network architectures, as described in Table 1. Each architecture was trained with a batch size of 1000 for 100 epochs. Output size denotes the number of parameters computed (4) and the number of frequencies is a recommended number (each architecture can accept from 1 to N frequencies, where N is the number of frequencies in the full dataset). Each architecture differs in the number of hidden layers; the addition of each hidden layer increases the number of neurons in the first (largest) hidden layer.

Table 1. Neural network architectures.

Architecture	Number of frequencies	Hidden layers	Output size
NN-1	1	4	4
NN-2	3	5	4
NN-3	6	6	4

3 Results

3.1 Experimental Testing Data

For a hopper-style bin located at the University of Manitoba (described previously in [1,2]), we collected 14 data sets with hard red winter wheat. In order to create a wide variety of data sets, the bin was filled and emptied several times, and we also manually flattened the grain in several data sets. Each time the grain was moved, we obtained the grain height and cone angle by manual measurement. These measured values of cone angle and grain height for each data set are shown in Figure 2 (black triangles). For these data sets, the permittivity of the grain was not measured via other means, so we have not provided accuracy estimates for the neural network. The average moisture content of the grain (8 samples, taken with a Dickey-John GAC2100) was measured to be 13.6%, and the bulk density of the grain was found to be between 0.80 and 0.85 g/cm^3.

3.2 Neural Network Performance

Using the 3 architectures described in Table 1, 5 neural networks were trained and tested against 14 sets of experimental data for which the grain height and cone angle were measured and recorded. Table 2 compares the average absolute error of the height and cone angle data relative to the measured (experimental) values for each of the 5 neural networks (NN) and 2 single-frequency simplex inversions (SI). Of the 5 neural networks evaluated, NN-3 (Table 1) had the lowest error. The 80-105-MHz network had the lowest error for grain height and the 85-100-MHz network had the lowest error for cone angle. The simplex inversion method yielded a lower error than the 80-105-MHz network for grain height, but both of these neural networks outperformed simplex inversion when predicting cone angle. Figure 2 shows the predicted and measured values for height and cone angle. For these figures the height and cone angle were independently sorted for increasing values. The lines in Figure 2 are not intended to suggest any connection between individual experimental data sets, but rather they are designed to emphasize the variations in each data series.

Table 2. Average absolute error for height and cone angle with each parametric inversion.

Frequency (MHz)	Method	Height (m) Error	Cone angle (°) Error
Neural Networks			
70	NN-1	0.4467	9.695
90	NN-1	0.2915	6.716
90-95	NN-2	0.2244	6.258
85-100	NN-3	0.2042	5.010
80-105	NN-3	0.1560	5.690
Simplex method			
70	SI	0.1175	6.388
90	SI	0.1384	6.698

True values for the bulk permittivities ($\varepsilon_{re} - j\varepsilon_{im}$) of the grain are not available for the experimental data set, posing a challenge for quantitative validation of the permittivity results. We compare the neural network predictions to those obtained through simplex inversion to provide preliminary validation of the results. The simplex method (70 MHz) predicted an average real permittivity of 4.112, with a standard deviation of 0.223, and an average imaginary permittivity of -0.572 with a standard deviation of 0.0984 over the 14 experimental data sets. The neural networks tested predicted average bulk permittivities between 4.169 and 4.251,

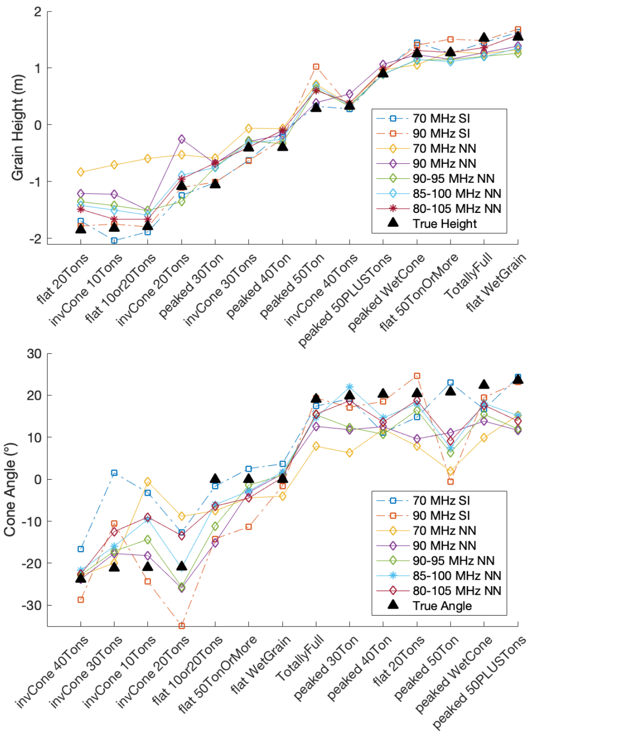

Figure 2. Plots of inversion results (neural network and simplex) for the predicted height (top) and predicted cone angle (bottom). In each plot the neural network with lowest error is marked with an asterisk for emphasis.

with a maximum standard deviation of 0.219, and -0.502 and -0.435, with a maximum standard deviation of 0.0690, for the real and imaginary permittivities, respectively. This demonstrates that the neural network predicted values are similar to those obtained by the simplex method and could be used for calibration and as prior information. Furthermore, we compared the predicted permittivities with Nelson and Kraszewski's composite model of the complex permittivity of cereal grain [7] at a moisture content of 13.6% with bulk densities ranging from 0.80 to 0.85 g/cm^3 at 90 MHz. The model predicts a range of bulk real permittivities between 3.90 and 4.13 and bulk imaginary permittivities between -0.38 and -0.42, which further supports that the neural network provides reasonable predictions of both real and imaginary bulk permittivities of the grain.

Synthetic data generation and neural network training was performed on a computer equipped with 1.5 TB RAM, 64 cores, running CentOS7. Testing was performed on a MacBook Pro (2.4 GHz Intel Core i5 processor, 8GB RAM). Neural network training time was under 30 minutes per network, and testing was completed in under a minute. A single frequency inversion using the simplex method takes approximately 3 hours (± 1 hour).

4 Conclusion

We demonstrate that a neural network trained on synthetic data can be used to perform phaseless parametric inversion on uncalibrated, experimental grain bin data. Independent of the ability to provide useful prior information for calibration and full-data inversion, simply having the height and cone angle of the grain in the bin can provide useful information for inventory management. Having a rapid method for obtaining these parameters, without the need for opening the bin to take measurements, has the potential to both reduce cost and improve worker safety. Performance of other neural network architectures will be presented at the conference.

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References

[1] C. Gilmore, M. Asefi, J. Paliwal, and J. LoVetri, "Industrial scale electromagnetic grain bin monitoring", *Computers and Electronics in Agriculture*, **136**, 2017, pp. 210–220, doi: 10.1016/j.compag.2017.03.005.

[2] C. Gilmore, I. Jeffrey, M. Asefi, N.T. Geddert, K.G. Brown, J. LoVetri, "Phaseless Parametric Inversion of System Calibration and Obtaining Prior Information", *IEEE Access*, **7**, 2019, pp. 128735–128745, doi: 10.1109/ACCESS.2019.2939725.

[3] I.T. Rekanos, "Neural-Network-Based Inverse-Scattering Technique for Online Microwave Medical Imaging", *IEEE Transactions on Magnetics*, **38(2)**, March 2002, pp. 1061–1064, doi: 10.1109/20.996272.

[4] Z. Wei, and X. Chen, "Deep-Learning Schemes for Full-Wave Nonlinear Inverse Scattering Problems", *IEEE Transactions on Geoscience and Remote Sensing*, **57(4)**, April 2019, pp. 1849–1860, doi: 10.1109/TGRS.2018.2869221.

[5] Martín Abadi, et al. "TensorFlow: Large-scale machine learning on heterogeneous systems", *White Paper*, 2015. [Online]. Available: tensorflow.org.

[6] A. Zakaria, I. Jeffrey, and J. LoVetri, "Full-vectorial parallel finite-element contrast source inversion method", *Progress In Electromagnetics Research*, **142**, October 2013, pp. 463–483, doi:10.2528/PIER13080706.

[7] A. Kraszewski, and S. O. Nelson, "Composite Model of the Complex Permittivity of Cereal Grain", *J. agric. Engng Res.*, **43**, 1989, pp. 211–219, doi: 10.1016/S0021-8634(89)80019-8