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Published in:
2021 IEEE MTT-S International Wireless Symposium (IWS)

DOI (link to publication from Publisher):
10.1109/IWS52775.2021.9499638

Publication date:
2021

Document Version
Accepted author manuscript, peer reviewed version

Link to publication from Aalborg University

Citation for published version (APA):
https://doi.org/10.1109/IWS52775.2021.9499638
Training of Deep Neural Networks in Electromagnetic Problems: a Case Study of Antenna Array Pattern Synthesis

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Abstract—This paper discusses the training of deep neural networks (DNNs) for electromagnetic problems. The main concerns include how to modify EM problems to take the advantage of the deep learning techniques and how to tailor conventional deep learning concepts with electromagnetic domain knowledge, which has been overlooked by most existing DNN based EM research. A $1 \times 8$ patch antenna array has been adopted as the test vehicle for investigation, with the aim to use deep learning for radiation pattern synthesis. It is analyzed via electromagnetic simulation first to collect sufficient training data sets containing different combinations of excitation signals and corresponding radiation patterns. These data are then pre-processed and passed to DNNs for training to imitate the mapping between excitation signals and radiation patterns. With careful feature selection and DNN architecture optimizations, two DNN models are obtained eventually. One of them aims at forward radiation synthesis in any certain excitation condition, and the other seeks out backward excitation signals needed for a given radiation pattern, and both achieved an accuracy over 80%. This paper may provide enlightenment and reference in applying deep learning to electromagnetic problems in terms of feature selection and architecture modification.

Index Terms—electromagnetic, deep learning, DNN, excitation deduction, radiation synthesis.

I. INTRODUCTION

Deep learning is a proven powerful tool for non-analytic problems, early in image classification, speech recognition and now in electromagnetic problems as well. Previously published works related to deep learning based EM solutions mainly include channel estimation [1]-[2], direction-of-arrival (DoA) estimation [3], nonlinear electromagnetic inverse scattering [4], inverse design of electromagnetic structures [5]-[6], and a few on antenna radiation pattern synthesis [7]-[8].

Theoretically, the radiation pattern of an antenna array in certain excitation condition is dependent on its element radiation patterns, array factors, and coupling factors. Among them, the element radiation pattern can easily be obtained by simulating an antenna element and the expression of array factor for any regular antenna array can be easily determined [9]. However, the coupling factors are still ambiguous and difficult to be clearly described since it is influenced by many uncertain and unquantifiable factors. Thus, conventional antenna array designs rely on electromagnetic simulations to obtain accurate radiation pattern estimation, which can be extremely expensive in computation especially for large arrays.

Deep learning may be able to help mitigate this challenge. In this paper, a deep learning-based synthesis solution for a $1 \times 8$ patch antenna array is developed. As demonstrated in section II, fed by different combinations of excitation signals, the $1 \times 8$ patch antenna array is simulated to generate corresponding radiation patterns. In total, 20000 sets of excitation signals and related radiation patterns are taken as initial data sets. After going through suitable feature selection, these data sets are passed to deliberately designed DNNs for training. It yields a forward radiation synthesis model with excitation signals as inputs and related radiation patterns as outputs, as exhibited in Fig. 1. A backward excitation deduction model shares the same network architecture and parameters but with inputs and outputs shifted. Training of the DNNs, preference on feature modification methods and DNN architectures are discussed in detail in section III. At last, section IV concludes the experiment conducted in this paper.

II. 1 × 8 ANTENNA ARRAY

As exhibited in Fig. 1, A patch array operating at 3.5 GHz side-fed through multi-order microstrip lines is taken as the element to form a $1 \times 8$ patch antenna array with a spacing of $0.5 \lambda$. The array is built in a and simulated via a commercial electromagnetic software (CST) to obtain the radiation patterns taking into account the mutual coupling between the radiation elements. With the amplitude and phase of the input signal for antenna element number 1 fixed at 1 and $0^\circ$, those for other seven elements are randomly chosen within a range from 0 to 2 at a step of 0.5 and a range from $0^\circ$ to $180^\circ$ at a step of $10^\circ$, respectively. 20000 sets of excitation signals and corresponding radiation patterns are collected as the raw data sets, where 70% are used for training and 30% for testing.

III. TRAINING OF DNNs

A. DNN architecture

As shown in Fig. 1, The DNN employed in this paper consists of three dense layers as its hidden layers, with 360, 200, and 100 neurons, respectively. All of the hidden layers utilize ReLU as the activation function, while the output layer uses a linear activation function. To obtain the forward radiation synthesis model, excitation data sets are initially fed as inputs and radiation data sets are set as outputs. Then the data sets for inputs and outputs are exchanged to train for the backward excitation deduction model. The DNN is implemented using TensorFlow with the Keras API in Python 3.6.8.
B. Feature modification

A certain excitation condition are defined by amplitudes and phases of input signals for 7 ports, which can be described as a vector containing 14 values. And as radiation patterns of this type of uniform linear arrays only vary in the plane where the array is aligned, the key features in its corresponding radiation pattern can be characterized by a 1-D curve, and mathematically a vector with 360 values. In short, each data set contains a 14-element vector and a 360-element vector representing a certain excitation state and its corresponding radiation pattern.

As mentioned in section I, array factor partially explains how excitation signals affect radiation patterns and the training of DNNs is to imitate the processing of excitation signals affecting radiation patterns. The part directly concerning excitation effects in array factor can be expressed as Real/Imaginary format, $I_m \cos \phi + j I_m \sin \phi$. This means that it takes efforts for DNNs to learn the excitation transformation from its initial format, amplitude and phase, to $R_e/I_m$ format if the initial format is directly utilized for training. Thus, it makes sense that pre-transforming the excitation data to the format of $I_m \cos \phi$ and $I_m \sin \phi$ before training would significantly release the burden on training of DNNs. As for radiation patterns, the radiation at a certain angle can either be expressed as a linear value or its logarithm. When using linear values, the emphasis is mainly on the main lobe as the linear values within main lobe are relatively high while those out of the main lobe generally approach zero. Comparing to linear values, logarithm format exponentially decreases so that the radiation level in each direction can be clearly visualized. Since radiation synthesis cares much more about accuracy, especially accuracy within main lobe, linearity format would be a better choice. This format emphasizes the effects of main lobe on loss function so that the output DNN model achieves higher performance within the main lobe.

C. Training and testing

Fig. 2 and Fig. 3 compare the loss and accuracy of the trained forward model and backward model, respectively. Here, the loss is defined as the mean square difference between simulated and predicted radiation curves, while the accuracy represents how much these two curves overlap. Both cases of using linear value or its logarithm to describe the radiation strength are shown. It can be seen that training with linear...
values takes much less epoch while being able to achieve even superior performance. It is worth pointing out that the total accuracy considers all the 360 pattern points equally including the low valued side lobe points, which take a major part of the radiation pattern data. Therefore the matching between the prediction and testing within the main lobe is satisfactory even though the total accuracy, 80%, seems not to be very high. Fig. 4 and Fig. 5 exhibit the testing examples of the radiation synthesis model and the excitation deduction model, respectively. The satisfactory match between the testing and prediction indicates that these two models can precisely imitate the mapping between the excitation signals and radiation patterns.

To investigate the influence of the size of data sets on the model performance, two models are trained with different sizes (1000, 5000, 10000, 20000) of data sets and the losses and accuracy are given in Fig. 6 and Fig. 7, respectively. It is reasonable that more data sets are more likely to lead to higher performance DNN models. But this improvement gradually slows down as the data set size keeps increasing.

IV. CONCLUSION

The main purpose of this paper is to investigate feature selection and modification suited in deep learning-based electromagnetic solutions. The case study on a patch antenna array is conducted. With electromagnetic simulation results as data sets, DNNs are trained to learn the mapping of excitation signals yielding radiation patterns and its reversion. During this case study, feature modification methods and DNN architectures are carefully compared, analyzed, and modified to fit electromagnetic problems. As verified by results, deep learning provides an efficient and reliable supplement for electromagnetic solutions. The results also showed clear benefit of applying feature selection (e.g. using linear values instead of values in dB) could significantly improve the training outcome, while sufficient data-set is still the key for ensuring the good training performance. For future work, the models can be extended for larger-scale antenna array, or utilized to assist inverse design of complex antenna array.

REFERENCES