Machine Learning Algorithms for EM Wave Scattering Problems

Anthony James McElwee, *MEng Student, DCU*

***Abstract* – This paper details the construction and evaluation of a deep learning emulator, Prescient2DL, to assist a Method of Moments (MoM) iterative solver, SolverEMF2, in generating solutions to two-dimensional, H-polarization, electromagnetic scattering problems at the 10 MHz range. The acceleration of conventional solvers at this frequency is of particular interest to the medical community where existing methods face computational disadvantage due to the high contrast nature of the scenes. Recent referenced works report successes in the general area of applying machine learning to electromagnetic scattering problems, however, there are conflicting testimonies to the potency of the efforts. This paper outlines a statistical experiment to assess the impact of the hybrid methodology, where Prescient2DL contributes to SolverEMF2. Experimental evidence indicates a considerably lower initial error than that associated with purely conventional solvers. However, negligible impact on more important metrics associated with conventional solvers is also reported. The paper also records a simple test of generalizability for Prescient2DL where results indicate a degradation in model performance. Finally, the coupling of the two predicted electric fields into a second stage model in an effort to reduce initial error fails to yield positive results.**

***Index Terms* – computational electromagnetics, deep learning, VEFIE, Volume Electric Field Integral Equation, Transverse Electric, Contrast-Source Integral Equations, U-net, scientific emulation, forward problem, frequency domain**

I. Introduction

Medical diagnostic tools, such as biological segmentation and classification models, constitute a methodology that can increase the capacity for healthcare practitioners to rapidly and accurately differentiate between benign and malignant biological tissue. Developing such aides requires the generation of large quantities of synthetic data using frequency-domain electromagnetic scattering simulations. The development of such simulations necessitates considerable learning investment [1].

As extolled in [2], significant benefits to patients and medical practitioners could arise through the deployment of Magnetic Induction Tomography (MIT). This requires the acceleration of high-contrast simulation scenarios in the 10 MHz carrier frequency range.

Generally, these simulations operate with a constrained set of input parameters, such as incident source wave configurations and dielectric material attributes of scatterers. Although input parameters are comparable across simulation incidences, conventional methods require full wave simulation and cannot be estimated with very low or high-frequency approximations. Generating large volumes of such simulations is currently uneconomical.

The motivation of this paper is to report on the construction of a electromagnetic scattering solver workflow, SolverEMF2, for a toy problem with low contrast values for an incident wave frequency of 10 MHz SolverEMF2 adapts code from [1] to use the Krylov iterative solver Biconjugate Gradient Stabilized Method (BICGSTAB), to calculate the solution to contrast-source integral equations. This high performance code uses circular convolutions to accelerate multiplication steps via Fast Fourier Transforms. SolverEMF2 is used to create a training data set for developing a deep learning model called Prescient2DL. Prescient2DL can feed back into SolverEMF2 to assist in the provision of solutions to the scattering simulations. Experiments to establish the impact of infusing Prescient2DL into SolverEMF2 are provided with commentary.

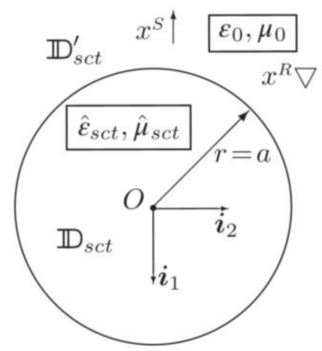

Fig. 1 Problem Diagram.

A. Problem Specification

The paper reports on the forward H-polarization problem, otherwise known as the Transverse Electric (TE) problem, solving for the electric field strength in a domain with two contrast scatterers, one inside the other, receiving a dipole incident wave with E_x, E_y and ZH_z components[1]. [CHECK: The full derivation and explanation of the problem is given in section 3.2.1 of [1]. Populate the formulae here and then discuss algorithms in the next section]. The problem requires finding two electric fields and as a result is a full vector problem. As the task motivation is based around future medical developments, and the permeability of biological tissues can be considered roughly equal that of the background vacuum embedding of the domain, no permeability contrast is assumed [2]. The permittivity contrasts also assume only a real component with zero conductivity and are frequency independent. This is a permittivity contrast only problem. The diagram, adapted from [1], illustrates the canonical version of the problem. A radially orientated electric dipole emitting incident waves is located at a fixed x-axis location in the negative direction above the larger cylindrical scatterer. Receivers form a ring around the main scatterer lying between the source and the scatterer boundary. Within the main scatterer lies a second scatter, not pictured, with contrast different to both the background embedding and main scatterer. [CHECK: NEED TO INCLUDE FORMULAE]

II. Existing work in the domain of electromagnetic scattering and machine learning

This is a survey of the state of the art. It should be more than a list of citations of prior work. Give this section a title relevant to your project ("Existing techniques for

Date of submission: 2023/08/21. e-mail: anthony.mcelwee2@mail.dcu.ie
Note: The author of this paper will be referred to as "the student" to avoid confusion.

[1] This is a more advanced problem than the E-polarisation problem described in the Literature Review appendix.

chronological displacement”). Organize prior work in groups and evaluate them. What are their common features, strengths and weaknesses? This section should be persuading the reader that there is a gaping hole in the research literature, and hint that the technique you are about to describe will fill that hole. The prior art on which you base this section will have already been discussed by you in your Literature Survey. However, you should have greater insight into prior research now, having completed your own project. Do not simply cut and paste text from your literature survey into this section rewrite it so that it is concise enough to meet the length requirements of a research paper and to reflect your improved understanding of your research topic.

End of page 1

- Look at [2] section A.
- Look at the project log!
- DO THIS WHEN OTHER SECTIONS ARE COMPLETE TO MANAGE SPACE. IF YOU NEED TO BULK OUT THEN DO SO, OTHERWISE NOTE THAT THE PROJECT LOG IN THE APPENDCICES CONTAINS MORE COMMENTRAY AND THE LITERATURE REVIEW REMAINS RELEVANT.

III. Technical Description

This section details the key aspects in the overall workflow required to test experimental hypothesis surround the hybrid-methodology as outlined in the abstract and introduction.

B. Conventional Solver Creation

As noted in the introduction, generating solutions to forward electromagnetic scattering problems is a vast, time-intensive task. MATLAB code, provided in conjuction with [1], was translated by the student to Python and then adapted to generate solutions in a bid to accelerate the experimental development. The source of the original code eminates from an extremely experienced researcher that is cited recurrently in other references consulted during the investigation of the paper[2]. Some key elements of the code are now described below[3].

1) Problem Formula Description

The problem is formulated in the s-domain (Laplace convention).

2) Green's Function

There are points where the Green's Function is singular.

3) Core Solver

BICGSTAB and why that algorithm was choosen

4) FFT Acceleration Technique

Power of 2 requirement, circulant matrices forming the convolutions can be computed using FFT more efficiently.

5) Bessel-Approach Validation

- *images of the validation in the appendices*

<u>End of page 2 (1 pages)</u>

[2] The final adapted code is attached as an appendix. Considerable effort has been made to maintain the original structure of the code as a source of truth so that it can be used more widely in future research efforts, as well as be tied back to the reference text for documentation. Significant gains have been made in the last decade in machine learning due to the open and transparent nature of shared code. The aspiration is that this adaptation can add to this development in the electromagetic scattering domain.

[3] The code is fully documented over the breadth of more than one hundred pages in [1] and is the culmination of over 50 articles.

C. Dataset Generation Description

The input parameters for all simulations were the same except for the geometry. A grid dimension of 128x128 was choosen in order to comply with the FFT requirement that the grid be an integer power of 2, and the typical computer vision approach of using grids divisible by 32. The carrier frequency was set at 10 MHz and the highest permitivity contrast was 1.75 for the smaller scatter resulting in the smallest wavelength of 22.7m. The grid delta was 2m giving rise to a sample per cell of roughly 11. Although the material contrast parameters in the medical domain are much more extreme, in order to initiate research in the general area a much lower contrast value was choosen to allow for a large volume of samples to be generated in a shorter time frame. Training a model where the grid dimension is greater than 128 is also computationally difficult for this domain as memory issues arise as the number of layers in the deep learning architecture increases. The source is located 170m in the negative x direction. The main scatterer in the scene has a relative permativiy of 1.25.

The final generation of the scatterer geometry was kept minimial and close to the canonical formulation in order to reduce generation time. A variation on the same generator was used to validate against the Bessel-Approach, generate the model training data and generate the generalisability experimental data. In the latter cases, all cells outside the major scatterer area were replaced with the zero contrast value, as illustrated in the CHECK: Figure.

- Put in geometry generation algorithms: base scatter; internal scatterers with base centered at origin; validation scatterers shifted around domain.

All iterative solver computations were carried out on a local laptop CPU i7-11800H @ 2.3 GHz using Python, in particular NumPy and SciPy libraries.

The generated data was saved in NumPy format on an external hard drive due to the excessive size of the samples. The outputs saved for each base sample, aside form the scatter geometry array, were as follows with each field splitting the real, imaginary and absolute components of the complex field by channel: the incident E field in the x and y direction; the ZH field in the z direction; the two scattered electric fields in the x and y directions.

In addition, two extra files were saved seperately to document the properties of the generated sample: a PNG file illustrating the contained scatter geometry; a separate NumPy file documenting the iterative solver run information documented in the experimental results section later in the paper.

- Illustrate with diagram similar to figure 2 in [3] that covers the incident & geometry inputs and the model architecture and the output predicted fields.
- Illustrate the training model dataset similar to figure 5 in [3] to show static nature of main scatterer.

D. Model Development Description

- for the iterative wrapping, the predicted scattered field needs to be transformed back into the contrast source formulation though the use of the FFT accelerated operator equation.

All deep learning computations were carried out on a local laptop GeForce RTX 3070 GPU using Tensorflow and Keras Python libraries.

- Model architecture: final model architecture; alternative model architecture with worse performance.
- Train/Test split approach, point out the lack of independence between test and training since the combination/permutation count. As you are building an emulator, this is perhaps intended.
- How is model saved and loaded
- Detail the reasoning behind activation function choice and architecture (use references)
- Standardization approach
- Loss function as an equation

E. Hybrid-Methodology Infusion

- Put in an algorithmic flow chart like in [4] figure 1
-

<u>End of page 3 (1 pages)</u>

IV. Results Obtained

Document your results here. Use tables and scatter plots, histograms, etc. to present numerical results. Make sure that the scenario used to obtain each set of results is described unambiguously. There should be sufficient information in this section and the previous one for the interested reader to replicate your results. Put some thought into how you visualize your results. If you generated lots of data, should it be presented in a 3D plot? On multiple 2D plots? What scales should use use? Log? Linear? If you use colour in your plots, will the traces still be distinguishable if printed in monochrome? Describe how you know your results are valid. What testing strategies were used? Were enough results obtained? Does your algorithm perform correctly? Does your code implement your algorithm accurately? Does your input data set contain features of the kind the algorithm is supposed to extract?

End of page 4 (1 page)

LOOK AT THE HYPOTHESIS IN THE PROJECT PLAN PROPOSAL

G. Dataset Generation Statistics

- Put in descriptive statistics around the time to generate the naïve guess and the model informed guess data samples.

H. Model Development Results

- Put in loss curves

I. Experimental Results

- T-tests for the three metrics from the project plan proposal. There needs to be results for the two architectures tested (final architecture and alternative with max pooling) and there needs to be results for the moved geometry validation set too.

V. Analysis

Interpret your results here. You've obtained lots of data. What have you learned from it? Does accepting transit traffic overload the router? What do the peaks in the spectral response indicate? Why are there no fluctuations in the EEG data? This section should be ONE PAGE in length. The division of the body of the report into three sections (here named "Technical Description", "Results Obtained" and "Analysis") may be inappropriate for some projects. If you wish to change this structure, you may do so only in consultation with your supervisor and only with his/her written agreement to the revised structure any such revised paper format must have an aggregate length of four pages for the sections equivalent to the above four.

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- Is this not a waste of energy and time…

VI. Conclusions

This is the conclusion. *Here you summarize what has been achieved and learned, and the implications for future research and suggestions for future work that could follow on from your work. This section resembles the introduction in some ways, but remember that by now the reader has read the body of the paper. The introduction was your attempt to encourage them to do so. You can present insights in the conclusions.*

References

[1] P. M. van den Berg, *Forward and inverse scattering algorithms based on contrast source integral equations*. Hoboken, NJ: Wiley, 2020. [Online]. Available: https://onlinelibrary.wiley.com/doi/book/10.1002/9781119741602

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