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Current-to-Field Prediction for Non-Linear Magnetic Systems via Neural Networks

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Abstract

Accurate magnetic field knowledge is crucial for magnetic particle imaging, affecting performance estimation, sequence generation, and reconstruction. Especially for non-linear field generators, such as those with built-in soft iron, conventional field simulations, such as the finite element method, are computationally demanding. We propose the use of neural networks to predict the coefficients of the spherical harmonic expansions of the fields from the input currents, drastically speeding up current-to-field prediction.

I. Introduction

Magnetic fields are a crucial component of any magnetic particle imaging (MPI) system. Precise knowledge of the fields is inherently important for the entire imaging process. While the Biot-Savart law efficiently determines the fields for air-core coils, it is not sufficient for field generators with non-linear properties, such as those with built-in soft iron. Typically, time-consuming finite element methods are used, where the calculation of the magnetic field from the coil currents, which is the *forward problem*, can take several minutes. However, the operation of an MPI system requires the determination of the currents needed to generate a given field. This *inverse problem* is a computationally complex optimization problem that can consequently take several hours [1].

In this work, we leverage neural networks to accelerate the forward problem for a field generator consisting of iron core coil arrays [2]. Unlike other works [3], the network predicts coefficients of the field's spherical harmonic (SH) expansion such that the field inherently satisfies the underlying Laplace equation component by component [4] rather than an interpolative model based on a grid of field measurements. Using this approach, a discrete set of values output from the network represent a continuous field progression. As a next step, this network could then be used as a differentiable surrogate to efficiently solve the inverse problem.

II. Methods and materials

The field generator comprises a total of 18 coils with soft iron cores. These are organized into two arrays of 9 coils each, arranged in a 3×3 configuration, facing each other [5]. In order to reduce the amount of training data required, we limit ourselves here to the field generation of four coils (see highlighted ones in Figure 1). A total of 9000 data samples were generated by computing fields with random input current combinations using the FEM software COMSOL[1] with a non-overlapping train/validation/test (7200/900/900) split.

[1] COMSOL Multiphysics v.6.0. www.comsol.com. COMSOL AB, Stockholm, Sweden, COMSOL Multiphysics

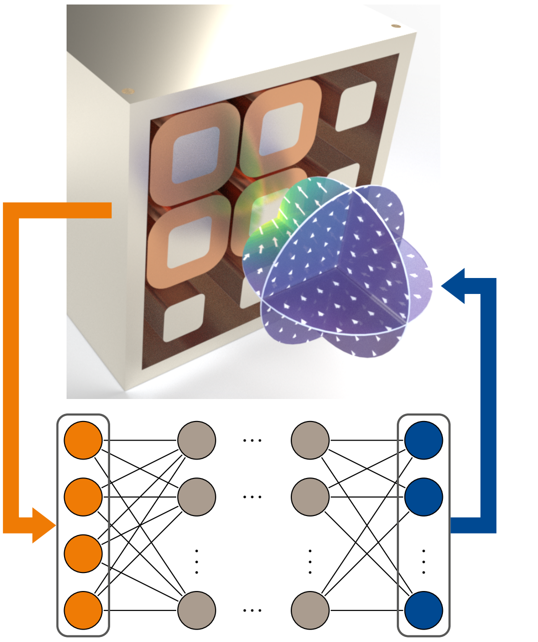

Figure 1: Visualization of the experimental setup and the proposed field estimation method. The upper part of the figure shows one 3×3 coil array of the field generator. For visualization purposes, only the four coils used for the field simulation are shown. A sphere in front of the coils indicates the volume in which the field was analyzed. The lower part shows the network that uses the four coil currents to predict the series expansion coefficients and thus determine the field in the sphere.

A spherical t-design, $t = 12$, is utilized to efficiently calculate the SH coefficients [4]. To this end, the magnetic field is simulated at 86 points on a sphere with 45 mm radius. The resulting 49 coefficients for each component of the field allow for a representation of the magnetic fields inside the sphere as a SH expansion with polynomial degree 6. In our implementation, we used a feed forward neural network with 10 hidden layers and 1024 nodes each to predict the coefficients. Each hidden layer was followed by the LeakyReLU activation function with a negative slope of 0.2. Using the mean squared error (MSE) loss function, the network was then trained for 250 epochs until the validation loss stagnated. The ADAM optimizer was used with default parameters and a learning rate of 0.001. Furthermore, whenever the loss plateaued with respect to the validation set, i.e., the loss did not decrease for 10 epochs, the learning rate was halved. Lastly, the input currents were normalized to the interval $[-1, 1]$ and for each parameter of the SH coefficients Z-score normalization was performed where mean and standard deviation were computed on the training set. The training was performed on an NVIDIA GTX 1080 Ti and took around 8 min.

To evaluate the networks predictive capabilities, we considered the relative mean absolute error over all coefficients. The error was not calculated relative to each coefficient but with respect to the coefficient with the largest magnitude for each degree of the corresponding SH basis functions, since the field is mainly characterized by them. Otherwise values near zero would dominate.

III. Results and discussion

Across the entire test set, the model was able to predict the SH coefficients with a mean relative error of 0.3 %, allowing for accurate field prediction. The fields fulfill the Laplace equation component by component, but a divergence-free field is not guaranteed and only stems from the nature of the training data.

IV. Conclusion

The proposed method effectively captures the nonlinear magnetization behavior of the system. For a given current vector, the trained model closely approximates the magnetic field, and its differentiability allows the inverse problem to be solved via gradient descent [6]. Future extensions could include all 18 coil currents and enforce physical constraints, such as a divergence-free field, making it an important tool for efficient MPI sequencing and simply applicable to other field generators.

Author's statement

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