AI for Plasma Diagnostics in Laboratory Astrophysics: Reconstructing Invisible Fields from Proton Images

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1. Introduction

Artificial intelligence is becoming a powerful tool in high-energy density physics [1]. In laboratory astrophysics, we use intense lasers to create extreme plasma conditions, such as shock waves and magnetic field generation [2, 3]. These experiments mimic cosmic phenomena, but understanding them requires measuring the transient electromagnetic fields inside the plasma. Proton radiography, also known as proton imaging, is a key diagnostic method for this purpose because it is very sensitive to these fields [4].

However, obtaining quantitative data from these images is a major challenge. Reconstructing 3D electric and magnetic fields from 2D proton images is a difficult "inverse problem." Because the image only captures the total deflection of protons along their path, different field structures can produce very similar image patterns [5]. To address this challenge, we propose a data-driven approach: AI for ion imaging [6, 7, 8]. By using neural networks to learn the relationship between the observed proton patterns and the hidden fields, we can infer electromagnetic structures that are difficult to recover with standard techniques [4].

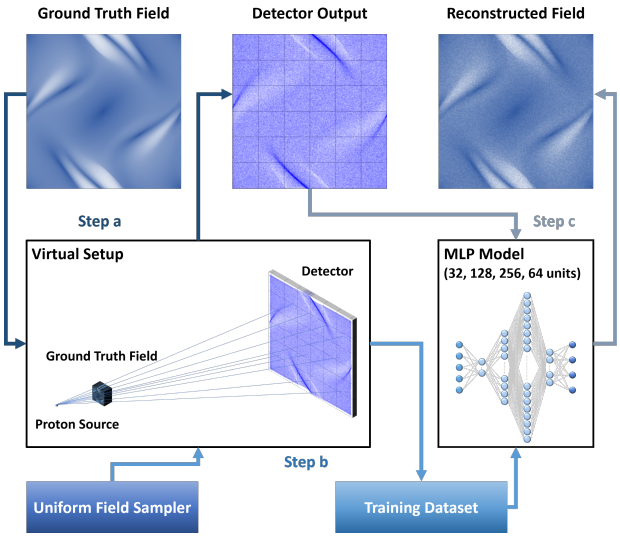

Fig. 1: Flowchart of the neural network-based magnetic field reconstruction process. The workflow consists of three stages: (a) synthetic data generation, (b) network training, and (c) field reconstruction.

2. Approach

Workflow and Architecture. Figure 1 illustrates our neural network-based reconstruction pipeline. We frame the physical reconstruction as a supervised learning task designed to solve the inverse particle-motion problem. The workflow proceeds in three stages: (1) data generation, where synthetic proton radiographs are produced by simulating particle trajectories through "ground truth" magnetic fields derived from numerical simulations; (2) network training, which utilizes a uniform field sampler to construct a dataset for learning fundamental particle-field interactions; and (3) inference, where the synthetic radiographs are input into the trained network to reconstruct the spatial magnetic field distributions.

Synthetic Environment Setup. We implemented a virtual experimental setup that mimics standard laboratory ion radiography. A point source emits protons that traverse a target magnetic field located 8 mm away. The field occupies a volume of 0.512 mm × 0.512 mm × 0.256 mm. After deflection, the protons are recorded by a detector placed 40 mm downstream. For validation, we utilized magnetic field snapshots from the Orszag-Tang (OT) vortex evolution [9]. This system provides complex, turbulent magnetic topologies, serving as a rigorous "ground truth" test for our reconstruction capability.

Localized Training Strategy. A key innovation in our approach is the training methodology. Instead of training on full, complex images (which requires massive datasets), we train the network on the fundamental unit of interaction: a single particle traversing a uniform local field. In each training sample, we inject a single particle into a randomized uniform magnetic field. The network receives the particle's final position and velocity at the detector as input and learns to predict the field strength and the particle's entry position. During inference, we apply this trained "local solver" to the millions of particles in a full radiograph. By aggregating these local inferences, the network reconstructs the global field distribution

piece by piece, effectively recovering the complex OT vortex structure from simple training priors.

Network Architecture and Training. We employ a Multi-Layer Perceptron (MLP) with four fully connected layers (32, 128, 256, 64 neurons) to predict magnetic field components and particle entry positions. The model minimizes a composite loss function defined as the sum of Mean Squared Errors (MSE) for both the field vector and the entry position. Training utilizes 50,000 samples (10% validation) generated with random uniform fields $B_{x,y} \in [-10, 10]$ T. We train for 2000 epochs using a batch size of 25 and a learning rate of 0.001.

Domain Randomization and Robustness. To ensure the model generalizes to realistic experimental conditions, we incorporate domain randomization into the training data. Since standard laboratory proton sources are not monoenergetic, we initially sample protons from a velocity distribution with a mean kinetic energy of $E_0 = 10$ MeV and an energy spread δ of 20%. We further augment the data by varying the spectral widths, enabling the model to remain robust against broadband spectral effects.

3. Evaluation

Reconstruction Accuracy. We evaluated the model using snapshots of the Orszag-Tang vortex evolution at simulation times $T = 2$ and $T = 3$. The left panels of Figure 2 display the ground-truth magnetic field profiles. The middle panels show the corresponding synthetic proton radiographs, generated using a proton source with mean kinetic energy $E_0 = 10$ MeV and an energy spread of 20%. When these radiographs are input into the trained network, the reconstructed field profiles (right panels) demonstrate high fidelity. Quantitatively, the model demonstrates high fidelity across the entire spatial domain, achieving a correlation coefficient $r > 0.989$ and a normalized root-mean-square error (NRMSE) < 0.055 for both cases. These metrics indicate that the model successfully captures complex field topologies.

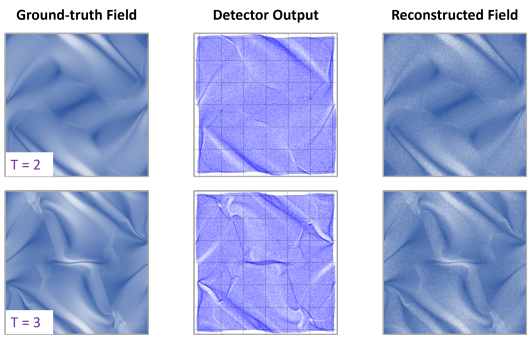

Fig. 2: Comparison of magnetic field reconstruction during the Orszag-Tang (OT) vortex evolution. Top panels correspond to simulation time $T = 2$, and bottom panels to $T = 3$. Columns from left to right show: the ground-truth magnetic field profile, the synthetic proton radiograph (detector output), and the neural network-reconstructed field profile.

Robustness to Source Variation. Real-world experiments are subject to uncontrollable factors, such as broadband spectra and shot-to-shot energy jitter. To assess robustness, we tested the network (which was trained on the fixed 10 MeV, 20% spread distribution) against data generated with varying energy spreads. Table 1 summarizes the results. Even when the test parameters deviate from the training distribution, the model maintains high prediction accuracy. This stability suggests that our method is well-suited for experimental conditions where source characteristics fluctuate.

Table 1: Evaluation of model robustness against source variations. The parameter δ represents the energy spread used to generate test radiographs. The metrics r and NRMSE indicate the reconstruction quality for the specific magnetic field component (B_n) when processed by the fixed-parameter neural network.

δ (%)	B_n	r	$NRMSE$
0	B_x	0.989	0.028
	B_y	0.992	0.051
10	B_x	0.988	0.079
	B_y	0.984	0.082
20	B_x	0.989	0.030
	B_y	0.991	0.055
30	B_x	0.783	0.139
	B_y	0.802	0.173

4. Conclusion

In this work, we demonstrate that neural networks can successfully reconstruct two-dimensional magnetic field profiles from proton radiography data. We designed a numerical experiment where simulated magnetic fields generate proton patterns through particle trajectory calculations. By training a neural network on this data, we approximate the inverse relationship between the proton motion and the fields. This allows us to infer the magnetic field strength at each grid point. With sufficient data sampling, the network combines these points to reveal the complete, high-resolution field profile.

Additionally, we address a key limitation in previous research. While many studies assume a monoenergetic proton source [4], this is often not true in real experiments. We demonstrate that our approach remains accurate even with realistic source effects, such as broadband proton energy spectra and shot-to-shot energy jitter. This improved robustness suggests that neural network-based field reconstruction is a feasible and practical tool for experimental diagnostics.

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