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Three-dimensional Radiation Reconstruction Based on X-ray Imaging via Convolutional Neural Network

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This study presents a novel approach for high-precision three-dimensional (3D) hot-spot X-ray radiation reconstruction in double-cone ignition (DCI) experiments by developing a convolutional neural network (CNN)-based algorithm. The proposed methodology integrates physics-driven simulations with deep learning techniques to address the inherent limitations of conventional function-fitting methods, offering significant improvements in the comprehensive analysis of laser-plasma asymmetry.

The research utilizes a virtual dataset generated from two typical hot-spot geometries (ellipsoid and toroid) with temperature distributions based on the Bremsstrahlung radiation formula. The radiation coefficients, derived from a robust physical model, are projected onto 2D planes from four different angles (front, side, top, and oblique views) to emulate experimental observation conditions. To enhance realism, noise effects such as Poisson noise and Gaussian blur are added to the synthetic data, creating a precise input-output mapping framework for CNN training.

The network architecture is designed as an encoder-decoder structure, processing a four-channel input of 100 $\times$100 pixel images. The encoder utilizes convolutional layers to extract multi-view features, while the decoder reconstructs these features into a 3D grid of radiation coefficients. The training process employs the Adam optimizer with a mean squared error loss function (target error $\leq$1%) and is conducted over approximately 100 epochs. Preliminary results demonstrate the model's ability to reconstruct 3D radiation coefficients and infer hot-spot density and temperature distributions, showcasing its potential for high-precision diagnostics.

The innovation of this work lies in the deep integration of physical simulations and deep learning, offering a high-precision, high-efficiency 3D reconstruction framework tailored for inertial confinement fusion diagnostics. Although the full implementation of high-precision reconstruction from multi-view 2D X-ray images to 3D radiation coefficients is still in progress, the current framework demonstrates promising capabilities. This approach is a robust and versatile solution that not only advances scientific understanding but also holds substantial practical value, paving the way for more accurate and reliable diagnostic capabilities in fusion research.

References

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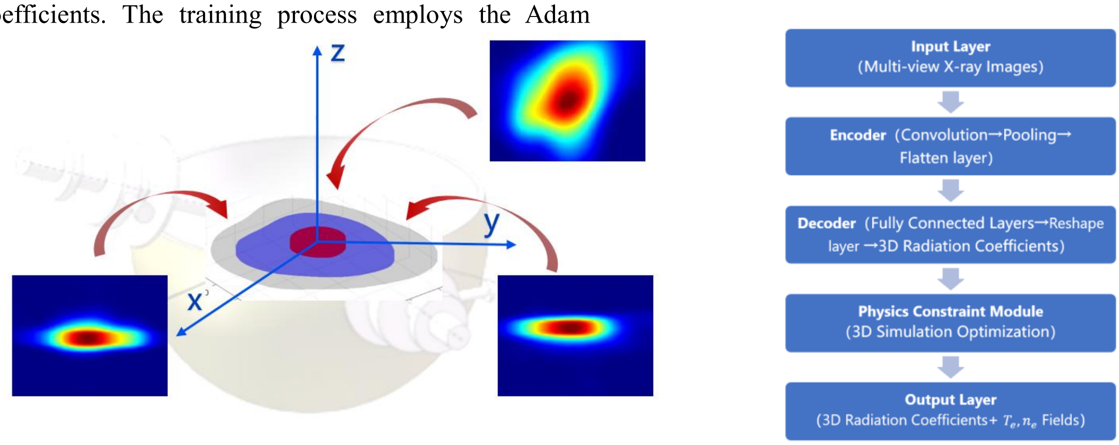

Figure 1. The left image is a schematic of three-dimensional radiation reconstruction. The 3D radiation image in the middle is reconstructed from the x-ray images obtained from diagnostic instruments from different observation angles. The right one is the algorithm flow chart of 3D reconstruction. The decoding layer uses a two-layer fully connected convolutional neural network.