Neural Estimation of Plasma Distributions from Imaging through Synthetic Data

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Introduction

Nuclear fusion is an alternative green energy source for future energy production with tokamaks being one of the most promising methods for generating energy from fusion. One of the key components in determining the energy produced by a tokamak is the fuelling of the reaction, specifically the transport of neutral deuterium throughout the vessel and its ionisation. As the spatial distribution of neutral deuterium depends on the ion formation through density and temperature, determining the spatial distribution of neutrals is difficult. Existing work for estimating the spatial distribution of neutrals in the Mega Ampere Spherical Tokamak (MAST) use optimisation and simulation [7, 4]. While effective, expert knowledge is required to determine convergence and validity.

We propose a neural network for estimating the spatial distribution of neutrals density, electron density and temperature in the MAST by leveraging the information in Dα-imaging and Thomson Scattering (TS) measurements. To train our model, we use a synthetic dataset of imaging/TS and plasma distribution pairs, generated from a synthetic data model that parameterises both the shape and the composition of the plasma using intuitive parameters. We demonstrate our model on a synthetic dataset of images and a synthetic image derived from the SOLPS simulation of [4]. Our choice of synthetic data is motivated by the lack of a dataset of high-quality pairs of ground truth camera image and Thomson Scattering measurements, and spatial distributions of neutral Deuterium, electrons and electron temperature. Our synthetic data model is orders of magnitude faster than simulation methods such as SOLPS [10, 2] and enables us to generate datasets on the order of 10^5 samples in less than 36 hours using 64 A100-SXM-80GB GPUs where each plasma distribution takes 1 seconds to generate and each camera image takes 1 minute to render. In addition to fast data generation, our neural model is able to estimate shape and composition of the plasma at a rate of 15Hz.

Method

Our network uses Dα images and Thomson Scattering measurements as input, and predicts the parameters of our synthetic data model as output, and is composed of three major components: An image encoder, a measurement encoder and a parameter decoder. The image encoder is a convolutional encoder network composed of 8 UNet Encoder blocks that downsamples the input Dα image into a latent vector of 2048 components, the measurement encoder is a feed-forward network that encodes the 130 TS measurements along with 64 positional encodings of the R and Z coordinates of each measurement into the latent space as the image encoder, and the parameter decoder converts the latent vector into the parameters of our synthetic data model ensuring spatial consistency.

Our training can be split into three major components: synthetic generation of plasma shape and composition, synthetic camera image rendering, and training of a neural network with a suitable architecture for multi-modal

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[1]See author list of [6]

Name	Symbol	Name	Symbol	Name	Symbol
Minor Radius	$a_{\min}$	Ellipticity	κ	Geometric Axis	(R_0, Z_0)
Magnetic Axis	(R_ψ, Z_ψ)	Upper/Lower Triangularity	$(\delta_{\mathrm{upper}}, \delta_{\mathrm{lower}})$	Rectangularity	$(\xi_{\mathrm{upper}}, \xi_{\mathrm{lower}})$

Tab. 1 The parameters of our analytic LCFS where the parameters with upper/lower separation are interpolated along the magnetic z-axis.

inference. As a full detailed description of the parameterization is outside the scope of this paper, we limit our discussion to the efficacy of the parameterization.

Generating Synthetic Data

As the ions and electrons are strongly coupled to the magnetic potential while the neutrals are weakly coupled by the ionisation, recombination and charge-exchange interactions with the plasma, the composition is determined by the magnetic field topology. Building on this assumption, our synthetic data model consists of two stages, first generating the shape and then generating the composition. Using a heuristic analytic model that considers the geometric features at each spatial location, specifically distance from the Last Closed Flux Surface (LCFS), the plasma legs, the second separatrix passing through the off-LCFS X-Point (if it exists), and the magnetic axis, we generate a ψ_n-map. We parameterise the LCFS using the parameters shown in Table 1 and

$$r(\theta) = R_0 + a_{\min} \cos\left(\theta + \delta \sin\theta - \xi \sin 2\theta\right) \tag{1}$$

$$z(\theta) = Z_0 + (\kappa + \zeta \sin\theta) a_{\min} \sin\theta. \tag{2}$$

The coordinates of the strike points and the strike angles are given as additional parameters, and, taking the X-Point coordinates as the apex/trough of the LCFS, we can determine cubic splines for the plasma legs. Our synthetic ψ_n-map is most accurate around the LCFS and less accurate further out due to only considering the parameterised shape of the plasma and not the magnetic coils. This inaccuracy does not impact our neural network as the emission is predominantly generated by the interaction of the hot plasma with the cooler neutrals in and around the LCFS.

We consider the plasma composition as functions of ψ_n which transition across the $\psi = \psi_{bnd}$ boundary as a tanh function, modelling the inside as a cubic function of ψ_n and a linear function outside. The neutrals are modelled with a simplified representation where both the core and the outside are linear functions of the ψ_n, and the densities are interpolated across four regions: the private region, the divertor region, the Low-Field Side Scrape-Off Layer and the High-Field Side Scrape-Off Layer.

We sample parameters using experimental EFIT for the shape parameters, and TS measurements for the electron density and temperature parameters which are fit to 288 shots from 29000 to 30417 excluding shots where the RBB camera is not mounted on the HM10 port. We train a Mixture Density Network (MDN) [1] on the simulation case of [4] to learn the statistical distribution of the ionisation as a function of the ψ_n and the vertical distance from the magnetic axis. The MDN model allows us to sample neutrals parameters for our synthetic model. We compute the emission using the Photon Emissivity Coefficients [9] and generate synthetic Dα-band images with the rendering algorithm of [7] in Mitsuba 3 [5] and the MAST wall geometry model.
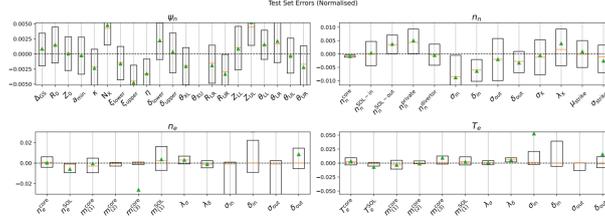
Fig. 1 Whisker plot showing the error distribution on the normalised parameters of our synthetic data model. Top-left is the shape parameters, top-right is the neutrals density parameters, bottom-right is the electron density parameters and bottom-left is the electron temperature parameters.
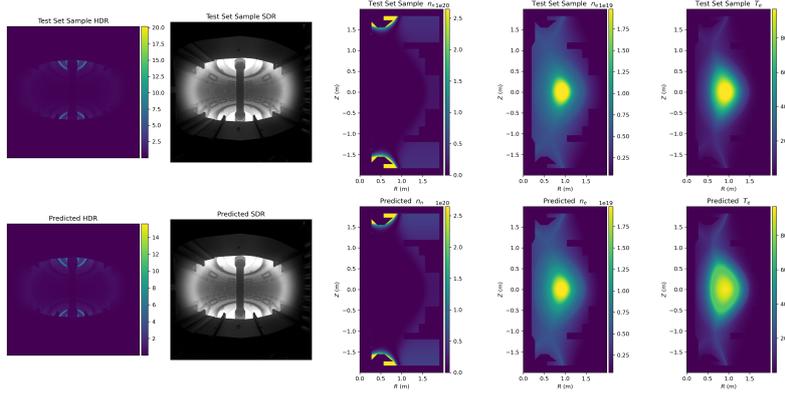
Fig. 2 Model predictions on sample from test set showing that the model is able to accurately capture the spatial distributions of neutrals, electrons and electron temperature from synthetic TS measurements and camera images.

Dataset and Training Hyperparameters

Our dataset of 131072 samples is split into train (75%), validation (12.5%), and test (12.5%) sets which we use to train, choose and evaluate our model respectively. The model is trained for 1000 epochs with an effective batch size of 2048 using a OneCycle learning rate schedule [8], the NAdam [3] optimizer and a Mean Absolute Error loss on the normalised parameters of our synthetic data model.

Results and Conclusion

Our model performs well on the test set achieving the normalised error distributions shown in Figure 1 with a ≤ 0.01 accuracy on most normalised shape parameters and ≤ 0.05 accuracy on most of the normalised spatial distribution parameters. We show an example prediction on the test set of our model in Figure 2 and we further test our model on a rendering of the SOLPS simulation data from [4], shown in Figure 3. We observe that the neutrals prediction is qualitatively accurate, but the electron density and temperature predictions are not correctly captured which shows that the MDN sampling is learned by the model although further work is required to improve the electron density/temperature predictions. As the SOLPS case is an idealised representation of experimental data where effects such as photometric camera calibrations are not considered, we conclude that the domain gap between synthetic and real data requires further consideration.
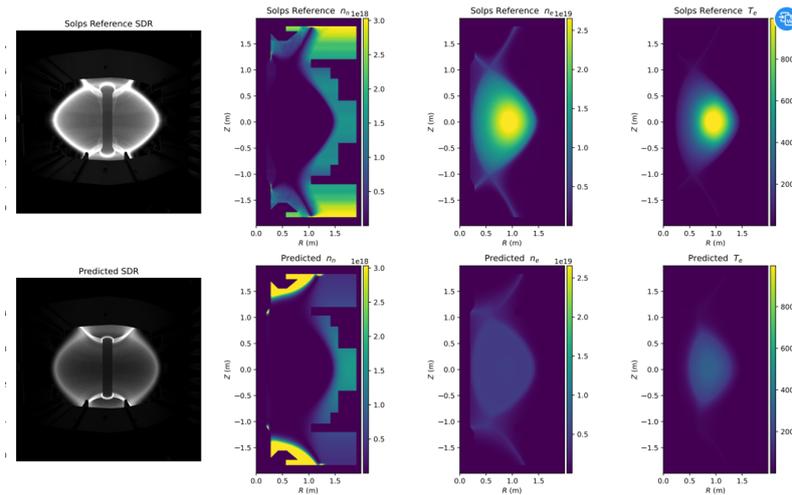
Fig. 3 Our model tested on the rendering of the SOLPS simulation data from [4]. The top row shows (in order) the SOLPS reference images, neutrals, electron density and electron temperature, and the bottom row our model predictions. The neutrals density is well estimated around the LCFS and in the core, but overestimated in the private region. Both the electron density and temperature are underestimated in the core.

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