Machine Learning techniques for diagnostics design and real-time data analysis

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1. Introduction

The fast and reliable reconstruction of plasma X-ray and neutron emissivity is crucial in nuclear fusion devices for real-time monitoring of essential parameters, such as electron temperature, impurity concentration and ion fuel ratio. The ongoing research aims to develop, validate and implement machine learning methods - in particular evolutionary algorithms (e.g. genetic algorithms, GA) and artificial neural networks (NNs) – for this purpose. This contribution highlights the following recent efforts and results: (i) Combining a GA with a customized Monte-Carlo (MC) code to optimize the design and performance of diagnostic systems for tokamak plasmas, (ii) Applying convolutional NNs to solve the inverse problem for X-ray tomographic reconstruction of the tokamak plasma emissivity field, which is essential to monitor impurity asymmetries, (iii) Employing fully-connected NNs to automate reconstruction of tungsten impurity concentration in the WEST plasma core, using a large experimental training database from multiple diagnostics.

2. Diagnostic Design Optimization with Genetic Algorithm (GA)

Work is ongoing [1] to combine a GA with a customized Monte-Carlo (MC) code to optimize the design and performance of diagnostic systems for tokamak plasmas. The current case study focuses on a thin-foil proton-recoil system for neutron spectroscopy, involving intensive computations in a GA-MC framework and its validation with the Geant4 toolkit [2]. It is demonstrated that the GA-MC approach is well-adapted to such multi-dimensional optimization problem and that it can quantify the trade-off between geometrical parameters (e.g. converter thickness, detector dimensions, etc.) to optimize both the detection efficiency and energy resolution of the system. In this study, the following fitness function F_{opt} to be minimized was defined as:

$$F_{opt} = \left(\frac{1}{\varepsilon} + \frac{\Delta E}{E} C\right)\left(1 + H(r - r_0)\right), \tag{1}$$

where ε is the detection efficiency [p/sn], $\Delta E/E$ – energy resolution (FWHM) [%], r – event rejection rate [%], C – resolution-efficiency trade-off parameter, r_0 – arbitrary chosen rejection rate threshold (5% has been used here) and H – Heaviside step function.

Ablation studies were performed to check the performance of the GA-MC framework in simple cases when only one design parameter is varied and all other parameters are kept fixed, see Figure 1. More details about the method and obtained results when several design parameters are optimized simultaneously can be found in [1].

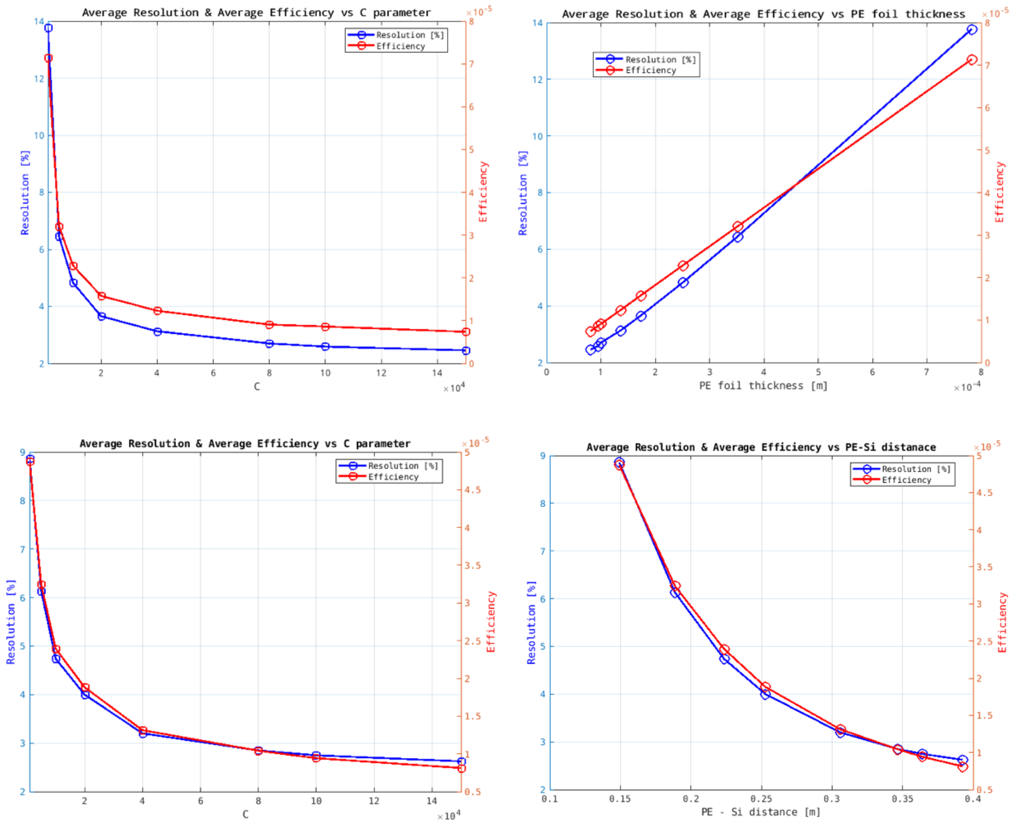

Figure 1. *GA-MC ablation studies with PE foil thickness (top) and PE-Si distance (bottom) optimization.*

3. X-ray tomography with neural networks (NN)

Convolutional NNs can be applied to solve the inverse problem for the tomographic reconstruction of the tokamak plasma X-ray emissivity, which is essential to monitor impurity asymmetries [3]. Since convolutional layers are adapted to techniques involving image processing [4], such architecture has been implemented for the Soft X-ray (SXR) WEST tomographic system and compared with existing methods involving Tikhonov regularization and fully-connected NN [5]. Very promising results were obtained, in particular lower reconstruction error and higher spatial resolution than for fully-connected NN with a computing time still several orders of magnitude lower than Tikhonov regularization.

Preliminary results show significant improvement of image structural similarity (SSIM) vs previous methods without additional computation cost vs. FC-NN, see Table 1 and Figure 2.

Table 1. *Comparison of tomography methods performances*

Method	Tikhonov (MFI)	Fully-connected NN	Convolutional NN
SSIM	0.9 – 0.95	0.9 – 0.95	≳ 0.99
Computing time	0.1 – 1.0 s	0.1 – 1.0 ms	0.1 – 1.0 ms

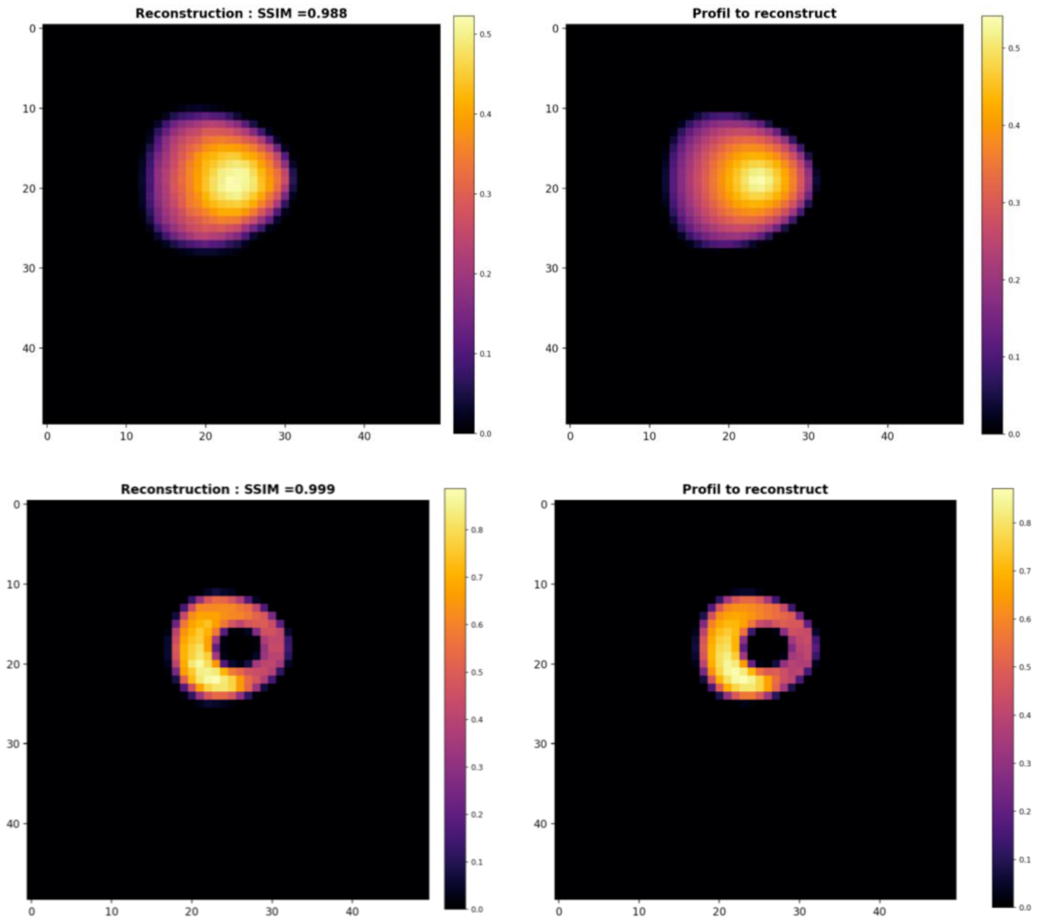

Figure 2. *Examples of CNN tomography from synthetic emissivity phantoms.*
Left – reconstructed image, Right – synthetic model.

4. Direct tungsten concentration NN reconstruction from SXR and other diagnostics

Fully-connected NNs have been employed to automate reconstruction of tungsten impurity concentration and distribution in the WEST plasma core (crucial information to control the radiated power), using a large experimental training database from multiple diagnostics [6]. Parametrization of the W profile has been recently introduced in the analysis, and the NN approach is validated for several WEST discharges against existing synthetic diagnostic tools based on forward modelling, showing a good consistency and a reduction in computing time by orders of magnitude. The hypothesis on the W radial profile that has been assumed is as follows, with c_W^0 the central W concentration value and α a parameter determining the profile shape:

$$c_W(\rho) = c_W^0 \left[1 + \alpha \left(1 - \cos\left(\rho \frac{\pi}{2}\right)\right)\right]. \qquad (2)$$

The preliminary results of NN scaling of c_W^0 and α parameters, based on numerous experimental WEST plasma discharges, are presented in Figure 3.

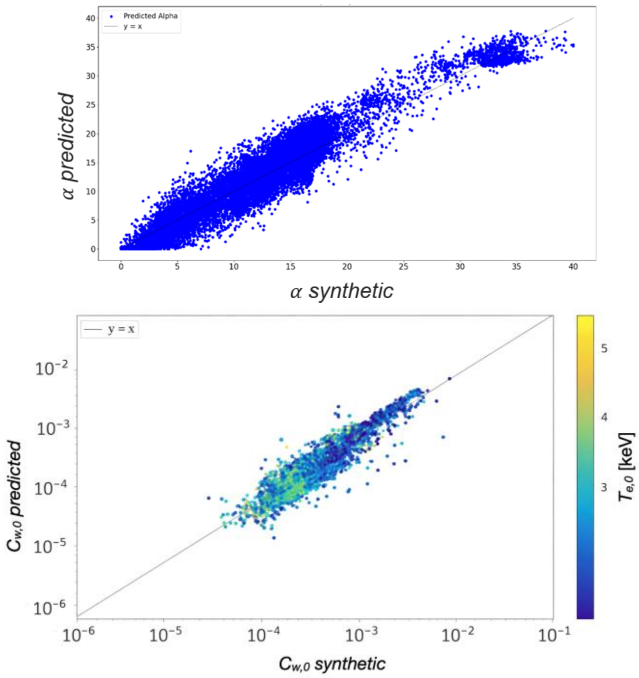

Figure 3. *NN experimental scaling of $c_{W,0}$ and α parameters.*

5. Conclusions & Perspectives

The proposed GA-MC methodology is generic and may be applied in future work to the design optimization of other neutron or X-ray diagnostic systems resilient to neutron flux in the ITER environment. Besides, the obtained NN preliminary results open the door to significantly enhanced capabilities for reconstructing plasma parameters, particularly to study ionization, transport and radiation properties of heavy impurities in tokamaks such as WEST or ITER with a substantial suprathermal electron population.

References

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