

## Neural networks for fast soft X-ray tomographic inversions in tokamaks

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### 1. The tomographic inversion problem

Reconstructing the local plasma emissivity in the soft X-ray (SXR) range 0.1 – 20 keV can be very useful to access crucial information on particle transport, magnetohydrodynamic activity or impurity content in tokamaks. In particular, radiative cooling of heavy impurities like tungsten (W) could be detrimental for the plasma core performances of ITER and developing robust and fast SXR diagnostics is an essential issue to monitor the impurities and to prevent their central accumulation. 2D tomography is the usual method to access the local SXR emissivity of the plasma in a poloidal cross-section of the tokamak from line-integrated measurements of two or more pinhole cameras. In the Line-of-Sight (LoS) approximation, the  $m_j$  measurements of the  $j$ -th detector (in  $\text{W.m}^{-2}$ ) looking at the plasma through the camera aperture is given by the following line integral, after spatial discretization of the plasma 2D emissivity field in  $N_p$  pixels:

$$m_j = \sum_{i=1}^{N_p} T_{ji} \varepsilon_i + \xi_j \quad (1)$$

where  $\varepsilon_i$  is the plasma emissivity (in  $\text{W.m}^{-3}$ ) in the  $i$ -th pixel filtered by the spectral response of the diagnostic, the transfer matrix element  $T_{ji}$  contains the length (in m) of the  $j$ -th LoS in the  $i$ -th pixel and  $\xi_j$  denotes systematic and statistical error such as electronic noise in the  $m_j$  measurements. This mathematically ill-posed and quite challenging problem is traditionally solved using the Tikhonov regularization, by adding *a priori* information on the emissivity distribution, which typically imposes smoothness of the reconstructed profile. The solution of Eq. 1 is then:

$$\boldsymbol{\varepsilon} = (\boldsymbol{tT.T} + \lambda \boldsymbol{H})^{-1} \cdot \boldsymbol{tT.m} \quad (2)$$

where  $\boldsymbol{H}$  is a regularization operator and the parameter  $\lambda$  acts as a balance between overfitting of the measurements and over-smoothing of the solution. The minimum Fisher information (MFI) method is the most commonly used in current European tokamaks like TCV [1], ASDEX Upgrade [2] or WEST [3]. Although significant progress is made on

Tikhonov regularization methods to shorten the inversion time [4], very fast tomography  $\leq 1\text{ms}$  with good resolution and real-time capabilities remains a challenging task.

Neural networks have been recently used in tokamaks for turbulent transport predictions [5] and JET bolometers [6], showing promising results in terms of computational time as well as quality of reconstruction. Thus, the aim of this contribution is to investigate the use of neural networks for fast soft X-ray tomographic reconstructions in the prospect of real-time impurity control in tokamak plasmas.

## 2. Neural networks

### 2.1. The artificial neuron: perceptron and sigmoid neuron

Neural networks are generally composed of several layers of individual neurons in interaction with the neurons of neighboring layers. One single artificial neuron has a simple structure including an input vector  $\vec{x} = (x_1, \dots, x_n)$  associated with a weight vector  $\vec{w} = (w_1, \dots, w_n)$  and one neuron output  $a = f(\vec{w} \cdot \vec{x} + b)$  where  $f(z)$  denotes the neuron activation function and  $b$  is the global neuron bias. The most simple artificial neuron is the perceptron for which the neuron activation function is the Heaviside step function:

$$f(z) = \begin{cases} 0 & \text{if } z = \vec{w} \cdot \vec{x} + b < 0 \\ 1 & \text{if } z = \vec{w} \cdot \vec{x} + b \geq 0 \end{cases} \quad (3)$$

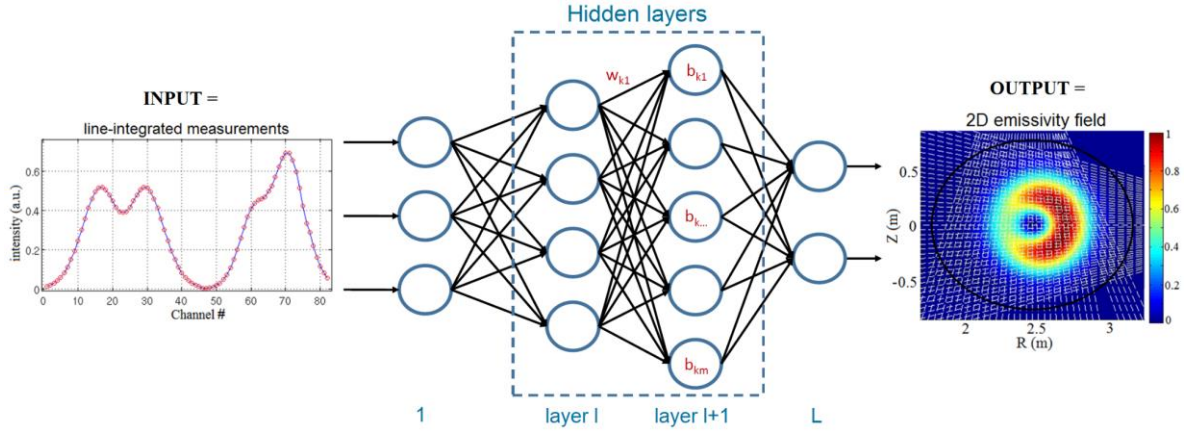
The major issue of the perceptron is that its output derivative is the discontinuous Dirac distribution, which is not convenient for the learning process. Thus, the sigmoid neuron with a smoother activation function is usually preferred:

$$f(z) = \frac{1}{1 + \exp(-z)} \quad (4)$$

A network of such artificial neurons and with a sufficiently high complexity is *a priori* able to fit any multidimensional function in a given input range, by adjusting adequately the weights and biases of the neurons.

### 2.2. Neural networks with fully-connected layers

A feedforward neural network with fully-connected layers is made of successive neuron layers such that each neuron of the  $(l+1)$ -th layer takes its inputs from the output of every neuron of the  $l$ -th layer as depicted in figure 1. Such structure benefits from a high number of connections between neurons and easy numerical implementation, however it can be subject to the vanishing gradient issue [7] slowing down the learning of the deepest layers, thus only two hidden layers were tested in this work to keep a low numerical cost of the training process.



**Figure 1.** Layout of the neural network adapted to the SXR geometry of Tore Supra.

The mean Square Error (MSE) is used as a cost function  $C(\vec{w}, b)$  to quantify the discrepancy between the desired outputs  $y(\vec{x})$  and outputs from the networks  $a(\vec{x}, \vec{w}, b)$ :

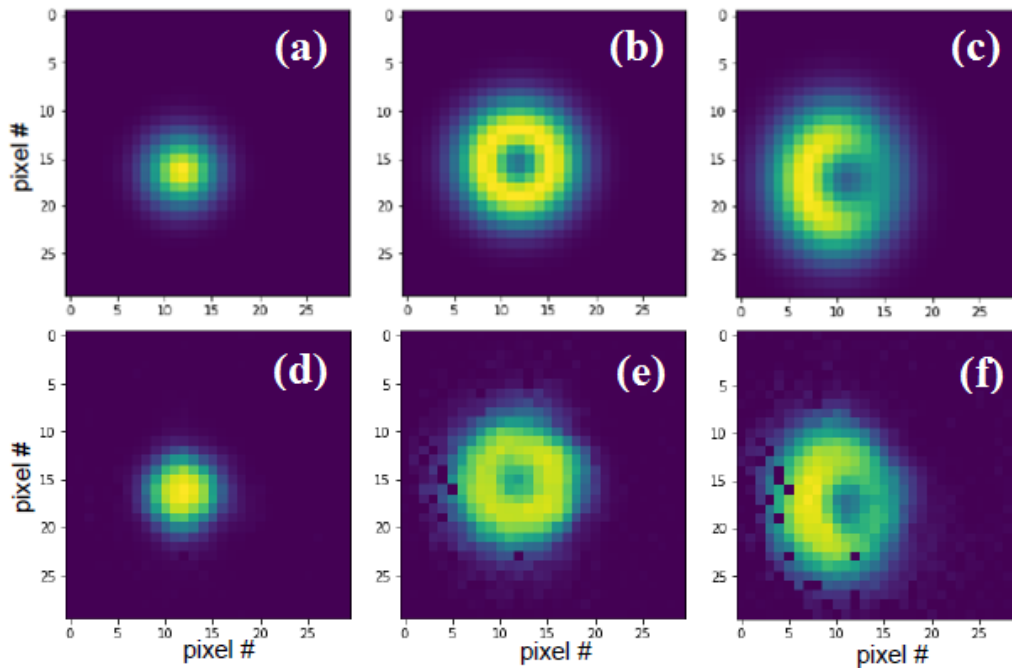
$$C(\vec{w}, b) = \frac{1}{2n} \sum_{\vec{x}} [y(x) - a(\vec{x}, \vec{w}, b)]^2 \quad (5)$$

where  $n$  is the number of samples  $(\vec{x}, y(\vec{x}))$  in the database. Although an efficient training of the neural network is correlated with a decreasing value of the cost function, the network should avoid overfitting of the database and still give acceptable results in the desired reconstruction range for inputs not included in the database. Therefore, a regularization procedure should be applied and a fraction of the database should be preserved for validation test. In this work, the cost function was minimized using a stochastic gradient-descent method [8] that updates iteratively the weights and biases in the direction of the negative gradient of the cost function. The cost function gradient is computed using a backpropagation algorithm [9, 10]. A fixed learning rate of 1.0 is used to naturally prevents overfitting of the database. The early stopping of the training process, when the validation loss starts to decouple from the training loss and to saturate, is a second key element of the regularization.

### 3. Preliminary results

The tomographic tests were performed in the Tore Supra geometry using one input layer of 82 sigmoid neurons (for the 82 diodes), two hidden layers of 30 neurons each and one output layer of 900 neurons (tomogram resolution  $30 \times 30$ ). A database of 2500 emissivity phantoms with different sizes, positions and shapes was used to train the neural network. 90% of the samples were devoted to the training process and 10% were kept for the validation test.

Promising inversion time  $\sim 10 - 50 \mu s$  and reconstructions of the position, size, shape and intensity of the 2D emissivity distribution are obtained as presented in figure 2.



**Figure 2.** (a,b,c) Three emissivity phantoms of the validation database where the SXR emissivity value is normalized to 1. (d,e,f) Tomographic reconstructions obtained from the trained neural network.

Several possibilities are foreseen in our future work: the benchmark of the two tomography options using either a synthetic database or experimental tomograms from Tikhonov regularization, to quantify the advantages and limits of the two approaches; the optimization of network parameters (*e.g.* learning rate, hidden layers) and regularization procedure (dropout, weight minimization term in the cost function); and finally the investigation of different neural network structures with a focus on deep “de-convolutional” networks [6].

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