§21. Optimizing the Hopfield Neural Network for Bolometer Tomography of LHD Plasma

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For the purpose of improving the bolometer diagnostics of LHD plasma, study of the Hopfield neural network for tomographic imaging [1] has been promoted with respect to the two fan-beam camera system, which was installed in a semi-tangential plane viewed with 3.5U/4-O ports [2].

The Hopfield neural net can be so designed that its energy function coincides with the Lagrange function of Tikhonov-Phillips (TP) type for linear image reconstruction problems $\boldsymbol{Hf}=\boldsymbol{g}$. Neurons as many as pixels are cross-coupled with symmetrical interconnecting weights related to a regularized inversion operator and given biases that are related to the backprojections of detector outputs. When the system dynamics are computer-simulated with a monotonically increasing activation function, one finds a solution (plasma image in our case) as a set of neuron outputs in the stationary state of the system. Updating the system state is made asynchronously with the use of random numbers.

To obtain the unsaturated positive values of plasma images and also to assure an efficient convergence of iteration, the skimmer function is employed as the activation function, and using the Laplacian operator C in Lagrange function is effective to obtain smooth image profiles. Also, the formats of compressed column/row storage (CCS/CRS) in computer coding is useful to decrease the computing time of each iteration since zero elements in the sparse projection matrix are omitted in multiplication.

With this software design, a study was made with special interest in optimizing the regularization parameter γ. Tests on numerically generated data of detector outputs ($\boldsymbol{g}=\boldsymbol{Hf}_{\mathrm{o}}+$ noise) showed that the L-curve was useful enough to optimize the value of γ; as far as our camera system of bolometer was concerned, the best approximation of the reconstructed image $\hat{\boldsymbol{f}}$ to the original $\boldsymbol{f}_{\mathrm{o}}$ was obtained for a value of γ a little larger than the curve-corner value. A result of the experimental data analysis is illustrated in Figs. 1 and 2. On a gas-puff experiment data (Shot No. 31721, t=2 [s]), the energy function was monotonically decreased as plotted in Fig. 1 when the neural net of K=32x32 neurons was iteratively updated. With respect to the plasma image $\hat{\boldsymbol{f}}$ obtained at the final state (after iterations of n=1500), the roughness $\| C\hat{\boldsymbol{f}} \|^2$ and the mean square error $\hat{\varepsilon}^2$ between $H\hat{\boldsymbol{f}}$ and $\boldsymbol{g}$ were changed with the parameter γ as displayed in Fig. 2. Numerical tests on the L-curve like this indicated that the image $\hat{\boldsymbol{f}}$ for $\gamma \simeq 1\times10^{-5}$ might be appropriate for this data.

In conclusion, we have successfully obtained a new nonlinear neural network method which has an advantage of giving smooth profiles like the TP method and guaranteeing the positive value of the image like the maximum entropy (ME) method. To take this advantage, one needs to compensate the computing time that is larger than that of the fast ME algorithm of Hosoda-Iwama.

The modification of the type of minimum Fisher information [3] can be adopted easily to the Hopfield neural network by inserting a matrix $D^{1/2} = \mathrm{diag}(f_1^{-1/2}, f_2^{-1/2}, \cdots, f_K^{-1/2})$ into the penalty function of the TP type. In the tests on the numerically generated data, this modification had an effect in decreasing the artifact which tended to appear in a region near the horizontal camera, but it had no significant effect on experimental data.

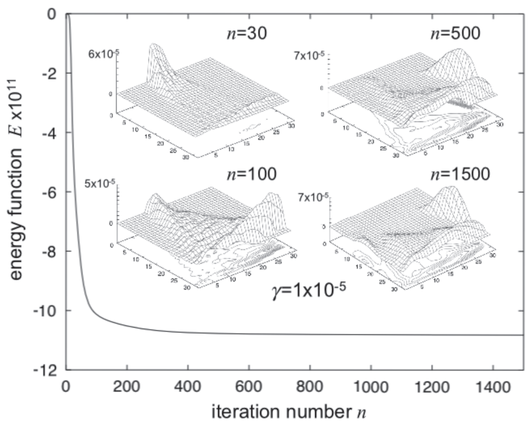

Fig. 1. Changes of the energy function E and the plasma image $\hat{\boldsymbol{f}}$ in updating the neural net with γ=1x10^{-5}.

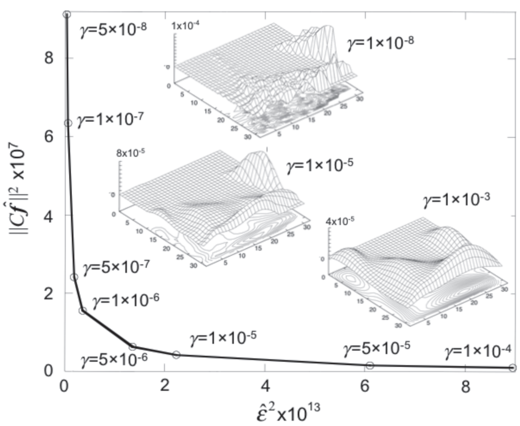

Fig. 2. L-curve: the diagram of $\| C\hat{\boldsymbol{f}} \|^2$ and $\hat{\varepsilon}^2$ with parameter γ; n=1500.

1) Iwama, N., Ichikawa, N., Hosoda, Y., Liu, Y., Tamura, N. et al.: Ann. Rep. NIFS (2006-2007) 176.
2) Liu, Y., Tamura, N., Peterson, B.J., Iwama, N. and LHD Exp. Group: Rev. Sci. Instrum. **77** (2006) 10F501.
3) Liu, Y., Tamura, N., Peterson, B.J., Iwama, N. et al.: Plasma and Fusion Research, **2** (2007) S1124.