

Deep Learning-Based Neutron Emission Profile Reconstruction for Real Time Diagnostics in K-DEMO

Gyeongjin Choi, Beomkyu Kwon, Kyoung-Jae Chung*

Department of Nuclear Engineering, Seoul National University, 1, Gwanak-ro, Gwanak-gu, Seoul, Republic of Korea

*Corresponding author: jkjlsh1@snu.ac.kr

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1. Introduction

Real time measurement of the two-dimensional neutron emission profile is important for plasma diagnostics and operational control in Deuterium-Tritium (DT) fusion reactor environments such as K-DEMO. In previous work, neutron emission profile reconstruction was performed using the Maximum Likelihood Expectation Maximization (MLEM) algorithm under detector layout conditions based on ITER [1] and EURO-DEMO [2]. The feasibility of reconstructing the neutron emission profile was demonstrated through optimization of the detector arrangement. However, because MLEM iteratively updates the reconstructed profile, it may be difficult to meet the 10 ms reconstruction time requirement [3] for real time diagnostics in fusion reactors, even when sufficient reconstruction accuracy is achieved.

In this study, a deep learning-based neutron emission profile reconstruction method was applied using the detector configuration and count rate conditions established in the previous work. The image quality and computational time were compared with those of MLEM-based reconstruction to evaluate the feasibility of real-time application in fusion reactor environments.

2. Methods

2.1. Dataset generation and neutron count calculation

Two-dimensional plasma neutron emission profiles were synthetically generated to represent a range of plausible plasma conditions. Each profile was normalized to its maximum value. A total of 10,000 profiles were then generated by varying the position, shape, and emission intensity to represent different plasma states. The generated profiles were divided into training, validation, and test datasets in an 8:1:1 ratio.

For each profile, neutron counts were calculated for 36 detectors arranged at the upper Vertical Neutron Camera (VNC) and lower VNC ports and at the Radial Neutron Camera (RNC) ports. The count of each detector was determined from the neutron emission profile using its geometric response. The generated profiles and their corresponding 36 detector counts were used as the ground truth profiles and model inputs, respectively.

2.2. Deep learning-based profile reconstruction network architecture

The deep learning network was designed to reconstruct a two-dimensional neutron emission profile of 100×100 pixels from the counts calculated by 36 detectors. The input counts were transformed into a 7,500-dimensional feature vector through two fully connected layers. The feature vector was then reshaped into a $12 \times 25 \times 25$ feature map and sequentially upsampled to 50×50 and 100×100 feature maps through two transposed convolutional layers. Finally, a convolutional layer produced a single channel image of the neutron emission profile. ReLU activation functions were applied after each fully connected and transposed convolutional layer.

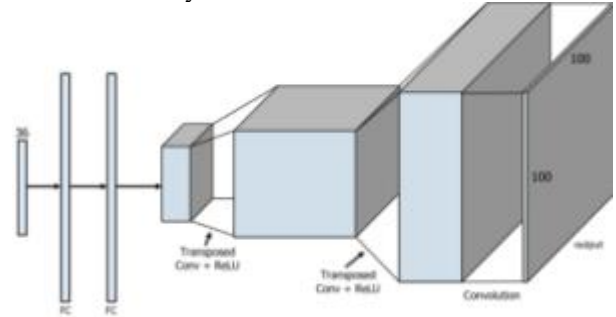


Fig. . Deconvolutional neural network for neutron emission profile reconstruction. The input layer receives count data from all 36 detector channels, and the output layer provides a reconstructed neutron emission profile with a resolution of 100×100 pixels.

2.3. Evaluation of reconstruction performance and computational time

Using identical detector counts as input, neutron emission profiles were reconstructed independently using the deep learning network and the MLEM algorithm. The reconstruction errors of the two methods were compared using the normalized mean squared error (NMSE). For the deep learning network, the structural similarity index measure (SSIM) was additionally calculated to evaluate the structural similarity between the ground truth and reconstructed images.

Computational time was measured by repeatedly performing inference on an independent plasma neutron emission profile that was not used for training, validation, or testing. Based on these measurements, the

feasibility of real time image reconstruction within 10 ms was evaluated.

3. Results and discussion

3.1. Deep learning-based neutron emission profile reconstruction results

Using the detector-layout conditions previously applied to MLEM-based image reconstruction [4], neutron emission profile reconstruction was performed using the deep-learning network. Figure 2 shows the ground-truth neutron emission profile generated under these detector-layout conditions and the corresponding reconstruction obtained with the deep-learning network.

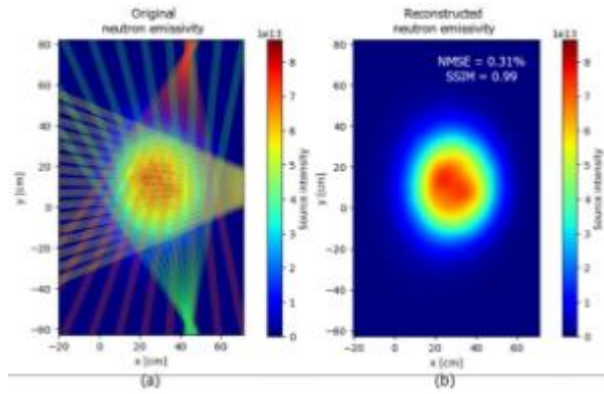


Fig. 2. Deep learning-based reconstruction under the same detector layout conditions used for MLEM-based neutron emission profile reconstruction. (a) Ground truth neutron emission profile overlaid with the fields of view of 36 detectors. (b) Neutron emission profile reconstructed by the deep learning network from the detector counts (NMSE = 0.31%; SSIM = 0.99).

The reconstructed profile reproduced the location of the high emission region in the plasma core and the overall elliptical shape of the profile. In particular, the central peak emission region and the gradual decrease in emission intensity toward the plasma periphery were consistent with the ground truth profile. However, fine local variations in the ground truth profile were somewhat smoothed during reconstruction. This may be attributed to the limited information available from the detector counts and the smooth, continuous emission profiles represented in the training dataset. Consequently, the network preferentially learned the locations of dominant emission regions and the overall profile shape rather than pixel level variations.

The deep learning-based reconstruction achieved an NMSE of 0.31% and an SSIM of 0.99, indicating low reconstruction error and high structural similarity relative to the ground truth profile. Under the same detector layout conditions, the MLEM reconstruction yielded an NMSE of 1.59%. Therefore, the deep learning network showed lower reconstruction error than MLEM under the present conditions,

demonstrating its potential for rapid and accurate reconstruction of neutron emission profiles.

3.2. Reconstruction results for various neutron emission profiles

Additional neutron emission profiles that did not overlap with the training, validation, or test datasets were generated and reconstructed using the proposed deep learning network. The results are presented in Figure 3.

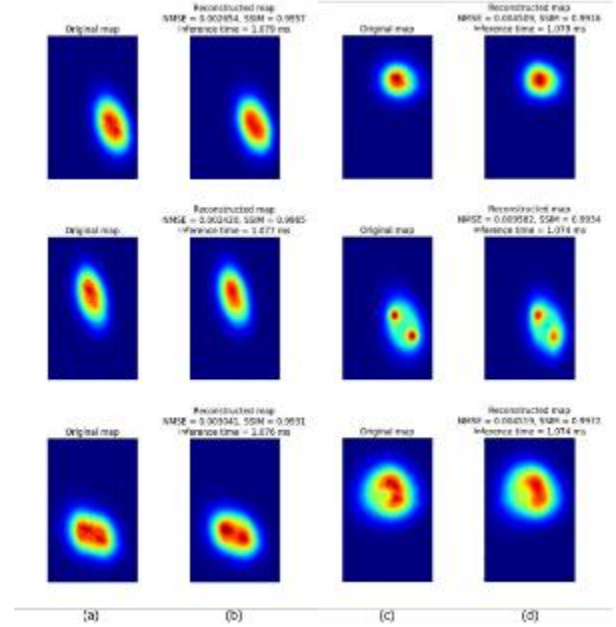


Fig. 3. Deep learning-based reconstruction results for various neutron emission profiles generated independently from the training, validation, and test datasets. (a) and (c) show the ground truth neutron emission profiles, while (b) and (d) show the corresponding deep learning reconstructions of (a) and (c), respectively.

The proposed network reconstructed profiles with different spatial characteristics, including vertically elongated distributions, spatially shifted localized peaks, double peaked distributions, and asymmetric emission profiles. In all cases, the locations of the dominant high emission regions and the overall profile shapes were reproduced similarly to those of the ground truth profiles. In particular, for the double peaked profile, the locations and relative intensity distributions of the two separated high emission regions were preserved. These results demonstrate that the proposed network is not limited to a specific plasma shape and can robustly reconstruct the major spatial features of different neutron emission profiles.

3.3. Analysis of reconstruction performance and inference time

Reconstruction performance and inference time were evaluated using 10,000 neutron emission profiles generated independently from the training, validation, and test datasets. Across the 10,000 reconstructions, the mean NMSE was 0.549 ± 0.738 % and the mean SSIM was 0.991 ± 0.008 . These results show that the proposed network maintained low reconstruction error and high structural similarity for various neutron emission profiles.

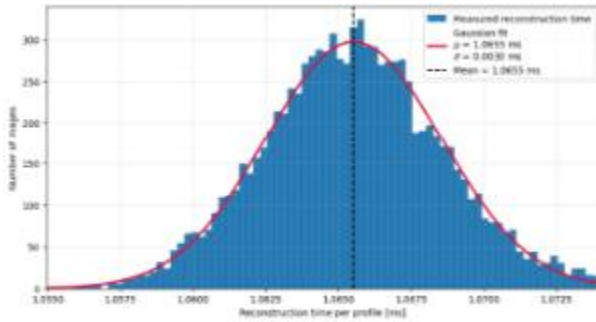


Fig. 4. Distribution of inference times per profile for deep learning-based neutron emission profile reconstruction.

Figure 4 shows the distribution of inference times per reconstructed profile calculated over 10,000 repeated trials. The mean inference time across all measurements was 1.067 ± 0.012 ms. After excluding 500 statistical outliers, Gaussian fitting was performed for the remaining 9,500 measurements. The inference times ranged from 1.055 to 1.074 ms, with a fitted Gaussian mean and standard deviation of 1.067 ms and 0.003 ms, respectively. This inference time is approximately 94 times shorter than the 10 ms requirement for real time neutron emission profile reconstruction, demonstrating the potential of the proposed deep learning-based reconstruction method for real time neutron diagnostics.

4. Conclusions

In this study, a deep learning-based method was developed to reconstruct plasma neutron emission profiles from neutron detector counts of the fusion reactor, and its reconstruction performance and computational time were compared with those of the MLEM algorithm. The proposed deep learning network reproduced the major spatial structures of the plasma neutron emission profiles with lower reconstruction error than MLEM. It also showed stable reconstruction performance for different plasma profile shapes and achieved an inference time of less than 10 ms per profile. These results indicate that the proposed method can overcome the computational time limitation of iterative reconstruction methods. This study demonstrates the potential of deep learning-based neutron emission profile reconstruction for real time neutron diagnostics and control in K-DEMO environments.

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