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Deep learning for tomographic reconstruction of imaging diagnostics

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Imaging diagnostics play essential roles in the analysis of internal structures of plasmas where insertion of detectors is impossible for avoiding damages in plasmas and/or diagnostics. The conventional method of tomography invokes a simple model of internal structure so that the parameters of the model are easily evaluated by inverting the integrated observables. Limited accessibility of diagnostic or influence of nonlocal optical effects (such as backlights from chamber walls) can cause a lack of data, resulting in numerical instabilities in the inversion problem. To overcome such problems, a deep learning method, particularly convolutional neural networks (CNN) was applied in JET to reconstruct the 2D plasma profile with satisfactory accuracy [1]. They proved that their method is even faster than the classical tomographic methods that generally need higher computational demands. CNN learns to minimize a loss function that scores the quality of results. Although the learning process is automatic, a lot of manual processes are necessary for designing an effective loss function. In order to learn a loss function automatically, Generative Adversarial Networks (GAN) has been proposed [2]. GAN learns a loss by distinguishing whether output images are real or fake, while simultaneously training a generative model to minimize this loss. In this work, we build a method using "conditional GAN" (cGAN) [3] and apply it to obtain local emissivity from line-integrated images [4].

We applied the reconstruction technique for the imaging diagnostic of He II 468.6 nm of Coherence Imaging Spectroscopy (CIS) [5] in RT-1, a laboratory magnetosphere created by a levitated superconducting ring magnet [6]. The pairs of local emissivity and line-integrated images which simulate an experimental system are prepared to train a network. The local emissivity has been generated by the model functions typically used for the electron density and temperature profile of RT-1 which is given as a function of the magnetic flux surface [7]. The line-integrated images were generated using the local emissivity by assuming the toroidal symmetry of the RT-1 plasmas. The reflection from chamber walls and levitation magnet (L-magnet) are considered in the images. In this calculation, we use the TensorFlow 1.13.1 implementation of cGAN named pix2pix [3]. Figure 1 shows the three sets of input, output and target image for the network.

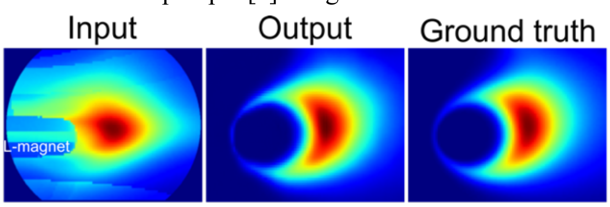

Fig. 1. Sample reconstructions produced by the network, with the line-integrated image (Input, left), reconstructed local emissivity (Output, middle), and target image (Ground truth, right).

Once the network is trained, we applied it to the obtained images from the CIS in RT-1. In helium plasmas, the CIS measured the spectral intensity, the ion temperature, and flow velocity of He^{+}. The ion cyclotron resonance frequency (ICRF) heating was successfully demonstrated in magnetospheric plasmas [8]. The input powers of 10 kW for the electron cyclotron heating (ECH) sustained the target plasma. Just after 0.1 sec from the start of the ECH injection, the ICRF heating of 9.4 kW was applied to the double loop antenna up to the termination of the discharge. The CIS was measured for the exposure time of 0.8 sec in the stable density period. Figure 2 shows the reconstructed images of local He^{+} intensity of these plasmas. The He^{+} intensity increases especially along the magnetic field lines near the levitation magnet. This result corresponds that the heated He^{+} ions around the double loop antenna in the high field side near the center stack move to the upper region of levitation magnet along the magnetic field lines.

The calculation of line-integrated image from local emissivity of emission is generally easier than the calculation of the opposite relation. In the present practice, we have taken into account the backlight reflected from the chamber walls, which makes even the line-integrals involved; hence the conventional inversion methods do not apply. This method can be applied to other diagnostics in other machines where reconstruction is difficult because of restrictions on measurements or complexities of the inversion problem.

References

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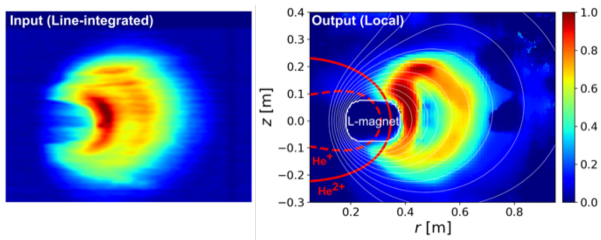

Fig. 2. Line-integrated emission intensity of CIS (left) and reconstructed local intensity profile (right) with ICRF. The ion cyclotron layers for He^{2+} and He^{+} are depicted.