

# Deep learning for tomographic reconstruction of imaging diagnostics 3<sup>rd</sup> Asia-Pacific Conference on Plasma Physics, November 5<sup>th</sup>, 2019, Crowne Plaza Hefei, Hefei, China

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### Introduction

- Conventional tomography employs a simple model of internal structure, and the model parameters are easily evaluated by inverting the integrated observables.
- **D** The limited accessibility of diagnostics or the influence of nonlocal optical effects (such as backscatter from the chamber walls) can cause a lack of data, resulting in numerical instabilities in the inversion problem.
- Deep-learning convolutional neural networks (CNNs) have been applied at JET to reconstruct the 2D plasma profile with satisfactory accuracy [1].
- Although the learning process is automatic, numerous manual processes are necessary to design an effective loss function.
- □ A Generative Adversarial Network (GAN) has been proposed to learn the loss function automatically via an adversarial process [2].
- We have built a method using cGAN and used it to obtain the local emissivity from line-integrated images [3].

Tomographic reconstruction with CNN in JET<sup>[1]</sup> Lines of sight Conventional

Tomographic reconstruction of imaging diagnostics<sup>[3]</sup>

# **Generative Adversarial Networks**



 $\checkmark$  A GAN learns a loss that tries to classify whether output images are real or fake, while simultaneously training a generative model to minimize this loss.

- ✓ A "conditional GAN" (cGAN) learns a conditional generative model, applying the same generic approach to problems that would traditionally require very different loss formulations [4].
- ✓ We used the TensorFlow 1.13.1 implementation of cGAN named "pix2pix" [4].

# The Ring Trap 1 (RT-1) experiment





The Ring Trap 1 (RT-1) device is a laboratory magnetosphere that is realized by a levitated superconducting ring magnet in vacuum [5, 6].

 $\checkmark$  The levitated coil weights ~100kg, which is made of Bi-2223 superconductor

✓ Radius of levitated coil : r=0.375 m

✓ Radius of vacuum chamber : R=1.0 m

Generating pairs of local-emissivity and line-integrated images that simulate the experimental system



- $\checkmark$  We applied this reconstruction technique to the He II 468.6 nm imaging diagnostic of Coherence Imaging Spectroscopy (CIS) [7] from RT-1.
- $\checkmark$  To train the network to reconstruct images, we generated pairs of local-intensity profiles and line-integrated images that simulate the optics of the CIS system.
- $\checkmark$  We generated the local emissivity using typical model functions for the electron-density and temperature profiles of RT-1 [8].

- $\checkmark$  We generated the line-integrated images from the local emissivity, assuming toroidal symmetry for the RT-1 plasmas.
- $\checkmark$  We took account of reflections from the chamber walls and the levitation magnet (L-magnet).
- $\checkmark$  We also employed the CIS optics to simulate the results, using the optical-engineering program ZEMAX.

## Training the generative model which generates the local-emissivity profiles from the line-integrated images

### Training data



Fake pairs

- $\checkmark$  We selected a total of 6500 pairs of images randomly as input for the training, which spanned one million iterations.
- ✓ We also generated another set of 1300 samples using the same strategy, which we employed as a validation set to avoid overfitting.
- Note that this particular reconstruction was not part of either the training set or the validation set.
- ✓ They show that the network can produce reconstructions with high accuracy.



Image-quality metrics **D**Structural similarity (SSIM) □Normalized root-mean-square error (NRMSE) **D**Peak signal-to-noise ratio (PSNR)

	SSIM	NRMSE	PSNR [dB]
Mean	0.9393	0.0631	25.957
Std. dev.	0.0224	0.0165	2.546

X Here, SSIM reaches a maximum value of 1.0 when the two images are equal (Note that one can recognize the difference between two images if the SSIM value is less than 0.9).

# Application for the He II-emission imaging diagnostic

pair ?



 $\checkmark$  We applied it to images obtained by the CIS from RT-1.

- $\checkmark$  For helium plasmas, the CIS measured the spectral intensity, ion temperature, and flow velocity of He<sup>+</sup>.
- $\checkmark$  The 10 kW input power of electron-cyclotron heating (ECH) sustained the target plasma. ✓ We applied 9.4 kW of ion-cyclotron-resonance-frequency (ICRF) heating to the double-loop antenna 0.1 sec after the start of the ECH injection and maintained it up to the termination of the discharge.
- $\checkmark$  The He<sup>+</sup> intensity increases, especially along the magnetic field lines near the L-magnet.  $\checkmark$  This result corresponds that the heated He<sup>+</sup> ions around the double-loop antenna on the high-field side near the center stack move to the upper region of the L-magnet along the magnetic field lines.

### References

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### Summary

- We have developed a new tomography method using a cGAN
- and have demonstrated its efficiency by converting a line-integrated image into local emissivity.
- Calculation of the line-integrated image from the local emissivity is generally easier than the calculation of the opposite relation.
- In the present work, we have taken into account backscattering from the chamber walls,
- which makes even the line-integrals involved; hence 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.