

Image reconstruction of lens-less microwave cameras using deep learning

Mayuko Koga¹

¹ Graduate School of Engineering, University of Hyogo
 e-mail (speaker): koga@eng.u-hyogo.ac.jp

Microwave imaging has the potential to revolutionize a wide range of applications, including medical diagnostics and security screening. However, its utility is often limited by the inherently low spatial resolution associated with long wavelengths. To address this limitation, we propose a novel lens-less microwave imaging approach.

In our method, microwaves are injected into the object, and the reflected waves are detected directly by an antenna array. The absence of a focal point necessitates the reconstruction of the object image, which presents a significant challenge due to the ill-conditioned nature of the inverse problem caused by the low resolution of the detector. Our research has demonstrated successful image reconstruction using mathematical techniques.^[1] Despite these advancements, the method is hampered by long computational times and sensitivity to noise.

To overcome these issues, we have incorporated deep learning neural networks to reconstruct images. We used a Convolutional Neural Network (CNN) implemented in Keras. In our calculations, 30 GHz microwaves were assumed to be injected into a target object with a surface reflectivity of 1, and the reflected received signal was calculated using three-dimensional electromagnetic field simulations. A set of object images (128x128 pixel) and received signal distributions (16x16 pixel) were used as the training data.

Figure 1 shows the input images of received microwave

signals, object surface images, and the output surface images predicted by our models. The color bars represent normalized intensities in microwave signals, surface positions in the depth direction in surface images. The numbers above the images indicate the numbers of training data used for each model. The output surface images clearly capture the features of the object images, and the small structures of objects are well reproduced as the amount of training data increases. Additionally, using two types of input data (real and imaginary parts) proved superior to using a single type (absolute values), or even another two types (phase and intensity). Reconstruction calculations performed by the trained model take only a few milliseconds, and its noise tolerance is robust.^[2]

These results suggest that deep learning can effectively mitigate the limitations of traditional microwave imaging techniques, paving the way for practical and high-resolution imaging solutions.

This work was supported by the NIFS Collaboration Research program (NIFS20KLEP036).

References

- [1] H. Tsuchiya, N. Iwama, S. Yamaguchi, R. Takenaka, and M. Koga, *Plasma Fusion Res.* **14**, 3402146 (2019).
- [2] R. Manabe, H. Tsuchiya, and M. Koga, *Plasma Fusion Res.* **17**, 2401072 (2022).

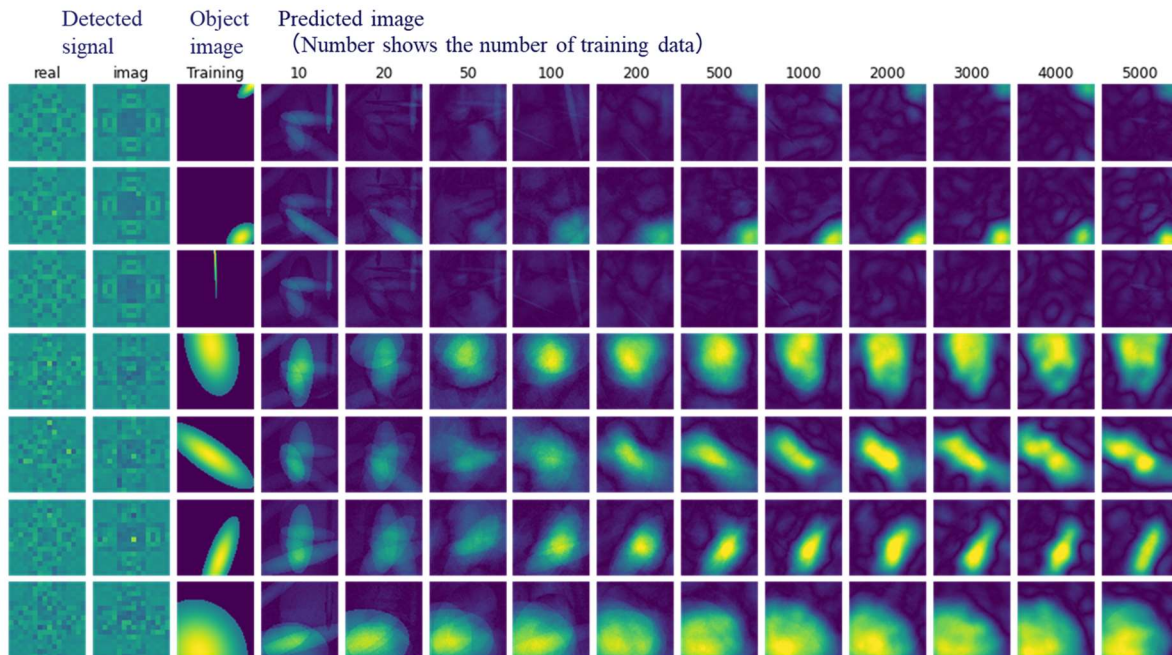


Figure 1. Input images of received microwave signals, object surface images and output surface images predicted by models with different numbers of training data.