Trial of Deep Learning for Image Reconstruction of Lens-Less Microwave Holography[*)]

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We perform the principal verification of reconstructing object surface images by using deep learning. Using the deep learning neural network based on convolutional neural networks, simple object surface images with 128×128 pixels are reasonably reconstructed with up-converting from rough microwave signal images with 16×16 pixels. The model captures large structural features of the object surface images even with small number of training data. As the number of training data increases, it captures small structures of objects. It is also found that noises of input signal images affect reconstructions of small structures of objects.

Keywords: microwave holography, deep learning, convolutional neural networks (CNNs), lens-less imaging, image reconstruction

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1. Introduction

In nuclear fusion research, one of interesting topics is plasma turbulence. Plasma turbulence is related to the structure formation of the plasma which determines the overall plasma confinement [1, 2]. Various measurement techniques have been studied for the experimental observation of plasma turbulence [3–7]. While the spatial resolution of visible light measurements is generally high, the position identification in the line-of-sight direction is difficult. For microwave measurements, position identification in the line-of-sight direction is generally possible by phase measurement, but the spatial resolution is not enough to discuss the turbulent structure due to its wavelength. To overcome above weakness, we have proposed lens-less microwave imaging.

The lens-less imaging has been developed in recent years and is also known as digital holography [8, 9]. In our imaging method called “lens-less microwave holography”, microwaves are injected into the object and the reflected microwaves are directly received by an antenna array. Due to no focus, it is necessary to reconstruct an object image. This is not easy because this is an ill-conditioned inverse problem due to the low resolution of the detector. However, we succeeded it in a preliminary experiment [10]. If we are able to reconstruct an object image of any resolution, we will be able to obtain a various size of plasma spatial structure. This is a great advantage. In addition, this method is easy to setup because there is no need to build an optical system.

In the previous paper [10], we reconstructed an object image by using mathematical method, which takes long computing time. In this paper, we try to apply deep learning for fast image reconstruction.

2. Method

2.1 Objects

It is difficult to obtain sufficient data for deep learning with real measurements. Therefore, we performed the electromagnetic wave calculations to make received microwave signals [11].

Since the final goal is to observe turbulence, it is necessary to set an object with a multi-scale structure, but this time, as a first step, we considered a mirror-like object with a protrusion shown in Fig. 1. The footprint of the protrusion is set to elliptical, whose length of major and minor axis are randomly set in the range of 1 mm to 65 mm, respectively. The protrusion shape is a Gaussian function like, whose top is 1 mm height. The position and the rotation angle of the protrusion are also randomly set. The reflectance of the object is set to 1. Thirty gigahertz microwave is irradiated to the object and completely reflected at the surface of the object. The reflected microwave signals are received by an antenna array [12]. The antenna array consists of horn antennas arranged in 16×16 pieces, with each antenna having a size of 10 mm square.

We randomly changed the structure of protrusion and calculated the corresponding received microwave signals. We repeated calculations to make 5100 sets of objects and corresponding received microwave signals. We divided these data into the training data set and the test data set.

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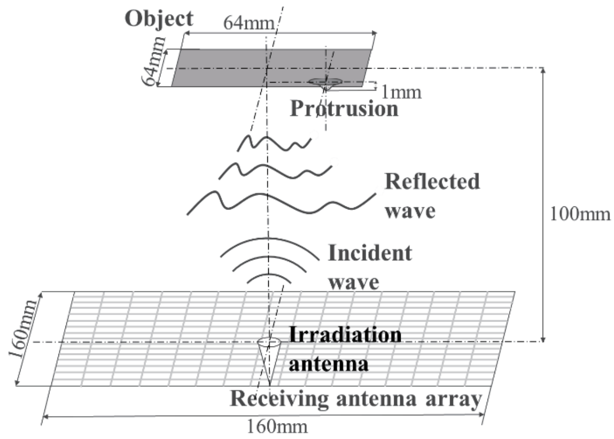

Fig. 1 Layout used for the electromagnetic wave calculation.

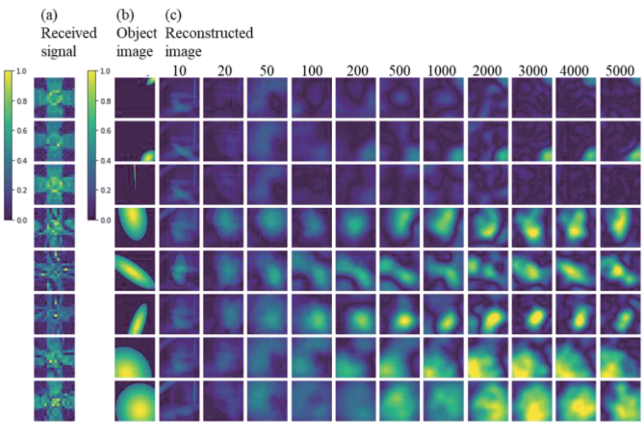

Fig. 2 (a) Received microwave signals, (b) object surface images and (c) corresponding reconstructed surface images by models with different numbers of training data. The input channels take absolute values of complex amplitudes. The numbers above images show the numbers of training data.

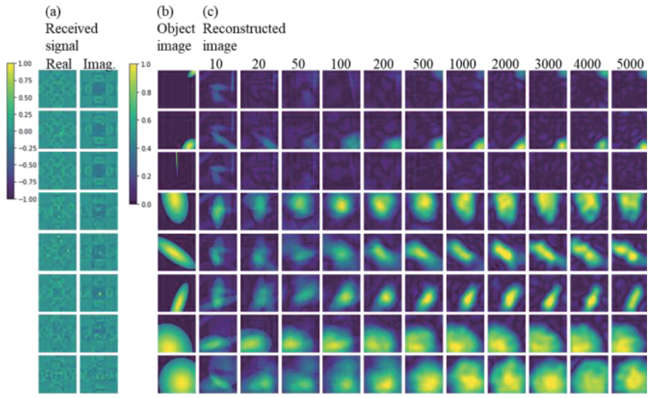

Fig. 3 (a) Received microwave signals, (b) object surface images and (c) corresponding reconstructed surface images by models with different numbers of training data. The input channels take real part and imaginary part of complex amplitudes. The numbers above images show the numbers of training data.

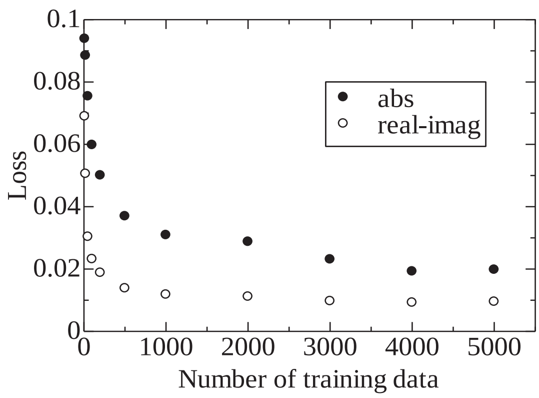

Fig. 4 Loss dependence on the number of training data.

The test data set includes 100 data. The number of training data is a scan parameter. In the case that the number of training data is less than 5000, the training data is selected randomly from 5000 data. The test data is fixed to compare the specifications of the models. As example, the typical 8 test data is shown in Figs. 2, 3, 5 and 6.

2.2 Network configuration

We used convolutional neural network (CNN) as the neural network for deep learning, which is one of the most used neural networks for image recognition. CNNs have the advantage of being able to take multiple channels for input images. Since intensities and phases are observed in microwave measurements, received signals can be written in terms of complex amplitudes. We tried two patterns as input channels, absolute values of complex amplitudes, real and imaginary part of complex amplitudes. The image of received microwave signals is input into the network with 16×16 pixels. It passes through a convolutional layer (karnel size: 6×6, number of filters: 50) and a max pooling layer (window size: 2×2). After that, it passes through 3 layers of the fully connected layer which contains 50 perceptron and one reshape layer. As for the activation function, four functions (relu, linear, tanh, sigmoid) were tried in advance. Then, tanh function was adopted because it showed the lowest loss of the loss function. Here, the loss function is the mean squared error. After passing through the reshape layer, a predictive image of object surface is outputted with 128×128 pixels. This means that the output image is upconverted from the input image.

3. Results

3.1 Reconstruction with different number of training data

Figures 2 and 3 show (a) input images of received microwave signals, (b) object surface images and (c) output images of surface predicted by models with different numbers of training data. The input channels take absolute values of complex amplitudes (Fig. 2) and real part and imag-

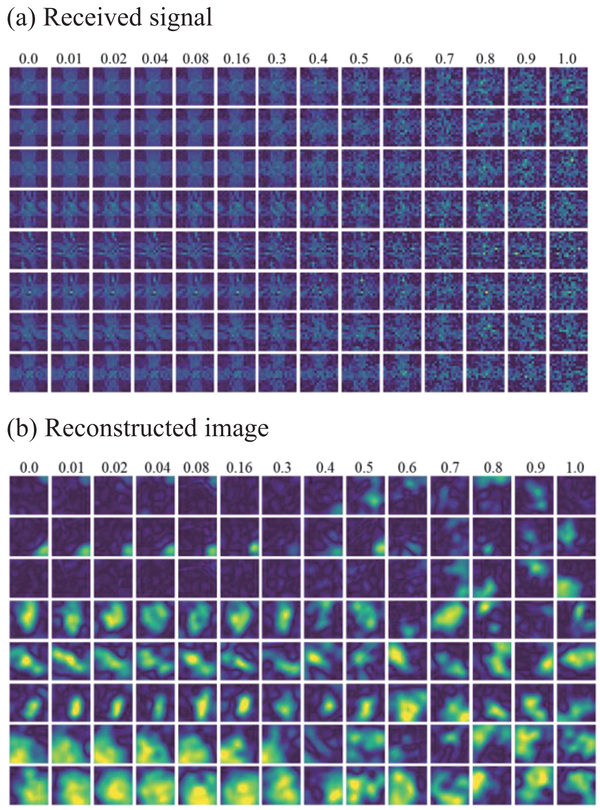

Fig. 5 (a) Received microwave signals and (b) corresponding reconstructed surface images when noises are added. The input channels take absolute values of complex amplitudes. The numbers above images show the noise levels.

inary part of complex amplitudes (Fig. 3). The color bars mean normalized intensities in (a), surface positions in the depth direction in (b) and (c). The numbers above images show the numbers of training data used for each model.

Both figures show that reconstructed images capture features of object images. As the number of training data increases, it is clear that small structures of objects are well reproduced.

Figure 4 shows loss dependence on the number of training data. It is shown that the loss becomes lower with the increase of the number of training data. Moreover, the loss is lower for complex-input than for absolute-input. This result suggests that two types of data (real-imaginary part) are more informative than one type of data (absolute value).

3.2 Noise tolerance

Since actual experimental data always contain noises, it is necessary to know how much noises affects reconstructions.

Random noises were added to received microwave signals. Figures 5 and 6 show (a) input images of received microwave signals and (b) corresponding reconstructed surface images when noises are added. The objects are the same as in Figs. 2 and 3 and are arranged in the same way. Figure 5 is absolute-input and Fig. 6 is complex-input. Colors show the same parameters as in Figs. 2 and 3. The number of training data is 5000. The numbers above images show the noise levels. The noise level 0 means no noise and noise level 1 means that the noise intensity is equal to the signal intensity. It is seen that input images are collapsed as added noises increases. It is found that the increase of noises makes it difficult to reconstruct small structures of objects.

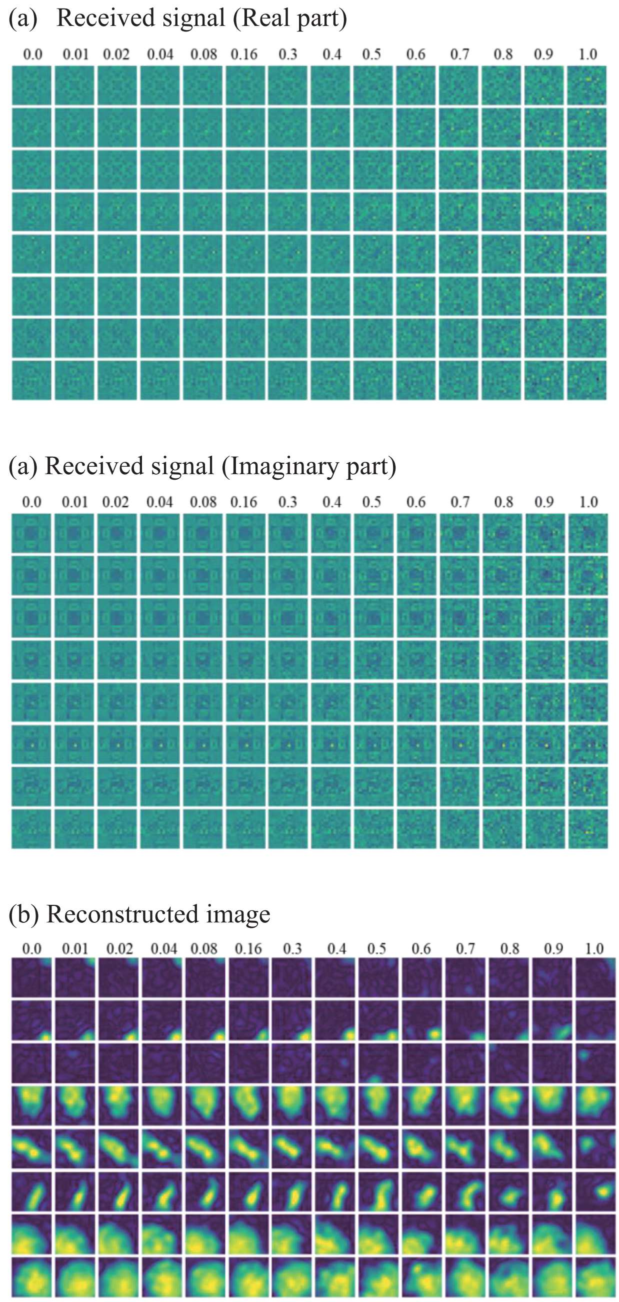

Fig. 6 (a) Received microwave signal and (b) corresponding reconstructed images when noises are added. The input channels take real and imaginary part of the complex amplitude. The numbers above images show the noise levels.

Figure 7 shows the effect of noises on the loss func-

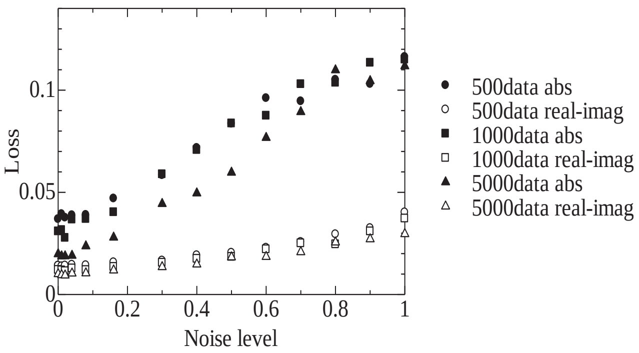

Fig. 7 Effect of noises on loss function.

tion. It is seen that the loss increases with an increase of noises. The increase in the loss is lower for the complex-input than for the absolute-input. This result indicates that the complex input is more tolerant to noise.

4. Summary

Deep learning method with CNN is applied for the image reconstruction of microwave holography. Simple object surface images are reasonably reconstructed with upconverting from rough input signal images. It was found that the model can capture large structural features even with a small number of training data. As the number of training data increased, it can also capture small structural features. Moreover, it was found that two types of input data (real-imaginary part) are better than one type of input data (absolute values). Reconstruction calculations on a trained model takes about milliseconds computing time, and could be applied for real-time feedback, etc in future. Next, we will attempt to reconstruct more plasma-like objects.

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