proceedings

Abstract

Cover Thickness Prediction for Steel inside Concrete by Sub-Terahertz Wave using Deep Learning †

Ken Koyama [1], Tomoya Nishiwaki [1,*] and Katsufumi Hashimoto [2]

[1] Tohoku University, 6-6-11-1209, Aoba, Aramaki, Aoba, Sendai, Miyagi, Sendai 980-9579, Japan; koyama.ken.r7@dc.tohoku.ac.jp
[2] Hokkaido University, A4-08, N13 W8, Kita, Sapporo, Hokkaido, 060-8628, Japan; hashimoto.k@eng.hokudai.ac.jp
* Correspondence: tomoya.nishiwaki.e8@tohoku.ac.jp
† Presented at Advanced Infrared Technology & Applications 2025, Kobe, Japan, 9-15 September 2025.

Abstract: Deep learning techniques are increasingly being incorporated into the inspection and maintenance of social infrastructure. In this study, we show that supervised deep learning applied to imaging data obtained sub-THz wave, the average recall exceeded 80% for all cover thicknesses of steel plate inside concrete, and more than 90% for rebar inside concrete with cover thickness up to 20 mm. Unsupervised deep learning enabled the classification for both steel plate and rebar, even at large cover thickness. These results are expected to improve the exploration depth, which has been limited in previous studies.

Keywords: Deep learning; Neural network; Sub-terahertz wave; Cover thickness

Academic Editor: Firstname Lastname

Published: date

Citation: To be added by editorial staff during production.

1. Introduction

Advanced technologies such as AI and deep learning are starting to be widely utilized in the field of concrete materials [1], which are commonly used as construction materials. Deep learning can be applied to non-destructive and non-contact inspection for social infrastructure, for example, and many studies exist [2]. We succeeded in obtaining locations of steel objects inside concrete by utilizing the high penetration and linear propagation characteristics of sub-THz wave [3], which has electromagnetic waves in the 30-300 GHz range. Furthermore, employing a sub-THz camera capable of detecting sub-THz range has made it possible to acquire contour plots through real-time scanning [4]. However, the applicability of those measurements has limitations, and there is a need to expand these limitations in order to apply them to actual structures.

This paper proposes a deep learning method to predict the cover thickness of steel plates and rebar in concrete using sub-THz wave measurements.

2. Outlines of experiments and analysis

2.1 Experimental Procedures

An overview of the specimens is shown in Figure 1(a) and Figure 1(b). The formwork used for beam specimens of 100 mm height and 400 mm length was used to fabricate specimens with an embedded steel plate (hereafter referred to as “steel plate specimen”) and specimens with embedded a rebar (hereafter referred to as “rebar specimen”). The internal steel plate and rebar were embedded with varying cover thicknesses from the concrete surface for each specimen. The thickness of the steel plate was 1 mm and the diameter of the rebar was 13 mm (deformed rebar). The cover thicknesses were set at 10, 20, 30, and 40 mm. Four steel plate specimens were prepared for each cover thickness, and two rebar specimens were prepared for each combination of cover thicknesses of 10 and 20 mm, and 30 and 40 mm, respectively. The water-cement ratio of the specimen was 55%.

2.2 Measurement methods

The measurement system using the sub-THz camera is shown in Figure 1(c). A microwave generator was used as the oscillator of the sub-THz wave, which was amplified and oscillated by a multiplier capable of oscillating from 18 to 52 GHz. In this paper, measurements were performed by continuously varying the frequency range from 30 to 50 GHz in 1 GHz steps. The sub-THz camera was used as the detector, consisting of 256 elements (16 × 16) with 1.5 mm spacing in a 2.4 cm square, which is suitable for the sub-THz band. As a result, a dataset consisted of 1680 data for the measurement with steel plate specimens and 2100 data for the measurement with rebar specimens. The amount of data used for supervised and unsupervised learning from this dataset is shown in Table 1.

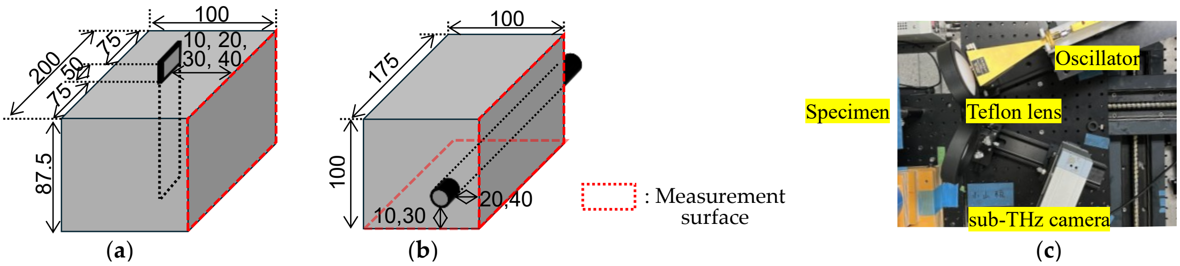

Figure 1 Specimen for measurement and measurement system. **(a)** Steel plate specimen (unit: mm). **(b)** Rebar specimen (unit: mm). **(c)** Measurement system with sub-THz camera.

Table 1. Amount of data used for deep learning.

Amount of data	Supervised deep learning		Unsupervised deep learning	
	Train	Test	Train	Test
Steel plate specimen	1260	420	315	420
Rebar specimen	1680	420	315	420

2.3. Structure of deep learning

The structure of deep learning model constructed in this paper by Neural Networks is shown in Figure 2. Measurement images obtained by the sub-THz camera and the input frequency value were employed as the input layer for the training data. After combining them in the input connection layer, the predicted cover thickness (PCT) was obtained by using Categorical Cross Entropy as the output layer for the error function. In unsupervised deep learning, measurement images obtained from actual cover thickness (ACT) of 40 mm were used as training data, and abnormal index was calculated by squaring the difference between the input and output data.

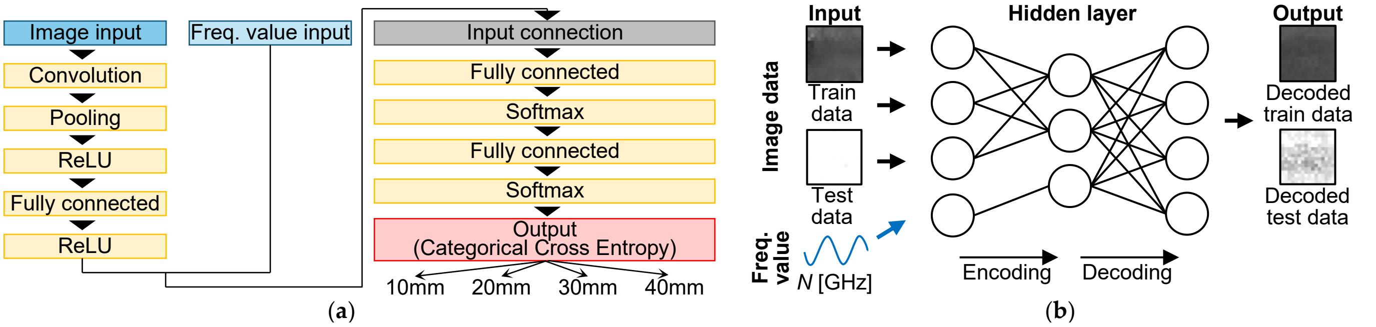

Figure 2 The constructed deep learning model. **(a)** Supervised model. **(b)** Unsupervised model.

3. Results and Discussion

3.1. Measurement result from sub-THz wave

Figure 3 shows some of the measurement images in the steel plate specimens and rebar specimens at 10 GHz intervals with the decoded images, which are discussed on the clustering results by unsupervised deep learning in the following section 3.2. The dashed line in the figure indicates the position of the rebar. When the ACT of the steel specimen is 10 mm, the presence of the steel plate can be confirmed remarkably at 30 GHz. The reflection intensity is close to zero at 50 GHz. These can be attributed to the fact that the reflected waves from the concrete surface and the reflected waves from the steel plate cancel each other out due to interference. For a cover thickness of 20 mm or greater, no significant difference in reflection intensity was observed. The results of the rebar specimens also show that the rebar inside the specimens could not be confirmed at any of the ACT. The above results are generally similar to those of previous research [4].

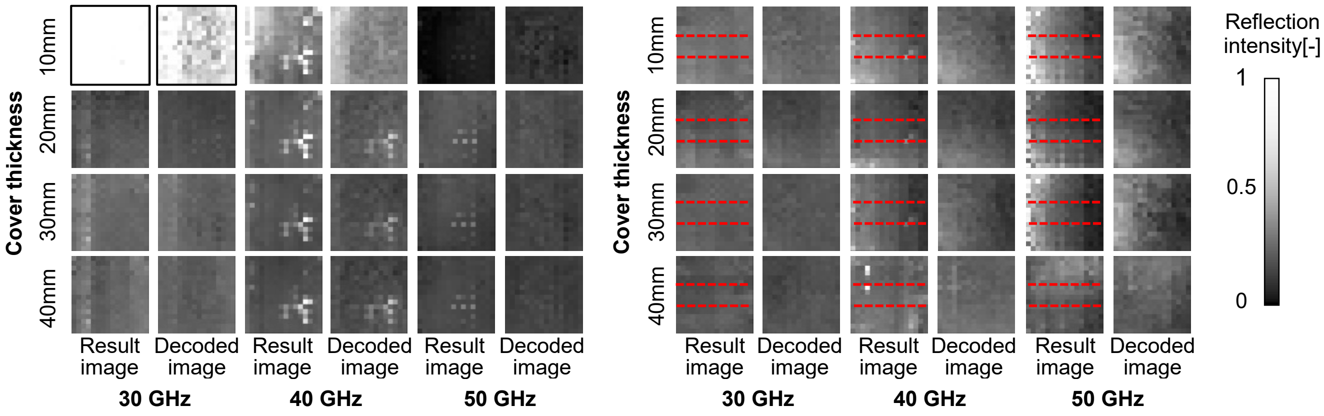

Figure 3. Images from measurement and unsupervised deep learning by each 10 GHz. **(a)** Measurement images from steel rebar specimen and decoded image by unsupervised deep learning. **(b)** Measurement images from rebar specimen and decoded image by unsupervised deep learning.

3.2. Results from supervised deep learning

Table 2 shows the confusion matrix of the ACT and the PCT of the steel plate specimens and rebar specimens. In the steel plate specimens, it is confirmed that the predictions are highly accurate for all cover thicknesses, especially for the ACT of 10 mm, 20mm, and 30mm. In the rebar specimens, the recall of the ACT of 10 mm and 20 mm is 96% and 91%, respectively. These above results suggest the possibility of predicting cover thickness, although it was impossible in the previous research [4]. In contrast, the recall for the ACT of 30 mm and 40 mm in the rebar specimens is 40% and 19%, respectively. This can be attributed to the limited availability of measurement images with sufficient reflection intensity for predicting cover thickness, due to differences in reflective surfaces.

Table 2. Confusion matrix showing the amount of data for the ACT and the PCT.

Amount of data		PCT from steel plate specimen					PCT from rebar specimen				
		10	20	30	40	Recall	10	20	30	40	Recall
ACT	10	104	0	1	0	0.99	101	0	0	4	0.96
	20	1	96	2	6	0.91	9	96	0	0	0.91
	30	0	1	100	4	0.95	13	17	42	33	0.40
	40	0	16	12	77	0.73	28	8	49	20	0.19
Precision		0.99	0.85	0.87	0.89		0.67	0.79	0.46	0.35	
F-score		0.99	0.88	0.91	0.80		0.79	0.85	0.43	0.25	

3.3. Results from unsupervised deep learning

Figure 3 shows the decoded images by the model on the steel plate specimen, and Figure 4(a) also shows some abnormal indexes. In this study, measurement images with the ACT of 40 mm were used for training, thus it can be confirmed that the abnormal indexes for the data with the ACT of 40 mm are quite small. On the other hand, the abnormal indexes for data with the ACT of 10 mm are high. From these results, it is confirmed that the abnormal indexes decreased as the ACT increased, and it is possible to identify the cover thickness from abnormal indexes with a small amount of data. Figure 3 shows the decoded images by the model on the rebar specimen, and Figure 4(b) also shows some abnormal indexes. These abnormal indexes indicate that it is possible to divide the cover thickness into four groups. However, unlike the steel plate specimens, no trend of abnormal indexes with respect to the change in cover thicknesses could be observed. Thus, it is expected difficult to identify the cover thickness from abnormal indexes.

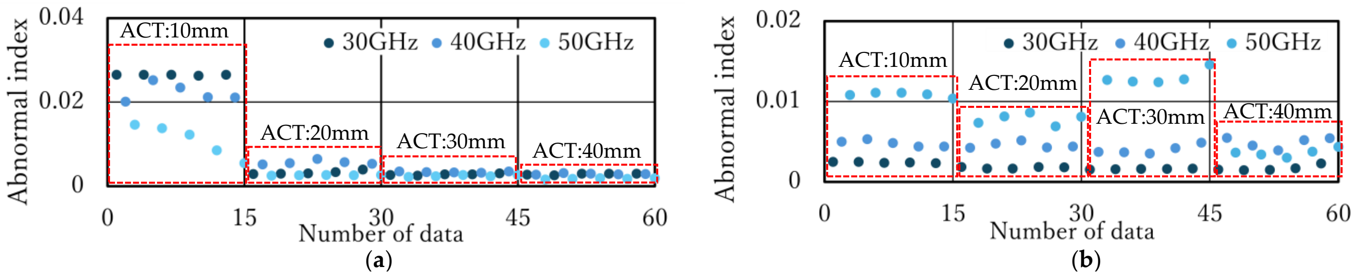

Figure 4. Clustering results by unsupervised deep learning. **(a)** Abnormal indexes by steel plate specimen every 10 GHz. **(b)** Abnormal indexes by rebar specimen every 10 GHz.

4. Conclusion

In this paper, we propose a deep supervised and unsupervised learning method to estimate cover thickness using sub-THz wave measurements. The findings are as follows:

1) The cover thickness of steel plates in concrete can be accurately predicted and classified using both supervised and unsupervised deep learning.
2) Supervised learning accurately predicts rebar in concrete up to a 20 mm cover thickness, but this accuracy declines at 30 mm and 40 mm.
3) Unsupervised deep learning enables clustering of cover thickness of rebar in concrete.

Author Contributions: Conceptualization, K.K. and T.N.; methodology, K.K.; software, K.K. and K.H.; validation, K.K., T.N. and K.H.; formal analysis, investigation, resources, data curation, and visualization, K.K.; writing—original draft preparation, K.K.; writing—review and editing, T.N. and K.H.; supervision, project administration, and funding acquisition, T.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by THE KAJIMA FOUNDATION's General Research Grants.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Z. Li.; J. Yoon.; *et al*. Machine learning in concrete science: applications, challenges, and best practices, *npj computational materials*, **2022**, *8(127)*, DOI: 10.1038/s41524-022-00810-x
2. S. S. Ansari.; H. Ansari.; *et al*. Comparative study of machine learning models for predicting the compressive strength of concrete using Non-Destructive Testing methods, *Materials Today: Proceedings*, **2024**, DOI: 10.1016/j.matpr.2024.04.009.
3. T. Tanabe.; Y. Oyama. THz non-destructive visualization of disconnection and corrosion status cover with opaque insulator, *IEEJ Transactions on Electronics*, **2019**, *139(2)*, pp. 149-153, DOI: 10.1541/ieejeiss.139.149
4. C. Kobayashi., T. Nishiwaki.; *et al*. Non-destructive testing of reinforced concrete structures using sub-terahertz reflected waves, *Developments in the Built Environment*, **2024**, *18*, 100423, DOI: 10.1016/j.dibe.2024.100423