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Recognition of wall boundary condition variance using convolutional neural network

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1. Introduction

When we considering the maintenance and monitoring of equipment, it is important to recognition of condition change. Because it is hard to observe the small changes with the naked eye, the skillful workers are needed to monitor the equipment.

In recent years, machine learning techniques have been developed dramatically because of the improvement of memory technology utilizing parallel computing. Machine learning can learn the feature of data and relationship between data. From the feature learned, the correlations are defined in the machine learning model. For example, MNIST data sets that collect images of numbers from 0 to 9 are learned with the machine learning model and the model can classify the images with high accuracy. The basic principle of the deep learning is making filter in the hidden layer. Number 1 has normally just a long line and number 9 has a long line and a circle in the end. Deep learning make the filter recognize this difference between number 1 and 9 like that human learn the difference through experience.

In this study, we would like to make the deep learning model classify the boundary condition. If the model could recognize the boundary condition change, we can easily get the information that the conditions of equipment has changed and operate those more stably just with the human.

2. Method

In this section, deep learning techniques are described from preparing the training data to making up the deep learning model.

2.1 Software to make the training data

Deep learning requires a lot of data for training the feature of those. In this study, SoundPLAN (noise modeling software) are used to make the training data. SoundPLAN is used in many engineering companies because of the high accuracy based on the law of physics. Ray tracing method is applied to the radiation of the sound and ISO specification is applied to the sound diffraction representation. Because these credible theory are applied, the training data are computed by SoundPLAN.

2.2 Geometry of training data

Geometry of data is a cube shape room. Length is 28m, width is 18m, height is 9m. It is assumed that the sound source is a simple monopole located in 4m(longitudinal), 9.5m(width), 1.5m(height). A wall has 10m width, 4m height. That moves 0.5m in the longitudinal direction. In the 1.5m height, sound pressure level(SPL) of 27 by 17 pixel image (longitudinal 27 nodes, width 17 nodes) is calculated by SoundPLAN according to the wall location like Fig.1. So the data of 52 cases are prepared for the training in the free field with a wall.

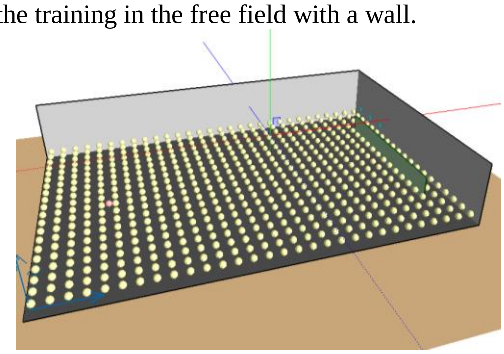

Fig. 1. Geometry of sound field analysis

2.3 boundary condition – wall

Just sound pressure field data cannot make the training model because our purpose is predicting the sound field with the boundary condition. So sound pressure field data are trained with the wall position and it will make that the model can learn the sound pressure variance according to the wall. Like Fig.2, the wall position image are made with same size of the sound pressure field data.

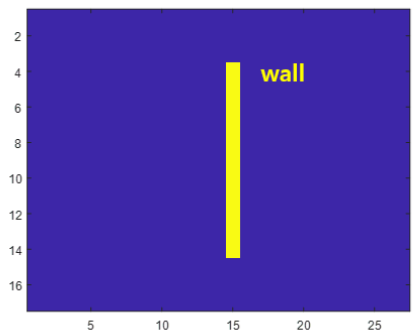

Fig. 2. Boundary condition of image

2.4 Deep learning model with convolutional neural network

The training data are made as the image format. For learning the features of image files, convolutional neural network is known that have good performance. Normally, more hidden layers make better results that reduce the loss of the model. But in this study, for preserving the image feature, 3 convolution layers model is chosen because the convolutional neural network make the input data size down. More convolution layers will make the 1 by 1 output image and lose the image feature.

2.5 Hyper-parametric study

In addition to creating a deep learning model architecture, hyper-parameter choices are important to learn the data feature. In this paper, the results are compared according to the activation function. Typically, sigmoid function, tanh function, ReLU functions are used as the activation function. If activation functions are linear, a lot of layers can be compressed as a simple layer. So non-linear activation functions are needed to make the relationship between the layers non-linear.

2.6 results

According to the activation function, loss of model are different. Especially, tanh function make good loss. It is estimated that tanh can represent minus value for output.

3. Conclusion

For the learning the sound pressure filed with the deep-learning model, convolutional neural network is chosen and applied. CNN can learn the sound pressure field variance according to the wall position. This results can show that boundary condition change can be recognized in AI. This technique will be extended to the monitoring something changed in the environment.

REFERENCES

[1] ISO 9613: Acoustics –attenuation of sound during propagation outdoors, 1996
[2] Z.Maekawa; Noise Reduction by Screens, Appl.Acoust. 1 (1968)
[3] UWe M.Stephenson, Simulation of multiple sound particle diffraction based on the uncertainty relation – a revolution in noise immission prognosis; part I : Principle and method, Euronoise 2018,
[4] Roska, T., & Chua, L. O. (1993). The CNN universal machine: an analogic array computer. *IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing*, *40*(3), 163-173.
[5] Shin, H. C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., ... & Summers, R. M. (2016). Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. *IEEE transactions on medical imaging*, *35*(5), 1285-1298.