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PREDICTION OF UNSTEADY HEAT TRANSFER OF TEMPERATURE FIELD ON A CIRCUIT BOARD USING SUB-VOXELS INPUT DATA STRUCTURE

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Abstract. In this study, we propose a sub-voxel learning method based on a Neural Operator and predict the thermal temperature field on a circuit board in unsteady heat conduction. CAE analysis reduces the cost of experiments using prototypes in the design phase. However, the computational cost is high because the number of trials increases due to changes in analysis conditions. Predictions made by machine learning are less accurate than those made by CAE analysis, but they can significantly reduce computational costs. In general, machine learning is difficult to extrapolate. Thus, the concept of a Neural Operator has attracted attention as one machine learning method incorporating physical laws. In this study, we propose a sub-voxel learning method based on the Neural Operator, inspired by the forward Euler method, and predict the thermal temperature field on a circuit board during unsteady heat conduction. The input data is the analysis data of the current cycle step, and the output data is the data of the next cycle step. Dummy temperatures were set according to the heat generation of each IC in the input data of the 0th cycle step, and pseudo-difference values were generated to extract features. The prediction accuracy of the next cycle step was compared with and without dummy temperatures. The results showed that the maximum

relative error decreased from 22.0% to 7.4%. After downsampling, the loss decreased at a slower rate. In addition, the number of data in the 20-40[°C] temperature field was reduced by more than half, and the learning cost decreased by 46.2%.

1 INTRODUCTION

In recent years, CAE analysis has been instrumental in reducing the number of experiments and costs in the manufacturing design process. However, high-accuracy CAE analysis remains computationally expensive. Our research offers a potential solution by proposing a machine learning method that is expected to provide accurate predictions in a shorter time than CAE. This could significantly reduce the computational costs associated with high-accuracy CAE analysis.

In general, it is challenging to predict extrapolation in regression problems. Physics-informed machine learning (PIML [1]), a method that allows machine learning models to learn the governing physical laws, has attracted much attention. PIML is a method for creating machine learning models by incorporating basic physical laws and domain knowledge as prior knowledge. Neural Operator [2-6] is an example of a PIML approach. Usually, simulations of physical systems are solved by giving initial and boundary conditions to the governing equations. Approximate solutions to the governing equations are obtained using numerical solution methods such as the difference method or the finite element method. However, if the governing equations of the physical system are not given or the equations are complex, it is not easy to find a solution. Then, there is a method called system identification, which black-boxes a physical system and models its behavior from data. Neural Operator is a method for system identification, where the physical system (partial differential equation) is modeled as a mapping between conditions (inputs) and solutions (outputs).

In this study, we propose a sub-voxel [7] method that adapts the Neural Operator to the forward Euler method (1), aiming to predict non-stationary heat conduction.

Forward Euler method formula:

$$y_{n+1} = y_n + h \cdot f(t_n, y_n) \tag{1}$$

2 UNSTEADY HEAT TRANSFER ANALYSIS AND GENERATION OF TRAINING DATASET

2.1 Analysis model

The board model is created and analyzed using scSTREAM, a thermo-fluid simulation software. Figure 1 shows an analytical model of a circuit board with dimensions of 80 mm × 80 mm. Five IC chips are placed on the board, and the heat generation [W] of each IC is as follows: yellow IC: 7 [W], purple IC: 6 [W], blue IC: 5 [W], and green IC: 3 [W]. Figure 2 shows an example of the analysis results. The training data is the thermal temperature field at each cycle step in the unsteady analysis. The initial temperature was set to 25°C, and the area around the circuit board was set to air (uncompressed/20°C). The flow field was laminar and incompressible, and the VF method was used for heat, taking radiation into account. An analytical model was created based on these conditions. After the analysis, input data design was conducted based on the data obtained (temperature, heat generation, IC placement, and so on).

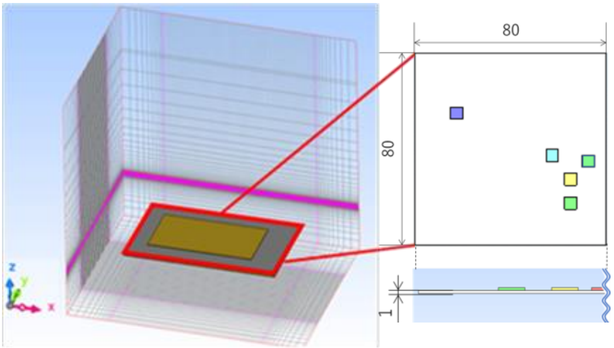


Figure 1: Simulation model of a circuit board with five IC chips.

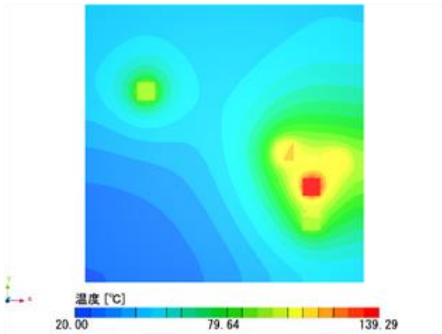


Figure 2: Temperature distribution analyzed by scSTREAM.

2.2 Sub-voxel

The predictor in our sub-voxel learning method uses local differential physical quantities and local material properties to compute the temperature at a given point. We propose a new learning method that uses subvoxels, which are containers of local physical quantities and material properties. The key innovation in our method is the use of the Neural Operator. This Operator allows the predictor to learn the physical laws by using the sub-voxel method, enhancing the accuracy and efficiency of our predictions. Figure 3 illustrates how the training data is extracted from the analyzed data using sub-voxels.

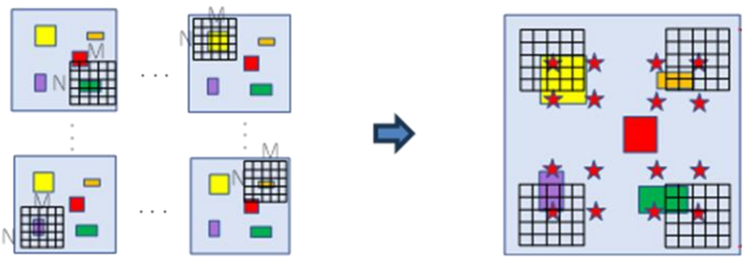


Figure 3: Example of placing sub-voxels.

2.3 Input data design

Figure 4 shows the input data design. The sub-voxel consists of 5 x 5 x 7 voxels. The main input parameters are temperature, difference calculation, and physical property values. The values are for first and second-order difference calculation and relative positions between IC and a center of sub-voxel. The first layer is temperature in sub-voxels.

The second layer is the temperature difference from the center of the sub-voxel in the x component. The third layer is the temperature difference from the center of the sub-voxel in the y component. The fourth layer consists of three physical properties. The first is the heat generation of 5 IC chips. The second is the distance vector between the sub-voxel center and 5 ICs. The third is the coordinates of heat sinks. The fifth layer is the second-order difference in the x component. The sixth layer is the second-order difference in the y component. The seventh layer consists of three physical properties. The first is coordinating the coordinates of five high-heat capacity bodies. The second is the heat generation of five IC chips. The third is with or without a heat sink.

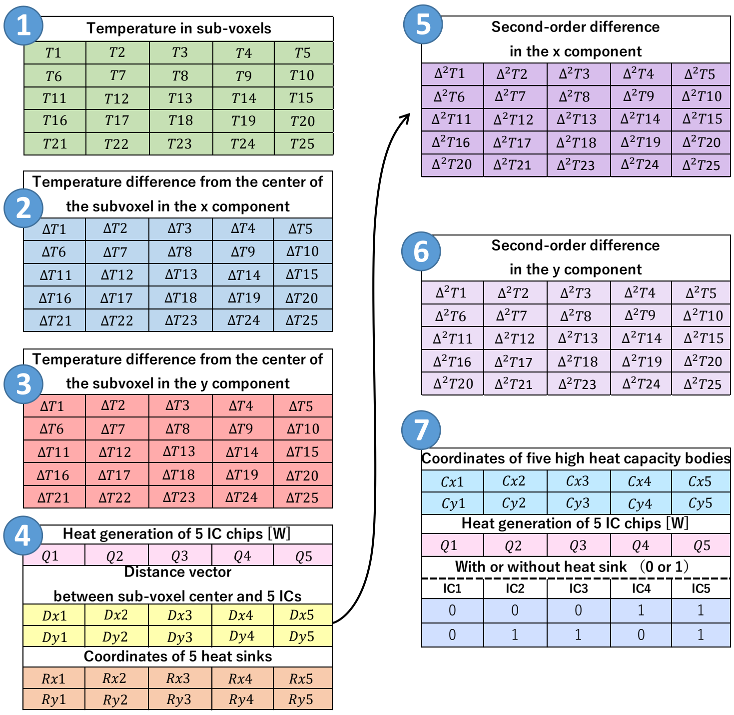


Figure 4: Input data design.

3 UNSTEADY HEAT TRANSFER PREDICTION METHOD

The network of the predictor consists of a two-dimensional convolutional neural (2D-CNN). Figure 5 shows the network configuration. Three all-combining layers are inserted after the convolutional layer in a centered manner. This auto-encoder structure compresses and restores information to remove noise and improve learning efficiency.

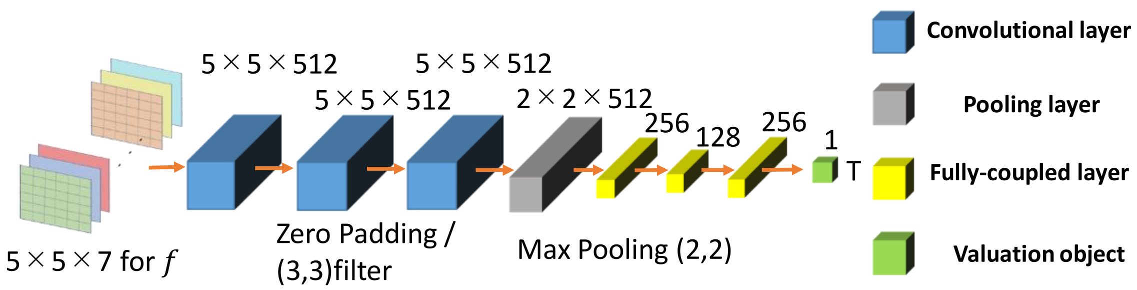


Figure 5: Network configuration for 2D-CNN.

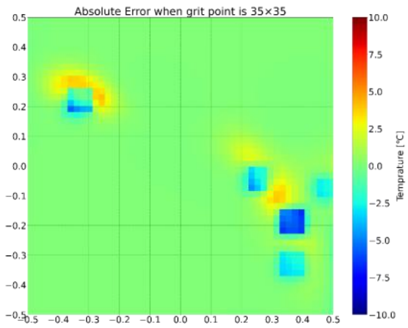
Hyperparameters of the predictor composed of 2D-CNN are shown in Table 1.

Table 1: Hyperparameter for 2D-CNN.

Activation function	tanh	Learning rate	5.0×10^-7
Optimization technique	Adam	Filter size	(3,3,7)
Loss function	MSE	Pooling size	(2,2,2)
Dropout	0.15	Convolutional layer	512-512-512
ResNet	off	Dense layer	256-128-256

4 SETTING DUMMY TEMPERATURES AND PREDICTION RESULT

A predictor was created to predict the temperature at the fifth cycle step based on the analysis data of the 0th cycle step. The number of measurement points on the circuit board was 1225, of which 1085 were training data, and 140 were validation data. Both the training and validation datasets were equally spaced on the circuit board. Figures 6 and 7 show the absolute error for each measurement point on the circuit board. Figure 6 shows the predicted results before downsampling, and Figure 7 shows the results after downsampling.



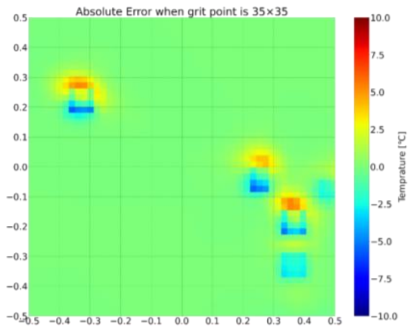


Figure 6: Absolute error without dummy temperature. **Figure 7**: Absolute error with dummy temperature.

Table 2 shows the maximum relative error with and without dummy temperature.

Table 2: The maximum relative error.

	Without dummy temperature	With dummy temperature
Maximum relative error [%]	22.010	7.429

Figure 6 and Table 7 show that the prediction accuracy error becomes lower when dummy temperatures are included. This is because the temperatures on the substrate at the 0 cycle step were all 20°C, and the difference value was 0, making it difficult to extract the feature values.

5 DOWNSAMPLING AND PREDICTION RESULT

The training data consisted of the input values from the 0, 5, 10, and 15 cycle steps and the reference values from the 5, 10, 15, and 25 cycle steps. For the validation data, the input values are the analysis values of the 0, 5, 10, and 15 cycle steps, and the output is the temperature of the next cycle step. For the validation data, the input values are the analytical values of the 0, 5, 10, and 15 cycle steps, and the output is the temperature of the next cycle step.

5.1 Analysis model of the training and validation dataset

The training data was created based on an analytical model with regular IC placement relationships for interpolation. Figure 8 shows the analytical model. The circuit board on the left is the analytical model used for the validation data, and seven analytical models for the training data were created based on the IC placement relationship of the analytical model for the validation data. Downsampling is a technique that reduces data for the majority of classes. It can improve prediction accuracy for minority classes by eliminating bias in the number of data between classes.

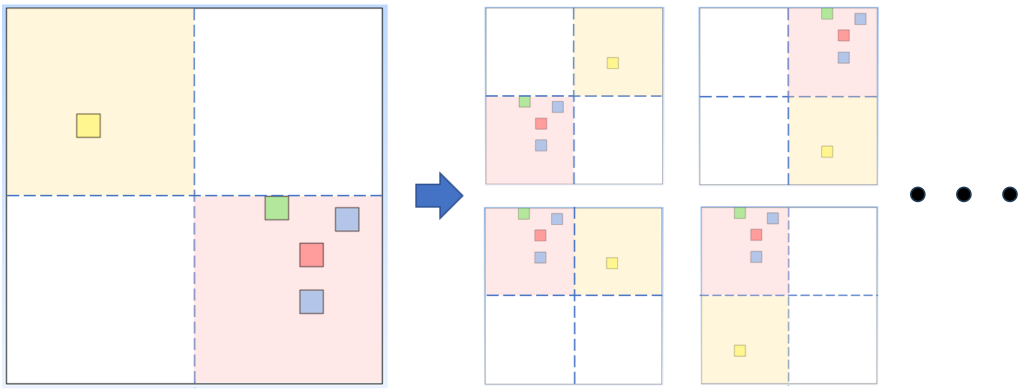


Figure 8: Creating an analytical model for interpolation.

5.2 Downsampling and prediction result

Table 3 shows the number of data and learning costs when downsampling temperature data at 20-40[°C].

Table ~~2~~: Number of data and training time in the range of 20-40[°C].

	Number of datasets : 20-40[℃]	Total	Percentage[%]	Training time[s/epoch]
Before	26329	34300	76.8	93
After	7904	15875	49.8	50

Table 3 shows that after downsampling, the number of datasets at 20-40[°C] is reduced, and the learning cost is lower.

The optimizer is Adam, the batch size is two, and the learning rate is 5.0×10^{-7}. The training dataset was trained for 10,000 epochs. Figure 9 shows the loss transition, and Figure 10 shows a comparison of reference and prediction, both before downsampling. In addition, the learning cost decreased by 46.2%.

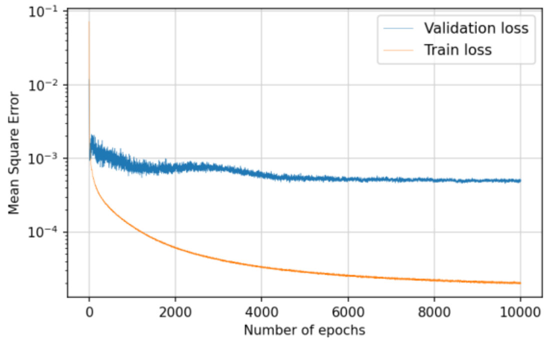


Figure 9: Transitions of validation and training losses.

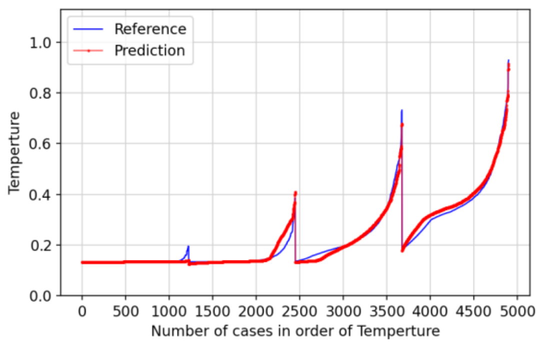


Figure 10: Comparison of reference and prediction.

The optimizer is Adam, the batch size is two, and the learning rate is 5.0×10^{-7}. The training dataset was trained for 10,000 epochs. Figure 11 shows the loss transition, and Figure 12 shows a comparison of reference and prediction, both after downsampling.

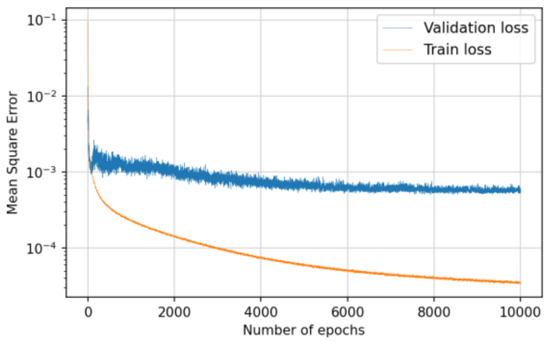


Figure 11: Transitions of validation and training losses.

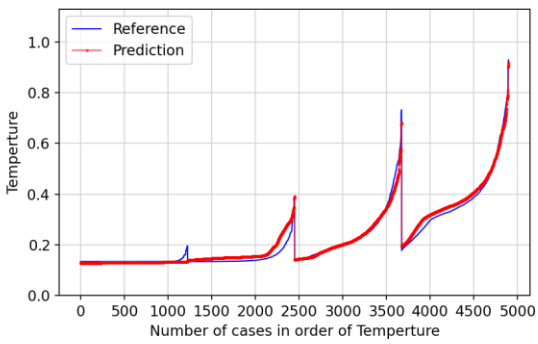


Figure 12: Comparison of reference and prediction.

Figures 9 and 11 showed a slower rate of loss reduction after downsampling. This is due to the reduced bias of the training data in the low-temperature field.

6 CONCLUSIONS

- We proposed a sub-voxel learning method based on the Neural Operator and were able to predict the temperature field on the circuit board in unsteady heat conduction.
- We created a predictor that interpolates by regularly placing ICs on the analyzed circuit board model.
- The learning cost was significantly reduced by downsampling the data in the low-temperature range of 20-40[°C].
- In the future, we will build a predictor that continuously predicts the temperature at each cycle step from the initial analysis conditions.

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