Deep Learning Based Prediction of Heat Transfer Coefficient Using Spectrogram Images from Boiling Sound

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Abstract

Cooling methods based on boiling have attracted attention as a thermal solution for electronic equipment. In this situation, it is necessary to measure the heat transfer coefficient (HTC) to design more efficient cooling systems. In this paper, we propose a method to predict of the HTC from boiling sound data using deep learning techniques. The accuracy improved by 1.12% compared to the conventional method through the development of Convolutional Neural Network (CNN) incorporate Convolutional Block Attention Module (CBAM).

Keywords: Boiling Sound, Heat Transfer Coefficient (HTC), Convolutional Neural Network (CNN), CBAM.

1. Introduction

The heat generation density of CPUs and GPUs is increasing year by year as they become more highly integrated [1]. Under these circumstances, the cooling method using water boiling is currently attracting attention. Boiling cooling has a high heat transfer coefficient (HTC) compared to gas forced convection cooling using heat sinks and fans [2], which is still in use today. Furthermore, since water serves as the boiling medium, it is environmentally friendly and economical. Since the boiling absorbs heat through the evaporation of the boiling liquid and the convection induced by the bubble motion [3], the HTC significantly depends on the number and size of the bubbles. In fact, the measured HTC shows a significant change when the number and shape of the bubbles are varied, as shown in Fig. 1. Therefore, it is important to accurately measure the HTC to develop more efficient and reliable cooling systems.

This paper proposes a method for predicting the HTC from spectrogram images of the boiling sound using Convolutional Neural Network (CNN). This method is based on the idea that there is a relationship between boiling sound and HTC. We conduct a classification task by categorizing the HTCs obtained through experiments into five classes. Then, we apply Convolutional Block

Attention Module (CBAM) [4] to a CNN model to improve the classification accuracy.

2. Method

2.1. *Creation of dataset*

We experimented with sound data acquisition to create a dataset of spectrograms. Then, this acquired sound data was transformed into a spectrogram using the Fast Fourier Transform (FFT) [5] to generate a 200 x 200 [pixels] image. Fig. 2 gave an overview of the experimental setup. A 1-mm-thick, 10-mm-square copper plate soldered to the top of a copper heater block into which cartridge heaters are inserted was used as a heat-transfer wall. Thermocouples inserted in the copper block were used to the surface measure temperature and heat flux. Before the boiling experiment, the pure water used as the boiling medium was degassed for more than 1 hour. Boiling sound was measured using Miniature Hydrophone Type 8103® [6] at a sampling frequency of 50 [kHz]. Table 1 shows the number of data for each the HTC class.

Fig. 1. Boiling state transitions and associated changes in the quantity and shape of bubbles

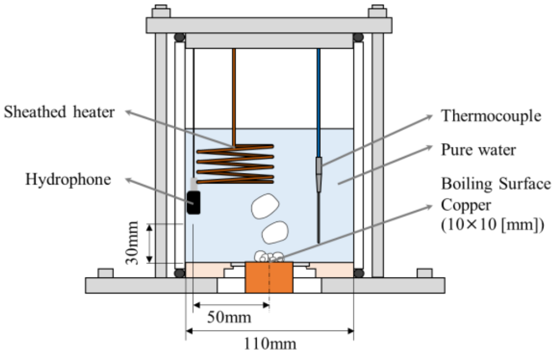

Fig. 2. Overview of experimental setup for sound data acquisition

2.2. *Classification by CNN*

The model is based on the CNN model developed by Tabata et al [7] and Sinha, K.N.R et al [8]. A basic block of CNN in Fig. 3 consists of a convolution layer (with a kernel size of 3 x 3 and 96 channels), batch normalization, ReLU functions (as activation functions) and average pooling (with a kernel size of 2 x 2). Then, four stacks of these blocks downsample the input images and construct a robust model against noise. We specify the labels for each class ranging from 10–20, 20–30, 30–40, and 40–50 [kW/m²/K]. These label numbers represent the HTC.

2.3. *Convolutional Block Attention Module (CBAM)*

In order to improve the accuracy of the conventional CNN model, we incorporate CBAM and compare its accuracy with that of the conventional model. The structure of the CNN model with CBAM is shown in Fig. 3. The CBAM architecture is based on the paper by S. Woo et al [4], where it is found that higher accuracy results can be obtained by connecting the Channel Attention Module and the Spatial Attention Module in series. The Channel Attention Module is a mechanism that learns and weights the importance of information in each channel based on the correlation of features between channels. The Spatial Attention Module is a mechanism that learns and weights the importance of information in the spatial axis, allowing the extraction of important information in the spatial direction in the feature map.

3. Experimental Result and Discussion

3.1. *Evaluation*

The evaluation method is the Five-Fold Cross Validation and average accuracy, which is the average of the accuracy of each class in the five-class classification and the average of the accuracy for all data in each dataset.

Table 1 The number of data in each class

Class [kW/m²/K]	Number
10–20	880
20–30	440
30–40	440
40–50	900
50–60	420
Total	3080

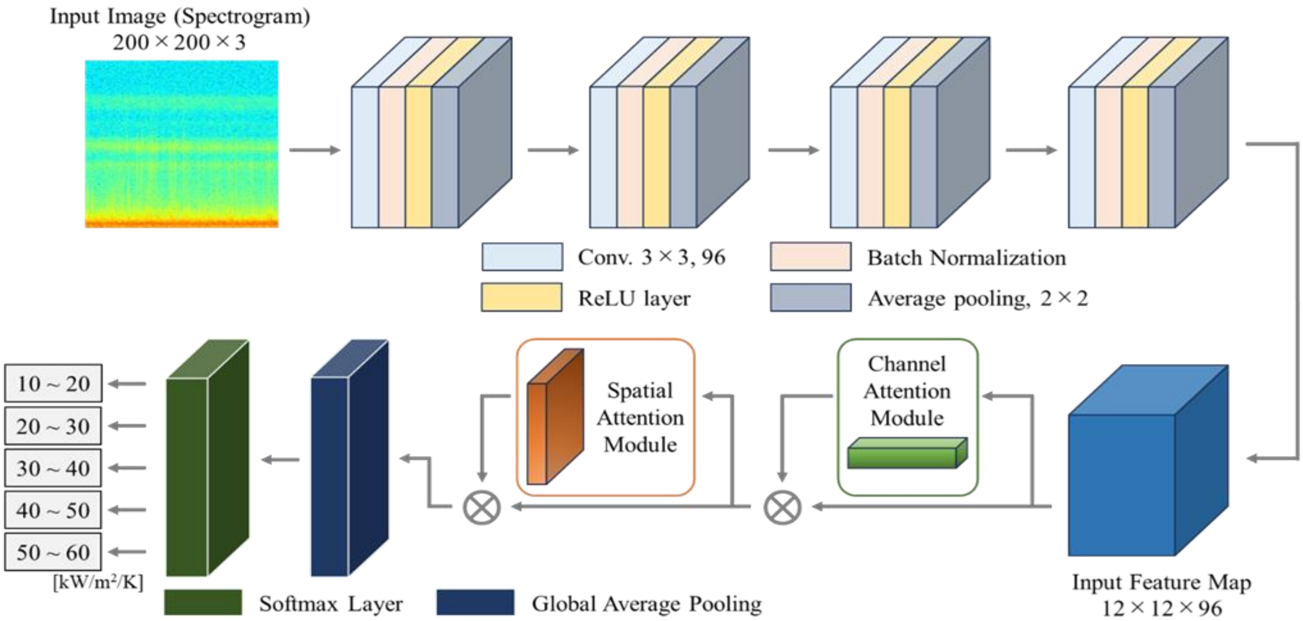

Fig. 3. Configuration of the proposed model with CBAM

(Accuracy is defined as the proportion of correct and predicted labels that match).

3.2. *Result*

The results of the proposed method using the datasets obtained from the experiments in Section 2.1 are shown in Table 2 and compared with the those of the conventional method. The accuracy in each class decreased by 1.09% in the 10–20 [kW/m^2/K] class and by 0.95% in the 30–40 [kW/m^2/K] class but increased significantly in the other classes. In particular, the accuracy in the 40–50 [kW/m^2/K] class improved by 3.38%. The average accuracy of the proposed method is 91.61% compared to 90.49% for the conventional method. That's an improvement of 1.12%.

3.3. *Discussion*

The main reason why the average accuracy was improved except for the 10–20 [kW/m^2/K] and 30–40 [kW/m^2/K] classes is that CBAM was able to extract the response of the constant-frequency component of the horizontal line, which is unique to each HTC. That allowed CBAM to maintain high accuracy even for noisy data sets. On the other hand, the inaccuracy could be attributed to the presence of various noises added during the creation of dataset, which aimed to construct a model that can be robust to noise. We have concluded that the spectrograms obtained from the experiments in Section 2.1 may not reflect the unique frequency characteristics found at each HTC. The spectrograms shown in Fig. 4 provide typical data for these classes, and we can recognize horizontal lines of constant frequency near the center of the images. On the other hand, Fig. 5 is an example of images that could not be classified correctly, showing that the features appeared in Fig. 4 are not clearly represented or are faded due to noises in Fig. 5. The CBAM mechanism may have made it more difficult to classify images like those in Fig. 5 by over-extracting features from data with typical features like those in Fig. 4.

4. Conclusion

In this paper, the incorporation of CBAM into the conventional CNN model decreased accuracy by 1.09% in the 10–20 [kW/m^2/K] class and by 0.95% in the 30–40 [kW/m^2/K] class, but significantly increased accuracy in the other classes, with the average accuracy improving by 1.12%. Future work will include increasing the number of experiments to build a CNN model that is more robust to noise, as one reason for the decrease in accuracy is the limited number of datasets. In addition, we will identify features common to each class and build a model that takes these features into account, with the aim of predicting the HTC in more detail and further improving accuracy.

Table 2 Results of five classes classification from spectrograms using two CNN model

	10 ~ 20	20 ~ 30	30 ~ 40	40 ~ 50	50 ~ 60	Average Accuracy [%]
CNN	95.01	84.90	88.45	90.08	89.80	90.49
CNN + CBAM	93.92	86.90	87.50	93.46	91.15	91.61

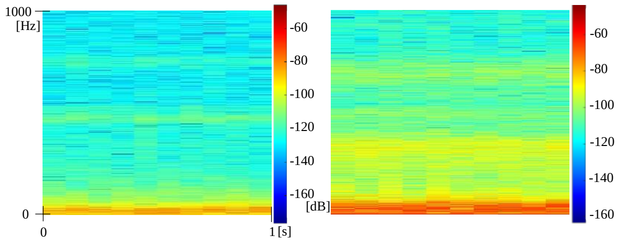

Fig. 4. Typical spectrogram of 10–20 and 30–40 [kW/m^2/K] class

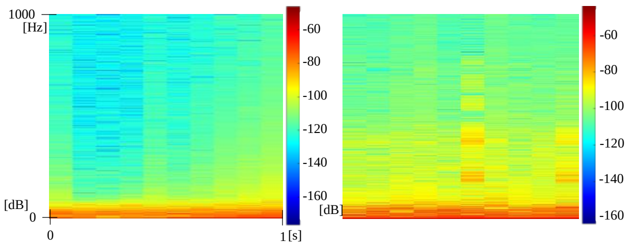

Fig. 5. Spectrogram of failed classification in the 10–20 and 30–40 [kW/m^2/K] class

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