Classification of Heat Transfer Coefficient Using Deep Learning Incorporated Boiling Images

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Abstract

Boiling cooling has been used as a cooling method for electronic devices due to its high heat transfer coefficient (HTC). The regularity of the boiling phenomenon is a crucial factor in the development of more efficient cooling systems. To develop such systems, it is essential to accurately measure the HTC, which is closely related to the boiling phenomenon. In this paper, we propose a method for predicting the HTC of two different heat transfer surfaces using deep learning with boiling sound and boiling images as inputs. The proposed method achieves an accurate improvement of 2.0% and 16.7% compared to models using only boiling sound and boiling images as input, respectively.

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

1. Introduction

As CPUs and GPUs become more highly integrated, their heat generation density continues to increase every year [1]. Under these circumstances, boiling water-cooling methods are attracting significant attention. Boiling cooling provides a significantly higher heat transfer coefficient (HTC) compared to conventional gas forced convection cooling methods using heat sinks and fans [1]. In addition, the use of water as the boiling medium ensures environmental sustainability and cost effectiveness. However, because boiling absorbs heat through the latent heat of liquid evaporation and convection along with bubble movement [2], HTC is largely dependent on the number and size of bubbles, which vary significantly depending on the surface roughness and wettability of the boiling surface. To develop more efficient and reliable cooling systems, it is crucial to clarify the relationship and regularity between the boiling behavior and the HTC, as well as to accurately measure the HTC, regardless of the properties of the boiling surface. In this paper, we propose

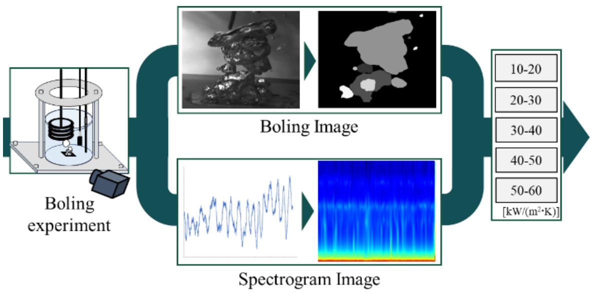

Fig 1. Overview of the proposed method with two input data

a method to predict HTC of two heat transfer surfaces with different nucleation site densities using a convolutional neural network (CNN) with two types of inputs: a spectrogram image of the boiling sound and a boiling image of the boiling behavior as shown in Fig. 1. The proposed method aims to develop a highly accurate prediction model by complementing each other with features that are not adequately captured by either the spectrogram or the boiling image alone.

2. Method

2.1. *Creation of dataset*

We conducted a boiling experiment to generate a data set for our proposed multimodal system. First, the sound data was processed to generate spectrogram images. The amplitude spectrum of the sound data acquired by the hydrophone [3] in the experimental setup as shown in Fig. 2 was calculated using a short-time Fourier transform (STFT) [4]. A 0.6 mm thick sapphire substrate with a sputtered titanium thin-film heater on its bottom surface is used as a heated wall as shown in Fig. 3. Additionally, artificial nucleation sites were formed on the heat transfer surface by patterning the superhydrophobic coating Glaco using photolithography. In this study, boiling experiments were conducted using two heat transfer surfaces with different nucleation site densities as shown in Fig. 3. Before the boiling experiment, the pure water used as the boiling medium was degassed for more than 1 hour through boiling degassing.

Harmonic/Percussive Sound Separation (HPSS) [5] was then applied to separate the harmonic and percussive components for the spectrogram. Then, a process called Linear Predictive Coefficient (LPC) [6] analysis was performed to generate spectrogram images. The boiling images were captured at a rate of 100 frames per second by the high-speed camera [7] shown in Fig. 2. The representative data of the boiling image corresponding to a given HTC was defined as the boiling image at the center time of each spectrogram in order to map it to the spectrogram data. The number of data for each class is given in Table 1.

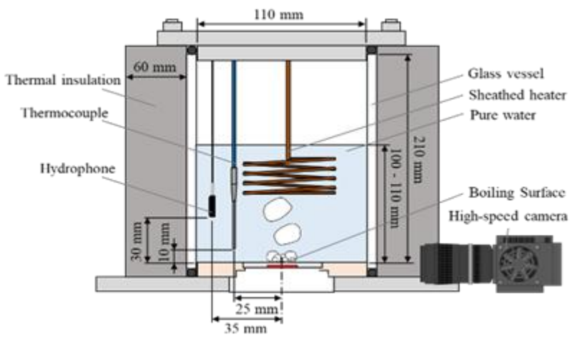

Fig 2. Overview of boiling sound experimental setup

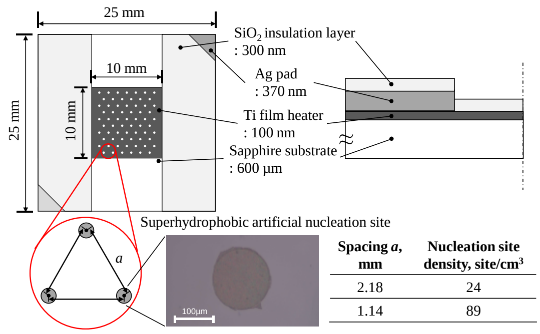

Fig 3. Sapphire substrate of the heated wall featuring superhydrophobic artificial nucleation sites

Table 1 The number of data in each class

Class [kW/(m^2·K)]	Number
10-20	960
20-30	1000
30-40	1000
40-50	980
50-60	600
Total	4540

2.2. *Classification for HTC*

The HTC prediction model proposed in this paper is trained using new features that integrate features obtained from spectrogram images using methods based on previous research [8] and Tabata et al. [9] and features obtained from boiling images using the method proposed by Suh et al. [10]. An overview of the entire system is shown in Fig. 4. The structure of each model is described below. We specify the labels for each class in the range of 10-20, 20-30, 30-40, and 40-50 [kW/(m^2·K)]. These label numbers represent the HTC.

2.2.1. *CNN with spectrogram*

The lower part of Fig. 4 shows the feature extraction model using spectrograms. The original spectrogram and the percussive component spectrogram generated by applying the HPSS to the original spectrogram were used as inputs. This is since the main component of the boiling sound is the percussive component, which is intermittent in the formation and bursting of bubbles and is considered to be an important element of the sound. A basic block of the CNN consists of a convolution layer (with a kernel size of 3 x 3 and 96 channels), batch normalization, rectified linear unit (ReLU) functions, and average pooling. Four stacks of these blocks then downsample the input images and construct a noise robust model.

2.2.2. *HyPR framework*

The upper part of Fig. 4 shows the feature extraction model using boiling images, where VGG16 [11] and the instance segmentation models MaskR-CNN [12] and Multi-Layer Perceptron (MLP) are used to extract features from the boiling images themselves and statistical data such as the number and size of bubbles, respectively, to

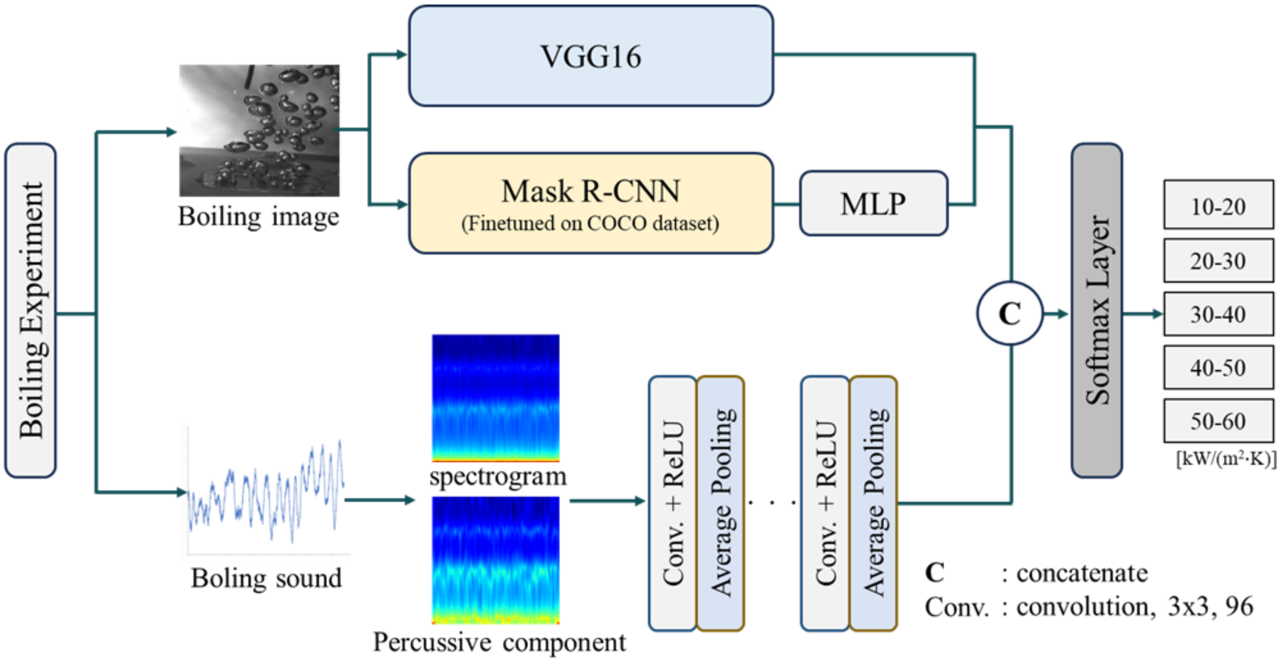

Fig 4. Detailed structure of the proposed method model

learn the nonlinear relationships between the images. We use a fine-tuned model in the COCO dataset for MaskR-CNN.

3. Experimental Result and Discussion

3.1. *Evaluation*

The generalization performance of the model is evaluated using fivefold cross-validation. The evaluation metric is accuracy, defined as the proportion of correct and predicted labels that match. The average accuracy is the mean of the accuracy for the validation on each dataset.

3.2. *Result*

An average accuracy of 90.2% was achieved with the proposed method CNN(spec)+HYPR model, the multimodal system using boiling images and spectrograms. When HTCs were predicted by each model alone, the accuracy was 88.2% for the HYPR model and 73.5% for the CNN(spec) model, an improvement of 2% and 16.7%, respectively.

3.3. *Discussion*

We discuss the classification results obtained in Section 3.2. First, Table 2 shows that the HyPR model achieved high accuracy despite using only boiling images as input, although the values for datasets 1 and 5 were low. This is probably since the input was a boiling image at a given time, which could not adapt to rapid changes in the bubbles, such as bubbles merging or separating. Figure 5 shows an actual boiling image that was misclassified by the HyPR model. On the other hand, the proposed method consistently achieved high classification accuracy on most datasets and was able to correctly classify data between adjacent classes, which was not possible with the HyPR model. The reason for this may be that the spectrogram images contain information within a certain time before and after each boiling image, which makes it easier to distinguish between other classes of images that suddenly become similar. In other words, while maintaining the high classification accuracy of the HyPR model, the addition of spectrogram information reduces the misclassification of adjacent classes and improves the accuracy of the model.

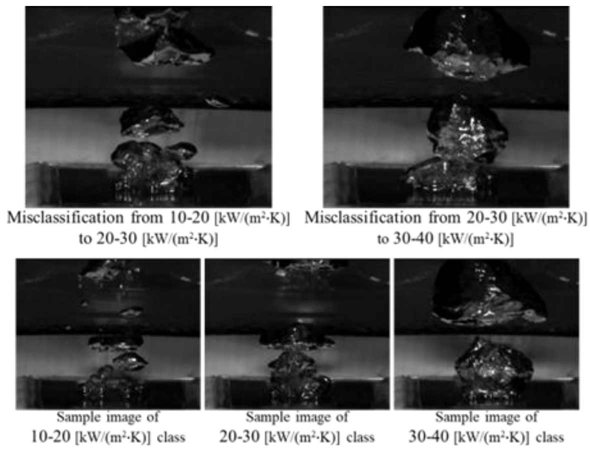

Fig 5. Comparison of misclassified images and boiling images at each HTC

Table 2 Comparison of accuracy for each model

	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5	Average acc [%]
CNN (spec) + HyPR	0.9	0.832	0.931	0.977	0.87	0.902
CNN (spec)	0.821	0.853	0.69	0.673	0.637	0.735
HyPR	0.842	0.859	0.92	0.977	0.811	0.882

4. Conclusion

The proposed methods using multimodal systems resulted in an improvement in accuracy of 16.7% and 2.0%, respectively, compared to the conventional methods of CNN(spec) and HyPR model, despite the difference in heat transfer surface properties. In future work, we would like to improve the segmentation accuracy of MaskR-CNN in the HyPR framework by adding image processing, such as contrast enhancement of the boiling images. The CNN(spec) model contains only one second of boiling sound information in the spectrogram image, which may be insufficient for accurate analysis. To improve the accuracy of the model, it would be beneficial to include data from a longer period. In addition, modifying the feature integration method could further improve the performance of models.

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