On the Use of Artificial Intelligence to Accelerate the Processing and Analysis of High-Throughput High-Resolution Experimental Boiling Heat Transfer Data

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Abstract. Boiling heat transfer is a cornerstone of energy systems, providing efficient thermal management in applications ranging from nuclear reactors to advanced thermal malmanagement technologies. State-of-the-art, high-resolution optical diagnostics offer a unique opportunity to shed light on these phenomena. However, experimental investigations in this domain generate large volumes of high-resolution, high-throughput data from advanced techniques such as infrared thermography, phase detection imaging, laser-induced fluorescence and particle velocimetry methods. The scale and complexity of these datasets present significant challenges for traditional analysis methods, creating bottlenecks in deriving actionable insights. This contribution explores the transformative potential of artificial intelligence (AI) to address these challenges, focusing on the application of machine learning (ML) architectures to accelerate and enhance the analysis of experimental boiling heat transfer data. Specifically, we demonstrate how convolutional neural networks (CNNs) and transformer-based models can be utilised for automated processing of infrared thermometry and phase detection datasets, enabling efficient extraction of spatial and temporal characteristics of boiling phenomena. Additionally, we discuss AI's ability to process planar laser-induced fluorescence (PLIF) based measurements of liquid-phase temperature fields. Through a detailed review of the state-of-the-art, we highlight recent breakthroughs and current limitations in applying AI to the analysis of data produced by these techniques. We also identify critical opportunities for integrating AI-driven data analytics into experimental workflows, emphasising the potential for real-time feedback, predictive modelling, and enhanced understanding of boiling mechanisms. Our findings underscore the growing importance of AI as a catalyst for innovation in boiling heat transfer, enabling researchers to overcome traditional barriers to data interpretation. By bridging experimental thermal sciences with cutting-edge AI methodologies, this work aims to inspire new research directions and foster interdisciplinary collaboration.

1. Introduction

Boiling heat transfer is an essential heat removal process encountered in many thermal energy systems. Accurate prediction of boiling heat transfer and a fundamental understanding of all boiling heat transfer mechanisms is therefore critical. One modelling paradigm that aims to achieve these goals is heat flux partitioning (HFP), which assumes that the total heat flux of the boiling surface can be expressed as a sum of several individual heat transfer mechanisms, such as microlayer evaporation, forced convection, and quenching heat transfer [1]. These individual heat transfer mechanisms can be determined from first principles if the fundamental boiling parameters (including nucleation site density, bubble size, growth time, and departure frequency) can be experimentally measured. It was only until recently that these parameters could be successfully experimentally measured thanks to advances in high-speed infrared (IR) thermometry and high-speed video (HSV) [2], which has provided a better understanding of the underlying mechanisms and more generalizable modelling frameworks. However, these advanced diagnostics, and others, including liquid-vapor phase detection (PD) [3], and planar laser-induced

fluorescence (PLIF) [4], generate voluminous data that are difficult to post-process in a generalizable manner (if we limit ourselves to conventional image-postprocessing techniques). These constraints pose major space and time constraints that make data-postprocessing the bottleneck in these investigations.

It is for these reasons that artificial intelligence (AI) is starting to become an integral part of data processing and analysis in boiling heat transfer research. Ravichandran et al. [5] demonstrated that neural networks can be constructed to extract the fundamental boiling parameters from raw IR thermometry data in real time, enabling rapid analysis of the data and comprehension of the results. Other works have leveraged HSV measurements to reconstruct the boiling curve in its entirety [6,7] or have used these measurements to deduce how far the operating condition is from the boiling crisis [8,9]. However, there are circumstances where data beyond boiling parameters or the proximity to criticality are important, such as the formation and evolution of dry areas [10]. Additionally, other information, such as the evolution of thermal boundary layer and change in temperature fields (data that can be obtained from PLIF), is important in order to better understand changes in heat transfer mechanisms. For these applications, robust and computationally efficient image segmentation algorithms are necessary, a need which is perfectly suited for machine learning (ML) models such as convolutional neural networks (CNNs). Therefore, in this work, we evaluate the broad reach and applicability of this modelling framework to segment IR, PD, and PLIF measurements. Specifically, we segment bubbles from these measurements and discuss how the technique can be extended to extract other important features related to the boiling process.

2. Advanced diagnostics

2.1. Pool boiling IR and PD segmentation

IR thermometry and PD videos are obtained from a pool boiling experiment, where the working fluid is water at atmospheric pressure. A schematic of the experimental apparatus and optical setup are shown in Figure 1a. Briefly, distilled water is degassed and maintained at saturated temperature inside a stainless-steel isothermal bath. At the bottom of the pool boiling facility is an optically transparent and infrared opaque thin-film heater (10 mm × 10 mm × 700 nm thick coating of indium tin oxide (ITO) deposited on 1 mm thick, 25 mm diameter sapphire substrate). The temperature of the heater is measured with an infrared camera (using the calibration technique by Bucci et al. [11]) at a 120 μm pixel^{-1} resolution and 0.4 ms temporal resolution. We then apply a radiation-conduction inverse problem to determine the local wall heat flux as a function of time. The PD images of the heater, on the other hand, are recorded (using the methods outlined in Kossolapov et al. [3]) at a 10 μm pixel^{-1} spatial resolution and 0.13 ms temporal resolution, which allows for direct imaging of the liquid-vapor distribution (i.e., liquid, vapor, and microlayer region) at the wall. To obtain both infrared thermometry and phase-detection at the same time, we use an IR (FTO) mirror and beam splitter to direct the light to our separate infrared and high-speed cameras. The cameras (IR: IRC806 high-speed infrared camera with a 100 mm IR lens recording at 2500 fps at a spatial resolution of 120 μm pixel^{-1}, PD: Phantom v25 high-speed camera with a Nikon 200 mm f/4D IF-ED Fixed Zoom lens recording at 7000 fps with a spatial resolution of 30 μm pixel^{-1}) are then triggered from the same signal to ensure the data are synchronized. More detailed explanation of the facility and test procedures can be found in earlier studies (e.g., Ref. [12]).

2.2. Flow boiling PLIF segmentation

PLIF data are acquired from a vertical upward flow boiling experiment using degassed HFE-7100 as the working fluid at nearly ambient pressure, the experimental apparatus of which is schematically shown in Figure 1b. Briefly, the test section is a square minichannel made of transparent polycarbonate with a cross section of 5 × 5 mm. A sapphire substrate (80 mm × 10 mm × 0.5 mm) coated with a 200-nm thick ITO film is mounted flush on one of the walls of the channel and is used as an electrical heater. The working liquid is seeded with Nile Red as the fluorescent tracer dye at a concentration of 7.5 mg/L, with ethanol used as an auxiliary solvent at a volume fraction of 2.5 vol.-%. The optical measurement system comprises a high-speed Nd:YLF laser (527 nm, 20 kHz) fitted with LaVision sheet optics, two sCMOS Phantom VEO-E 310L high-speed cameras (1280 × 800 pixels; 12 bit; pixel pitch = 20 μm) each equipped with a

Sigma 105 mm f/2.8 EX DG Macro lens, three extension rings (36 mm, 20 mm and 12 mm) and an appropriate band-pass optical filter (540–570 nm and 650–750 nm). The cameras capture images at a spatial resolution of 11.5 µm pixel^{-1}, synchronised with the laser using the DaVis software at a sampling frequency of 3000 fps. The fluorescence emissions from the two oppositely temperature-sensitive spectral bands of the fluorophore are captured separately by the two cameras observing the test channel through a beam splitter, in front of which a notch filter is used to cut off the excitation wavelength of the laser radiation, thus enabling a ratiometric analysis of the intensities of both signals as a function of temperature. After a series of post-processing procedure including background subtraction, spatial correction, flat field correction and intensity ratio calculation on the raw images, two-colour ratio maps are obtained, which are finally converted to temperature maps using an in-situ temperature calibration curve. More details about the flow boiling test facility and PLIF measurements can be found in the previous study [4].

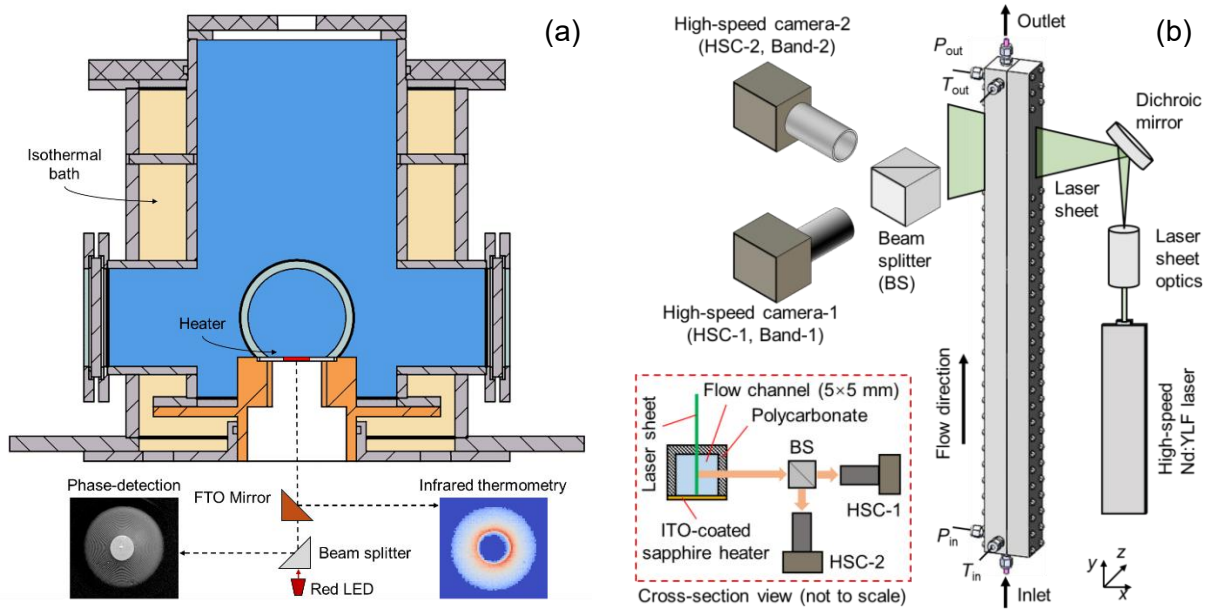

Figure 1. (a) Pool boiling facility and IR/PD diagnostics; (b) flow boiling facility and PLIF diagnostics.

3. Transfer learning and model development

Briefly, CNNs are a class of deep feedforward neural networks that aim to extract local features of an image. This is done by performing convolutions on the input feature maps with a fixed number of kernels at some predefined size. For this study, we employ the U-Net framework originally proposed by Ronneberger et al. [13], schematically shown in Figure 2. Essentially, the network contains an encoder-decoder style, where the encoder part of the CNN downsamples the original image but retains key pieces of information that describe the structure of the image. The decoder then reconstructs a segmented image of the input based on those fundamental features of the image. Concatenation is also employed to combine the detailed and abstract features of the image to obtain more precise segmentation results. To minimize training time and procurement of ground-truth data, we leverage transfer learning [14], which essentially borrows weights obtained from training on extremely large datasets, thus eliminating the need for millions of ground-truth images. In fact, this study only requires 20 images of bubbles for training and validation and can use the same model architecture to segment bubbles from a variety of different optical diagnostics of boiling.

To train the model, we use pre-trained weights obtained from ImageNet [15] data and freeze all the weights of the encoder. Then, we take 75% of the dataset (consisting of 256 × 256 RGB images) to train the model and use 100 epochs and a learning rate of 10^{-5} to refine the decoder weights. Then, we unfreeze all weights and perform 5-fold cross validation to optimize the model weights. This process is repeated for the IR, PD, and PLIF measurements and the final models are stored and used later to perform bulk postprocessing of

all the images from the experimental campaign. It should be noted that the rectangular PLIF images are tiled and resized so that square images can be sent to the CNN model for training and testing.

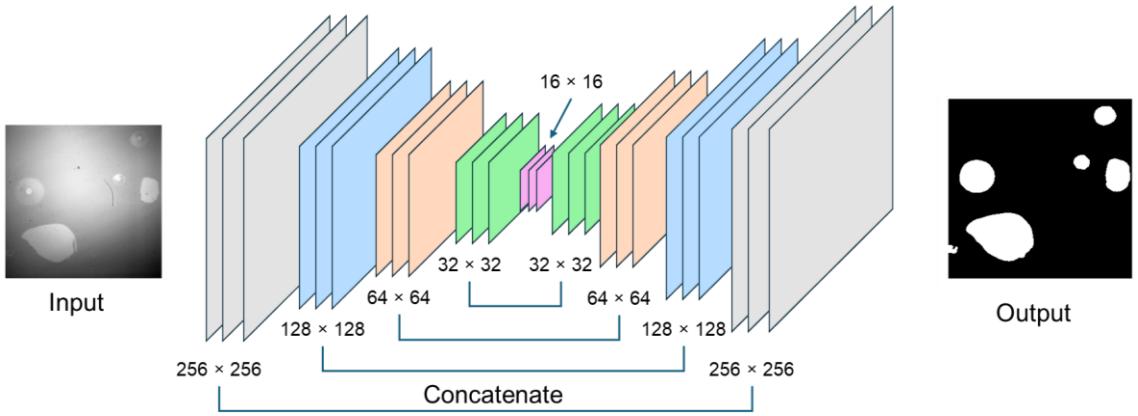

Figure 2. CNN model architecture. The input is a phase detection image based on which the CNN evaluate the bubble footprint area (output image).

4. Sample results and future applications

Figure 3 illustrates the ability of the CNN to segment bubble footprints (i.e., the dry spot and microlayer region) from raw IR and PD images. It can be seen that these images can be easily segmented with this approach. In fact, the training and testing results yielded a F1 score of 0.963, indicating the model has excellent precision and recall performance. This is to be expected as it has been highlighted in past works that this kind of encoder-decoder architecture is known to be highly adaptable to different types of images with different levels of brightness, contrast, and abstract features [16, 17]. This makes it much easier to analyse a wide range of optical data and provides more robust segmentation capabilities. For instance, conventional image segmentation using approaches such as adaptive thresholding may not be able to track where bubbles originated from. In this framework, it is possible to train the CNN to separate bubbles growing from different nucleation sites even if nearby bubbles have coalesced.

Figure 4 shows a sample of the PLIF temperature fields and corresponding bubble segmentation images from the same CNN architecture used to segment IR and PD images. Here, we note that the bubble volume is being segmented in the PLIF images, as opposed to the bubble footprint which was segmented in the IR and PD images. Overall, the model was able to segment all images (~18,000) with an F1 score of 0.937. It can be seen that apart from the vapour bubbles (shown as the discrete, nearly circular or elliptical domains on the heated wall), the original PLIF image contains many complex features, such as a thermal boundary layer near the wall (shown as a thin high-temperature layer in red-green colour on the heated wall) and thermal plumes or vortical structures (shown as the green regions in the bulk flow). Yet, the CNN can accurately separate bubbles from these complex structures, even with a limited amount of training data that cannot encompass all possible combinations of thermal plumes, bubble locations, and thermal boundary layer thicknesses. After training the CNN with the data from one boiling condition (4.6 kW/m^2), it can be used to accurately segment bubbles for the data in another condition (5.2 kW/m^2), which was not used in any training of the CNN. This demonstrates that CNN-based segmentation can extract bubble features in images that are even more complex than the past IR and PD images that have been explored in previous works.

Beyond bubble detection, this technique can also be applied to track thermal features and changes in the temperature field of the liquid phase, such as thermal boundary layers, thermal plumes, and thermal vortical structures. The presence of such events can then be compared with the times bubbles are present to understand the role of bubble dynamics such as nucleation, growth, and motion on the temperature field of the surrounding liquid. The interactions between the vapour and liquid phases can then be clearly

revealed to investigate the heat transfer mechanisms of boiling flows from a fundamental view. Further applications include combining the outputs of this optical data with the bulk operating conditions of the flow to predict heat transfer coefficients of a multiphase flow ahead of time, which can be used as a potentially powerful tool for optimization design in research and industry.

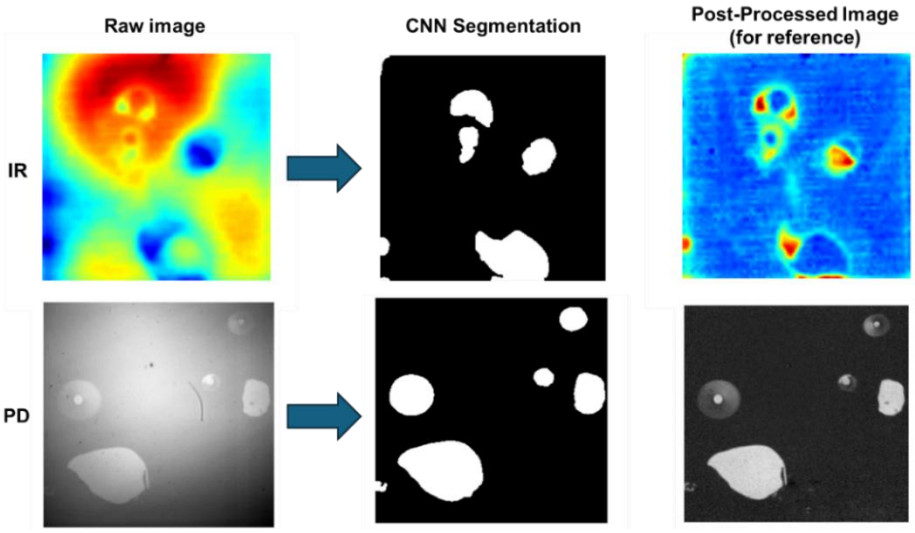

Figure 3. IR and PD CNN segmentation model results. Post-processed images are also shown for reference to more clearly illustrate what is being segmented.

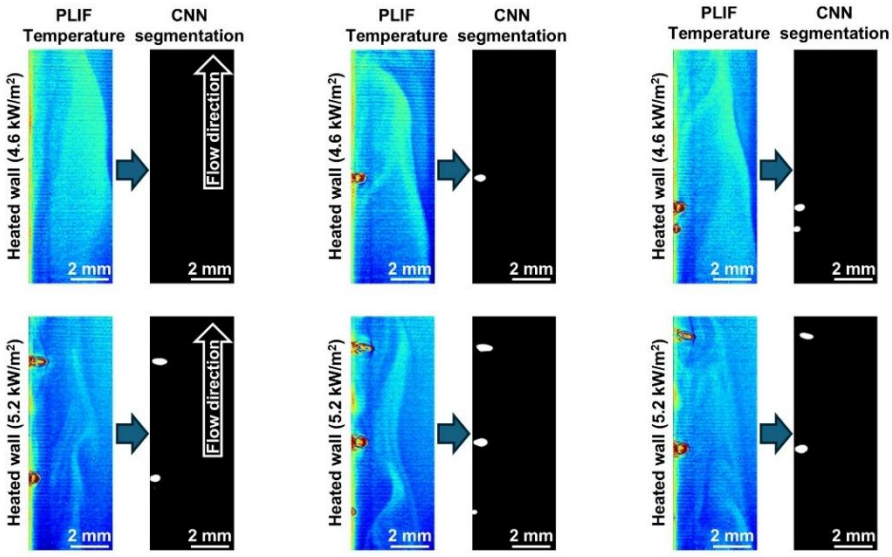

Figure 4. PLIF CNN segmentation model results. NV: the 5.2 kW/m^2 data was not used for any training.

5. Conclusions

In this study, we have shown that the very same tools used to automate image segmentation of IR thermometry and PD videos can be readily applied to PLIF measurements. This was achieved by developing a CNN model inspired by the U-Net framework with pre-trained weights from an extremely large and extensive image database. The weights are then adjusting by providing 20 images, and corresponding ground-truth segmentation images, to fine tune the parameters and ensure accurate segmentation. Results show that extremely accurate and computationally efficient image segmentation can be obtained with the use of AI, and we discuss how to extend these capabilities further to extract

liquid-phase temperature field features, such as changes in thermal boundary layers and evolutions of thermal plumes and vortices, as well as prediction of heat transfer performance.

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