CNN-based visual analysis to study local boiling characteristics

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Abstract. Visual analysis allows an estimate of different local boiling characteristics including bubble growth rate, departure diameters and frequencies of nucleation, nucleation site density and evolution of bubbles and dry spots in time. At the same time, visual determination of the presented characteristics in case of big amounts of data requires the development of the appropriate software which will allow not only determination of bubble location, but also an estimate of their sizes based on high-speed video. The presented problem can be solved by using the instance segmentation approach based on a convolutional neural network. In the presented work Mask R-CNN network architecture was used for estimation of the local boiling characteristics.

1. Introduction

Nowadays, in the literature on boiling process a special attention is paid to its local characteristics, such as the bubble departure diameters, the bubble growth rate, the nucleation site density and the frequency of nucleation. This interest relates to the fact that these characteristics are directly associated with the heat transfer rate and the development of crisis phenomena \[1, 2\]. To study the local boiling characteristics a high-speed video recording is used most often \[3-7\]. The most convenient way to visualize the boiling process is high-speed video recording through a transparent heater \[6, 7\] because such format of visualization, in contrast to side view visualization, allows you to observe each bubble on the surface of the heater. This advantage simplifies the study of the abovementioned local boiling characteristics.

The development of computer and digital technologies can significantly simplify the processing procedures of experimental data, including visual measurements. In particular, the automation of experimental data processing allows the detailed statistical analysis based on a large amount of data. In the case of visual data processing, the main task of automation is identification and marking out of objects in the image for subsequent post-processing in terms of measuring their characteristics.

Nowadays, convolutional neural networks are the most powerful and promising tools for identifying objects in an image \[8\]. They are well suited for problems that are difficult to formalize, such as the problem of recognizing an individual bubble during boiling, especially at high heat fluxes.

Difficulties of this problem relates to the fact that at high heat fluxes frequent mergers of neighboring bubbles results in complex shapes of bubbles. Furthermore, there are a large number of detached and floating bubbles, which create an undesirable background for identifying bubbles attached to the surface of the heater.
The goal of the presented work is to train a neural network that will be able to recognize the bubbles located directly on the surface of a transparent heater at boiling of saturated water.

2. General approach
To locate the bubbles and estimate their diameters we have used the instance segmentation of the video stream where the bubbles acted as the segmented objects. During instance segmentation a set of bit masks will be generated for input image. All generated masks correspond to the detected locations of the detected objects. Unlike the case of semantic segmentation where the only one mask will be generated for each class of objects, in case of instance segmentation a separate mask will be generated for each of the detected objects.

Nowadays, the most efficient algorithms of instance segmentation are based on convolutional neural networks. Such approach allows additional training of the pretrained models for the given classes of problems. So, preparation of balanced training and validation datasets is the most important part of the presented work.

We used our own tool for additional training of the neural networks as well as for instance segmentation of the objects in images and videos. The tool was developed in Python and was based on the following project: https://github.com/matterport/Mask_RCNN.

3. Dataset preparation
To train the neural network we used the data on the evolution of vapor bubbles, obtained in [6, 7] during the experiments on saturated water boiling at subatmospheric pressures in the range of 8.8 – 101.3 kPa. The main feature of these studies is the use of a special heater design presented in figure 1; it is a film (1 μm thick), transparent in the visible wavelength range ITO (indium tin oxide), deposited on a 3-mm thick sapphire substrate by ion-plasma sputtering. This design of the heater allows visualization of the boiling pattern from the bottom side, through a transparent heater. Such a format of visualization has a number of advantages as compared to visualization of the boiling process from the side. At visualization from the side view, a problem arises due to the fact that, even at low heat fluxes, activation of a small number of nucleation sites leads to overlapping of bubbles. Overlapping of the bubbles makes it difficult to select individual vapor bubbles and, consequently, to determine their characteristics. At the same time, as it is shown in figure 2, visualization from the bottom side allows obtaining a wide range of data on the local boiling characteristics, including the density of nucleation sites, the frequency of nucleation, departure diameters of bubbles, as well as studying the evolution of individual bubbles and plotting their growth curves. The described experiments were carried out using a high-speed video camera «Vision Research» Phantom v.7.0 with a resolution of 800x600 and a frequency of up to 5000 fps. The spatial resolution in the experiment was 35 μm per pixel.

**Figure 1.** The scheme of the transparent heater [6, 7].

**Figure 2.** A frame of high-speed visualization of the boiling process from the bottom side of a transparent heater at atmospheric pressure and heat flux density set to 100 kW/m².
4. Results and discussion

In the presented work we used the Mask R-CNN network architecture because it allows the instance segmentation with high accuracy even in case of small training dataset size. The result of work of the neural network is a set of bit masks corresponding to localization of bubbles for each frame of the high-speed video.

The results of instance segmentation of one of the frames are presented in figure 3. All the detected objects have been classified, localized with bounding boxes and masked in accordance with their real shape. The goal of the frame processing was to detect all the bubbles attached to the heater and ignore all the detached bubbles. As you can see from the presented image, the current implementation of the bubble segmentation software works correctly in most cases, but it still can fail and mark detached bubbles if the bubbles are small and there are flares of their surfaces like in case of a small bubble at the bottom-left of the frame. We are currently working to increase the selectivity and accuracy of the segmentation software and hope to avoid such kind of errors in the future. We also plan to implement a multi-frame analysis algorithm that will fix the errors of single-frame segmentation.

Using the retrieved data, it is possible to estimate such local boiling characteristics as bubble growth rate, departure diameters and frequencies, nucleation site density, etc. The presented approach can be used not only for visual analysis of two-phase layer evolution in case of boiling, but also for a wide range of problems, e.g., for analysis of gas phase characteristics of multiphase flows in different applications such as mini and micro channels.

Figure 3. Results of the instance segmentation performed by Mask R-CNN.
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