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Determination of Void Fraction in Microchannel Flow Boiling Using Computer Vision

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Extended Abstract

The void fraction is one of the most critical parameters for characterizing two-phase flow boiling in microscale channels. Several important thermal-hydraulic parameters such as two-phase viscosity and two-phase density can be derived from the knowledge of the void fraction. In addition, it is used in numerous models to predict heat transfer, pressure drop and flow patterns in microchannels. The most commonly used definition of void fraction in this context is the cross-sectional void fraction, which is the ratio of the cross-sectional area occupied by the vapor phase to the total cross-sectional area at a given location in the channel [1]. This void fraction is often determined roughly by electrical impedance measurements using the Maxwell-Garnett equations, which relate impedance and void fraction [2], or with high precision by optical studies at specific locations in the microchannel. However, the lack of suitable image processing makes the optical determination of the void fraction very time-consuming, since it must be calculated manually for each frame.

In this study, computer vision was applied to realize an automatic and accurate calculation of cross-sectional void fractions perpendicular to the fluid flow direction at different locations in microchannels. The void fractions of each channel location could be linked together to provide a map of the average void fraction of the entire channel. Therefore, two-phase flow boiling experiments were performed with DI water in rectangular stainless-steel microchannels with hydraulic diameters of 430 and 750 µm and lengths of 65 mm. The mass flow rate ranged from 1.5 to 5 g/min and the heat load applied to the bottom of the microchannels ranged from 11 to 25 watts. The microchannels, open at the top due to the manufacturing process (milling), were sealed by a transparent glass lid with an O-ring mounted in-between surrounding the channel. During the experiments, the flow boiling was recorded with a high-speed camera at several locations along the microchannel from above through the transparent glass lid. Then, the recorded videos from the high-speed camera were analysed using Python's OpenCV library to extract the cross-sectional void fraction using computer vision.

This approach was primarily concerned with separating the vapor bubble fractions from the rest of the liquid in the channel. Upon close inspection, it was found that the vapor bubbles had lower pixel values in contrast to the liquid. Pre-processing techniques such as image thresholding, gamma correction, and image blurring helped to calculate the void fraction of each frame in the videos recorded by the high-speed camera to allow a more discriminating comparison. Some irregularities were observed due to fragments of brighter liquid-like pixels within the vapor bubble contours. Differentiation based on texture differences between these spots and the liquid inside the microchannel might resolve this issue by creating tailored features, as a direct approach is not yet available in Python's OpenCV library.

In the future, these features can be published as an open access library to provide other scientists with a standardized detection of void fractions using computer vision. Furthermore, the use of computer vision for the determination of the void fraction allows an unprecedented amount of optical data to be analysed in a quantitative procedure and to be put into relation with other measurement signals (e.g. impedance, temperature and differential pressure measurements). This allows not only the formulation of accurate models for the prediction of heat transfer, differential pressure and flow patterns in microchannels but also the use of deep learning algorithms for the tailored description of two-phase flows in different microchannel systems [3].

References

[1] J. R. Thome, *Engineering Data Book III*. Wolverine Tube Inc, 2010.
[2] E. S. Rosa, "Design and performance prediction of an impedance void meter applied to the petroleum industry," *Meas. Sci. Technol*., vol. 23, no. 5, 2012.
[3] S. Kadish, D. Schmid, J. Son, E. Boje, "Computer Vision-Based Classification of Flow Regime and Vapor Quality in Vertical Two-Phase Flow," *Sensors,* vol. 22, no. 3, 2022.