**Multifunctional Properties**

Two-phase cooling devices, such as vapor chambers,[1] capillary pumped loop heat pipes,[1, 2] loop heat pipes,[1-4] and thermosyphon heat pipes,[5] operate in an evaporation, liquid-transport, and condensation cycle that utilize micro/nanoscale porous media called the wick (Figure).[1] The wick plays a vital role within the cooling devices by vaporizing, absorbing, and transporting the working fluid to maximize heat dissipation. Therefore, an optimal wick should have properties such as efficient working-fluid delivery (i.e., permeability),[3, 6] large surface area to volume ratios,[7] low thermal resistance,[5] and high effective thermal conductivity.[5]

### Microscale Thermofluidic Transport Analysis

As an emerging technique, laser induced fluorescence (LIF) gains attention as a powerful tool to characterize thermal profiles at multiple scales with high fidelity. In general, LIF utilizes temperature-and light-sensitive molecules called fluorophores. At the macroscale, LIF has been conventionally used to analyze bulk thermofluidic physics typically over the mm scale.[8-10] On the other hand, micro laser induced fluorescence (μLIF) employs fluorescent microscopes to improve spatial and thermal resolutions up to 0.1 – 0.3 μm and 0.01 K, respectively. [11-19] The methods generally employ fluorescence, where temperature-sensitive fluorophores absorb photons of a specific wavelength (i.e., excitation) and emit photons of a longer wavelength (i.e., emission) (Figure 1.3). The emitted fluorescence signals are selectively transmitted through an optical filter to produce fluorescence intensity-based imaging, which is then converted into temperature-based pictures. A great advantage of using μLIF is to observe temporal micro/nanoscale pixel-based fluorescent intensity profiles of the liquid-vapor interface. In other words, even some of the smallest liquid-vapor surface features are easily detected by observing fluorescence signals and can be used to assess local drying phenomena in complex structures.

### Structural Optimization

Among various modern fabrication techniques, self-assembly continuously gains attention as an excellent method to create novel nanoscale structures with a wide range of applications in photonics, optoelectronics, biomedical engineering, and heat transfer applications. However, self-assembly is governed by a diversity of complex interparticle forces that cause fabricating defectless large scale (> 1 cm) colloidal crystals, or opals, to be a daunting challenge. Despite numerous efforts to find an optimal method that offers the perfect colloidal crystal by minimizing defects, it has been difficult to provide physical interpretations that govern the development of defects such as grain boundaries. In order to address the issues above, we systematically reveal the governing physics that control grain boundaries by apply different combinations of fabrication parameters.

### Metrology

Current advances in deep learning and, in particular, convolutional neural networks (CNNs) have enabled automatic and scalable image analysis for, e.g., object detection[20-23], classification[24-29], and even image-based predictions[30-36]. Many CNN-based deep learning frameworks are effective because CNNs emulate the human brain’s natural visual perception mechanism by systematically learning features through multiple operational layers[37]. Image-based deep learning models can play a vital role in fully understanding boiling physics because boiling images are richly embedded with bubble statistics, which are quantitative measurements of the dynamic boiling phenomena. Despite the potential for understanding image-based boiling physics via deep learning frameworks, very few attempts have been made to build them. In PyPhase, we are developing a data-driven framework that predicts boiling heat flux based on high-quality bubble images in real-time (Figure). Our framework conceptualizes state-of-the-art CNNs and object detection algorithms to automatically extract hierarchical image features as well as physics-based bubble statistics to learn inherent boiling physics. By training on these features, the framework not only describes the manner in which the bubbles nucleate and depart under boiling conditions, but also predicts the boiling curves with high precision. The framework thereby provides quantitative descriptions of underlying boiling activities that can potentially help discover unknown boiling laws.

[1] A. J. J. o. h. t. Faghri, **2012,** *134*, 123001.

[2] S. Launay; V. Sartre; J. Bonjour, *Int J Therm Sci* **2007,** *46*, 621.

[3] C. C. Yeh; C. N. Chen; Y. M. Chen, *Int J Heat Mass Tran* **2009,** *52*, 4426.

[4] B. Weisenseel; P. Greil; T. J. A. E. M. Fey, **2017,** *19*, 1600379.

[5] G. Huminic; A. Huminic; I. Morjan; F. Dumitrache, *Int J Heat Mass Tran* **2011,** *54*, 656.

[6] J. Lee; Y. Suh; P. P. Dubey; M. T. Barako; Y. Won, *Acs Appl Mater Inter* **2019,** *11*, 1546.

[7] K. K. Bodla; J. A. Weibel; S. V. Garimella, *J Heat Trans-T Asme* **2013,** *135*.

[8] H. Rochlitz; P. Scholz, *Experiments in Fluids* **2018,** *59*.

[9] R. S. Volkov; P. A. Strizhak, *Applied Thermal Engineering* **2017,** *127*, 141.

[10] W. Chaze; O. Caballina; G. Castanet; F. Lemoine, *Experiments in Fluids* **2017,** *58*.

[11] J. Feng; L. Xiong; S. Q. Wang; S. Y. Li; Y. Li; G. Q. Yang, *Adv Funct Mater* **2013,** *23*, 340.

[12] P. Low; B. Kim; N. Takama; C. Bergaud, *Small* **2008,** *4*, 908.

[13] D. Erickson; D. Sinton; D. Q. Li, *Lab on a Chip* **2003,** *3*, 141.

[14] R. Samy; T. Glawdel; C. L. Ren, *Anal Chem* **2008,** *80*, 369.

[15] T. Glawdel; Z. Almutairi; S. Wang; C. Ren, *Lab on a Chip* **2009,** *9*, 171.

[16] D. Ross; M. Gaitan; L. E. Locascio, *Analytical Chemistry* **2001,** *73*, 4117.

[17] F. Vetrone; R. Naccache; A. Zamarron; A. J. de la Fuente; F. Sanz-Rodriguez; L. M. Maestro; E. M. Rodriguez; D. Jaque; J. G. Sole; J. A. Capobianco, *Acs Nano* **2010,** *4*, 3254.

[18] J. Feng; K. J. Tian; D. H. Hu; S. Q. Wang; S. Y. Li; Y. Zeng; Y. Li; G. Q. Yang, *Angew Chem Int Edit* **2011,** *50*, 8072.

[19] Y. Suh; C.-H. Lin; H. Gowda; Y. Won In *Evaporation Rate Measurement at Multiple Scales Using Temperature-Sensitive Fluorescence Dyes*, ASME 2019 International Technical Conference and Exhibition on Packaging and Integration of Electronic and Photonic Microsystems, American Society of Mechanical Engineers Digital Collection.

[20] R. Lindsey; A. Daluiski; S. Chopra; A. Lachapelle; M. Mozer; S. Sicular; D. Hanel; M. Gardner; A. Gupta; R. Hotchkiss; H. Potter, *P Natl Acad Sci USA* **2018,** *115*, 11591.

[21] D. Shen; G. Wu; H.-I. Suk, *Annual review of biomedical engineering* **2017,** *19*, 221.

[22] J. M. Newby; A. M. Schaefer; P. T. Lee; M. G. Forest; S. K. Lai, *P Natl Acad Sci USA* **2018,** *115*, 9026.

[23] G. Lio; R. Fadda; G. Doneddu; J. R. Duhamel; A. Sirigu, *Nat Commun* **2019,** *10*.

[24] M. S. Norouzzadeh; A. Nguyen; M. Kosmala; A. Swanson; M. S. Palmer; C. Packer; J. Clune, *P Natl Acad Sci USA* **2018,** *115*, E5716.

[25] Y. Qu; H. Zhu; Y. Shen; J. Zhang; C. Tao; P. Ghosh; M. Qiu, *Science Bulletin* **2020**.

[26] S. M. Mousavi; W. L. Ellsworth; W. Zhu; L. Y. Chuang; G. C. Beroza, *Nat Commun* **2020,** *11*, 1.

[27] A. Ziletti; D. Kumar; M. Scheffler; L. M. Ghiringhelli, *Nat Commun* **2018,** *9*.

[28] Z. Geng; Y. F. Wang, *Nat Commun* **2020,** *11*.

[29] Z. Q. Tang; K. V. Chuang; C. DeCarli; L. W. Jin; L. Beckett; M. J. Keiser; B. N. Dugger, *Nat Commun* **2019,** *10*.

[30] B. Huval; T. Wang; S. Tandon; J. Kiske; W. Song; J. Pazhayampallil; M. Andriluka; P. Rajpurkar; T. Migimatsu; R. Cheng-Yue, *arXiv preprint arXiv:1504.01716* **2015**.

[31] F. Milletari; N. Navab; S. A. Ahmadi, *Int Conf 3d Vision* **2016**, 565.

[32] D. M. Pelt; J. A. Sethian, *P Natl Acad Sci USA* **2018,** *115*, 254.

[33] J. Wu; X. Yin; H. Xiao, *Science bulletin* **2018,** *63*, 1215.

[34] F. Wang; J.-F. Yang; M.-Y. Wang; C.-Y. Jia; X.-X. Shi; G.-F. Hao; G.-F. Yang, *Science Bulletin* **2020**.

[35] S. Grossman; G. Gaziv; E. M. Yeagle; M. Harel; P. Megevand; D. M. Groppe; S. Khuvis; J. L. Herrero; M. Irani; A. D. Mehta; R. Malach, *Nat Commun* **2019,** *10*.

[36] A. A. K. Nielsen; C. A. Voigt, *Nat Commun* **2018,** *9*.

[37] Y. Oktar; D. Karakaya; O. Ulucan; M. Turkan, *arXiv preprint arXiv:1912.10201* **2019**.

[38] G. M. Hobold; A. K. da Silva, *Int J Heat Mass Tran* **2018,** *125*, 1296.

[39] G. M. Hobold; A. K. da Silva, *Int J Heat Mass Tran* **2019,** *134*, 511.

[40] J. Jie; Z. Hu; G. Qian; M. Weng; S. Li; S. Li; M. Hu; D. Chen; W. Xiao; J. Zheng, *Science Bulletin* **2019,** *64*, 612.