Deep digital holographic microscopy

Maxime Jacquot[1*], *Remi* Kieber[1], *Stéphane* Cuenat[1], *Mohammad* Saim Khan[1] and *Raphael* Couturier[1]

[1] Université Marie et Louis Pasteur, CNRS, Institut FEMTO-ST, Besançon, France

Abstract. This paper presents recent developments in hybrid computational imaging approaches for 3D motion analysis and quantitative phase imaging in automated microscopy. By integrating digital holographic microscopy with deep learning models, this work enhances the capabilities of machine microvision. High-tech fields such as micro-robotics and photonics require accurate, robust and rapid in situ measurements using complex multi-scale parameters. Unlike conventional data-driven methods, physics-based deep learning does not require training or requires minimal data, enabling real-time optical information processing. A prototype of digital holographic microscope, with a hybrid deep neural network for autofocusing and phase imaging is proposed. The main challenge is to achieve sub-micrometre-scale accuracy whilst ensuring reliability and interpretability in environments where the 'hallucinations' of standard AI models must be avoided.

1 Introduction

Holography is a coherent imaging technique that has been in existence since the 1960s. From the late 1990s onwards, the advent of high-resolution digital cameras marked the beginning of the digital era of holography, giving rise to new capabilities such as autofocusing, and quantitative phase imaging [1]. Recently, digital holography has leveraged deep learning to improve upon and surpass standard classical methods of digital hologram processing, despite the needs of huge dataset [2]. In this work, we develop a deep digital holographic microscopy (DHM) system that performs automatic optical focusing—without any mechanical movement—based on advanced deep learning architectures, and enables the reconstruction of an object's phase profile.

1. Method and experimental setup

When it is a question of performing automated operations on real-world samples in microscopy, generalising many tasks remains difficult with data-driven deep learning, and artefacts still appear when the datasets used for training are corrupted.
One solution to overcome this limitation is to introduce physical constraints into the neural networks involved, and to train them without ground truth data [3]. These constraints can be integrated into the networks in the form of a custom layer or within the cost function. In this

* Corresponding author: maxime.jacquot@umlp.fr

© The Authors, published by EDP Sciences. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

work, a hybrid DHM system was developed, in an online and off-axis configuration (Fig. 1). The proposed architectures are in particular based on an adaptation of the differential digital model (DDM) concept for autofocusing [4].

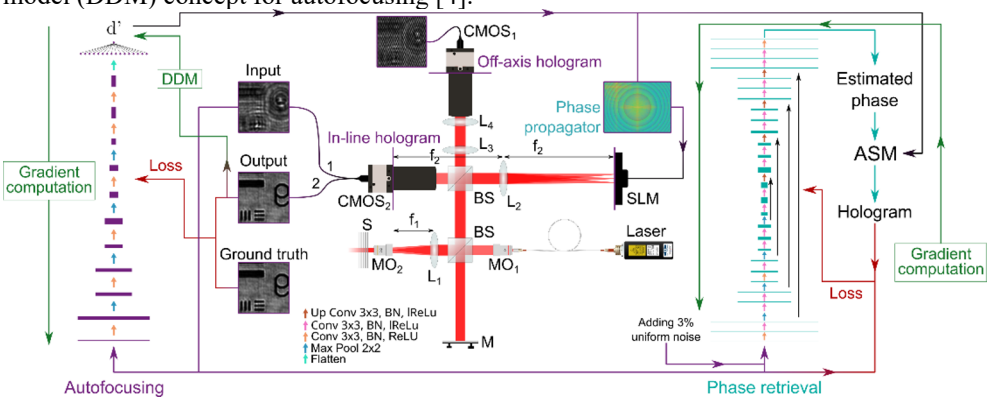


Fig. 1. Deep holographic digital microscope setup

This system is also capable of reconstructing the phase profile of a complex object. It comprises a convolutional neural network that records holograms in real time in order to deduce the in-focus distance. This distance is then used to display a corresponding phase mask on a spatial light modulator (SLM), which emulates wave propagation. The resulting image is compared to the ground truth used to train the neural network, using a loss function based on mainly the MSE. Training is carried out using 1,000 digital holograms over propagation distances ranging from 0 to 100 µm. Initial results show good performance in simulation, though a critical sensitivity to noise in experimental conditions.

Deep architectures and more advanced training methods are also being investigated for phase retrieval, such as the use of self-trained neural networks, like the spatial-frequency-domain-based GedankenNet [5]. Recent advances in deep learning have introduced data-driven solutions to the phase retrieval problem. Notably, the GedankenNet framework has demonstrated that a single Fourier Neural Operator (FNO) can learn the inverse holographic mapping in a self-supervised manner by exploiting the known physical principles of light propagation. It is also possible to propose other learning configurations using a ensemble learning framework that sequentially trains multiple FNOs to mitigate the low-frequency bias inherent in these operators.

References

1. Y. Park, C. Depeursinge, G. Popescu, “Quantitative phase imaging in biomedicine,” Nature Photonics, **12**, 10, (2018).
2. S. Cuenat, L. Andréoli, A. N. André, P. Sandoz, G. J. Laurent, R. Couturier, M. Jacquot, “Fast autofocusing using tiny transformer networks for digital holographic microscopy,” Optics Express, **30**, 14, (2022).
3. Wang, F., Bian, Y., Wang, H. *et al*. “Phase imaging with an untrained neural network,” Light Sci Appl **9**, 77 (2020).
4. Wright, L.G., Onodera, T., Stein, M.M. *et al.* “Deep physical neural networks trained with backpropagation.” Nature **601**, 549 (2022).
5. L. Huang, H. Chen, T. Liu, and A. Ozcan, “Self-supervised learning of hologram reconstruction using physics consistency,” Nature Machine Intelligence, **5**, 895 (2023).