Self-Autofocusing using Deep Learning for Digital Holography and Applied to Position Measurement

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Abstract

The numerical wavefront backpropagation principle of digital holography (DH) confers unique extended focus capabilities. However, the determination of the correct focus distance is a difficult and time consuming problem. To cope with this problem, a deep learning solution is proposed to cast the auto-focusing as a classification problem. The experiments show that a good accuracy (1-3 µm) can be reached for a set of holograms ranging on a distance of 10 µm and using a 10x microscope objective.

1. Introduction

DH records the wavefront incident on the image sensor through the interference pattern produced by its coherent combination with a known reference wavefront. The amplitude and phase of the incident beam thus determined allows numerical backpropagation to reconstruct images of the object of interest at various distances without depth-of-focus limitations tied to conventional refractive imaging techniques. These extended focus capabilities offered by DH require however the correct determination of the focusing distance to be inserted in computations. Nowadays, Deep Learning (DL) is reshaping the world of computer science and it is used in many application areas including DH. Particularly, DL helped in coping the time consumption and heavy computation concerns of the older techniques to determine depth position: instead of applying many diffraction calculations, training a deep neural network is adopted to enable it to do the depth predictions [1]. These predictions can be approached either as a classification problem or a regression problem. Most of the work in DH are applied to simple objects like biological cells. The proposed solution tackles more complicated objects [2].

2. Applicative context

At the microscale, optical microscopy provides a convenient non-contact tool for the measurement of position and displacements of objects versus one to six degrees of freedom and with resolution down to the nanometer range. However, the short depth-of-focus of microscope objectives restricts drastically the allowed displacements along the axial direction. This limitation is released by DH that integrates the phase term associated to refractive lenses into computations and thus allows in-focus images of objects far beyond the nominal range of the objectives used. Furthermore, DH reconstructs the interferometric phase representative of the out-of-plane position of objects with an unbeatable resolution. In our microrobotic application, encoded pseudoperiodic patterns are observed by a DH microscope (DHM by Lyncee Tec Corp.) to measure the position and displacements of mobile objects versus the six degrees of freedom [3, 4, 5].

3. Proposed solution

The objective is to localize objects at the micrometre scale. We use holograms of a target to retrieve the 6 degrees of freedom (DoF) of a structured target. The target is generated in such that it encodes the position (X and Y) using a binary code. The object image needs to be reconstructed first. For that purpose, we are relying on the known methods which are implying a series of Fourier and inverse transformations. These transformations consume most of the time and do not allow one to get an idea of the re-constructed object (6 DoF) in a real-time approach. In this paper, a method is proposed to extract the reconstruction distance Z (which is the distance along the optical propagation) only using deep learning and classification models. As input, produced holograms on a distance Z over 10 µm are considered. Each hologram (see Figure 1) is recorded using the same target. In a first step, this problem is approached using

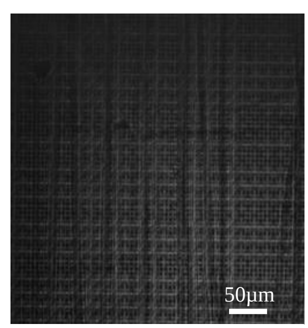

Figure 1: example of an original hologram.

a classifier model. For that purpose, the set of holograms have been split in 10 classes. Each class contains a total of 360 holograms. The digital holography microscope used is producing holograms with a resolution equal to 1024x1024.

4. Preliminary results

Three neural network architectures have been evaluated: Densenet169 & Densnet201, Efficientnet B4 & B7, VIT B16, B32, L16 & L32 [6]. All the trainings, validations and testings have been executed on a NVidia GPU V100 series. A simple split rule on the input dataset has been applied: 80% for training and 20% for validation, basically 3,400 images in total (2,720 images taken to train the models and 680 images used as validation dataset). 200 random images have been extracted from the full dataset to build our test dataset randomly. Each training has been executed with a max of 200 epochs. Two sets of holograms have been created: the original hologram (Figure 1) and the negative version. Each set has been devided in 2 subsets applying an additional filter before feeding the neural network: a Sobel operator (algorithm used to create an image emphasising edges) of the hologram and without any filter applied. The results (Table 1) show the value of the valuation and test accuracy for the best configurations. Figure 2 shows the needed time for a single inference.

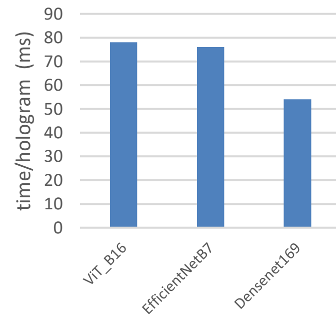

Figure 2: speed results for the three best architectures (VIT/B_16, EfficientNetB7 and Densenet169) using a test dataset.

	Valuation accuracy	Test accuracy
ViT/B_16	0.90*	0.94*
EfficientNetB7	0.9941**	0.99**
Densenet169	0.9955**	0.945**

Table 1: valuation and test accurary for the three best architectures (VIT/B_16, EfficientNetB7 and Densenet169).
*Using a dataset of holograms without applying an additional filter (negative version of holograms).
**Using a dataset of holograms on which a Sobel operator has been applied (negative version of holograms).

5. Conclusion

Our experiments show that the reconstruction distance for digital holography using deep learning techniques can be found, especially using classification models. The 1-3 μm scale has been reached for a dataset of holograms on a scale of 10 μm. This solution allows to surpass of a factor 2-3 the optical resolution of the microscope (using a 10x microscope objective) knowing that the optical resolution is defined as: $r = \frac{\lambda}{NA^2} = 6.6\ \mu m$ (with NA = 0.3: numerical aperture and $\lambda = 0.6\ \mu m$). The above shows an approach based on classification models, a regression should bring us to the next level. The first preliminary results points an error of 1.5 μm taking a larger dataset ranging over a distance of 100 μm. As for the next step, the goal is to tackle the decoding of the position (X and Y in the focal plane of the hologram).

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