Learning from Examples in Optical Imaging

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Abstract: Imaging systems can be designed using examples and methods similar to the techniques used in deep learning. We describe experimental results demonstrating optical tomography based on the learning approach.
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1. Introduction

Most microscopy techniques, both linear and nonlinear, assume ballistic illumination. This is the case for diffraction tomography [1-3]. However, in order to surpass the current limits in term of resolution and penetration, multiple scattering has to be taken into account. A recently investigated approach is to build a digital model of the object, represented by its refractive index distribution, and to optimize it so that it matches the experimental measurements [4-6]. The physical forward model that relates the refractive index to the measured scatted field can be chosen so that it includes multiple scattering. In this paper, we use the beam propagation method (BPM) in the transmission geometry. Here, we especially study the minimal number of views that is required to form an image and compare it to diffraction tomography. We illustrate the improvement provided by learning tomography with experimental images of HeLa cells.

2. Method

The general scheme of the experimental apparatus is that of a Mach-Zehnder interferometer, one arm being used as a reference and the other arm containing the sample (see Fig. 1). As light source, we use a 406nm continuous wave laser diode. The beam is spatially filtered, expanded, and steered by two galvo-mirrors placed in conjugated plane of each other. The beam is then focused in the back focal plane of an illumination objective (1.4N.A. 100x ApoPlan Olympus) in order to have a collimated wave incident on the sample. The scattered and transmitted light is collected on the other side by another objective and a digital hologram is recorded on a CCD camera. Phase stability is maintained by performing a differential measurement. A phase reference is measured in a portion of the field of view that does not contain the object, and is subtracted from the phase everywhere else.

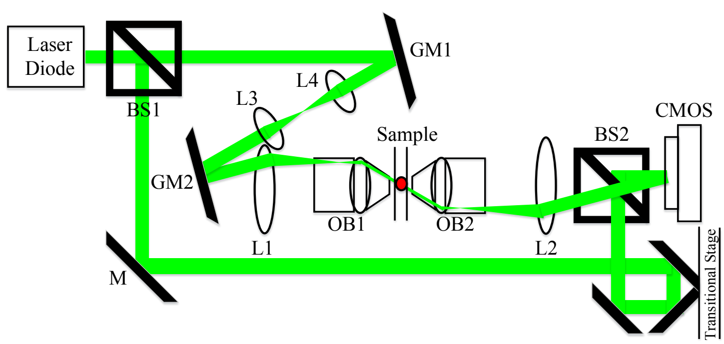

Fig. 1: Experimental apparatus. (BS: beam splitter, GM: galvo-mirror, L: lens, OB: objective; and M: mirror).

We take measurements at different view angles, typically 100, from -55° to 55°. Note that reconstruction can be made from fewer measurements. The object is then represented by a digital model *f*. An initial guess of the model is made, for example from the diffraction tomography reconstruction. The field scattered from the digital model (the refractive index distribution $n(x, y, z)$) is simulated using the beam propagation method (BPM) as depicted in Fig. 2. The BPM operation can be thought of as a neural network. The vertices in the network represent the diffraction (propagation) and the nodes represent the phase modulation (refractive index contrast). Each layer of neuron corresponds to an x-y slice in the BPM model. As a consequence, the deep learning methods developed so far to train neural network can, in principle, be applied here.

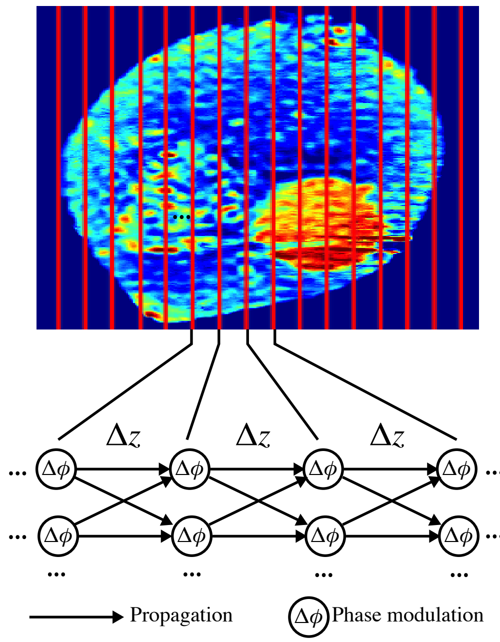

Fig. 2: Schematic representation of the beam propagation forward model that is used to simulate the measurements from the digital model. The model is split into slices that can be represented as neuron layers in a neural network.

In order to train (optimize) the network, we define an error function as the difference between the simulated measurements $A(n)f_i$ and the actual measurements m_i , as follows:

$$\varepsilon(n) = \sum_i \left\| m_i - A(n) f_i \right\|^2 \quad . \tag{1}$$

where A is the BPM operator. This operator allows us to compute the gradient of the error function very efficiently. For that reason, we perform a simple gradient descent on this error function. Because the problem is nonlinear, we need to add a regularization operator S. In this case, we chose total variation in order to keep sharp edges in the final image while suppressing noise. The optimization is performed on the spatial distribution of the refractive index contrast $\Delta\hat{n}(x,y,z)$ using the following scheme:

$$\Delta\hat{n} \leftarrow \Delta\hat{n} - \left(\frac{1}{N} \sum_{l=1} \varepsilon_l \frac{\partial \varepsilon_l}{\partial \Delta\hat{n}} + \tau \frac{\partial S(\Delta\hat{n})}{\partial \Delta\hat{n}} \right), \tag{2}$$

where N is the number of measurements (number of views), and τ the strength of the regularization.

3. Results

In Fig. 3, we compare learning tomography and diffraction tomography reconstructions of a HeLa cell for different number of views. For a large number of views (81 here), both reconstructions are visually good. In the learning tomography reconstruction though, part of the granular artifact in the cell cytoplasm has been removed by the regularization while keeping details such as the nucleus. As the number of views is reduced to 21 and then 6, the diffraction tomography reconstruction becomes more and more blurry, whereas the learning tomography reconstruction quality remains almost constant.

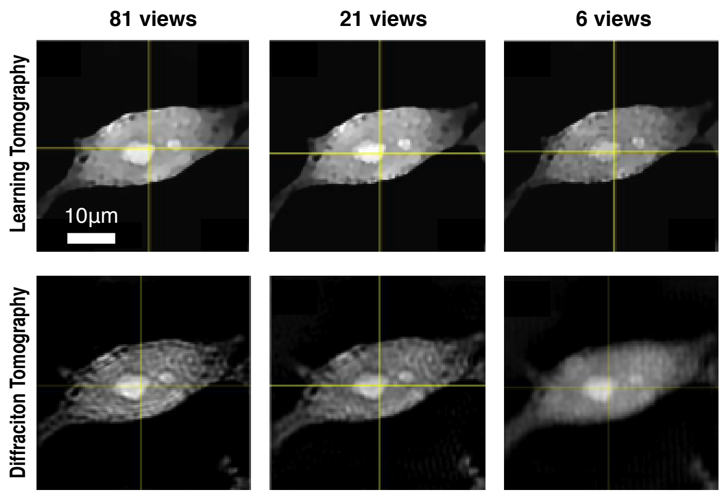

Fig. 3: Comparison of x-y slices of an HeLA cell, learning tomography versus diffraction tomography, for three different numbers of views.

In the case of diffraction tomography, we have to use a threshold operation in order to suppress the projection artifacts that appear outside of the cell, especially when using fewer views. We interpret the superior performance of the learning tomography as being the result of multiple scattering. Indeed, Fourier components of the object that are out of reach with a linear method, such as diffraction tomography, can be naturally included in the learning.

4. Conclusion

In this work, we have experimentally demonstrated the performance of the learning tomography technique, which makes use of the beam propagation method as a forward model. In particular, we show that we can get three-dimensional images of a HeLa cell even with as few as 6 measurements. With so few measurements, diffraction tomography yields blurry images and needs to be thresholded in order to suppress artifacts. The main advantage of the learning method is that it can handle multiple scattering as opposed to linear methods such as diffraction tomography. In addition, the combination of the learning with a total variation regularization operator leads to an efficient removal of artifacts both outside and inside the object while keeping sharp feature, such as the cell nucleus in this case. The learning approach is very general and can be implemented in various ways. The beam propagation method is only one particular case of forward model and other can be chosen that include reflection for example. This study paves the way for other methods based on deep learning to handle multiple scattering.

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