Super-resolution optical metrology and imaging of 3D nano-scale objects

Jin-Kyu So[1]*, Eng Aik Chan[1], Giorgio Adamo[1], and Nikolay I. Zheludev[2]

[1] *The Photonics Institute & Centre for Disruptive Photonic Technologies, Nanyang Technological University, Singapore 637371*

[2] *Optoelectronics Research Centre & Centre for Photonic Metamaterials, University of Southampton, SO17 1BJ, UK*

Abstract - We show experimentally that a deep learning-enabled analysis of intensity patterns of diffracted light allows three-dimensional metrology of subwavelength objects with precision reaching λ/467. This remarkable precision is helped by the information provided by the training process that prior to the measurement gathers prior information on the diffraction patterns from similar objects.

1. Introduction

Retrieving physical parameters of nanoscale objects from the diffracted light corresponds to inverse scattering problem and solving it involves various approximations and assumptions chosen carefully for the specific problem under consideration. In deep learning-enabled analysis, such prior assumptions or approximations can be replaced with a priori examinations of similar class of objects and it has demonstrated superb measurement precision of a fraction of hundreds to thousands of the wavelength in retrieving physical parameters of one- (1D) and two-dimensional (2D) systems such as nano-gaps and nano-holes under various forms of light illumination. Here, we extend the approach to three-dimensional (3D) systems and explore the optical metrology of subwavelength objects with the extra degrees of freedom. In proof of principle experiments, we show that precision exceeding λ/467 can be achieved in retrieving the dimensions of platinum nanopillars.

2. Results and Discussion

In deep super-resolution optical metrology enabled by deep learning analysis, a beam of light illuminates a set of similar class of objects and the recorded diffraction patterns are fed into a neural network for training (Fig. 1). The network trained with a set of optical diffraction patterns from similar class of objects can predict the physical parameters of an unseen object of similar kind and the precision of a fraction of hundreds to thousands of the wavelength has been demonstrated in 1D systems such as nanoslits.

As the systems evolve into a more complicated and realistic configuration such as three-dimensional (3D) sub-wavelength objects, the increase in the degrees of freedom and noise challenges the neural network's capability of retrieving the physical parameters. Here, we explore how neural networks perform with 3D sub-wavelength objects and ways to augment the networks in solving the inverse scattering problem.

As a representative 3D object, we consider platinum nanopillars, which presents two degrees of freedom, i.e. diameter, *d*, and height, *h* (see Fig. 1b). In contrast to the previously considered nanostructures where only the geometrical parameters along the plane transverse to the light propagation were considered, nanopillars possess an additional degree of freedom along the propagation direction of light. The platinum nanoparticles were patterned on ITO-coated glass substrates with focused-electron-beam-induced deposition which patterns nanostructures by irradiating focused electron beam while flowing a precursor gas near the target region.

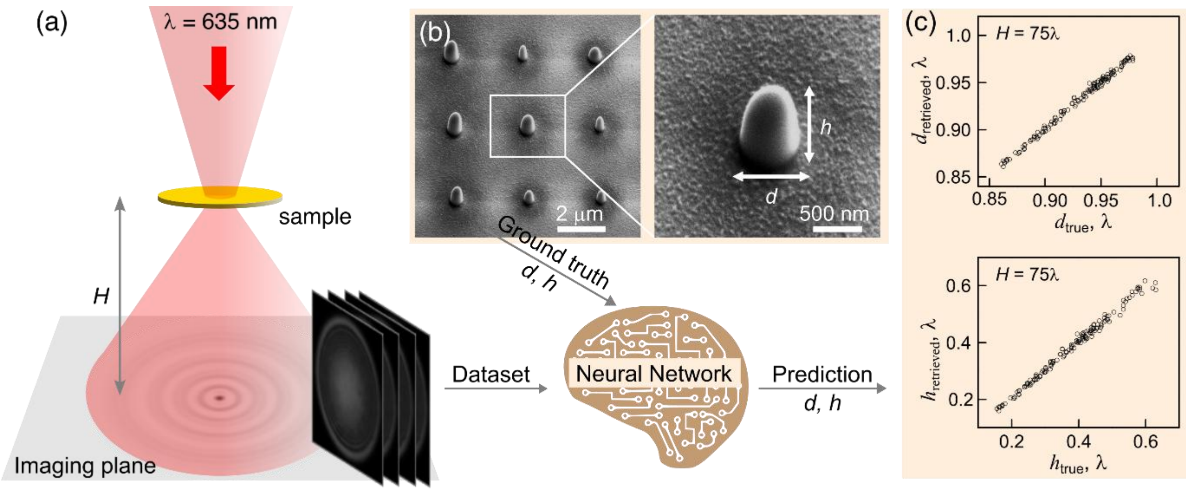

Fig. 1: Super-resolution metrology of 3D nanoscale objects. (a) A beam of laser radiation illuminates a sample and the resulting diffraction pattern is recorded, then fed into a neural network. The trained network can predict the geometrical parameters of unseen objects of similar kind. (b) SEM images of platinum pillars fabricated by focused electron beam-induced deposition on a glass substrate. Ground truth values of *d* and *h* were prepared from AFM topography. (c) Comparison of predicted and truth values of diameter and height of nanopillars are shown for an imaging distance, $H = 75\ \lambda$.

Super-resolution optical metrology and imaging of 3D nano-scale objects

Jin-Kyu So[1]*, Eng Aik Chan[1], Giorgio Adamo[1], and Nikolay I. Zheludev[2]

[1] *The Photonics Institute & Centre for Disruptive Photonic Technologies, Nanyang Technological University, Singapore 637371*

[2] *Optoelectronics Research Centre & Centre for Photonic Metamaterials, University of Southampton, SO17 1BJ, UK*

A dataset of light diffraction patterns for nanoparticles was prepared by illuminating a Gaussian beam of coherent light (λ = 635 nm, FWHM = 1.1 λ) on the sample through a microscope objective lens (NA = 0.9) and recording the resulting diffraction patterns at a distance, *H*, away from the sample (Fig. 1a) by another microscope objective lens (NA = 0.9) and an sCMOS camera. The effective pixel size of the imaging system was 41.7 nm on the sample plane.

The dataset of optical diffraction patterns was collected from three sets of samples: dataset#1) 500 nanopillars with *d* = 356-440 nm and *h* = 91-356nm, dataset#2) 500 nanopillars with *d* = 465-529 nm and *h* = 94-393 nm, dataset#3) 500 nanopillars with *d* = 545-615 nm and *h* = 101-419 nm. For each nanopillar, diffraction patterns were taken at *H* = 0, 2, 5, 10, 15, 20, 50, 75, 100 λ to study the relationship between the information content and imaging distance. To prevent the neural network from learning the background intensity patterns instead of the contribution from the light scattered by the nanoparticles, the diameter and height of nanoparticles were randomized in the given range of the dataset.

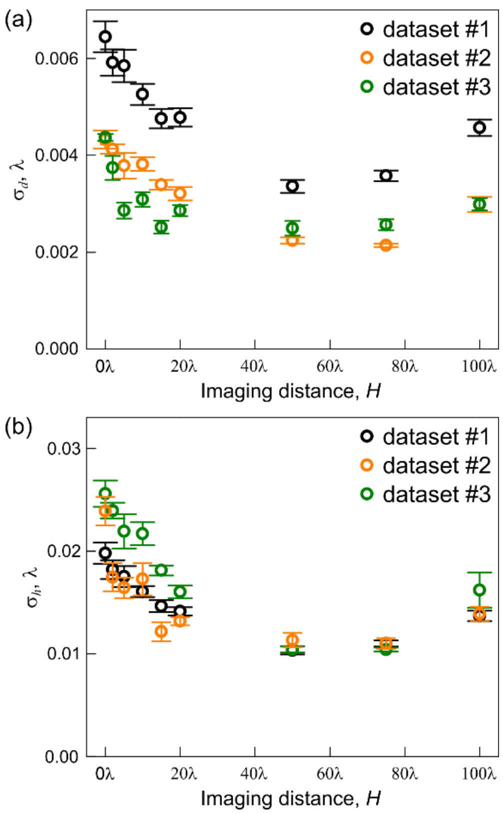

Fig. 2: Subwavelength optical metrology of nanopillars. Measurement precision of retrieving (a) diameter, σ_d, and (b) height, σ_h, of nanopillars are shown for imaging distances, *H* = 0 - 100 λ.

To retrieve the physical parameters from the intensity patterns of diffracted light, we used an artificial neural network, ResNet-34 [1], which is a convolutional neural network made up of 34 layers widely used in image recognition. In the neural network analysis, 80%, 10%, and 10% of the dataset was used for training, validation, and test of the network, respectively.

As a measure of the metrology's accuracy, we present the standard deviation, *σ*, between the retrieved parameters and the ground truth obtained from AFM measurement. Figure 2a shows the calculated precision for retrieving the diameter, *d*, as a function of imaging distance, *H*. For all the three datasets, an optimum precision is observed for H = 50-75 λ while the best measurement precision of λ/467 was achieved at *H* = 75 λ for nanopillars with *d* = 465-529 nm. A similar dependence is observed for the height measurement where a precision of λ/96 was achieved at *H* = 75 λ (Fig. 2b). The observed dependence of the measurement precision on the imaging distance is supported by the Fisher information analysis of the diffraction patterns.

3. Conclusion

In conclusion, we report on a deeply sub-wavelength optical metrology technique of 3D nanoscale objects by using Gaussian beam illumination and deep learning analysis. With the reported metrology, a measurement precision as high as λ/467 was achieved for retrieving the diameter of platinum nanopillars at imaging distance of *H* = 75 λ. An optimum imaging distance for diffraction patterns, ~ 75 λ, existed to yield the best precision and this is corroborated by the lowest Cramer-Rao bound at the optimum imaging distance. The application of the reported optical metrology technique to more complicated 3D nanoscale objects and its extension to the imaging of such objects will be discussed further.

Acknowledgments

This work was supported by the Singapore National Research Foundation (Grant No. NRF-CRP23-2019-0006), the Singapore Ministry of Education (Grant No. MOE2016-T3-1-006), and the Engineering and Physical Sciences Research Council UK (Grants No. EP/T02643X/1).

References

[1] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778, 2016.