DOI 10.5162/SMSI2020/E2.4

Deep Neural Networks for optical form measurements

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Summary:

Deep neural networks have been successfully applied in many different fields like computational imaging, medical healthcare, signal processing or autonomous driving. We demonstrate in a proof-of-principle study that also optical form measurement can benefit from deep learning. A data-driven machine learning approach is considered for solving an inverse problem in the accurate measurements of optical surfaces. The approach is developed and tested using virtual measurements with known ground truth.

Keywords: machine learning, U-Net, inverse problem, virtual experiment, optical form measurement

Motivation

Deep neural networks and machine learning in general enjoy a rapidly growing impact on science and industry. Their application has proven beneficial in many different domains including medical image processing [1], anomaly detection in quality management [2], signal processing [3] or analysis of raw sensor data [4]. The great success of deep networks and machine learning is based on its ability to learn complex relations from data without knowing the underlying physical laws. In this study deep learning is applied to a novel field of applications – to optical form measurements.

Deep neural networks are artificial neural networks with ten and more hidden layers. A basic neural network with a single hidden layer is a nonlinear function $f_\Phi: \mathbb{R} \to \mathbb{R}$, with parameters $\Phi = \{\omega_i, b_i \in \mathbb{R} \,|\, i = 1, \dots, n\}$, where n is the number of neurons in the hidden layer. The univariate output of the network is modeled through:

$$f_\Phi(x) = \sum_{i=1}^{n} \sigma(\omega_i x + b_i)\,, x \in \mathbb{R},$$

where σ is a nonlinear activation function. In general, input and output can be higher dimensional, and the architecture can get arbitrarily deep by adding more layers. An example deep network architecture is shown in Fig. 1, where two outputs are predicted from three given inputs after processing the information through several hidden layers. The network parameters can be optimized via backpropagation on given training data by minimizing a chosen loss function between the predicted and known output. It is crucial to have sufficiently many, representative training data in order that the trained net generalizes well. While such networks are viewed as black-box functions, techniques such as layer-wise-relevance-propagation [5] have been developed for understanding their behavior.

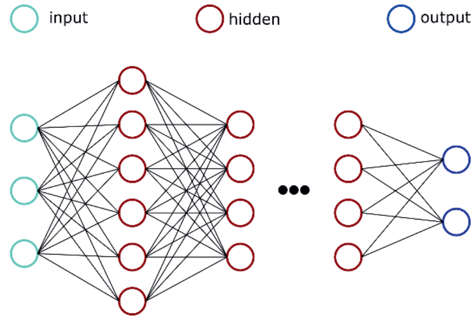

Fig. 1: Schematic of a deep neural network architecture.

Accurate measurement techniques become more and more important as technology advances. Any object can be manufactured from a given design just as accurately as it can be measured. The novel deep learning application is based on the tilted-wave interferometer (TWI) [6]. It is a promising technique providing highly accurate reconstructions of optical aspheres and freeform surfaces using contact-free interferometric measurements. A scheme of the TWI is shown in Fig. 2. Multiple wavefronts are created from a 2D point source array. The rays pass

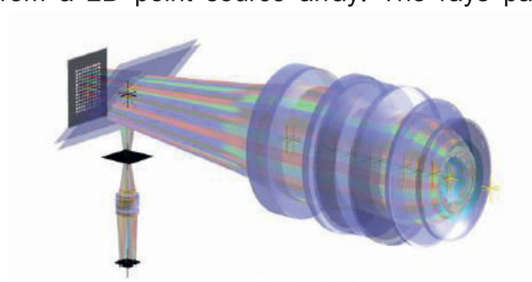

Fig. 2: Schematic of the tilted-wave interferometer without reference arm.

through various optical elements including the surface of the specimen under test and interfere at the CCD with rays from a reference arm. The test topography is then reconstructed by solving a numerically expensive inverse problem from the measured intensity images at the CCD.

Methods

The simulation toolbox SimOptDevice [7] has been used to construct a database of virtual measurement results. The test topographies were constructed by altering a specified design topography through adding random deviations. Fig. 3 shows some of these generated deviations. The simulation toolbox was applied to calculate the optical path length differences obtained for each test topography and for the design topography. In a real measurement, the optical path length differences for the specimen under test are measured by the CCD, while those of the design are calculated virtually. The constructed data base consists of 22.000 test topographies, together with the corresponding optical path length differences.

The data base was split into a training and test set. The latter contains 10% of randomly drawn samples from the data base. A U-Net [8] architecture with 69 layers was chosen to solve the inverse problem of reconstructing the test topography from the optical path length differences. A U-Net is a deep neural network with bottleneck structure and skip-connections. All data have been normalized prior to feeding the network. About two hours of training were carried out using the Adam optimizer, with an initial learning rate of 0.0005 with drop factor 0.75 every 5 periods and a mini batch size of 64. Training has been stabilized by applying a 2-norm regularization of the network parameters with a regularization parameter equal to 0.004.

Results and Conclusion

The trained network has been applied to predict the topographies from the optical path length differences for all cases in the test set. Note that none of the cases in the test set has been used for training. Fig. 3 shows some example results. The root mean squared error of the reconstructed topographies on the test set was 35 nm, compared with 560 nm root mean squared deviations between the test topographies and the design topography.

The obtained results are encouraging and suggest that deep learning can be successfully applied in the context of optical form measurements. The presented results are based on simulated data only and they constitute a proof-of-principle rather than a final method ready for application. Testing the approach on real measurements and accounting for fine-tuning such as the calibration of the numerical model of the experiment are next steps. Nevertheless, these first results are encouraging and once trained, a neural network solves the inverse problem orders of magnitudes faster than currently applied conventional methods. We conclude from our findings that also optical form metrology can benefit from deep learning.

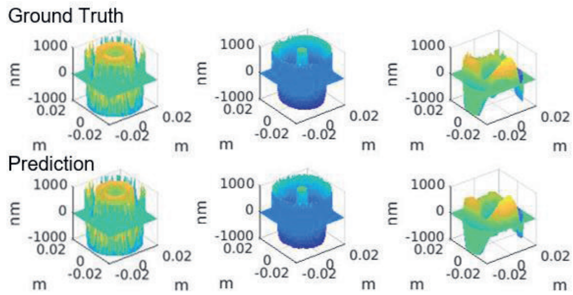

Fig. 3: Deep network results on random test data: ground truth and prediction.

Acknowledgement

The authors thank Manuel Stavridis for providing the software tool SimOptDevice and Ines Fortmeier and Michael Schulz for helpful discussions about optical form measurements.

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