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Ensemble Learning for Computational Optical Form Measurement

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Summary:

Deep learning has become a powerful tool of data analysis with applications in such different areas as medical imaging, language processing or autonomous driving. Recently, deep learning techniques have also been applied to an inverse problem in optical form measurement. In a proof-of-principle study it was shown that an accurate solution of the inverse problem can be achieved by a deep neural network that is trained on a large data base. This work augments the developed method with a quantification of its uncertainty by considering an ensemble of networks. The approach is tested using virtual experiments with known ground truth.

Keywords: deep learning, uncertainty, inverse problem, virtual experiment, optical form measurement

Motivation

Deep learning techniques have already been successfully used in many different domains such as medical imaging quality assurance [4], natural language processing [8] or autonomous driving [2]. In this study deep learning is applied to computational optical form measurements. The goal is to extend the deep learning approach proposed in [3] by quantifying the uncertainty associated with predictions made by a trained network ensemble.

Deep neural networks are neural networks with many hidden layers. Each layer consists of neurons, which are connected to the previous layer through a linear combination of its neurons and an additional bias. The nonlinear behavior of the network results from a nonlinear activation function per layer. The architecture can get arbitrarily deep by adding more layers, which makes neural networks a powerful tool to emulate highly complex functions. Fig. 1 shows an example of a deep neural network architecture. It has three input neurons, two output neurons and several hidden layers. The network parameters can be optimized via gradient-descent techniques using backpropagation by minimizing a chosen loss function on given training data. A common problem with deep learning models is their black-box behavior. In general, it is not possible to understand why the network made a certain prediction which challenges the trust in its prediction. Different techniques have been developed to tackle this problem, for example by using the Fisher information [5]. In this work we focus on estimating the uncertainties of the network predictions.

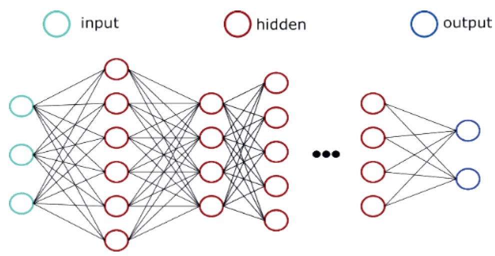

Fig. 1: Example of a deep network architecture.

The continuous technological advancements imply a growing relevance of accurate measurement techniques. The deep learning application here is based on the tilted-wave interferometer (TWI) [1]. The TWI is a highly accurate measurement technique for the reconstruction of optical aspheres and freeform surfaces using contact-free interferometric measurements. Topographies are reconstructed by solving a numerically expensive inverse problem from the measured intensity images using a numerical model for the wave propagation through the optical system.

Methods

A database of virtual measurement results has been constructed using the simulation toolbox SimOptDevice [7]. First, the test topographies were generated by adding randomly chosen difference topographies to a specified design. Then, the optical path length differences were calculated by the simulation toolbox. The task of

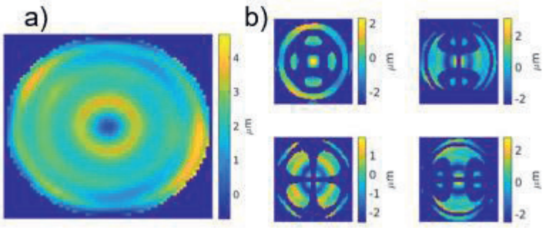

Fig. 2: Example of a data sample consisting of a) a test topography deviation and b) the corresponding differences of optical path length differences.

the inverse problem is to reconstruct a topography deviation from the corresponding deviations of optical path length differences. Fig. 2 shows an example of a data sample consisting of a test topography deviation and the corresponding differences of optical path length differences. The quantity and quality of the data have an essential impact on the network performance, especially considering its generalization capability. The constructed data base consists of $40{,}000$ test topographies (one channel output of the network), together with the corresponding optical path length differences (four channel input of the network) for training. A disjoint set was generated containing $2{,}000$ randomly generated samples for testing. The generated data are very diverse ranging from a root mean squared deviation of 20nm to several µm.

A U-Net architecture [6] was chosen to solve the inverse problem of reconstructing the test topography deviations from the optical path length differences. The U-Net is a deep neural network with bottleneck structure and skip-connections and has been already successfully applied in various computational imaging tasks. It is desirable to have an idea of the trustworthiness of individual network predictions in addition to the overall accuracy on a test set. A relevant quantity in this context is the uncertainty of an output generated by the network. Uncertainty quantification was realized by learning an ensemble of networks and computing its standard deviation per output pixel. The ensemble prediction is given as the mean of the different network predictions.

Results and Conclusion

The topography deviations were predicted together with their corresponding uncertainties from the optical path length differences in the test set after having trained the ensemble of U-Nets on the disjoint training set. Some results are shown in Fig. 3. More precisely, the profiles of some reconstructed topography deviations are shown together with their uncertainties and the known ground truth. The obtained results show that the estimated uncertainties cover the errors of the prediction. Furthermore, the root mean squared error of the predictions is an order of magnitude smaller than the variability of the

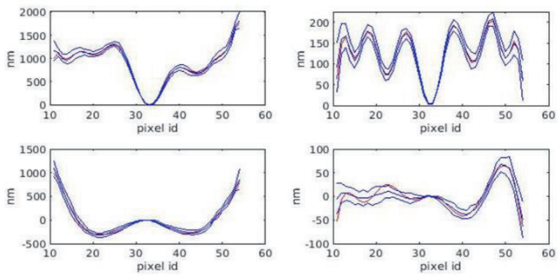

Fig. 3: Profile plots of the ensemble results on random test data. The prediction with uncertainty interval is shown in blue and the underlying ground truth in red.

topography deviations within the test set. The median error is even less.

We conclude that deep learning can be successfully applied in the context of computational optical form measurement, assuming ideal measurement conditions. Uncertainty quantification in terms of an ensemble of networks yields a reliable uncertainty characterization of network predictions. Comparing the proposed approach to the conventional method [1] as well as incorporating calibration errors and testing on real measurements are referred to future work.

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