euspen's 26th International Conference & Exhibition, Krakow, PL, June 2026

www.euspen.eu

Deep learning-based removal of phase shift errors in phase-shifting interferometry for high-accuracy surface metrology

Young-Sik Ghim[1, 2,*], Manh The Nguyen[1], Hyug-Gyo Rhee[1, 2]

[1]*Length and Dimensional Metrology Group, Division of Physical Metrology, Korea Research Institute of Standards and Science (KRISS), Science Town, Daejeon 34113, South Korea*
[2]*Department of Science and Measurement, University of Science and Technology (UST), Science Town, Daejeon 34113, South Korea*

**young.ghim@kriss.re.kr*

Abstract
Accurate 3D surface metrology is indispensable in high-technology sectors such as semiconductor and aerospace industries. Phase-shifting interferometry is a well-established optical technique, renowned for its exceptional precision and speed, making it suitable for industrial inspection and measurement. However, phase-shift inaccuracies between interferograms can result in fringe-print-through errors, effecting the precision of surface measurements. In this paper, we present a novel deep learning-based method to mitigate these errors in phase-shifting interferometry. Our proposed approach utilizes a UNet++ deep learning model that processes an error-embedded surface phase map as input to directly predict the corresponding phase-shifting errors. Trained exclusively on simulated datasets, the model learns to isolate and quantify these specific inaccuracies. Both simulation and experimental results confirm that our deep-learning approach effectively eliminates phase-shifting errors with high versatility, rapid processing, and robustness. This advancement results in a significant improvement in the measurement accuracy of phase-shifting interferometry, enhancing its reliability for demanding metrological applications.

Phase-shifting interferometry, Fringe-print-through error, Deep learning

1. Introduction

Optical interferometry plays a crucial role in measuring the flatness, surface roughness, and film thickness of semiconductor wafers with high precision. The phase-shifting technique [1, 2] provides 3D surface profiles with sub-nanometer resolution, making it a key metrology solution in the semiconductor industry. However, in phase-shifting interferometry, measurement errors typically arise from inaccurate phase shift amounts and environmental factors such as temperature, vibration, and air turbulence [3, 4].

Dynamic interferometry using polarization-based retrieval [5-8] offers real-time single-shot measurements, but is highly susceptible to errors from optical components. The fringe-print-through (FPT) phenomenon [9, 10], caused by inaccurate phase retardation, misaligned polarization angles, and nonuniform transmittance, introduces ripple-like phase errors that significantly compromise measurement accuracy. While various approaches have been proposed to address these errors, model-based algorithms struggle to fully adapt to varying conditions. This paper proposes a novel deep learning-based measurement algorithm using Unet++ architecture to effectively remove FPT errors while maintaining the real-time advantage of dynamic interferometry [11].

2. Fringe-print-through error removal using deep learning

2.1. Network architecture and training strategy

The proposed FPT error removal method uses Unet++ deep learning architecture. The input is the phase map with FPT error after removing 64 Zernike terms, and the output is the corresponding FPT error. The network learns to predict FPT error directly from the input phase map through proper training. The encoder path consists of convolution blocks with filter size of 32, kernel size of 3, ReLU activation, and MaxPooling layers. The input size is defined as (None, None) to accept different image sizes during inference

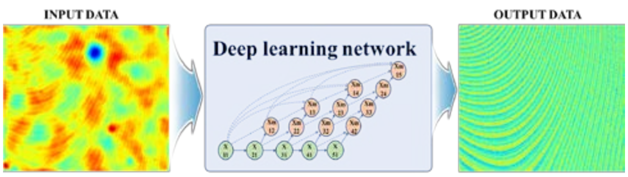

Figure 1. General diagram of proposed method. Our general idea is by training a deep learning network with the input is phase map with nonlinearity error from polarized camera and output is the corresponding nonlinearity error, the model can learn how to predict error from new phase map

2.2. Training data generation

An interferometry system with polarized camera and a piezoelectric deformable mirror (Thorlab DMH40/M-P01) was used to generate training data. By randomly changing Zernike coefficients, different mirror shapes were generated. For each shape, 10 phase-shift patterns were captured with 50nm steps. The ground truth phase (without FPT error) was obtained by averaging 10 unwrapped phases. The phase from a single interferogram contains FPT error and is used as input. The output training data is the difference between the input phase and the ground truth phase. After Zernike polynomial fitting up to 64 terms to remove the free-form shape, the FPT error becomes clearly visible. A total of 1,000 training data (1024×1224 pixels) were generated and cropped into 16,000 images (256×256 pixels), divided into 13,000 training and 3,000 validation set.

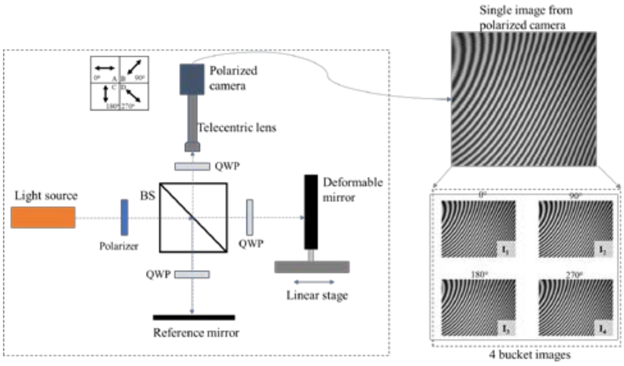

Figure 2. System setup for generating training data. Polarized camera captured the single interferogram images which contain 4 phase-shift images

3. Results

In real application, after getting the new input phase from single image using polarized camera, we remove the first 64 Zernike terms to get the phase with FPT error presented as input data. Then, DL network will be used to predict the FPT error from input data and the final error-free phase is obtained by subtracting the input data to predicted phase error as described in Fig. 3.

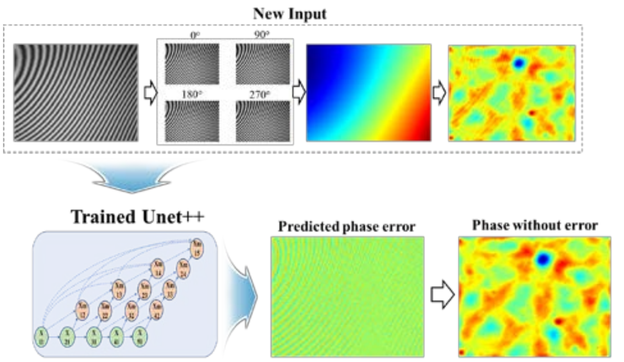

Figure 3. General FPT error removal process from a single polarized camera image with trained deep learning network

In order to evaluate the effectiveness of proposed method, we performed an experiment by measuring a concave mirror. The concave mirror sample is Thorlabs CM508-200-G01. As we can see in Fig. 3 (c), the FPT error is greatly reduced compare to original one even though it is still not completely removed. There are still small amount of FPT error presented in the phase map. This could be improved by using more phase-shifting images to improve the ground-truth in the training and increasing the number of training data.

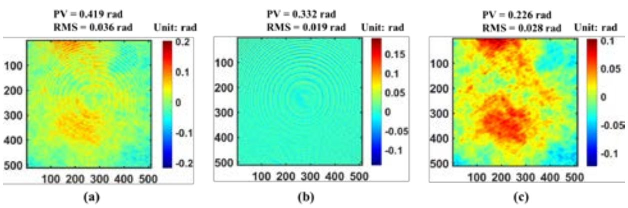

Figure 4. FPT error removal in free-form surface measurement using interferometer. (a) Phase of concave mirror with FPT error, (b) Predicted FPT error, and (c) Phase after subtracting the FPT error.

4. Conclusion

In conclusion, we demonstrated a deep learning based- FPT error removal method for polarized camera. By using deformable mirror to obtain training data and averaging technique to obtain error-free ground truth, trained deep learning network could effectively help to reduce the FPT error on the phase map by half as demonstrated in the experimental section. The performance of deep learning network could be improved more if we can obtain better error-free ground truth by increasing the number of phase-shift and increasing the number of data in the averaging step with the trade-off of increasing the time for preparing training data. However, once model is trained, we can removed the FPT error on the phase map obtained from polarized camera very quickly and efficiently which help perform one-shot or real-time measurement with higher accuracy. The performance of deep-learning based FPT error removal could also be improved if we can optimize and apply state-of-the-art deep learning networks. In general, this deep-learning based FPT method open up a new robust, high-speed method in improving the measurement accuracy of dynamic interferometry.

5. Funding

This work was supported by the Technology Innovation Program (or Industrial Strategic Technology Development Program) ("RS-2023-00237714", Development of Dynamic Metrology Tool for CMP Process Stabilization) funded By the Ministry of Trade, Industry & Energy (MOTIE, Korea) (1415187786)

References

[1] J. H. Bruning, D. R. Herriott, J. E. Gallagher, D. P. Rosenfeld, A. D. White, and D. J. Brangaccio, "Digital Wavefront Measuring Interferometer for Testing Optical Surfaces and Lenses," Appl. Opt. 13, 2693-2703, 1974.

[2] J. C. Wyant, “Interferometric optical metrology: basic system and principles,” Laser Focus 65–71, 1982

[3] K. Kinnstaetter, Adolf W. Lohmann, Johannes Schwider, and Norbert Streibl, "Accuracy of phase shifting interferometry," Appl. Opt. 27, 5082-5089, 1988.

[4] J. Schmit and K. Creath, "Extended averaging technique for derivation of error-compensating algorithms in phase-shifting interferometry," Appl. Opt. 34, 3610-3619, 1995.

[5] J. Millerd, N. Brock, J. Hayes, M. North-Morris, M. Novak and J. C. Wyant, “Pixelated phase-mask dynamic interferometer,” Fringe 2005: The 5th International Workshop on Automatic Processing of Fringe Patterns. Springer Berlin Heidelberg, 2006

[6] N. Brock, J. Hayes, B. Kimbrough, J. Millerd, M. North-Morris, M. Novak and J. C. Wyant, "Dynamic interferometry." Novel optical systems design and optimization VIII. Vol. 5875. SPIE, 2005.

[7] D. M. Sykora, and Peter de Groot. "Instantaneous measurement Fizeau interferometer with high spatial resolution." Optical manufacturing and testing IX. Vol. 8126. SPIE, 2011.

[8] Y.-S. Ghim, Y. B. Seo, K.-N. Joo, and H.-G. Rhee, "Single-shot spectrally resolved interferometry for the simultaneous measurement of the thickness and surface profile of multilayer films," Opt. Express 29, 25524-25534, 2021.

[9] B. Kimbrough, "Correction of errors in polarization based dynamic phase shifting interferometers." Int. J. Optomechatronics 8(4), 304-312, 2014

[10] C. T. Farrell and M. A. Player. "Phase step measurement and variable step algorithms in phase-shifting interferometry." Meas. Sci. Technol. 3(10) 953, 1992.

[11] M. Th. Nguyen, I. K. Park, H. -G. Rhee, and Y.-S. Ghim, , "Deep learning based fringe-print-through error and noise removal for dynamic phase-shifting interferometry," Opt. Laser Technol. 191, 113313, 2025.