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Integrating convolutional neural network and physical models to enhance denoising in envelope-based surface reconstruction from coherence scanning interferometry

Ruidong Xue[1], Helia Hooshmand[1], Richard Leach[1]

[1]*Manufacturing Metrology Team, Faculty of Engineering, University of Nottingham, UK*

Ruidong.Xue@nottingham.ac.uk

Abstract
Coherence scanning interferometry (CSI) is an optical technique for measuring surface topography. However, it is sensitive to environmental noise and vibration. This research integrates a machine learning algorithm with a physical model to enhance the robustness and accuracy of surface reconstruction in CSI. We developed a convolutional neural network-based physical model (CNNP) that combines the strengths of CNNs with the Hilbert transform (HT)-envelope method, a well-known surface reconstruction technique based on the envelope peak detection. By employing the HT within a machine learning framework, we improved noise handling in CSI data. Our experiments used simulated CSI data for a sinusoidal and a rectangle grating profile with random noise, achieving mean squared error results with the CNNP method that were an order of magnitude lower than those obtained using the HT-envelope method alone. This approach demonstrates an enhancement over conventional physics-based methods, illustrating the effectiveness of integrating machine learning with physical principles in reducing the effect of noise in CSI processing.

Machine learning, CNN, noise reduction, surface reconstruction, CSI

1. Introduction

Coherence scanning interferometry (CSI) has enabled precise and accurate measurements of surface topography [1]. As industries ranging from semiconductor manufacturing to biomedical devices increasingly rely on ultra-precise components, the demand for accurate surface characterisation under various environmental conditions has become critical. However, the sensitivity of CSI data to environmental noise and vibrations presents a significant challenge.

CSI employs localised interference fringe patterns to derive surface height maps using surface reconstruction methods [2]. While effective under controlled conditions, some methods face limitations in noisy environments, a common scenario in practical applications. It is not always feasible to use strict environmental controls or complex hardware setups for noise reduction.

Machine learning (ML) introduces an additional paradigm in optical metrology, providing powerful tools for handling complex and noisy data [3]. Traditional data mining techniques have been utilised for signal processing [4,5]. However, recent research has demonstrated that ML can enhance the accuracy of measurement results by effectively reducing noise. Nonetheless, relying solely on ML often lacks integration with the domain-specific knowledge that is crucial for ensuring the reliability and interpretability of the results.

This research introduces a surface reconstruction approach that integrates a ML model, a convolutional neural network (CNN), with a physical model, the Hilbert transform (HT) envelope-based model to enhance noise reduction in CSI. This CNN-based physical model (CNNP) leverages the strengths of both data-driven and physics-based methodologies, offering a reduction to the impact of environmental noise in CSI. The integration of CNN with HT, a method used for envelope detection through signal processing techniques, promises to maintain high accuracy even in low signal-to-noise ratio (SNR) environments.

2. Method

The objective of this study was to integrate a CNN with a physical modelling approach to enhance the noise reduction capabilities in CSI. This integration aimed to combine the robust, data-driven capabilities of ML with the precision of the established HT envelope-based method. The methodological approach was divided into several key components as described below.

2.1. Model design

The core of our methodology involved the design and implementation of a CNNP. This model combined the architectural strengths of CNNs for feature extraction with HT for envelope peak detection in CSI signals. The CNN architecture was designed to handle the interference fringe patterns observed in CSI data. The CNN comprised several convolutional layers followed by batch normalisation layers to process the signals effectively.

2.2. Hilbert transform integration

In the HT method, the fast Fourier transform (FFT) is used to convert the signal into its spatial frequency components. The coefficients corresponding to negative frequencies are set to zero, and the inverse FFT is then performed on the positive frequency components to reconstruct the envelope [6]. HT is applied to the outputs of the CNN layers to obtain the envelope of the fringe patterns.

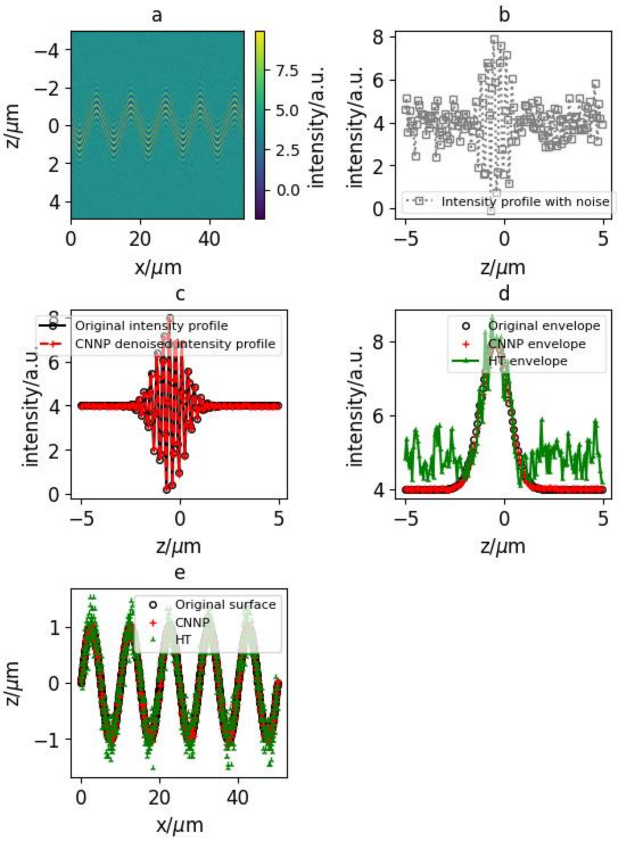

Figure 1. Visualisation of simulated CSI signal data with added noise, along with corresponding envelope detection and surface reconstruction for a sinusoidal profile. The sinusoidal profile spans 50 μm along the x-axis with 0.1 μm^{-1} spatial frequency and 1 μm amplitude, featuring a noise level with an SNR of 20 dB. (a) Intensity map. (b) A randomly selected intensity signal along the *z*-axis at *x* = 25.8 μm. (c) Comparison between the denoised intensity profile, obtained using the CPNN from (b), and the original intensity profile. (d) Envelope detection MSE results comparing the benchmark with those achieved using the CNNP (1.241×10^{-2} μm^2) and the HT (6.444×10^{-1} μm^2) methods. (e) Surface reconstruction MSE results comparing the benchmark with those achieved using the CNNP (5.015×10^{-3} μm^2) and the HT (5.219×10^{-2} μm^2) methods.

3. Experiment

To evaluate the effectiveness of the CNNP model, we utilised simulated CSI signal data representing a sinusoidal and a rectangle grating profile with a spatial frequency of 0.1 μm^{-1} and an amplitude of 1 μm. Noise was randomly added to these signals to simulate real-world measurement conditions, with a range of SNRs from 30 dB to 10 dB. This comparison was performed across the different noise levels specified, providing an understanding of the model's robustness and accuracy in noise reduction. The MSE of heights of the reconstructed profile using CNNP is an order of magnitude smaller than that of the HT method alone in Figure 1 and Figure 2.

4. Conclusion

We introduced a CNNP that combines ML with the HT method to improve the robustness and accuracy of surface reconstruction from noisy data.

Our findings demonstrate that the integration of ML with the HT-envelope method enhances the accuracy of surface reconstruction in CSI under noisy conditions when it has been tested by two kinds of geometries. The combination of CNNs with the physical principles of the HT method reduces the impact of environmental noise and low SNRs, crucial for applications requiring precise surface measurements in uncontrolled environments.

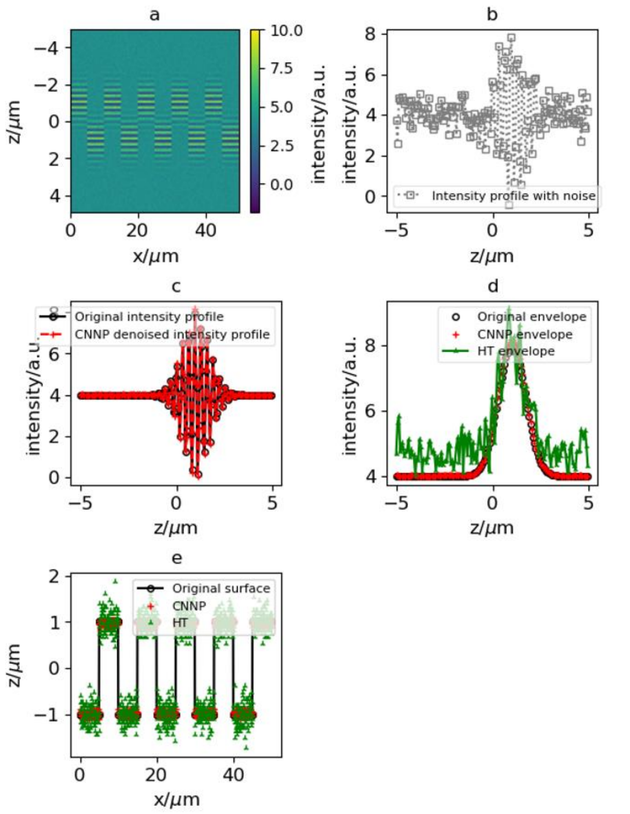

Figure 2. Visualisation of simulated rectangle grating profile. (a) Intensity map. (b) A randomly selected intensity signal along the *z*-axis at *x* = 24.85 μm. (c) Comparison between the denoised intensity profile, obtained from (b), and the original intensity profile. (d) Envelope detection MSE results comparing the benchmark with those achieved using the CNNP (8.647×10^{-3} μm^2) and the HT (6.397×10^{-1} μm^2) methods. (e) Surface reconstruction MSE results comparing the benchmark with those achieved using the CNNP (3.785×10^{-3} μm^2) and the HT (5.11×10^{-2} μm^2) methods.

Acknowledgments

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