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INVESTIGATION OF THE SOURCES OF MEASUREMENT UNCERTAINTY IN THE CALIBRATION OF MEASURING INSTRUMENTS

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ABSTRACT

Digital holographic interferometry (DHI) is a well-established noncontact optical technique for measuring sub-micrometre in-plane and out-of-plane displacement fields. However, its application to dynamic measurements is limited by speckle decorrelation noise and the computational demands of phase reconstruction, spatial phase unwrapping, and noise filtering. This study proposes a hybrid measurement framework that combines a conventional Mach–Zehnder/Twyman–Green DHI configuration with a convolutional neural network (CNN) for joint speckle-noise suppression and phase unwrapping. The physical principles of hologram recording, numerical reconstruction using angular-spectrum and Fresnel methods, and the relationship between unwrapped optical phase and displacement are used to generate a physically consistent synthetic training dataset covering different levels of speckle decorrelation, fringe density, and detector noise. A U-Net-based encoder–decoder architecture is proposed and evaluated against classical windowed Fourier-transform filtering and quality-guided phase unwrapping using phase root-mean-square error, unwrapping success rate, and computational latency. Because experimental hardware validation has not yet been completed, all quantitative performance values are reported as targets derived from synthetic data. The results indicate that the proposed learning-based approach can potentially reduce processing latency while maintaining measurement fidelity, supporting near-real-time vibration monitoring, non-destructive testing, and characterization of elastic properties in engineering materials.

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Keywords: *digital holographic interferometry; convolutional neural network; phase unwrapping; speckle denoising; vibration measurement; optical metrology.*

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Introduction

Digital holographic interferometry (DHI) is a coherent optical metrology technique that records the complex amplitude of a scattered wavefront on a digital sensor and reconstructs it numerically, enabling full-field, non-contact measurement of out-of-plane and in-plane displacement with sensitivity at the sub-wavelength scale (Kreis, 2005; Schnars & Jüptner, 2002). Since its introduction by Yamaguchi and Zhang (1997) as phase-shifting digital holography, the technique has been applied to deformation analysis, vibration monitoring of mechanical structures, non-destructive testing (NDT) of composite and metallic components, and characterization of the elastic properties of engineering materials (Rastogi, 2001). Its

principal advantage over point-wise techniques such as laser Doppler vibrometry is that it delivers a two-dimensional displacement or strain map from a single or a small sequence of recorded holograms, without physical contact with the specimen and without the need for surface preparation.

Despite these advantages, the conventional DHI processing chain has three well-documented bottlenecks. First, the reconstructed phase map is corrupted by speckle decorrelation noise, which is intrinsic to coherent imaging of optically rough surfaces and is the dominant noise source in holographic interferometry (Goodman, 2020). Second, the phase is recovered only modulo 2π, so a spatial phase-unwrapping step is required to recover a continuous displacement field; classical unwrapping algorithms (path-following, minimum-norm, and quality-guided methods) are prone to error propagation in the presence of noise, phase discontinuities, and steep gradients associated with high-density fringe patterns (Ghiglia & Pritt, 1998). Third, the iterative or path-dependent nature of conventional filtering and unwrapping algorithms limits processing throughput, which is a practical obstacle for near-real-time vibration monitoring and in-line production inspection.

Over the past decade, deep-learning methods have been applied with increasing success to each of these three bottlenecks individually. Convolutional neural networks have been used for speckle-noise suppression in holographic phase data (Montresor et al., 2020), for end-to-end spatial phase unwrapping (Wang et al., 2022), and for single-shot fringe-pattern analysis that bypasses phase-shifting acquisition altogether (Feng et al., 2019). Deep networks have also been used to detect vibration-induced decorrelation directly from hologram statistics during multiwavelength measurement, achieving above 96% classification accuracy with microsecond-scale inference (Störk et al., 2024). These results indicate that a learning-based processing stage, once trained on a sufficiently representative and physically realistic data distribution, can approximate the outcome of classical iterative algorithms at a small fraction of their computational cost. However, the majority of reported architectures address denoising and unwrapping as two separate stages, each requiring its own network and its own error budget, and comparatively few studies quantify the achievable measurement uncertainty against the classical processing chain under a common, physically grounded evaluation protocol.

The present work makes three contributions. First, it formulates the DHI measurement chain - from hologram recording to displacement field - in a form that yields a physically consistent forward model, which is then used to generate synthetic training and evaluation data with controllable and realistic speckle decorrelation, fringe density, and detector noise. Second, it proposes a single CNN stage, based on a U-Net encoder–decoder architecture, that performs joint denoising and unwrapping directly on the wrapped phase map, reducing the processing chain from two learned or iterative stages to one. Third, it defines an evaluation protocol - phase RMSE, unwrapping success rate as a function of fringe density, and computational latency - against which the proposed network is compared with classical windowed Fourier-transform filtering combined with quality-guided unwrapping. Because hardware validation on an experimental DHI rig has not yet been completed at the time of writing, all quantitative figures in the Results section are explicitly presented as targets computed on the physically modeled synthetic dataset, and the Limitations and Required Experimental Validation section specifies the experimental campaign required to qualify the method metrologically.

Physical Principles of Digital Holographic Interferometry

Hologram Formation and Numerical Reconstruction

In off-axis digital holography, a coherent object wave $O(x,y) = A_O(x,y)\cdot\exp[i\varphi_O(x,y)]$ scattered from the specimen interferes on the sensor plane with a reference wave $R(x,y) = A_R(x,y)\cdot\exp[i\varphi_R(x,y)]$ incident at a small angle θ relative to the object wave. The sensor records the intensity

$$I_H(x,y) = |O|^2 + |R|^2 + O\cdot R^* + O^*\cdot R$$

The cross terms $O\cdot R^*$ and $O^*\cdot R$ carry the object's complex amplitude and its conjugate, respectively, and are numerically isolated in the reconstruction step, either by angular-spectrum

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propagation or by Fresnel-transform reconstruction, followed by spatial filtering in the Fourier domain to separate the +1 diffraction order from the zero order and the conjugate twin image (Kreis, 2005; Schnars & Jüptner, 2002). In phase-shifting digital holography, several holograms are recorded with a known reference-phase increment (typically $\pi/2$), which permits direct extraction of the complex object field without spatial filtering and without loss of spatial-frequency bandwidth (Yamaguchi & Zhang, 1997).

Interferometric Phase and Displacement

Holographic interferometry compares the reconstructed phase of the object wave at two states, $\varphi_1(x,y)$ before and $\varphi_2(x,y)$ after deformation, vibration, or loading. The wrapped phase difference

$$\Delta\varphi_w(x,y) = W[\varphi_2(x,y) - \varphi_1(x,y)]$$

where $W[\cdot]$ denotes wrapping onto the interval $(-\pi, \pi]$, is related to the out-of-plane displacement component $d(x,y)$ along the sensitivity vector by

$$\Delta\varphi(x,y) = (4\pi/\lambda)\cdot d(x,y)\cdot\cos(\alpha)$$

for a single-illumination, single-observation configuration with illumination/observation angle α to the surface normal and laser wavelength λ, and by a corresponding sensitivity-matrix relation when double-illumination or dual-wavelength configurations are used to separate in-plane and out-of-plane components (Rastogi, 2001). Recovering $d(x,y)$ requires the unwrapped, continuous phase $\Delta\varphi(x,y) = \Delta\varphi_w(x,y) + 2\pi k(x,y)$, where the integer field $k(x,y)$ is precisely what spatial phase-unwrapping algorithms must estimate, and what the proposed network in the Methodology section is trained to predict jointly with noise suppression.

Noise Sources and Classical Processing Limitations

The dominant phase-corrupting mechanism in DHI is speckle decorrelation, arising because the optically rough specimen surface produces a random speckle field whose statistics change between the reference and deformed states; this decorrelation noise is multiplicative and spatially correlated with the local fringe density, unlike additive detector (shot and read) noise (Goodman, 2020). Classical de-noising approaches - spatial averaging, windowed Fourier-transform filtering, and wavelet-based filtering - trade spatial resolution for noise suppression and can bias the phase estimate near high-gradient regions, precisely where accurate unwrapping is most critical. Classical unwrapping algorithms are, in turn, sensitive to residual noise left by the denoising stage: path-following methods can propagate local errors across the entire field, and quality-guided methods depend on a reliable local quality map that itself degrades under high noise or steep gradients (Ghiglia & Pritt, 1998). These coupled sensitivities motivate a joint, learned approach to denoising and unwrapping rather than two independently optimized stages.

Deep Learning in Digital Holographic Interferometry: Related Work

Montresor et al. (2020) demonstrated a deep-learning-based algorithm for de-noising phase data corrupted by speckle decorrelation in DHI, trained on a dedicated database of phase-fringe images and reporting substantial fringe-quality improvement over classical filters at comparable spatial resolution. Fang et al. (2022) extended this line of work with a conditional generative adversarial network for speckle denoising, reporting improved preservation of high-gradient fringe regions relative to non-adversarial CNN baselines. On the unwrapping side, Wang et al. (2022) provide a comprehensive comparative review of deep-learning spatial phase-unwrapping architectures, classifying methods into direct regression, wrapped-count-map classification, and semantic-segmentation-style approaches, and reporting that classification-based architectures are generally more robust to noise than direct regression under matched training conditions. Feng et al. (2019) demonstrated that CNNs can perform single-shot fringe-pattern analysis, recovering the wrapped phase directly from a single fringe pattern without phase-shifting acquisition, which is directly relevant to dynamic and vibration measurement where multiple sequential exposures are impractical. Störk et al. (2024) showed that a deep network trained to predict the standard deviation of the hologram phase can detect vibration-induced decorrelation during the early stage of hologram reconstruction with 96–97% accuracy and microsecond-scale inference, enabling real-time

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rejection of corrupted measurement frames in a production environment. Vithin et al. (2022) reported direct estimation of phase derivatives using a Y-Net architecture, while Narayan and Gannavarpu (2025) later demonstrated simultaneous estimation of first- and second-order phase derivatives embedding strain and curvature. These approaches can bypass explicit unwrapping for applications where derivative fields, rather than absolute displacement, are the quantities of interest.

The present work differs from this body of literature in combining denoising and unwrapping into a single network trained on a physically derived forward model of the DHI measurement chain (the Physical Principles of Digital Holographic Interferometry section), rather than treating the two operations as independently trained stages, and in explicitly separating the metrologically validated components of the pipeline (the physical model and the classical baseline) from the components whose performance is, at this stage, established only on synthetic data (the proposed CNN).

Methodology

Optical Configuration

The measurement configuration is a Mach–Zehnder off-axis digital holographic interferometer with a frequency-stabilized continuous-wave laser source, a beam-splitter arrangement dividing the beam into object and reference arms, and a CMOS sensor recording the interference pattern. For vibration measurement, a high-speed CMOS camera synchronized to the excitation source is used, following the high-speed acquisition approach established for rotating and vibrating structures (Pedrini et al., 2006). For quasi-static deformation and elasticity characterization, phase-shifting acquisition with a piezo-driven reference mirror is used to maximize phase accuracy in the reconstructed object field.

Physically Grounded Synthetic Dataset Generation

Training data are generated from the forward model of the Physical Principles of Digital Holographic Interferometry section rather than from unconstrained simulated fringe patterns, to ensure that the learned mapping is consistent with the underlying physics. Ground-truth displacement fields d(x,y) are generated from finite-element models of representative specimen geometries and loading conditions (uniform pressure loading, point loading, and harmonic excitation at frequencies from 50 Hz to 2 kHz for the vibration case). The corresponding phase field is computed from the sensitivity relation of the Interferometric Phase and Displacement section, wrapped, and corrupted with (i) multiplicative speckle decorrelation noise generated from a correlated random-phase model with decorrelation parameter matched to reported experimental ranges (Goodman, 2020), (ii) additive Gaussian detector noise at signal-to-noise ratios from 15 dB to 35 dB, and (iii) fringe densities spanning 2 to 25 fringes across the field of view to represent both low- and high-gradient deformation regimes. This procedure yields paired (wrapped, noisy phase → unwrapped, denoised phase) training examples with known ground truth, which is not available from experimental data alone without an independent reference metrology.

Network Architecture

The processing network is a U-Net-style encoder–decoder with skip connections, following the general architecture shown effective for DHI phase denoising and for classification-based unwrapping in the reviewed literature (Montresor et al., 2020; Wang et al., 2022). The wrapped, noisy phase map is provided to the network as a two-channel input, $\sin(\Delta\varphi_w)$ and $\cos(\Delta\varphi_w)$, which avoids the discontinuity artefacts that a direct wrapped-phase input would introduce at the $\pm\pi$ boundary. The encoder path consists of four downsampling blocks (convolution, batch normalization, ReLU, max-pooling), a bottleneck block, and a symmetric decoder path with transposed-convolution upsampling and skip connections from the corresponding encoder stage. The network produces two outputs: a denoised wrapped-phase estimate (sin/cos pair) and a per-pixel integer wrap-count map, following the classification-based unwrapping formulation reported to be more noise-robust than direct phase regression (Wang et al., 2022). The two outputs are combined to yield the final unwrapped, denoised phase field, from which the displacement field is computed via the sensitivity relation of the Interferometric Phase and Displacement section.

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Training and Evaluation Protocol

The network is trained with a composite loss combining mean-squared error on the sin/cos denoised phase channels and cross-entropy loss on the wrap-count classification map, using the Adam optimizer with a learning-rate schedule and early stopping on a held-out validation split of the synthetic dataset. Evaluation uses an independent synthetic test set spanning the full noise and fringe-density range described in the Physically Grounded Synthetic Dataset Generation section, plus, where available, phase maps from a canonical experimental benchmark dataset (Montresor et al., 2020) for cross-checking against a real (non-simulated) noise distribution. Three metrics are reported: (i) phase RMSE between the network output and ground truth, expressed in radians; (ii) unwrapping success rate, defined as the fraction of pixels for which the estimated wrap-count matches the ground-truth wrap-count, as a function of local fringe density; and (iii) end-to-end inference latency per interferogram on a single GPU, relevant to near-real-time vibration monitoring.

Results (Synthetic-Data Targets - Not Yet Experimentally Validated)

IMPORTANT: The optical hardware described in the Optical Configuration section has not yet been assembled and no experimental holograms have been recorded at the time of writing. All figures in this section are performance targets computed on the physically modeled synthetic dataset of the Physically Grounded Synthetic Dataset Generation section, intended to establish expected feasibility and to guide the experimental validation campaign of the Limitations and Required Experimental Validation section, and must not be cited as measured or metrologically qualified results.

On the synthetic test set, the proposed joint denoising/unwrapping network is targeted to achieve a phase RMSE below 0.15 rad at signal-to-noise ratios at or above 20 dB, compared with a target of 0.3–0.4 rad for windowed Fourier-transform filtering followed by quality-guided unwrapping under matched noise conditions, consistent with the order of improvement reported for CNN-based denoising over classical filters in the reviewed literature (Fang et al., 2022; Montresor et al., 2020). Unwrapping success rate is targeted to remain above 95% for fringe densities up to approximately 15 fringes across the field of view, degrading at higher densities where wrap-count ambiguity increases; the classical quality-guided baseline is targeted to fall below 90% success rate beyond approximately 10 fringes under the same noise conditions, consistent with reported error-propagation behaviour of path-dependent unwrapping algorithms (Ghiglia & Pritt, 1998; Wang et al., 2022). End-to-end inference latency for the proposed network is targeted at under 50 ms per interferogram on a single consumer-grade GPU, versus a target of several hundred milliseconds to several seconds for iterative classical unwrapping of a comparable field size, in line with the sub-millisecond-to-millisecond inference times reported for related CNN architectures applied to hologram-quality classification (Störk et al., 2024).

A summary of the targeted comparison is given in Table 1.

Table 1

Targeted Comparison Between the Classical Pipeline and the Proposed CNN

Metric	Classical pipeline (target)	Proposed CNN (target)
Phase RMSE (rad), SNR ≥ 20 dB	0.30 – 0.40	< 0.15
Unwrapping success rate at ≤10–15 fringes	< 90%	> 95%
Inference latency per interferogram	10^2–10^3 ms (iterative)	< 50 ms (GPU)

Note. Values are design targets computed on physically modeled synthetic data; they are not measured results. See the Results and Limitations and Required Experimental Validation sections.

Discussion. The physical model of the Physical Principles of Digital Holographic Interferometry section shows that the quantity a learning-based processing stage must recover - the continuous, denoised

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phase field - is fully determined by the same displacement field that governs the classical processing chain; the CNN therefore does not introduce a new physical observable, but replaces two error-prone numerical estimation steps (noise filtering and integer wrap-count estimation) with a single learned mapping trained directly against physically consistent ground truth. This reframing is consistent with the broader deep-learning-for-holography literature, in which learned methods are understood as approximating a known forward/inverse physical relationship rather than as a black-box substitute for the underlying optics (Feng et al., 2019; Wang et al., 2022). The expected latency advantage is particularly relevant to the vibration-measurement application identified in the collaborators' prior work, where hologram sequences must be processed at rates compatible with the excitation bandwidth, and to production-line non-destructive testing, where throughput constraints make iterative classical unwrapping impractical (Pedrini et al., 2006; Störk et al., 2024).

At the same time, the reliance on a synthetic training and evaluation corpus is a genuine limitation rather than a methodological convenience: speckle decorrelation statistics, sensor noise characteristics, and mechanical vibration spectra of real specimens and real optical hardware inevitably differ from the modeled distributions in ways that can only be bounded, not eliminated, by careful forward-model design. The domain gap between synthetic and experimental data is a recognized risk for all deep-learning approaches to holographic phase processing, and is the reason the quantitative comparison in the Results section is reported strictly as a target rather than as a validated result.

Limitations and Required Experimental Validation

The following limitations define the scope of the present results and the experimental work required before the method can be considered metrologically qualified for the 01.04.05 (Optics) specialty:

1. No experimental holograms have yet been recorded on the optical configuration described in the Optical Configuration section; all performance figures in the Results section are computed exclusively on physically modeled synthetic data and are explicitly labeled as targets.
2. Assembly and calibration of the Mach–Zehnder DHI rig, including wavelength stabilization, reference-arm phase-shifting calibration, and sensor geometric calibration, is required before any hologram can be recorded with known measurement uncertainty.
3. Cross-validation against an independent reference metrology (e.g., a calibrated laser Doppler vibrometer for the vibration case, or a strain-gauge/extensometer reference for the deformation and elasticity cases) is required to establish absolute measurement accuracy and traceability, which cannot be established from synthetic ground truth alone.
4. The domain gap between the synthetic speckle-decorrelation model and real specimen/optics noise statistics must be quantified experimentally; a transfer-learning or fine-tuning stage on a modest experimental dataset is anticipated to be necessary and is planned as part of the validation campaign.
5. Generalization across specimen material classes (metals, composites, biological tissue) and across the full intended fringe-density and vibration-frequency range has not been tested experimentally and should not be assumed from the synthetic-data results alone.

Conclusion

This paper has formulated the physical measurement chain of digital holographic interferometry and used it to derive a physically consistent framework for training a single CNN stage that jointly performs speckle denoising and phase unwrapping, in place of the conventional two-stage classical pipeline. On physically modeled synthetic data, the proposed approach is targeted to substantially reduce phase RMSE and processing latency relative to classical windowed Fourier-transform filtering and quality-guided unwrapping, while improving robustness at high fringe density. These results motivate, but do not yet constitute, a metrologically validated measurement method: the immediate next step is assembly of the experimental DHI rig and a controlled validation campaign against independent reference instrumentation, as specified in the Limitations and Required Experimental Validation section, after which the method's

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applicability to non-contact deformation, vibration, and elasticity measurement within the scope of specialty 01.04.05 (Optics) can be properly established.

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