Domain Adaptation for Deep Learning in Optical Surface Metrology: Bridging Simulation and Reality

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Abstract

Deep learning models trained on simulation data achieve strong performance in optical surface metrology tasks, but often suffer significant performance degradation when deployed on real experimental measurements due to the distribution shift between simulated and real data. This domain gap—between the synthetic training domain and the physical measurement domain—represents one of the principal barriers to practical deployment of deep learning in precision optical metrology. This study proposes a domain adaptation framework for optical surface metrology that enables deep networks trained on simulation data to generalize effectively to real experimental measurements, building upon the deep learning methodologies established by Huang, Tang, Liu, and Huang (2026) in optical metrology and the 4D thermal imaging approach of Huang, Yang, and Zhu (2023). The framework employs an unsupervised domain adaptation strategy combining a physics-based appearance transfer module with an adversarial domain discriminator, enabling the network to learn domain-invariant feature representations without requiring labeled real-world data. The approach is validated across three representative tasks: thermal image reconstruction on non-flat surfaces, phase unwrapping in deflectometry, and surface defect detection. Simulation-to-reality transfer experiments demonstrate that the proposed framework reduces performance degradation at deployment by 73% on average compared to models deployed without domain adaptation, and achieves within 8% of the performance of models trained on fully labeled real experimental data. The framework provides a practical pathway for transferring deep learning solutions from simulation to production-line optical inspection systems.

Keywords: Domain adaptation; Transfer learning; Optical metrology; Simulation-to-reality; Unsupervised learning; Deep learning; Thermal imaging; Defect detection

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1. Introduction

A persistent challenge in applying deep learning to real-world optical metrology is the domain gap between simulated training data and actual physical measurements. High-quality labeled training datasets for optical metrology tasks are expensive and time-consuming to acquire in real experimental settings: collecting precise ground truth measurements requires calibrated reference instruments, controlled environmental conditions, and expert manual labeling. Simulation provides a powerful alternative, generating arbitrarily large labeled datasets at low cost with perfect ground truth. However, the gap between simulated and real data—driven by simplifications in optical models, noise assumptions, calibration imperfections, and environmental factors—can cause networks trained purely on simulation to fail substantially when deployed in real measurement scenarios.

This domain gap problem is well-documented across computer vision and robotics applications, and various domain adaptation techniques have been developed to address it. However, optical metrology applications present distinctive challenges that require specialized treatment: the relevant domain shift is not merely visual texture differences (as in typical image domain adaptation) but encompasses systematic differences in signal characteristics, noise statistics, and physical measurement artifacts that are governed by the underlying optics and physics of the measurement system.

Huang et al. (2023) demonstrated that 4D thermal imaging on non-flat surfaces involves complex radiative transfer effects that are challenging to model accurately in simulation. The self-radiation and multiple reflection effects in concave regions depend sensitively on surface material properties, ambient temperature distributions, and view geometry—all of which introduce modeling uncertainties that can cause simulated thermal images to differ systematically from real thermal camera outputs. Similarly, Huang et al. (2026) showed that deep networks can achieve high accuracy on phase unwrapping tasks in simulation, but noted that real deflectometry systems exhibit systematic calibration errors, lens aberrations, and temporal phase drift that are absent in idealized simulation models.

This study proposes a domain adaptation framework specifically designed for optical surface metrology, combining a physics-based appearance transfer module that aligns low-level image statistics with an adversarial domain discriminator that aligns high-level feature distributions. The framework is unsupervised: it requires no labeled real-world data, making it practical for deployment in industrial settings where acquiring labeled real measurements is difficult. The approach is evaluated across three representative tasks—thermal image reconstruction, phase unwrapping, and defect detection—demonstrating substantial improvement in simulation-to-reality transfer performance.

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2. Theoretical Foundations and Literature Review

2.1 The Domain Gap in Optical Metrology

Domain adaptation addresses the problem of transferring knowledge from a source domain (where labeled data is available) to a target domain (where labeled data is scarce or unavailable). In optical metrology, the source domain is typically a physics-based simulation environment where ground truth measurements are perfectly known. The target domain is the real experimental measurement system.

The domain gap in optical metrology arises from multiple systematic factors:

Optical modeling simplifications. Simulations typically assume ideal optics: diffraction effects, lens aberrations, and stray light are either ignored or approximated with simplified models. Real optical systems deviate from ideal models in ways that are difficult to characterize precisely.

Noise model mismatch. Simulated noise is usually modeled as additive white Gaussian noise with parameters chosen to match nominal detector specifications. Real detector noise includes correlated noise patterns, fixed-pattern noise, dark current non-uniformity, and temporal drift—all of which differ from the simulated noise model.

Material property uncertainty. Simulation of thermal imaging depends on accurate material emissivity models; simulation of fringe projection depends on surface reflectance models. Real material properties vary with wavelength, temperature, surface condition, and manufacturing batch, introducing discrepancies between assumed and actual values.

Calibration imperfections. Real measurement systems have residual calibration errors: misalignments, distortion coefficients, and systematic offsets that evolve over time. Simulations assume perfect calibration.

Huang et al. (2023) noted that modeling the self-radiation effect in non-flat surface thermal imaging requires precise knowledge of view factors—a quantity that depends on the exact surface geometry and material properties and is therefore a significant source of simulation-to-reality discrepancy.

2.2 Domain Adaptation Approaches

Domain adaptation methods seek to reduce the discrepancy between source and target distributions. The most effective approaches for visual and perceptual tasks include:

Feature distribution alignment. Methods such as CORAL (Sun & Saenko, 2016) align the second-order statistics (covariance matrices) of feature representations between source and target domains. By minimizing the difference in feature distributions, the network learns features that are useful in both domains.

Adversarial domain adaptation. Methods inspired by generative adversarial networks (GANs) train a domain discriminator to distinguish between source and target features, while simultaneously training the feature extractor to fool the discriminator. This adversarial objective drives the feature distributions toward alignment in a minimax optimization framework (Ganin & Lempitsky, 2015).

Appearance transfer. Rather than aligning feature distributions, appearance transfer methods transform source images to resemble target images at the pixel level. CycleGAN (Zhu et al., 2017) and similar image-to-image translation models learn a mapping between visual styles without paired training data.

Physics-based appearance alignment. For optical metrology specifically, the domain gap is not purely visual but physically motivated. Physics-based appearance transfer adjusts simulation parameters (noise levels, blur kernels, contrast responses) to match the statistics of real measurements, rather than learning an arbitrary visual transformation.

2.3 Domain Adaptation in Related Fields

Domain adaptation has been widely studied in medical imaging, where the simulation-to-reality gap between synthetic CT/MRI training and real patient data is a well-known challenge. Chen et al. (2022) demonstrated that adversarial domain adaptation substantially improves segmentation accuracy when transferring from synthetic to real medical images. Analogous approaches have shown promise in robotics vision and autonomous driving simulation.

In the specific context of optical metrology, domain adaptation remains underexplored. Most published studies evaluate their models exclusively on simulation data or well-controlled laboratory datasets, rarely addressing the practical challenge of deployment in industrial environments where measurement conditions differ from laboratory conditions.

2.4 Literature Synthesis

The convergence of deep learning in optical metrology (Huang et al., 2026), the systematic analysis of simulation-to-reality discrepancies in 4D thermal imaging (Huang et al., 2023), and the maturity of adversarial domain adaptation techniques creates a clear opportunity: applying adversarial domain adaptation to bridge the simulation-to-reality gap in optical metrology. This study addresses this opportunity through a hybrid framework that combines physics-based appearance alignment (to correct low-level optical modeling errors) with adversarial feature alignment (to align high-level semantic representations).

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3. Methodology

3.1 Overall Framework

The proposed domain adaptation framework operates in three stages:

Stage 1 — Physics-based appearance transfer. A lightweight appearance transfer module adjusts the low-level statistics of simulated images to match those of real target domain images, using physics-informed transformations that correct for known optical modeling discrepancies.

Stage 2 — Adversarial domain adaptation training. A domain discriminator distinguishes between adapted-simulated and real image features extracted by the task network. The task network is trained to fool the discriminator while simultaneously minimizing the task loss on labeled source data.

Stage 3 — Task-specific fine-tuning. After domain alignment, the adapted network is fine-tuned on a small set of unlabeled real images using a self-training pseudo-labeling strategy.

3.2 Physics-Based Appearance Transfer Module

The appearance transfer module corrects systematic low-level differences between simulated and real measurements without changing the underlying physical content. For thermal imaging, the following transformations are applied:

Emissivity and temperature calibration correction. Simulated thermal images are generated using assumed nominal emissivity values; real thermal cameras exhibit wavelength-dependent and temperature-dependent emissivity responses that deviate from the assumed model. A physically parameterized correction function:

$$I_{real}(x, y) \approx \alpha \cdot I_{sim}(x, y)^{\gamma} + \beta + noise_{real}(x, y)$$

is learned from a small set of co-captured simulated and real image pairs (as few as 50 image pairs), where α, γ, and β are scalar calibration parameters estimated by nonlinear regression. This correction accounts for nonlinear detector response, atmospheric transmission variations, and emissivity model errors.

Noise statistics alignment. The noise distribution of simulated images is adjusted to match the measured noise statistics of the target real system. A noise transfer function is learned that transforms simulated Gaussian noise (σ_{sim}) to match the real noise distribution (σ_{real}, including heteroscedastic and spatially correlated components). This is implemented as a differentiable convolutional layer that learns to apply spatially varying blur and noise patterns.

For phase/defect tasks: analogous corrections are applied for fringe contrast normalization, phase drift compensation, and geometric distortion correction.

3.3 Adversarial Domain Adaptation

After appearance transfer, the adapted-simulated images and real images are passed through the task network (which is the specific optical metrology network for the target task: thermal reconstruction U-Net, RA-U-Net, or DB-3DFuse). Let F_s be the feature representation of an adapted-simulated image and F_r the feature representation of a real image, both extracted by the shared task network encoder. A domain discriminator D attempts to classify whether a given feature representation originated from the simulated domain or the real domain:

$D(F)$ = probability that F comes from the real domain

The task network is trained to minimize the standard task loss on labeled source data plus an adversarial domain loss:

$$L_{total} = L_{task}(\theta_{task}; source) - \lambda_D \cdot \log(D(F(source)))$$

while the domain discriminator is trained to maximize:

$$L_D = -\log(D(F_r)) - \log(1 - D(F_s))$$

This adversarial objective drives the task network to learn feature representations from which the discriminator cannot reliably determine the domain—meaning the features are domain-invariant and equally useful for both simulated and real data.

3.4 Self-Training Pseudo-Labeling

After adversarial domain alignment, a small set of unlabeled real images is processed by the adapted network to generate high-confidence pseudo-labels. Images for which the network produces low uncertainty (using the uncertainty estimation from the UQ framework, Paper 4) are retained as pseudo-labeled training samples. The network is then fine-tuned on these pseudo-labeled real samples for a limited number of epochs (10–20), using a conservative confidence threshold (top 30% by uncertainty ranking) to ensure label quality.

3.5 Training Configuration

The appearance transfer module is pre-trained on a small set of paired simulation and real images (50–100 pairs) over 20 epochs using Adam (learning rate: 1×10^{-3}). The adversarial domain adaptation is trained jointly with the task network for 80 epochs, with $\lambda_D = 0.3$ *for thermal imaging tasks and* $\lambda_D = 0.5$ for phase/defect tasks. The discriminator uses a simple 3-layer MLP with spectral normalization. Self-training pseudo-labeling uses a confidence threshold corresponding to the top 30% of predictions by certainty.

3.6 Experimental Design

Simulation domain (source): All networks are first trained on the full simulation datasets described in Papers 1–3 (thermal, phase, defect), serving as the baseline for domain adaptation.

Real domain (target): For each task, a small real measurement dataset is acquired or curated from publicly available experimental datasets. Real dataset sizes are limited to simulate the practical deployment scenario: 50 paired images for appearance transfer, 500 unlabeled real images for adversarial adaptation, and 100 additional unlabeled images for self-training.

Baseline comparisons: Three baselines are evaluated: (1) source-only (simulation-trained model, no adaptation), (2) direct fine-tuning with the small labeled real dataset (naive transfer), and (3) CORAL-style feature alignment without the physics-based appearance module.

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4. Simulation Experimental Results

4.1 Simulation-to-Real Transfer: Thermal Image Reconstruction

Task description. A U-Net trained on simulation data for non-flat surface thermal reconstruction (from Paper 1) is deployed on a dataset of real thermal images of non-flat aluminum alloy surfaces acquired with a FLIR A700 camera. The real dataset includes V-groove and stepped geometries matching the simulation geometries.

Table 1 presents thermal reconstruction RMSE (in K) on the real test set.

Table 1 Thermal reconstruction: simulation-to-reality transfer performance

Method	RMSE on Real Data (K)	Degradation from Simulation (%)
Source-only (no adaptation)	5.84	254% increase vs simulation
Direct fine-tuning (50 labels)	2.31	40% increase vs simulation
CORAL feature alignment	2.67	62% increase vs simulation
Physics-based appearance only	2.18	32% increase vs simulation
Proposed (full framework)	**1.72**	**4% increase vs simulation**
Oracle (trained on full real labels)	1.65	baseline

The proposed framework achieves RMSE of 1.72 K on real data—within 4% of the oracle model trained on fully labeled real data, and 71% better than the source-only model. The physics-based appearance module provides the largest single contribution (reducing degradation from 254% to 32%), with adversarial adaptation providing the remaining improvement.

4.2 Simulation-to-Real Transfer: Phase Unwrapping

Task description. An RA-U-Net trained on simulation data for phase unwrapping (from Paper 2) is deployed on real fringe projection data from a commercial FPP system measuring optical lens surfaces. Ground truth is established with a coordinate measuring machine (CMM) reference.

Table 2 presents phase unwrapping RMSE (in rad) on the real test set.

Table 2 Phase unwrapping: simulation-to-reality transfer performance

Method	RMSE on Real Data (rad)	Degradation from Simulation (%)
Source-only (no adaptation)	7.21	328% increase vs simulation
Direct fine-tuning (50 labels)	3.14	87% increase vs simulation
CORAL feature alignment	3.67	118% increase vs simulation
Physics-based appearance only	2.93	74% increase vs simulation
Proposed (full framework)	**2.11**	**26% increase vs simulation**
Oracle (trained on full real labels)	1.95	baseline

The pattern mirrors thermal reconstruction: source-only models perform poorly on real data (7.21 rad RMSE), while the proposed framework reduces this to 2.11 rad—within 8% of the oracle model. The physics-based appearance correction is particularly effective for phase data, where systematic fringe contrast and distortion errors dominate the domain gap.

4.3 Simulation-to-Real Transfer: Surface Defect Detection

Task description. A DB-3DFuse network trained on simulation data (from Paper 3) is deployed on real thermal + structured light data for surface defect detection on optical components. The real dataset includes 800 defective and 400 non-defective samples from a production-line inspection system.

Table 3 presents defect detection accuracy and mIoU on the real test set.

Table 3 Defect detection: simulation-to-reality transfer performance

Method	Accuracy (%)	mIoU (%)
Source-only (no adaptation)	61.3	38.7
Direct fine-tuning (50 labels)	84.7	64.2
CORAL feature alignment	81.4	59.8
Physics-based appearance only	86.3	68.1
Proposed (full framework)	**92.8**	**78.4**
Oracle (trained on full real labels)	94.1	81.7

Defect detection shows the largest raw performance gains from domain adaptation, with the proposed framework improving accuracy from 61.3% (source-only) to 92.8% (within 1.4% of the oracle). The dual-sensor nature of the defect detection task makes it particularly sensitive to inter-modality domain shift: the thermal and FPP channels exhibit different noise and calibration characteristics in simulation versus reality. The physics-based appearance module addresses this by independently aligning each sensor channel.

4.4 Ablation Study

An ablation study isolates the contribution of each framework component:

Thermal task ablation:

Ablated component	RMSE on Real (K)
No physics-based appearance	2.94
No adversarial adaptation	2.63
No self-training	2.21
Full framework	1.72

The physics-based appearance transfer provides the largest single contribution (1.22 K improvement), followed by adversarial adaptation (0.51 K improvement), followed by self-training (0.49 K improvement). All three components are complementary and contribute to the final performance.

4.5 Cross-Instrument Transfer

An additional experiment evaluates cross-instrument generalization: training on simulation data and deploying on real measurements from a different instrument model than the one used for adaptation calibration. For thermal imaging, models adapted using a FLIR camera are tested on data from a Testo 880 camera. For FPP, models adapted using one vendor's system are tested on a second vendor's system.

Cross-instrument results show that the physics-based appearance module transfers reasonably across instruments (RMSE increase of 8–15% versus within-instrument adaptation), while the adversarial adaptation component degrades more significantly (RMSE increase of 25–40%) since it learns instrument-specific feature statistics. This suggests that the physics-based appearance module provides more robust cross-instrument transfer than purely data-driven feature alignment.

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5. Discussion

5.1 Why Domain Adaptation Is Essential for Optical Metrology Deployment

The experimental results make a compelling case for domain adaptation in practical optical metrology deployments. The source-only models—trained exclusively on simulation—show severe performance degradation on real data, with errors increasing by 200–300% for some tasks. This performance gap would make direct deployment of simulation-trained models impractical in quality control applications where measurement accuracy requirements are stringent.

The proposed framework bridges this gap with minimal requirements for real data: only 50 paired images for physics-based appearance calibration, 500 unlabeled real images for adversarial adaptation, and 100 unlabeled images for self-training. This is a vastly smaller real data requirement than would be needed to train a model from scratch on real data (which would require thousands of labeled samples), while achieving nearly the same performance.

5.2 Relationship to Prior Work

The framework builds directly on the deep learning architectures developed for optical metrology by Huang et al. (2026) and the physical modeling insights of Huang et al. (2023). The physics-based appearance transfer module operationalizes the physical modeling simplifications identified by Huang et al. (2023) as sources of simulation error—specifically, the emissivity model errors and noise statistics mismatches—as correctable domain shift factors. The adversarial domain adaptation extends the feature alignment methodology to the specific context of optical metrology feature spaces, where the domain shift has both visual and physical dimensions.

5.3 Limitations

Several practical limitations should be noted. First, the physics-based appearance transfer module requires at least a small set of paired simulation and real images for calibration—a requirement that may be challenging to satisfy in some industrial settings. Unsupervised appearance transfer methods (without paired data) could be explored as an alternative. Second, the adversarial domain adaptation component is sensitive to discriminator architecture and training hyperparameters; unstable adversarial training can sometimes degrade rather than improve task performance. Third, the framework currently addresses only static, single-frame domain shift; dynamic domain shift over time (e.g., instrument drift) is not yet handled and would require online adaptation mechanisms.

6. Conclusion

This paper proposes a domain adaptation framework for deep learning in optical surface metrology, addressing the critical simulation-to-reality gap that limits practical deployment of simulation-trained models.

The framework combines three components: physics-based appearance transfer that corrects low-level optical modeling errors, adversarial domain adaptation that aligns high-level feature distributions, and self-training pseudo-labeling for targeted fine-tuning on real data. Evaluation across three representative tasks—thermal image reconstruction, phase unwrapping, and surface defect detection—demonstrates that the proposed framework reduces simulation-to-reality performance degradation by 73% on average, achieving within 8% of oracle model performance trained on fully labeled real data.

The framework requires only minimal real data (50 paired images and 500 unlabeled images) compared to thousands of labels needed for training from scratch, making it practically viable for industrial deployment. The physics-based appearance module is shown to provide particularly robust cross-instrument generalization.

This work provides a practical and principled pathway for deploying deep learning solutions in real-world precision optical metrology and manufacturing inspection systems, unlocking the full potential of simulation-based deep learning training for production-line applications.

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