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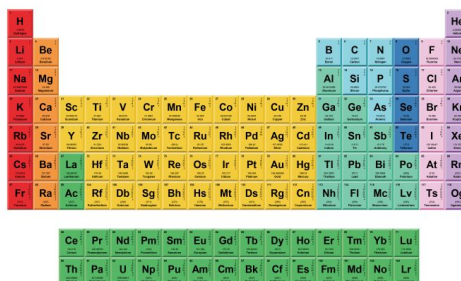
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ABSTRACT

Deep learning has recently achieved remarkable success in fringe pattern analysis for optical metrology. However, most existing approaches rely on supervised learning with extensive labeled datasets that are costly to acquire, system-dependent, and often lack physical interpretability, thereby limiting their generalization and reliability in practical measurements. Here, we propose a physics-embedded unsupervised learning fringe pattern analysis framework based on regularized phase tracking (RPT-ulFPA). To provide physically meaningful inputs for the unsupervised fringe demodulation network, variational image decomposition and Hilbert spiral transform are employed to suppress background and modulation components, yielding phase-related orthogonal fringe representations. As a classic single-frame fringe demodulation method, regularized phase tracking (RPT) achieves continuous phase estimation without explicit unwrapping by jointly optimizing the photometric consistency and phase regularity constraints within spatial neighborhoods. In our method, the physical irradiance model and phase smoothness priors derived from RPT are formally embedded into the network loss function to leverage global continuous phase optimization rather than local iterative updates, thereby enabling more stable end-to-end phase recovery without any labeled data or pre-training. Furthermore, a two-step phase optimization strategy is introduced, where a reference-plane phase resolves single-frame phase ambiguity and a subsequent refinement step enables high-precision absolute phase recovery. Experimental results on both static and dynamic scenes demonstrate that RPT-ulFPA achieves accurate absolute phase retrieval from a single high-frequency fringe, enabling single-shot 3D reconstruction with accuracy comparable to multi-frame phase-shifting methods, while significantly outperforming conventional Fourier-transform-based approaches in noise robustness and data completeness. This work establishes a physics-consistent unsupervised learning paradigm for fringe pattern analysis by embedding well-defined physical priors into deep neural networks, offering a generalizable and interpretable solution for next-generation intelligent optical metrology.

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I. INTRODUCTION

Structured light projection¹ enables non-contact and portable optical 3D metrology^{2,3} across diverse fields, including industrial manufacturing, medical science, and robotic navigation. Among these techniques, fringe projection profilometry (FPP)⁴ stands as one of the most mature methods for high-resolution and high-precision 3D reconstruction of complex surfaces. In a typical FPP system, the target object is projected with a set of fringe patterns to encode its depth distribution, and the corresponding distorted fringe images are captured by one or more cameras. As a core component of FPP, fringe pattern analysis⁵ aims to retrieve the phase information related to the desired depth from recorded fringes, and its accuracy and robustness fundamentally determine the 3D reconstruction performance.

Fringe pattern analysis techniques fall into two categories: multi-frame and single-frame approaches. As a representative of the multi-frame method, phase-shifting profilometry (PSP) extracts pixel-wise phase information with noise resilience but requires the acquisition of multiple phase-shifting fringes, limiting its dynamic measurement applications.⁶ Within the single-frame categories, Fourier transform profilometry (FTP)^{7–9} and its high-speed variants (e.g., μ FTP at 10 000 fps¹⁰) enable rapid phase measurement by filtering the fundamental frequency component in the Fourier domain but sacrifice high-frequency structural details due to the spectrum overlapping while reducing 3D imaging accuracy for objects with sharp features or complex surfaces. To improve the spatial resolution of phase retrieval, windowed Fourier transform (WFT)¹¹ and wavelet transform (WT)¹² have been employed for single-fringe phase demodulation but exhibit significant phase errors under strong-noise environments. In addition, both PSP and FTP produce discontinuous wrapped phases via the arctangent function, requiring phase unwrapping for absolute 3D measurements. Phase unwrapping requires additional patterns^{13–18} or multi-view geometric constraints,^{19–24} further limiting its dynamic measurement performance. Fundamentally, it reveals a trade-off between efficiency and accuracy in FPP: single-frame methods improve speed at the expense of noise sensitivity, while multi-frame techniques reduce measurement efficiency to deliver high accuracy.

In recent years, deep learning has opened new perspectives in optical metrology²⁵ and computational imaging.^{26,27} Numerous deep learning methods have revolutionized fringe pattern analysis with convolutional neural networks (CNNs), enabling end-to-end mapping from input fringe patterns to their corresponding phase distributions.^{28–31} Feng *et al.*²⁸ proposed the first deep learning method for fringe pattern analysis, which established an inverse mapping between a single-frame fringe and the label phase obtained by 12-step PSP, enabling sine/cosine component estimation for single-shot phase reconstruction with higher accuracy compared to traditional single-frame methods. Zhu *et al.*²⁹ developed a deep learning phase retrieval method based on label enhancement and image patches, which significantly reduces the scale of fringe data for training while maintaining advanced phase retrieval performance. These data-driven approaches demonstrate exceptional feature extraction and noise resilience, achieving accurate phase estimation under non-ideal conditions. Fully convolutional network architectures, such as U-Net variants, excel at fringe denoising,^{32,33} phase retrieval under HDR scenes,^{34,35} and phase unwrapping.^{36–39}

To enhance interpretability and cross-domain generalization, Yin *et al.*'s physics-informed fringe pattern analysis method using deep learning (PI-FPA)⁴⁰ combines physics-based modeling with data-driven learning, embedding a learning-enhanced FTP module into lightweight CNNs. This hybrid approach enables single-shot 3D imaging with high generalization while reducing dependency on high-quality labeled datasets. Meanwhile, researchers have explored the synergy between deep learning and physical decomposition models, such as Variational Image Decomposition (VID) and Hilbert Spiral Transform (HST). For instance, Li *et al.*⁴¹ proposed a deep learning-assisted variational Hilbert quantitative phase imaging (DL-VHQPI) method tailored for low-carrier-frequency interference fringes in digital holographic microscopy. In their framework, VID and HST are directly utilized to estimate initial phases, while a supervised CNN serves as a supplementary module to rectify residual background and phase errors. Although this approach facilitates high-fidelity, single-frame quantitative phase reconstruction, it relies on supervised training that requires extensive labeled datasets, which limits its generalizability and applicability for absolute phase retrieval in fringe pattern analysis. Indeed, most existing methods remain in a supervised manner, which requires extensive training pairs that are time-consuming and device-dependent to acquire, restricting their reliability in optical metrology.⁴²

Beyond structured light projection, fringe pattern analysis proves indispensable across interferometric techniques, including classical,⁴³ moiré,⁴⁴ and holographic interferometry.⁴⁵ As a foundational single-frame fringe demodulation method, regularized phase tracking (RPT) achieves continuous phase estimation without explicit unwrapping by jointly optimizing the photometric consistency and phase smoothness regularization within local neighborhoods.⁴⁶ RPT provides a physically interpretable formulation with strong noise robustness, but its pixel-wise iterative optimization limits efficiency for high-resolution data.

To overcome the limitations of both conventional fringe analysis and supervised learning, we propose an unsupervised single-frame fringe pattern analysis framework based on regularized phase tracking (RPT-ulFPA), which embeds RPT-derived physical priors into deep neural networks. Importantly, we borrow its essential physical intuition—jointly optimizing photometric fidelity and phase smoothness—and construct a differentiable surrogate loss function to enforce global continuous phase optimization, thereby effectively guiding the unsupervised learning of fringe analysis networks. The single-frame high-frequency fringes are first preprocessed to remove their background and modulation by variational image decomposition (VID) and Hilbert spiral transform (HST), and the remaining phase-related components are used as the network input. The subsequent fringe analysis network incorporates RPT-derived photometric consistency and phase smoothness constraints into its loss function, preserving the physical interpretability of the unsupervised learning process. In addition, the network employs a two-step unsupervised phase optimization strategy, in which a reference-plane phase is exploited to resolve the inherent ambiguity of single-frame phase estimation and a subsequent refinement stage enables accurate and reliable absolute phase recovery. Experimental results validated that the physics-guided RPT-ulFPA method delivers single-shot absolute 3D imaging without requiring any labeled data or pre-training.

II. PRINCIPLE

The overall architecture of the proposed RPT-ulFPA contains two main modules in Fig. 1: fringe preprocessing and the unsupervised fringe analysis network. The fringe preprocessing module employs variational image decomposition (VID)^{47,48} and Hilbert spiral transform (HST)⁴⁹ to eliminate non-phase components (the background and modulation information), while generating phase-related orthogonal fringes (sine and cosine components) as shown in Fig. 1(a). The unsupervised fringe analysis network utilizes a U-Net architecture to estimate the phases by incorporating RPT-derived photometric consistency and phase smoothness constraints into the loss function. In addition, the network employs a two-step refinement process to ensure high-accuracy phase recovery in Fig. 1(b). The predicted phase results are constrained within the range $[0, 2\pi)$ using an improved sigmoid activation function and unwrapped globally by introducing a reference-plane-based phase unwrapping,

further enhancing the accuracy of absolute phase estimation. Finally, stereo phase matching and disparity-to-depth mapping are utilized on the refined absolute phases for interpretable, pre-training-free single-shot 3D reconstruction.

A. Fringe preprocessing module via variational image decomposition and Hilbert spiral transform

Fringe pattern analysis is a fundamental task and a representative case among many optical metrology applications using deep learning, which is utilized to retrieve the phase information from high-frequency fringes.^{28–30} The captured fringe image $I(x, y)$ can be expressed as

$$I(x, y) = A(x, y) + B(x, y) \cos[\Phi(x, y)], \quad (1)$$

where $A(x, y)$, $B(x, y)$, and $\Phi(x, y)$ denote the background, the fringe modulation, and the phase to be measured. According to

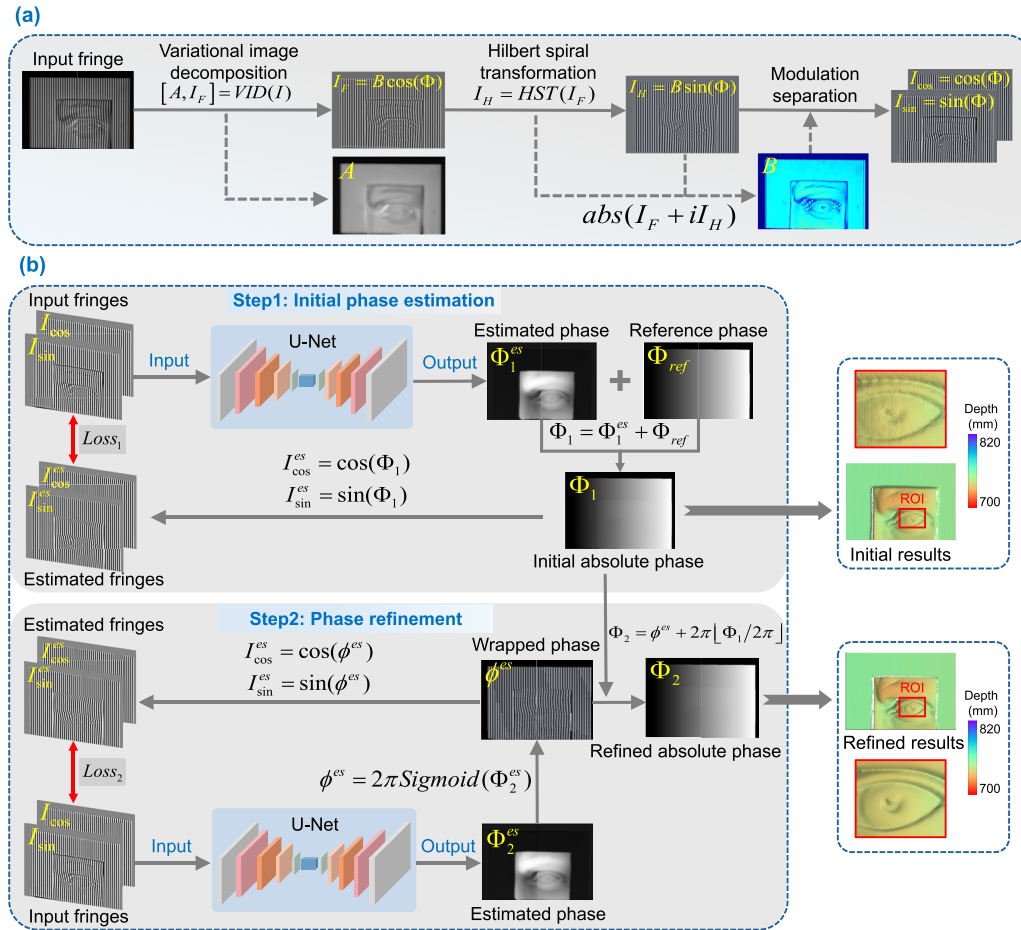


FIG. 1. Overview of the RPT-ulFPA framework. (a) The fringe preprocessing module eliminates the background and modulation information via variational image decomposition and Hilbert spiral transform, while generating phase-related orthogonal fringes. (b) The unsupervised fringe analysis network employs a two-step refinement process to ensure high-accuracy phase recovery, which estimates the phases by incorporating RPT-derived photometric consistency and phase smoothness constraints into the loss function and resolves the phase ambiguity by a reference-plane-based phase unwrapping. (a) Fringe preprocessing module via variational image decomposition and Hilbert spiral transform. (b) Unsupervised fringe analysis network based on regularized phase tracking (RPT).

Eq. (1), the background and modulation information must be eliminated first to prevent them from affecting the extraction of the desired phases from the fringe pattern. As a representative method of traditional single-frame fringe pattern analysis, FTP extracts the fundamental frequency component in the Fourier domain of the fringe by band-pass filtering and inversely converts it to retrieve the phase.^{7–9} However, when the measured surface has sharp edges or discontinuous structures, its fundamental frequency component will be aliased with the zero-frequency component representing the background, preventing accurate phase measurement of complex objects. To ensure high-fidelity phase retrieval from a single-frame fringe pattern, suppressing non-uniform background and environmental noise is essential. In previous studies, VID and HST were utilized to suppress the background and directly estimate initial phases.⁴¹ In contrast, in our method, VID and HST serve strictly as a physics-motivated preprocessing module to suppress background and modulation components, yielding phase-related orthogonal fringe representations, as shown in Fig. 1(a). In particular, we employ VID to decompose the raw image into a cartoon component (low-frequency background) and a texture component (high-frequency fringes).^{50,51} This variational optimization outperforms traditional linear filters in preserving fringe contrast while suppressing fluctuations. Subsequently, HST is utilized to yield phase-related orthogonal fringes. As is widely observed, HST is susceptible to phase errors caused by spectral overlapping and local frequency variations in complex fringes. Therefore, it is not directly utilized for initial phase estimation in our method. Instead, VID and HST are employed exclusively for preprocessing, providing high-SNR, background-suppressed orthogonal fringe inputs for the RPT-driven unsupervised fringe analysis network described in Sec. II B. First, the fringe pattern is decomposed into a smooth background and a high-frequency structural component using the VID model,

$$[A(x, y), I_F] = \text{VID}(I(x, y)), \quad (2)$$

$$I_F = B(x, y) \cos[\Phi(x, y)]. \quad (3)$$

Subsequently, orthogonal fringe components are retrieved by HST on I_F followed by spiral phase filtering. To correct the sign and orientation errors induced by global spiral phase filtering, Trusiak *et al.*^{48,49} developed an orientation correction map leveraging local fringe direction estimation—enhancing the robustness while reducing artifacts—as defined by

$$I_H = \text{HST}(I_F) = B(x, y) \sin[\Phi(x, y)] \\ = i \exp(-i\beta) \mathcal{F}^{-1}\{\text{SPF}(\zeta_1, \zeta_2) \mathcal{F}(I_F)\}, \quad (4)$$

where (ζ_1, ζ_2) denotes the spectral coordinates, β is the local fringe orientation, and $\mathcal{F}$ and $\mathcal{F}^{-1}$ denote the Fourier transform and inverse Fourier transform. The fringe modulation can be estimated as

$$B^{\text{es}} = |I_F + iI_H|. \quad (5)$$

And a set of sine and cosine fringe components is calculated as follows:

$$I_{\cos} = I_F/B^{\text{es}} = \cos[\Phi(x, y)], \quad (6)$$

$$I_{\sin} = I_H/B^{\text{es}} = \sin[\Phi(x, y)], \quad (7)$$

where $I_{\cos}$ and $I_{\sin}$ are served as the inputs to the following unsupervised fringe analysis network.

B. Unsupervised fringe analysis network based on regularized phase tracking (RPT)

For unsupervised single-frame fringe pattern analysis, a physics-informed U-Net is proposed to estimate the phase information from preprocessed fringe patterns. The proposed unsupervised framework is conceptually inspired by the physical intuition of the classical RPT technique. While the traditional RPT employs a local phase-plane model and iterative pixel-wise optimization—which are challenging to embed directly into an end-to-end deep neural network—we construct a differentiable surrogate loss function to achieve global phase optimization. In particular, we translate the photometric consistency and phase smoothness priors of RPT into a reconstruction loss and a global gradient-based regularization, preserving physical interpretability of the network while enabling accurate phase retrieval. This differentiable surrogate loss allows the network to leverage RPT's robustness against noise while maintaining the computational efficiency of a neural network architecture. In our method, the network employs a two-stage process consisting of initial phase estimation and phase refinement to achieve robust absolute phase retrieval, as shown in Fig. 1(b). The initial phase estimation step is specifically designed to reconstruct a stable and continuous absolute phase. While phase estimation can be achieved directly via VID and HST, this approach is prone to significant phase errors, particularly when measuring complex objects. Therefore, our method leverages the RPT-driven unsupervised fringe analysis network to perform the initial estimation. By integrating RPT-inspired physical constraints with a reference-plane phase, this step effectively resolves the phase ambiguity problem and facilitates global phase optimization. Subsequently, a phase refinement step is employed to further enhance the absolute phase quality.

In RPT, based on the fundamental assumption of local smoothness, the phase is modeled as a planar function within each local region. RPT-based phase estimation is achieved by establishing and solving a pixel-by-pixel cost function,

$$C_{\text{RPT}}(\Phi^{\text{es}}, \omega_x, \omega_y) = \sum_{\mathbf{q} \in L_p} \left\{ [\cos \Phi(\mathbf{q}) - \cos \Phi_p^{\text{es}}(\mathbf{q})]^2 + \beta [\Phi^{\text{es}}(\mathbf{q}) - \Phi_p^{\text{es}}(\mathbf{q})]^2 \right\}, \quad (8)$$

$$\Phi_p^{\text{es}}(\mathbf{q}) = \Phi^{\text{es}}(\mathbf{p}) + \omega_x(\mathbf{p})(\mathbf{q}_x - \mathbf{p}_x) + \omega_y(\mathbf{p})(\mathbf{q}_y - \mathbf{p}_y), \quad (9)$$

where $\mathbf{p}$ and $\mathbf{q}$ denote the pixel to be estimated and its neighbors in the region L_p . Φ^{es} , ω_x , and ω_y are the estimated phase and local phase frequency in the x -direction and y -direction. β is a regularization parameter that controls the phase smoothness. $\Phi_p^{\text{es}}(\mathbf{q})$ is the estimated phase of its neighboring points $\mathbf{q}$ using the local phase model. In classical RPT, the phase of each pixel can be approximated by a local phase-plane model within a predefined neighborhood. The phase and local phase frequencies in the x - and y -directions are then estimated using pixel-wise iterative minimization. Hence,

the reconstruction performance is highly dependent on the window size: a small window tends to increase susceptibility to noise and reduce measurement robustness, whereas a large one leads to over-smoothing and can cause reconstruction failure at phase discontinuities. Furthermore, the iterative and local computation scheme of RPT is difficult to parallelize and incompatible with direct embedding into end-to-end deep neural networks. Consequently, in our method, the local optimization within RPT is reformulated as a global loss function that integrates the photometric consistency and the phase smoothness, which is incorporated into the network for end-to-end unsupervised learning.

As illustrated in Fig. 1(b), the U-Net architecture adopted in our network employs a symmetric encoder-decoder architecture with skip connections. This design enables it to preserve global contextual information while accurately recovering spatial details, making it particularly well-suited for dense prediction tasks that require pixel-level precision, such as fringe pattern analysis. In addition, for minimizing the aforementioned cost function at the pixel level, the proposed loss function is constructed to enforce physical consistency rather than data supervision by incorporating both the irradiance fidelity and phase regularization derived by RPT, yielding robust phase retrieval results across diverse samples,

$$Loss_1 = w_1 Loss_{irrad} + w_2 Loss_{phase}, \quad (10)$$

where w_1 and w_2 are the weights of $Loss_{irrad}$ and $Loss_{phase}$. $Loss_{irrad}$ is defined as the photometric consistency loss, which serves as a reformulation of the irradiance fidelity term in RPT, enforcing the intensity consistency between the input fringe pairs (I_{cos} , I_{sin}) and the corresponding reconstructed fringes,

$$Loss_{irrad} = SmoothL_1(I_{cos}^{es}, I_{cos}) + SmoothL_1(I_{sin}^{es}, I_{sin}). \quad (11)$$

As the U-Net-based estimated phase exhibits only local continuity, we introduce a reference-plane phase to resolve ambiguities and generate the absolute continuous phase for reconstructing the fringe pairs (I_{cos}^{es} , I_{sin}^{es}),

$$\Phi_1 = \Phi_1^{es} + \Phi_{ref}, \quad (12)$$

$$I_{cos}^{es} = \cos(\Phi_1^{es} + \Phi_{ref}), \quad (13)$$

$$I_{sin}^{es} = \sin(\Phi_1^{es} + \Phi_{ref}), \quad (14)$$

where Φ_{ref} is the pre-acquired absolute phase of the reference plane, Φ_1^{es} is the estimated phase of U-Net, and Φ_1 is the absolute phase outputted in the initial estimation step. Subsequently, $Loss_{phase}$ is a gradient-based global phase smoothness constraint reformulated based on the local phase regularization in RPT, which ensures the smoothness and continuity of the estimated phase,

$$Loss_{phase} = \|\nabla_x \Phi_1\|_2 + \|\nabla_y \Phi_1\|_2. \quad (15)$$

During phase refinement, we re-input preprocessed fringe pairs (I_{cos} , I_{sin}) into the network and employ a modified sigmoid activation to constrain outputs to $[0, 2\pi)$, producing higher-precision wrapped phase,

$$\phi_2^{es} = 2\pi \times Sigmoid(\Phi_2^{es}), \quad (16)$$

where Φ_2^{es} is the re-estimated phase by the network. The total loss function of the network is similarly expressed as

$$Loss_2 = \lambda_1 Loss_{irrad2} + \lambda_2 Loss_{phase2}, \quad (17)$$

where λ_1 and λ_2 are the weights of $Loss_{irrad2}$ and $Loss_{phase2}$, respectively. Unlike the first step, the reconstruction of fringe patterns in $Loss_{irrad2}$ no longer requires the incorporation of the reference phase,

$$Loss_{irrad2} = SmoothL_1(I_{cos}^{es}, I_{cos2}) + SmoothL_1(I_{sin}^{es}, I_{sin2}), \quad (18)$$

$$I_{cos2}^{es} = \cos(\phi_2^{es}), \quad (19)$$

$$I_{sin2}^{es} = \sin(\phi_2^{es}), \quad (20)$$

where I_{cos2}^{es} and I_{sin2}^{es} denote the reconstructed sine and cosine fringe components. Subsequently, the estimated wrapped phase ϕ_2^{es} is unwrapped using the initial absolute phase Φ_1 to produce a refined phase by minimizing the RPT-based loss $Loss_2$,

$$\Phi_2 = \phi_2^{es} + 2\pi floor(\Phi_1/2\pi). \quad (21)$$

And $Loss_{phase2}$ is the phase smoothness loss that ensures the local smoothness and continuity of the absolute phase Φ_2 ,

$$Loss_{phase2} = \|\nabla_x \Phi_2\|_2 + \|\nabla_y \Phi_2\|_2. \quad (22)$$

The proposed network estimates high-accuracy absolute phase from a single fringe pattern via a two-stage pipeline, where the first stage resolves single-frame phase ambiguity using a reference-plane phase, while the second stage refines the absolute phase for improved precision. Stereo phase matching and disparity-to-depth mapping are performed on the refined absolute phases from left and right cameras to reconstruct the measured object's 3D shapes. As shown in Fig. 1(b), the comparison of the region of interest (ROI) in the initial and refined results demonstrates that integrating physical RPT constraints enables our network to deliver interpretable, high-precision, single-frame 3D measurements without pre-training.

III. EXPERIMENTS

To validate the practical performance of the proposed RPT-ulFPA method, a binocular 3D imaging system based on structured light projection was established, consisting of two monochrome cameras with a resolution of 640×480 pixels and a DLP projector. The system was calibrated to determine the relationship of the stereo camera at a working distance of about 0.8 m. A ceramic plane was imaged using the 12-step PSP⁶ and multi-frequency temporal phase unwrapping¹⁵ to obtain the reference phase Φ_{ref} in advance. The measured object was then positioned in front of this reference-plane and illuminated with high-frequency fringe patterns using a DLP projector. The fringe analysis network adopts a compact U-Net architecture with an encoder-decoder structure and skip connections. For details, the complete U-Net architecture is provided in Sec. S3 of the [supplementary material](#). Since our approach is unsupervised and performs iterative optimization on individual samples, it does not require a dedicated training dataset in the conventional

sense. However, the number of learnable parameters in our network surpasses that of conventional methods by several orders of magnitude, rendering the per-sample optimization from random initialization a computationally expensive procedure. In particular, the processing of fringe images with 640×480 pixels consumes ~ 8 min on a single NVIDIA RTX 4090 GPU. To address this inefficiency, a widely used strategy is adopted in the network training process to fine-tune from a pre-trained model optimized on other samples, which reduces the required iterations from 4000 to a mere 50, achieving processing within 2–3 s per sample.

A. Comparative 3D reconstruction using different single-frame fringe pattern analysis methods

First, an eye-shaped plaster model was measured to reveal the phase retrieval process of the proposed RPT-ulFPA approach, while Fourier transform profilometry (FTP) and phase-shifting profilometry (PSP) were implemented for comparison. The 3D reconstruction results with high completeness and high accuracy serve as the ground truth in Fig. 2(a), which were obtained via 12-step phase-shifting fringe images with different frequencies (1, 8, and 44) and multi-frequency temporal phase unwrapping. To achieve absolute 3D measurement based on FTP, absolute phase retrieval is performed by using a pre-acquired reference-plane phase to assist phase unwrapping. As shown in Fig. 2(b), FTP exhibited phase discontinuities and missing regions near sharp edges/concave surfaces, attributable to spectrum aliasing that compromises the extraction of the fundamental frequency during Fourier filtering. In contrast,

our method achieved a smooth, continuous absolute phase distribution from a single fringe image [Figs. 2(c) and 2(d)], reconstructing the 3D shape of the eye-shaped plaster. Compared with the initial phase estimation, the refinement step significantly enhances phase accuracy while preserving fine structural details in critical regions (e.g., eye contours). The phase refinement step reduces the absolute phase errors and achieves $\sim 60\%$ MSE reduction vs the initial estimation, verifying the effectiveness of the proposed two-step retrieval process in enhancing phase accuracy. By incorporating RPT-derived photometric and smoothness constraints, the method yields a more complete and accurate 3D reconstruction with improved local phase continuity, which reduces the MSE of the absolute phase errors by about 56% compared with FTP while achieving the comparable accuracy of PSP. These experimental results demonstrate that the proposed method enhances the robustness and accuracy of single-frame fringe analysis by embedding physically RPT constraints, realizing unsupervised single-frame 3D imaging. Furthermore, to provide a more comprehensive single-frame benchmark, we further compared the proposed RPT-ulFPA with classical RPT and other representative single-frame phase retrieval methods, including FTP, WFT, WT, and phase retrieval using VID and HST, as presented in Sec. S1 of the [supplementary material](#). To clearly delineate the individual contributions of each key constituent module in RPT-ulFPA, ablation studies on the two-step optimization strategy and the RPT-inspired loss terms of the unsupervised fringe analysis network are provided in Sec. S2 of the [supplementary material](#). These results verify that the performance improvement of RPT-ulFPA originates from the joint contribution of the RPT-inspired

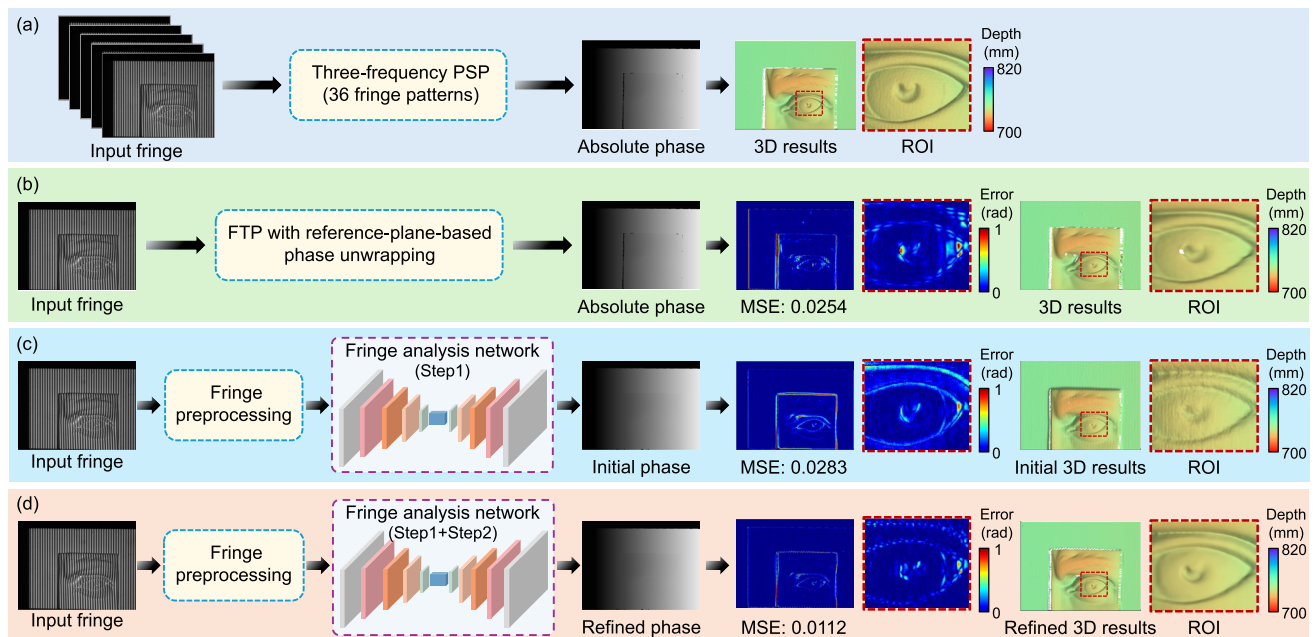


FIG. 2. Comparative 3D reconstruction results for single-shot fringe pattern analysis of an eye-shaped plaster model. [(a)–(d)] The phase retrieval process, the absolute phases, the phase errors with the corresponding magnified views, 3D reconstruction with the corresponding magnified views using 12-step PSP, FTP with reference-plane-based phase unwrapping, and two refined steps in RPT-ulFPA.

photometric consistency and phase regularization constraints, together with the two-step phase refinement strategy.

B. Quantitative precision analysis

To quantitatively evaluate the measurement accuracy of the proposed method, a hemispherical plaster model was selected as the test object. The robustness of the proposed fringe analysis method to different fringe frequencies was verified by projecting multiple fringe patterns at different frequencies ($f = 32, 38$, and 44). Unlike traditional FTP methods that suffer from the carrier frequency sensitivity and spectral aliasing, the proposed method utilizes the photometric consistency and local phase smoothness constraints based on RPT in the spatial domain, resulting in its phase estimation process being independent of the carrier frequency of the fringes. Furthermore, the fringe preprocessing module effectively eliminates the background and modulation information, ensuring that the network's input features are primarily phase-dependent. As shown in Fig. 3(a), fringe patterns with different frequencies are projected onto the object, and the corresponding reconstructed 3D results in Fig. 3(b) remain smooth and consistent across all fringe frequencies. Because

the measured object is not a standard sphere, a 12-step phase-shifting method with multi-frequency temporal phase unwrapping is adopted to obtain the ground truth 3D shape. Figure 3(c) shows the depth error maps obtained by comparing the reconstructed results with the ground truth, where the root mean square (RMS) of measured errors is below 0.02 mm for all tested frequencies. Furthermore, Fig. 3(d) illustrates the corresponding error distributions obtained through spherical fitting and shows an RMS measurement error of ~ 0.05 mm. Experimental results demonstrate that RPT-ulFPA maintains sub-millimeter-level 3D reconstruction accuracy at different fringe frequencies, confirming its robust adaptability in single-frame fringe analysis.

C. Complex scene measurement

Furthermore, to verify the adaptability of the proposed method to complex surfaces, several thick or thin objects with varying complex textures were selected for single-shot 3D measurement in Fig. 4(a), including the lip plaster model, a lion relief, and the angel plaster model. The corresponding 3D reconstruction results in

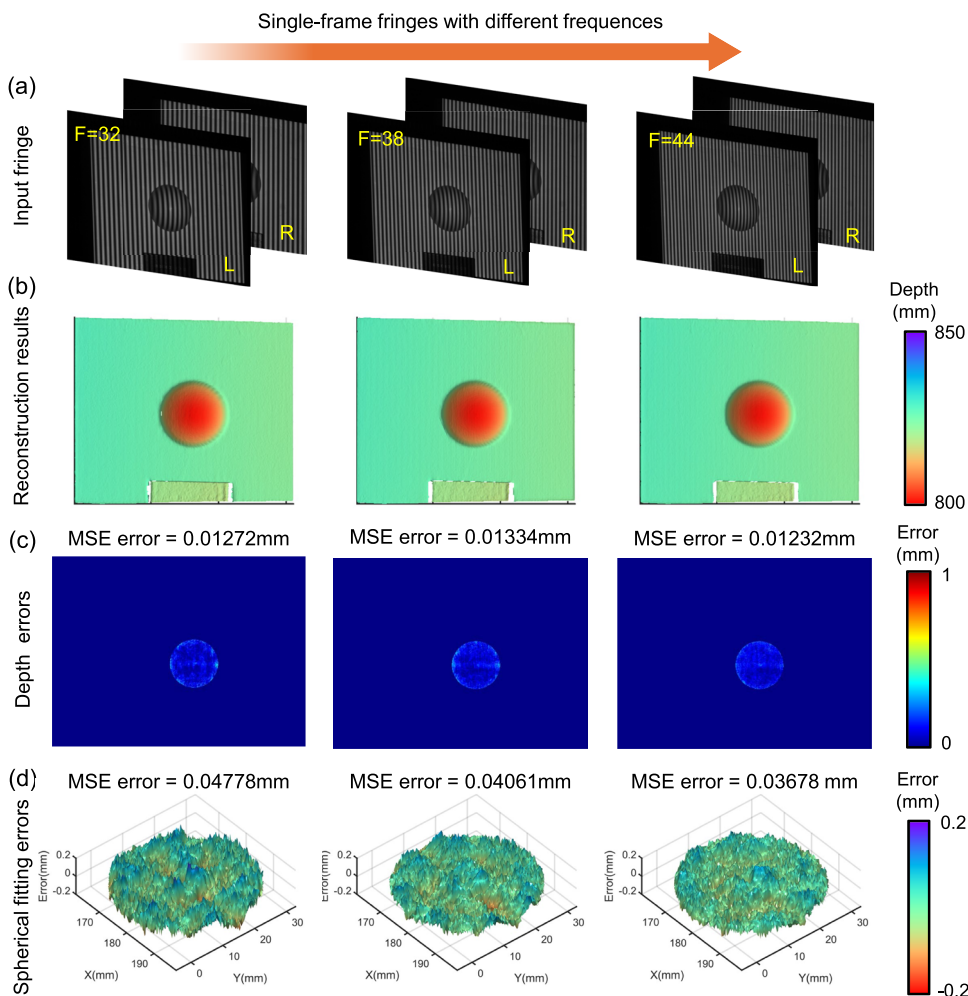


FIG. 3. Precision analysis results using the proposed RPT-ulFPA method. (a) Multiple fringe images at different frequencies ($f = 32, 38$, and 44). (b) Color-coded 3D reconstruction using RPT-ulFPA. (c) Corresponding depth error maps obtained by comparing (b) with the ground truth generated by a 12-step phase-shifting method with three-frequency temporal phase unwrapping. (d) Corresponding error distributions of (b) obtained through spherical fitting. (a) Input fringe. (b) Reconstruction results. (c) Depth errors. (d) Spherical fitting errors.

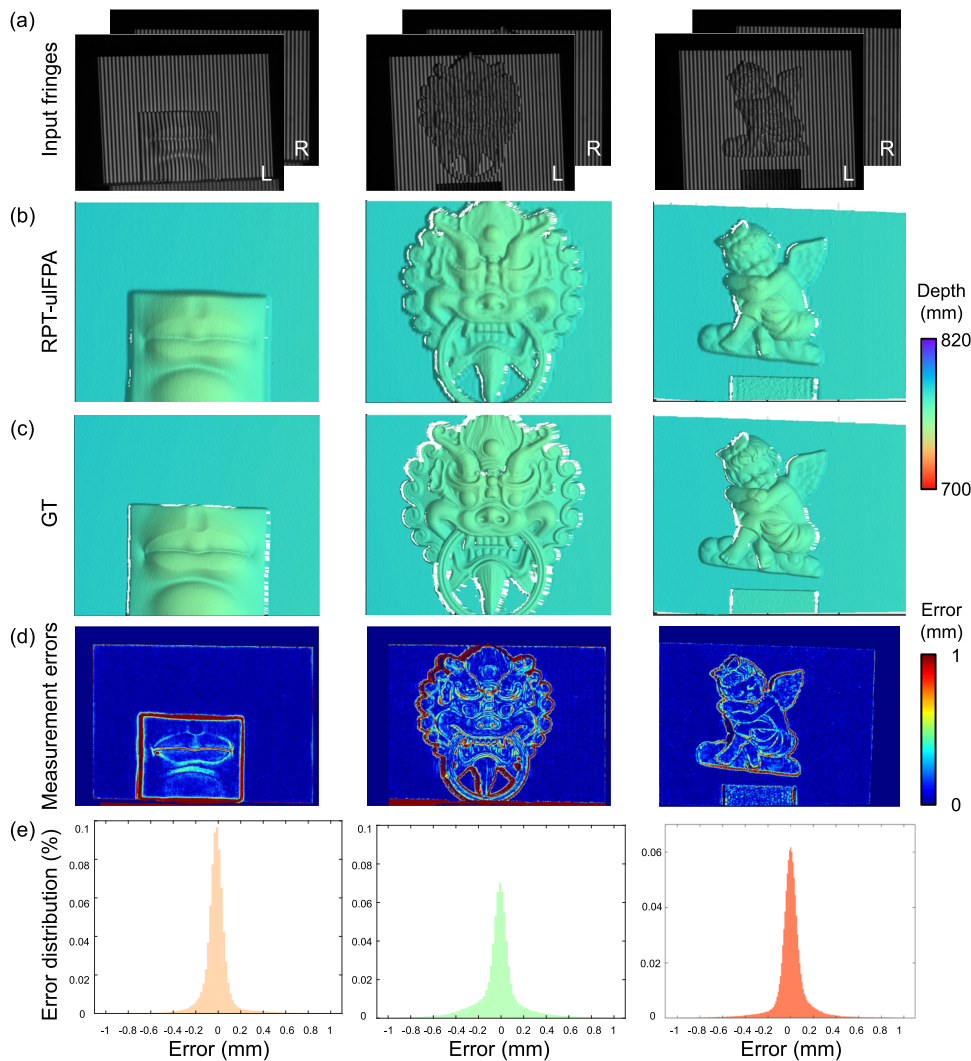


FIG. 4. Comparative 3D reconstruction results for the lip plaster model, a lion relief, and the angel plaster model. [(a)–(c)] Fringe images, 3D reconstruction results of the proposed RPT-ulFPA method, and the ground truth. [(d) and (e)] Corresponding depth error maps and the error histograms of (b). (a) Input fringes. (b) RPT-ulFPA. (c) GT. (d) Measurement errors. (e) Error distribution (%).

Fig. 4(b) demonstrate that the proposed method effectively recovers accurate and high-completeness absolute phase and successfully reconstructs the complex geometric structures of the objects. As shown in Figs. 4(d) and 4(e), the depth error maps and the error histograms compared with the ground truth indicate that the main measured errors are less than 0.2 mm across all test cases, demonstrating the high robustness of the proposed method to various complex surfaces. These results establish that embedding RPT-derived physical priors enables unsupervised and interpretable single-frame 3D measurements of complex objects without pre-training, enhancing the adaptability and reliability in challenging scenarios.

Finally, to validate the dynamic 3D imaging capability of the proposed method, the built single-frame 3D imaging system was applied to a dynamic scene—a lion plaster model moving at a speed of 5 mm/s, as shown in Fig. 5 (Multimedia available online) and Visualization 1. In this experiment, the refresh rate of the DLP projector and the camera frame rate were both set to 100 Hz to achieve

high-speed projection and acquisition synchronously. Figures 5(a) and 5(b) show representative fringe images and corresponding 3D reconstructions at different time points, demonstrating high-fidelity dynamic measurement of dynamic scenes with complex textures and geometries.

D. Generalization analysis

To further evaluate the generalization ability of RPT-ulFPA under different material and surface reflectance conditions, two additional objects were measured, including a smooth ceramic vase and a resin mask, as shown in Fig. 6. The ground truth 3D results were obtained by 12-step PSP with three-frequency temporal phase unwrapping, while RPT-ulFPA used only a single high-frequency fringe for absolute phase retrieval and 3D reconstruction. For the ceramic vase, RPT-ulFPA still achieves a relatively complete 3D reconstruction despite the presence of specular highlights, with a measurement-error MSE of 0.0183 mm. For the resin mask with

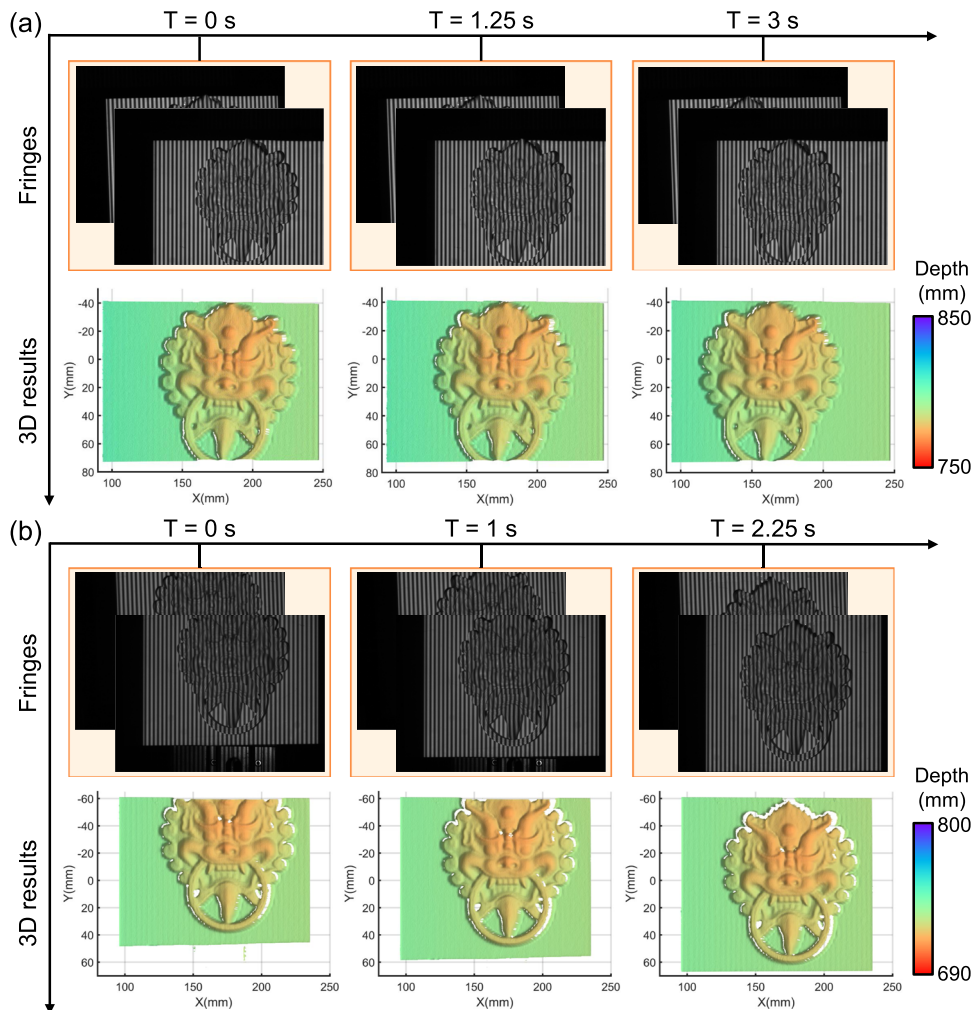


FIG. 5. Dynamic 3D reconstruction results for the moving lion relief along the X or Y axis. [(a) and (b)] Representative fringe images at different time points and corresponding color-coded 3D reconstruction results. (Multimedia available online).

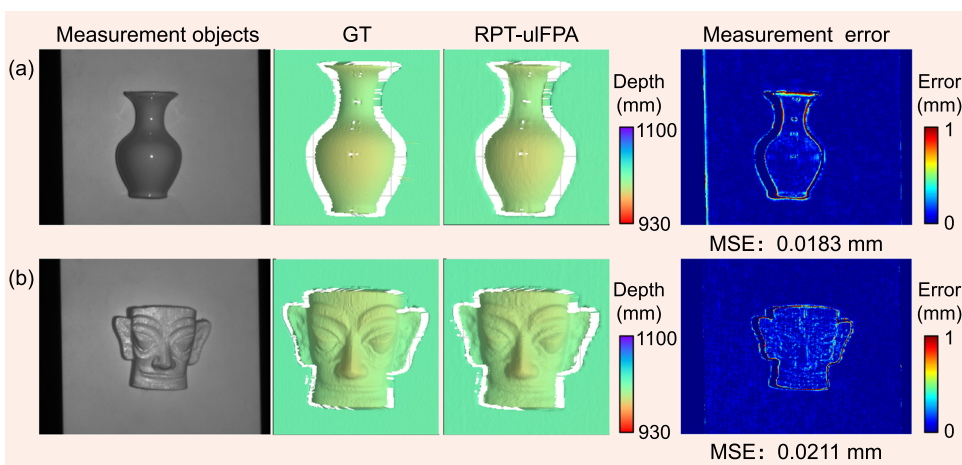


FIG. 6. Generalization analysis of RPT-ulFPA on objects with different materials and surface reflectance. (a) Ceramic vase. (b) Resin mask. From left to right: the measured object, the 3D reconstruction results of the ground truth (GT), the proposed RPT-ulFPA method, and the corresponding depth error maps.

more complex geometry and diffuse surface reflectance, the corresponding measurement-error MSE is 0.0211 mm. The residual errors are mainly distributed around object boundaries and regions with steep surface gradients, while the overall shapes and local surface structures are well preserved. These results indicate that the proposed physics-guided unsupervised framework maintains stable and consistent single-frame 3D reconstruction performance on objects with different materials and reflectance properties, underscoring its strong generalization ability.

IV. CONCLUSIONS AND DISCUSSIONS

In summary, we have proposed an unsupervised single-frame fringe pattern analysis method based on regularized phase tracking (RPT-ulFPA) for accurate and generalizable single-shot 3D imaging. By embedding the physical priors of RPT into a deep neural network, the proposed method synergizes conventional model-based fringe analysis with data-driven learning, enabling reliable phase retrieval without requiring labeled data or pre-training. The method integrates variational image decomposition (VID) and Hilbert spiral transform (HST) as a dedicated fringe preprocessing module to effectively remove background and modulation components from the single-frame high-frequency fringe, which retains only phase-related information for the subsequent unsupervised fringe analysis network. By incorporating RPT-derived photometric consistency and local phase smoothness constraints into the network's loss function, the network preserves the interpretability and robustness of the phase retrieval while significantly enhancing processing efficiency. Furthermore, the proposed unsupervised network introduces a pre-acquired reference-plane phase and a two-step refinement strategy to explicitly resolve the inherent phase ambiguity and improve the phase accuracy in single-frame absolute phase estimation. The two-step strategy generates a globally continuous initial absolute phase using a reference phase under RPT-based physical constraints in the first step, which is used to guide refined wrapped phase estimation and phase unwrapping secondly. This refinement effectively enhances phase accuracy and stability while preserving fine structural details in critical regions. The effectiveness of RPT-ulFPA has been verified by several experiments measuring various types of static and dynamic scenes. The comparative 3D reconstruction results of an eye-shaped plaster model confirmed that RPT-ulFPA can retrieve high-quality and high-completeness absolute phase from single-frame fringe pattern, outperforming traditional FTP in preserving fine structural details. Quantitative precision analysis on a hemispherical plaster model demonstrated that the method maintains sub-millimeter accuracy across different fringe frequencies, verifying its robustness and reliability of phase retrieval. Moreover, experiments on complex surfaces (including a lion relief and a polyhedron) and dynamic scenes (a lion model moving along the X and Y axes) revealed the applicability of RPT-ulFPA for fast, high-fidelity dynamic 3D measurement without pre-training, highlighting its improved adaptability capability for single-frame fringe analysis across diverse surface geometries.

Collectively, RPT-ulFPA offers a physics-consistent solution to the long-standing trade-off among data efficiency, generalization, and reconstruction quality in fringe pattern analysis. It demonstrates that embedding physical priors into neural networks can

achieve robust performance of single-frame 3D imaging in diverse optical metrology scenarios. Nevertheless, we acknowledge certain limitations: the current framework necessitates a reliable calibration step due to the reliance on a pre-acquired reference-plane phase, which may be sensitive to system vibrations in harsh industrial environments; the performance for measuring surfaces with diverse materials or textures—especially those with extremely high dynamic range (HDR) or specular reflections—could be further optimized. Addressing these challenges will be the focus of our future work, specifically by introducing additional informative cues (such as geometric constraints, polarization information) to enhance the method's flexibility in some practical scenarios, and integrating advanced illumination models into the physical loss function to extend its application potential. Ultimately, we aim to develop more efficient network architectures to further advance next-generation intelligent optical metrology.

SUPPLEMENTARY MATERIAL

The following [supplementary material](#) is available with this paper: Visualization 1: A video showing the dynamic 3D reconstruction results for the moving lion relief along the X or Y axis. This video is submitted as part of the initial submission and will be made available online upon acceptance of the manuscript. [Supplementary material](#): Section S1: Comparative experiments across multiple representative single-frame fringe pattern analysis methods; Sec. S2: Ablation studies for the unsupervised fringe analysis network; Sec. S3: Network architecture.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

K.D. and B.W. contributed equally to this work.

Kunmei Ding: Writing – review & editing (equal). **Beibei Wang:** Writing – original draft (equal); Writing – review & editing (equal). **Wei Yin:** Supervision (equal). **Shijie Feng:** Project administration (equal). **Qian Chen:** Resources (equal). **Chao Zuo:** Funding acquisition (equal).

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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