

Article

Progressive Adaptive Fringe Projection Without Additional Projected/Captured Images for High-Dynamic-Range 3D Measurement

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Abstract

Highly reflective surfaces often cause intensity saturation in captured fringe images, leading to phase errors and inaccurate 3D reconstruction. High-dynamic-range (HDR) fringe projection profilometry is an effective solution to this problem, but existing methods usually require additional image acquisition or auxiliary calibration, which limits their applicability to high-speed online inspection. In this work, we propose a phase-optimization-guided progressive adaptive fringe projection method for HDR 3D measurement. First, quality-guided RGB phase fusion is used to fuse reliable phase information from RGB channels, reducing unreliable phase regions and identifying residual overexposed areas. Second, local phase repair restores pixels that cannot be directly mapped in overexposed regions, thereby establishing stable camera–projector correspondence. Third, an adaptive optimal projection intensity is estimated through local intensity fitting to adjust the brightness of highly reflective regions. These steps are embedded into the frequency-varying phase-unwrapping process of conventional digital fringe projection, progressively suppressing saturation-induced phase distortion without additional projected/captured images or calibration operations. Experiments on a highly reflective blade and a white plaster bust demonstrate that the method suppresses saturation without extra image acquisition. Comparative results show high measurement accuracy and low missing ratios with fewer images.

Keywords: fringe projection; high dynamic range; phase optimization; progressive adaptive projection; 3D measurement



Received: 2 July 2026

Revised: 30 July 2026

Accepted: 4 August 2026

Published: 6 August 2026

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1. Introduction

Fringe projection profilometry (FPP) has been widely used for non-contact three-dimensional (3D) measurement because of its full-field acquisition, high spatial resolution, simple optical configuration, and suitability for fast inspection [1–4]. In phase-shifting FPP, fringe intensity is encoded as phase information and then converted into 3D coordinates

through phase demodulation, phase unwrapping, and system calibration. Accurate measurement requires the captured fringe waveforms to retain sufficient modulation within the valid dynamic range of the camera. Once the gray levels are clipped at the upper bound or become too weak near the lower bound, the sinusoidal intensity model is violated, causing phase bias, fringe-order errors, and inaccurate 3D reconstruction.

Highly reflective surfaces make this dynamic-range problem particularly challenging. Industrial objects such as metal parts, solder joints, blades, ceramic surfaces, and electronic packaging devices often contain regions with different reflectance and localized specular highlights. A fixed exposure time and a uniform projection intensity cannot adapt to all these regions simultaneously. Highly reflective areas may suffer from local overexposure and fringe clipping, whereas weakly reflective areas may have insufficient modulation. In multifrequency phase-shifting measurement, such intensity errors can further propagate through phase unwrapping: distorted low- or medium-frequency phases may lead to incorrect high-frequency fringe orders, while damaged camera–projector correspondence may result in missing points, discontinuities, or geometric distortion. Therefore, high-dynamic-range (HDR) 3D measurement remains a key issue in practical FPP systems [5,6].

Existing HDR-FPP methods mainly include multi-exposure or multi-intensity fusion, hardware-assisted imaging, saturated-fringe restoration, and adaptive projection. Multi-exposure and multi-intensity methods fuse fringe or phase information from image groups captured under different exposure times or projection intensities [7–11]. Their principle is straightforward and they can effectively extend the measurable reflectance range, but each additional exposure or brightness level requires another complete phase-shifting sequence. The object, camera, projector, and illumination environment must also remain stable across repeated acquisitions. These requirements reduce measurement efficiency and increase motion sensitivity, especially in online inspection scenarios such as 3D inspection of electronic assemblies, where reflective solder joints, pins, and metallic regions must be measured within a strict cycle time.

Hardware-assisted methods, such as polarization imaging, auxiliary illumination, multiple projection units, or special optical modulation devices, improve the imaging condition at the physical level [12–14]. These strategies can be effective for specific reflective objects, but they increase system cost, optical complexity, calibration difficulty, and deployment burden. Saturated-fringe restoration methods compensate for clipped intensities or phases from already captured images by exploiting phase-shifting relationships, local spatial continuity, or intersection constraints [15]. Such methods can be incorporated into existing FPP pipelines without extra hardware; however, saturation is an information-loss process at the acquisition stage. When several phase-shifting images of the same pixel are clipped, the amplitude and phase-related information become insufficient, and restoration has to rely more heavily on model assumptions or spatial interpolation, which may introduce local oversmoothing, phase discontinuities, or reconstruction errors.

Adaptive projection suppresses saturation before image acquisition and has become an important direction for HDR-FPP [16–23]. It adjusts the local projection intensity according to the surface response, so that highly reflective regions receive lower brightness while normal regions retain sufficient fringe modulation. Lin et al. established the camera response relationship using uniform-gray patterns and used maximum-intensity prescanning fringes to identify saturated regions and determine the camera–projector mapping [19]. Subsequent studies further considered surface coefficients, ambient light, indirect reflection, and local response modeling, improving the measurement accuracy for high-reflectance surfaces [21–23]. Nevertheless, most adaptive projection methods still require additional calibration or prescanning patterns. Uniform-gray images are commonly used to estimate the relation between projected and captured gray levels, while high-intensity prescanning

is used to locate saturated regions and build the mapping from the camera plane to the projector plane. These additional patterns weaken the efficiency advantage of adaptive projection and limit its applicability to fast online measurement.

Achieving HDR 3D measurement without additional projected or captured images remains challenging because camera–projector phase mapping and projection-intensity prediction are tightly coupled. Adaptive projection requires reliable phase-derived mapping from camera pixels to projector positions, so that the optimized intensity can be written to the correct region. However, the highly reflective regions that need intensity adjustment are also the regions where overexposure most severely corrupts the phase. Once the phase becomes unreliable, the saturated area cannot be accurately projected back onto the projector plane, and the subsequent adaptive pattern may be incorrectly assigned. In addition, without uniform-gray calibration or prescanning, the local radiometric response cannot be fully determined from a single measurement stage, making it difficult to calculate an accurate adaptive projection intensity in one step. Although the saturated-fringe restoration method proposed by Wei et al. [23] does not require additional images, it mainly restores saturated fringes by constructing mirrored gray-level information from neighboring unsaturated fringes. However, in practical measurements, the captured fringe intensities are affected by ambient light, nonlinear camera–projector response, and surface-reflectance modulation, and therefore often deviate from the ideal cosine model. Therefore, HDR 3D reconstruction without additional image acquisition remains highly challenging.

In this work, we propose a phase-optimization-guided progressive adaptive fringe projection method for HDR 3D measurement without additional projected or captured patterns beyond the standard multifrequency phase-shifting sequence. The method is embedded into the frequency-varying phase-unwrapping process of conventional digital fringe projection. First, quality-guided RGB phase fusion uses a phase-quality metric based on fringe modulation, mean gray level, and saturation degree to fuse reliable phase information from different color channels, reducing unreliable phase regions and identifying residual overexposed areas. Second, for pixels whose three color channels remain severely saturated after fusion, local phase repair recovers the phase only within the marked saturated regions, thereby establishing stable camera–projector correspondence. Third, based on this correspondence, the known projected gray levels and unsaturated captured gray levels already available in the current phase-shifting sequence are reused to estimate the local intensity response and calculate the adaptive projection intensity for the next frequency. In this way, the low-, medium-, and high-frequency stages progressively update the phase, valid response samples, and projection intensity without extra projected/captured images, uniform-gray calibration, maximum-intensity prescanning, or auxiliary hardware.

The main contribution of this paper is a scan-efficient adaptive projection method that combines local phase repair with progressive response estimation inside the regular measurement sequence. Local phase repair improves the reliability of the phase in highly reflective regions without modifying reliable surrounding phases. The progressive adaptive fringe projection method reuses valid gray-level samples contained in the standard multifrequency phase-shifting sequence, enabling local response estimation and projection-intensity updating from low to high frequencies. Experiments on a highly reflective blade and a white plaster bust, together with comparisons with conventional FPP, saturated-fringe restoration, and classical adaptive projection methods, demonstrate the accuracy, low missing ratios, and image efficiency of the proposed method.

The remainder of this paper is organized as follows. Section 2 describes the phase-shifting model, camera–projector phase-coordinate mapping, quality-guided RGB phase fusion, local phase repair, and progressive adaptive fringe projection. Section 3 presents the experimental setup, validation of key components, and comparative measurement results.

Section 4 discusses the mechanism and characteristics of the proposed method. Section 5 concludes the paper.

2. Principle

The proposed method integrates four connected functional modules—quality-guided RGB phase fusion, local phase repair, camera–projector mapping, and adaptive fringe generation—into the conventional multifrequency measurement sequence. Low-frequency fringes are first projected and captured to obtain the initial RGB phases. Quality-guided fusion uses complementary valid information from the three color channels, and local repair recovers only the residual unreliable phase regions. The resulting phase supports multifrequency phase unwrapping and establishes the camera–projector correspondence needed to extract projected/captured gray-level pairs.

The extracted gray-level pairs are used to fit the local response and estimate the optimal projection intensity for the next frequency stage. Medium-frequency adaptive fringes suppress saturation and provide additional unsaturated samples, which update both the phase and the local response model before high-frequency projection. The same progression is repeated from the medium- to high-frequency stage, and the high-frequency phase acquired under the optimized illumination is finally used for 3D reconstruction. Thus, phase optimization and adaptive projection are coupled across frequency stages without introducing an independent calibration or prescanning sequence, as illustrated by the overall framework in Figure 1.

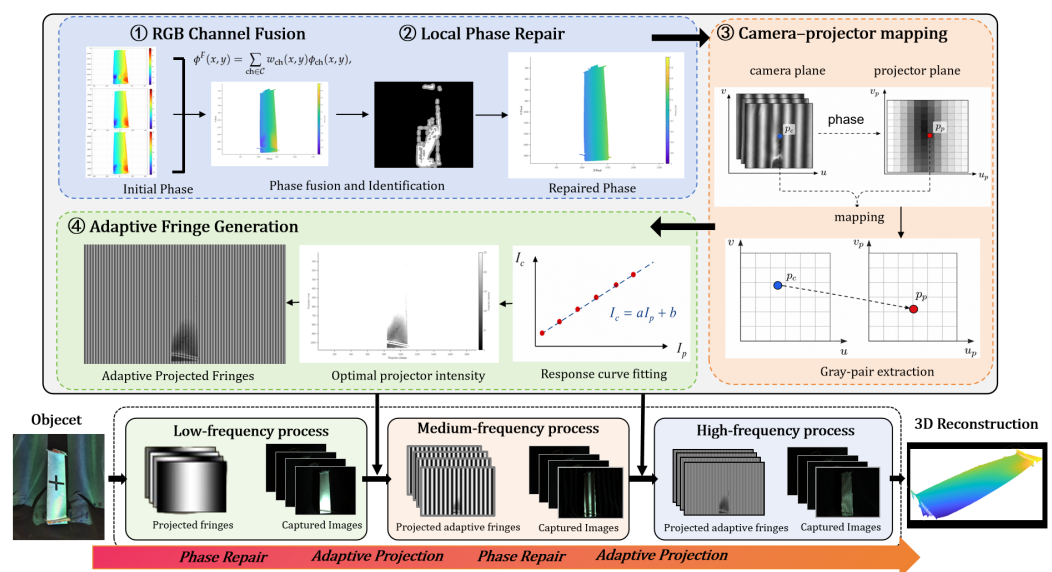


Figure 1. Overall framework of the phase-optimization-guided progressive adaptive fringe projection method.

2.1. Phase-Shifting Fringe Model and Camera–Projector Phase-Coordinate Mapping

In a single-camera, single-projector FPP system, the projector casts phase-shifting fringe patterns onto the object surface, and the camera records the patterns after surface reflection, superposition with ambient light, and camera response [2,6]. Throughout this paper, superscripts *c* and *p* identify camera and projector quantities, respectively, whereas the subscript *n* indexes the phase-shifting step. The projector column coordinate corresponding to camera pixel (*x*, *y*) is denoted by *u_p*, and the two-dimensional projector

pixel coordinate is denoted by $\mathbf{p}_p = (u_p, v_p)$. For the n th phase-shifting image, the gray level captured at camera pixel (x, y) can be approximated as

$$I_n^c(x, y) = kt \left\{ L_a(x, y) + \rho(x, y) \left[L_i(x, y) + L_n^p(\mathbf{p}_p) \right] \right\} + \varepsilon_n^c(x, y), \quad (1)$$

where I_n^c is the gray level captured by the camera, k is the camera sensitivity, t is the exposure time, ρ is the surface reflectance of the object, L_a is the ambient-light component, L_i is a locally slowly varying indirect-light component, L_n^p is the output intensity of the n th projected pattern at $\mathbf{p}_p$, and ε_n^c denotes additive imaging noise and residual model discrepancy in the n th captured frame. For a fixed object pose, exposure time, gain, and ambient illumination, the terms in Equation (1) that are independent of projection intensity can be combined into an intercept, while the surface reflection and system transfer characteristics can be combined into a local response slope. Following the local camera-response approximation used in HDR fringe-projection measurement [19,24], the relationship between the camera and projector gray levels within the unsaturated range can therefore be written as

$$I^c(x, y) = a(x, y)I^p(\mathbf{p}_p) + b(x, y) + \varepsilon^c(x, y), \quad (2)$$

where I^p and I^c are the paired projector and camera gray levels, respectively, a is the local response slope, b is the background intercept, and ε^c is the residual error of the local linear approximation. This approximation does not require globally uniform reflectance. Instead, it describes the local relationship between the projector and captured gray levels near each camera pixel under fixed measurement conditions, providing a basis for subsequent adaptive projection-intensity estimation. The corresponding light paths for the projected and captured intensities are illustrated in Figure 2.

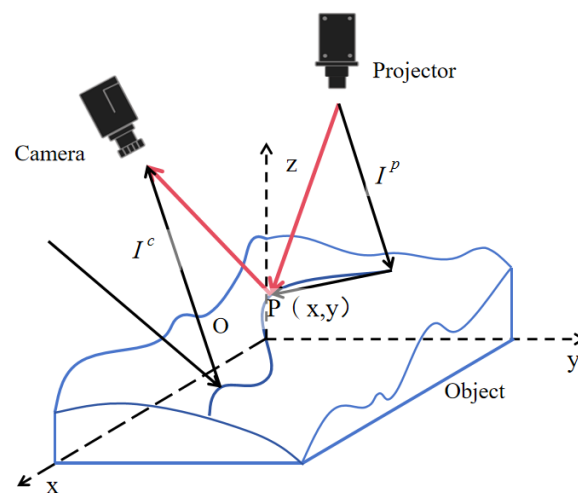


Figure 2. Light paths in capturing fringe-pattern images. The red arrows trace the illumination and reflection path through point P , whereas the black arrows indicate the projector and camera intensity paths I^p and I^c , respectively.

For camera pixel (x, y) , the gray level captured in the n th frame of an N -step phase-shifting sequence can be expressed as

$$I_n^c(x, y) = A^c(x, y) + B^c(x, y) \cos[\phi(x, y) + \delta_n] + \varepsilon_n^c(x, y), \quad n = 1, 2, \dots, N, \quad (3)$$

where $A^c(x, y)$ is the captured background gray level, $B^c(x, y)$ is the captured fringe modulation, $\phi(x, y)$ is the wrapped phase to be determined, $\delta_n = 2\pi(n - 1)/N$ is the phase shift at the n th step, and $\varepsilon_n^c(x, y)$ represents the additive imaging noise and model discrepancy introduced in Equation (1). For equally spaced N -step phase shifting, the wrapped phase, background gray level, and fringe modulation can be written as

$$\phi(x, y) = \text{atan2} \left[- \sum_{n=1}^N I_n^c(x, y) \sin \delta_n, \sum_{n=1}^N I_n^c(x, y) \cos \delta_n \right], \quad (4)$$

$$A^c(x, y) = \frac{1}{N} \sum_{n=1}^N I_n^c(x, y), \quad (5)$$

$$B^c(x, y) = \frac{2}{N} \sqrt{\left[\sum_{n=1}^N I_n^c(x, y) \cos \delta_n \right]^2 + \left[\sum_{n=1}^N I_n^c(x, y) \sin \delta_n \right]^2}. \quad (6)$$

When $N = 4$, Equations (4)–(6) reduce to the standard four-step phase-shifting formulas; the expressions also remain valid for three- or five-step phase shifting. If any phase-shifted gray level is clipped by the upper limit of the camera, the sinusoidal relationship in Equation (3) is disrupted, producing a systematic bias in the phase obtained from Equation (4). In the proposed method, the low- and medium-frequency phases are used not only for multifrequency phase unwrapping but also to determine the locations of camera pixels in the projector plane. Saturation-induced phase errors therefore affect both phase-coordinate mapping and the placement of subsequent adaptive projection intensities.

The proposed method uses single-direction fringe patterns for projection, acquisition, and phase-coordinate mapping. Following the adaptive projection mapping used by Lin et al. [19], the unwrapped phase is converted into the corresponding projector column. Let $\Phi(x, y)$ denote the unwrapped phase at camera pixel (x, y) , m represent the number of periods in the sinusoidal fringe pattern, and W^P the number of projector columns. The projector column is written as

$$u_p = \text{round} \left[\frac{W^P}{2\pi m} \Phi(x, y) \right] + 1, \quad (7)$$

where $\text{round}[\cdot]$ denotes rounding to the nearest integer. More generally, the correspondence used for adaptive projection is obtained by matching the phase $\Phi^c(x, y)$ recovered in the camera image plane to the known phase distribution Φ^P encoded by the projector-plane fringe patterns. This phase-coordinate lookup is denoted by

$$p_p = \mathcal{M}_\Phi(x, y; \Phi^c, \Phi^P), \quad (8)$$

where $\mathcal{M}_\Phi(\cdot)$ is the phase-derived camera–projector mapping and its coordinate along the fringe-modulation direction satisfies Equation (7). Neither Equation (7) nor Equation (8) uses the intrinsic or extrinsic geometric calibration parameters. This phase-derived correspondence is used to read the projected gray level associated with each camera pixel, extract projected/captured gray-level pairs, and write the predicted intensity into the projector-plane template.

Geometric calibration is introduced only when the final measurement phase is converted into three-dimensional coordinates. In a calibrated FPP system, the camera pixel and phase-derived projector-column constraint determine the corresponding 3D point through the back-projection phase-to-3D mapping [25]:

$$\hat{P}(x, y) = \mathcal{B}_\Theta(x, y, u_p), \quad (9)$$

where $\mathcal{B}_\Theta(\cdot)$ is determined by the camera–projector calibration parameters Θ , and $\hat{P}(x, y)$ is the 3D point reconstructed by intersecting the camera ray with the projector column plane. Thus, calibration errors propagate through the triangulation model to the final point-cloud coordinates, but they do not enter the preceding phase demodulation, RGB phase fusion, local phase repair, gray-level-pair extraction, or adaptive intensity-template placement. If the low- or medium-frequency phase is biased by saturation, Equations (7) and (8) instead assign the camera pixel and its predicted intensity to an incorrect projector location. Therefore, reliable phase is required before estimating the local response.

2.2. Quality-Guided RGB Phase Fusion

The color channels of a color camera have different spectral responses. In highly reflective regions, one channel may be clipped while another channel still contains usable fringe modulation. The proposed method therefore uses the mutually complementary phase information acquired in the same fringe sequence to improve the phase without introducing additional scans. The central problem is to assign a physically meaningful reliability to each channel so that the fusion is guided by phase precision rather than by gray intensity alone.

The reliability measure is derived from the precision model of fringe projection profilometry. Lv and Kemao established an intensity-dependent camera noise model and linked the camera electronic noise to the phase precision of phase-shifting profilometry [26]. Let $\text{ch} \in \mathcal{C} = \{\text{R}, \text{G}, \text{B}\}$ index a color channel. For a captured gray level $I_{\text{ch}}^c(x, y)$, the gray-level noise variance can be expressed as

$$\sigma_{I,\text{ch}}^2(x, y) = \sigma_0^2 + \kappa I_{\text{ch}}^c(x, y), \quad (10)$$

where σ_0^2 denotes the intensity-independent camera-noise variance, and κ is the overall gain coefficient associated with photon-to-electron conversion and camera amplification. Substituting this noise model into an equally spaced N -step phase-shifting algorithm gives the approximate phase variance

$$\sigma_{\phi,\text{ch}}^2(x, y) = \frac{2}{N [B_{\text{ch}}^c(x, y)]^2} [\sigma_0^2 + \kappa A_{\text{ch}}^c(x, y)], \quad (11)$$

where $A_{\text{ch}}^c(x, y)$ and $B_{\text{ch}}^c(x, y)$ are the captured background term and fringe modulation of channel ch , respectively. In the proposed experiment, the effective gray level in the object region is sufficiently high, and the intensity-dependent term dominates the readout-noise term. Equation (11) can then be simplified as

$$\sigma_{\phi,\text{ch}}^2(x, y) \approx \frac{2\kappa A_{\text{ch}}^c(x, y)}{N [B_{\text{ch}}^c(x, y)]^2}, \quad (12)$$

which indicates that the phase precision increases with the modulation-to-noise ratio $B_{\text{ch}}^c(x, y) / \sqrt{A_{\text{ch}}^c(x, y)}$. This term is used as the basic signal-to-noise component of the channel reliability.

The modulation-to-noise term alone cannot distinguish a high-modulation but clipped phase from a reliable phase. Following the quality-guided fusion idea in the hybrid-quality-guided phase fusion model [27], a saturation penalty is added to the modulation-based metric. Let $q_{\text{ch}}(x, y)$ denote the number of saturated frames in channel ch among the N

phase-shifting images, and let σ_s control the attenuation rate of the saturation penalty. The channel quality is defined as

$$Q_{\text{SNR, ch}}(x, y) = \frac{B_{\text{ch}}^c(x, y)}{\sqrt{A_{\text{ch}}^c(x, y)}} \exp\left[-\frac{(q_{\text{ch}}(x, y)/N)^2}{2\sigma_s^2}\right], \quad (13)$$

where the first factor reflects the phase-noise model, and the exponential term suppresses channels affected by gray-level clipping. A channel is allowed to participate in fusion only when its saturation count is smaller than a preset threshold q_{th} . The validity mask and normalized weight are written as

$$m_{\text{ch}}(x, y) = \begin{cases} 1, & q_{\text{ch}}(x, y) < q_{\text{th}}, \\ 0, & q_{\text{ch}}(x, y) \geq q_{\text{th}}, \end{cases} \quad (14)$$

$$\begin{aligned} Z(x, y) &= \sum_{\text{ch} \in \mathcal{C}} m_{\text{ch}}(x, y) Q_{\text{SNR, ch}}(x, y), \\ w_{\text{ch}}(x, y) &= \frac{m_{\text{ch}}(x, y) Q_{\text{SNR, ch}}(x, y)}{Z(x, y)}, \end{aligned} \quad (15)$$

where $\mathcal{C} = \{\text{R}, \text{G}, \text{B}\}$ is the set of available color channels, and Z is the normalization factor. If $Z(x, y) = 0$, the pixel is excluded from the fusion result and is transferred to the local phase-repair stage.

The final fused phase is calculated by weighted averaging of the valid channel phases:

$$\phi^F(x, y) = \sum_{\text{ch} \in \mathcal{C}} w_{\text{ch}}(x, y) \phi_{\text{ch}}(x, y), \quad (16)$$

where $\phi_{\text{ch}}(x, y)$ is the phase of channel ch , and $\phi^F(x, y)$ is the fused phase. This formulation uses only reliable channel information from the current acquisition. As a result, the valid phase region used for camera–projector mapping is enlarged without increasing the number of projected fringe images.

2.3. Local Phase Repair

After quality-guided RGB phase fusion, most pixels can obtain a usable wrapped phase from at least one valid color channel. The RGB wrapped phases are first fused according to Equation (16) and then unwrapped using the multifrequency relationship. Local phase repair is applied to this unwrapped phase rather than to the final high-frequency measurement phase. When all three channels contain two or more saturated frames at the same pixel, the captured phase-shifting sequence no longer provides sufficient information for reliable fusion. These pixels are therefore marked as local repair pixels. Let $q_{\text{ch}}(x, y)$ be the saturation count of channel ch defined in Section 2.2. For the four-step phase-shifting sequence used in this work, $q_{\text{rep}} = 2$ is adopted; for other phase-shifting steps, this threshold can be adjusted according to the number of projected patterns and the saturation tolerance. Following the same threshold convention as Equation (14), the repair mask is defined as

$$M_{\text{rep}}(x, y) = M_{\text{sat}}(x, y) = \begin{cases} 1, & q_{\text{ch}}(x, y) \geq q_{\text{rep}}, \forall \text{ch} \in \mathcal{C}, \\ 0, & \text{otherwise,} \end{cases} \quad (17)$$

where M_{sat} is the multichannel saturation mask, and $\mathcal{C} = \{\text{R}, \text{G}, \text{B}\}$ is the set of color channels. Thus, only pixels whose R, G, and B channels are all severely affected by saturation are transferred to the local repair stage. Pixels outside M_{rep} retain the fused phase and are not modified by the subsequent spatial fitting. For each connected repair

region Ω_i , the mask is dilated adaptively until the surrounding annular neighborhood contains sufficient reliable external samples. Candidate pixels are retained only when they lie outside the repair mask and have a valid fused phase ϕ^F . Boundary-supported fitting has also been used to recover invalid phase regions after phase-validity classification in high-reflectivity structured-light measurement [28]. In the proposed implementation, fitting remains restricted to each local repair region. The retained neighboring samples are taken from the valid unwrapped phase, aligned to the same local phase branch when necessary, and the phase to be repaired is then estimated using a local quadratic surface:

$$\hat{\phi}(x, y) = \beta_0 + \beta_1 x + \beta_2 y + \beta_3 x^2 + \beta_4 xy + \beta_5 y^2, \quad (18)$$

where β_0 – β_5 are the surface coefficients estimated from the neighboring reliable phase samples by least squares. The quadratic surface is used as a compromise between local shape description and fitting stability. A linear model is less able to represent the slowly varying curvature of the blade surface, whereas a higher-order polynomial may overfit or oscillate when only a limited number of reliable boundary samples are available. Therefore, this repair is intended for locally continuous phase regions with sufficient reliable neighboring samples. Its reliability may decrease near sharp edges, true depth discontinuities, or large continuous saturated areas. The estimated phase $\hat{\phi}$ replaces only pixels within M_{rep} , while the original reliable phase outside the mask remains unchanged. This restriction makes the repair support both phase unwrapping and camera–projector mapping while preventing the spatial fitting result from spreading into normal regions or replacing the final high-frequency measurement. The complete procedure is shown in Figure 3.

Figure 3 further illustrates the two-stage implementation of phase optimization. In the primary stage, the color phase-shifting images are first separated into R, G, and B gray-level sequences, from which the wrapped phases and quality maps of the three channels are calculated. Pixel reliability is then jointly evaluated using fringe modulation, mean gray level, and the saturation penalty, followed by weighted fusion of the RGB wrapped phases and multifrequency unwrapping. This stage preferentially retains valid phase information that is actually captured in each color channel. The secondary stage processes only the pixels marked by the multichannel saturation mask after fusion. Morphological closing connects fragmented saturated regions and suppresses isolated noise, while connected-component labeling identifies individual regions to be repaired. Each region is then dilated outward to collect surrounding reliable samples, and its interior unwrapped phase is finally recovered by local quadratic surface fitting. Thus, the morphological operations determine the repair region and its reliable support without altering the reliable phase outside the mask.

2.4. Progressive Adaptive Fringe Projection

At each frequency stage, fringes are projected and captured before the current phase is unwrapped. The algorithm then determines whether the highest frequency has been reached. At the highest-frequency stage, the recovered phase is used directly for 3D reconstruction. Otherwise, the phase-processing branch first performs quality-guided RGB phase fusion and then applies local phase repair to the remaining unreliable regions. The repaired phase is used for camera–projector mapping, after which the optimal projection intensity for the next frequency is estimated and the resulting adaptive fringes are fed back to the projector. The “RGB channel Phase Fusion” and “Local Phase Repair” blocks together constitute the phase-optimization process detailed in Sections 2.2 and 2.3. The response fitting, intensity constraints, degradation strategy, and adaptive-fringe formulation invoked within this branch-and-feedback loop are detailed below.

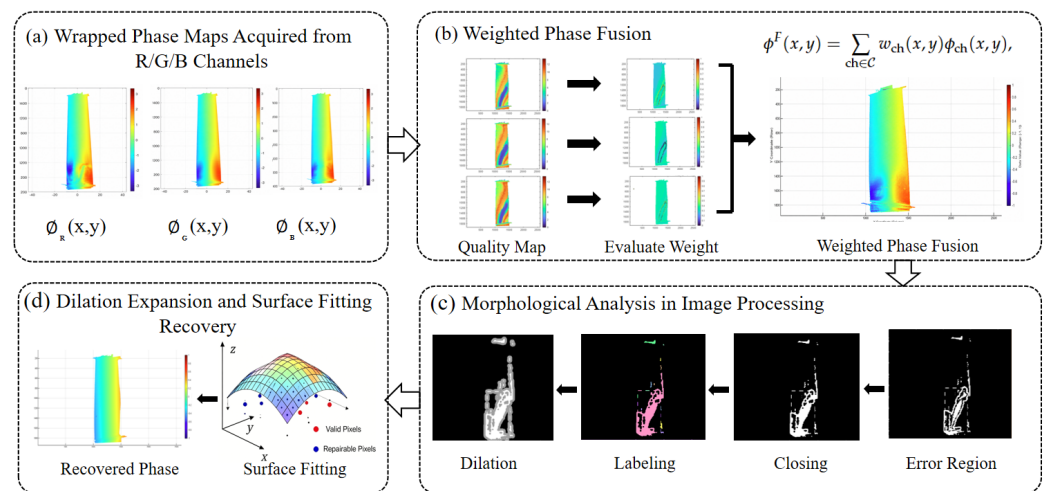


Figure 3. Flowchart of phase optimization. (a) Wrapped phase maps obtained from the R, G, and B channels, with phase values in radians (rad); (b) quality-map evaluation, weight calculation, and weighted RGB phase fusion; (c) morphological processing of the multichannel saturation region by closing, connected-component labeling, and dilation; (d) local surface fitting using valid pixels around the dilated repair region, followed by local phase repair. In (c), different colors distinguish connected components after labeling; in (d), red and blue points denote valid fitting samples and pixels to be repaired, respectively.

At the low-frequency stage, four-step phase-shifting fringes are projected onto the object and recorded by the color camera. Initial wrapped phases are calculated separately from the R, G, and B channels. In the “RGB Channel Fusion” module in Figure 1, pixelwise weights are determined from the phase quality of the three channels, and quality-guided RGB phase fusion combines their complementary phase information. This operation reduces errors caused by local saturation, low modulation, or noise in an individual channel. The fused result is also used to identify local regions in which all three channels are unreliable.

The “Local Phase Repair” module performs local phase repair only within these unreliable regions. Morphological closing, connected-component labeling, and dilation determine the continuous error regions and their supporting neighborhoods, after which the missing or erroneous phase is recovered by local quadratic surface fitting using surrounding reliable phase samples. Reliable phase values outside the identified regions remain unchanged. The repaired phase supports subsequent multifrequency phase unwrapping and restores phase continuity in highly reflective regions, allowing these regions to participate in camera–projector mapping and adaptive intensity calculation. It is not used to replace the final high-frequency measurement phase for 3D reconstruction.

The repaired phase is then passed to the “Camera–projector Mapping” module. According to the single-direction phase-coordinate relationship described in Section 2.1, the absolute phase at a camera-plane pixel $p_c = (x, y)$ determines its corresponding projector-plane position $p_p = (u_p, v_p)$. In Figure 1, “phase” denotes the correspondence between a camera pixel and the projector phase coordinate established through the absolute phase, whereas “mapping” denotes the resulting spatial camera–projector pixel correspondence.

This mapping allows the known projected gray level I^p at p_p to be read from the projected phase-shifting pattern and paired with the captured gray level I^c at p_c . The “Gray-pair Extraction” operation therefore forms projected/captured gray-level pairs that refer to the same mapped surface location. Only unsaturated samples within the valid camera response range,

$$30 < I_j^c < 250, \quad (19)$$

are retained for local response estimation.

For each pixel to be optimized, at least two valid projected/captured gray-level pairs are required. Their local linear response follows Equation (2), consistent with response-function and adaptive-projection models used in HDR FPP [19,22–24]. The “Response Curve Fitting” module estimates the local parameters $\hat{a}(x, y)$ and $\hat{b}(x, y)$ by least squares. Because these gray-level pairs are extracted directly from the regular multifrequency phase-shifting sequence, this response estimation does not require an additional sequence of uniform-gray calibration images.

Given the target captured gray level I_{target}^c and the camera-domain safety margin ΔI^c , the “Optimal Projector Intensity” for the next frequency stage is calculated as

$$I_{\text{opt}}^p(x, y) = \text{clip}\left(\frac{I_{\text{target}}^c - [\hat{b}(x, y) + \Delta I^c]}{\hat{a}(x, y)}, I_{\text{min}}^p, I_{\text{max}}^p\right). \quad (20)$$

Equation (20) is applied only to valid positive-slope fits satisfying $\hat{a}(x, y) > \tau_a > 0$; otherwise, the conventional projection intensity or the median-filtered neighboring estimate is retained. Here I_{min}^p and I_{max}^p denote the allowable lower and upper bounds of the projector gray level, respectively. The margin ΔI^c accommodates noise, local reflectance variations, and errors from the linear approximation. It places the predicted peak near the upper end of the camera’s linear response, avoiding excessive dimming while balancing saturation suppression and fringe modulation.

If fewer than two valid projected/captured gray-level pairs are available or the fitted response fails the reliability criterion, I_{opt}^p cannot be calculated directly. A degradation strategy is then used: the median optimal intensity of successfully fitted neighboring pixels initializes the projection intensity at that pixel for the next stage. If no reliable neighboring estimate is available, the conventional projection intensity is retained. This degradation strategy changes only the initialization of the next-stage projection intensity; it neither replaces local surface fitting for phase recovery nor directly modifies the final reconstruction phase.

The locally optimal intensity is first calculated in the camera plane and then written into the projector plane through the phase-derived mapping $\mathcal{M}_\Phi$ in Equation (8); this operation does not use the geometric calibration parameters. Because the camera and projector have different resolutions and viewing directions, multiple camera pixels may correspond to the same projector position. Let $\mathcal{X}(\mathbf{p}_p)$ denote the set of camera pixels mapped to the same projector position $\mathbf{p}_p$. The projection-intensity template is defined as

$$T(\mathbf{p}_p) = \min_{(x, y) \in \mathcal{X}(\mathbf{p}_p)} I_{\text{opt}}^p(x, y). \quad (21)$$

The minimum is used to prevent a high-reflectance region covered by the same projector pixel from saturating again because of a larger candidate intensity. The conventional projection intensity is retained at positions without valid mapped samples, and isolated holes in the template are filled only within local neighborhoods to avoid modifying regions already determined by reliable samples. In Figure 1, the resulting template is the “Optimal Projector Intensity,” and the next-stage patterns modulated by this template are the “Adaptive Projected Fringes.” The n th adaptive fringe pattern is written as

$$I_{n, \text{adp}}^p(\mathbf{p}_p) = \frac{T(\mathbf{p}_p)}{2} \left\{ 1 + \cos[\phi^p(\mathbf{p}_p) + \delta_n] \right\}, \quad (22)$$

where ϕ^p is the designed projector phase and δ_n is the phase shift at step n . Equation (22) preserves the original fringe frequency and phase-shift relationship, while locally scaling

both the mean intensity and modulation so that the peak intensity is bounded by $T(p_p)$. Consequently, low-reflectance and normal regions retain relatively high fringe modulation, while the peaks in high-reflectance regions remain within the recordable range of the camera.

The lower part of Figure 1 shows how the four functional modules form a progressive closed loop across the three frequency stages. The low-frequency process provides the initial fused and repaired phase, the first camera–projector correspondence, and the initial set of valid projected/captured gray-level pairs $\mathcal{D}_L$, from which the medium-frequency adaptive fringe patterns are generated. After the medium-frequency fringe patterns are projected and captured, newly obtained unsaturated samples are combined with the historical samples to update the local response dataset:

$$\mathcal{D}_i = \mathcal{D}_{i-1} \cup \mathcal{D}_i^{\text{cur}}, \quad (23)$$

where $\mathcal{D}_i^{\text{cur}}$ denotes the valid projected/captured gray-level pairs newly acquired at the current frequency stage. The updated medium-frequency phase and response model are then used to calculate the optimal high-frequency projector intensity and generate the high-frequency adaptive fringe patterns. Thus, as the fringe frequency increases, additional unsaturated projected/captured gray-level pairs are progressively accumulated to refine the local response estimate and projector-intensity distribution.

The repaired low- and medium-frequency phases support multifrequency phase unwrapping, camera–projector mapping, projected/captured gray-level-pair extraction, and adaptive intensity placement. Final 3D reconstruction is performed with the high-frequency phase captured under the progressively optimized illumination. Accordingly, quality-guided RGB phase fusion and local phase repair are integrated with camera–projector mapping and adaptive intensity control. Valid gray-pair accumulation, response fitting, intensity prediction, and adaptive fringe generation then form a continuous measurement process. This design improves phase reliability and reduces reconstruction point loss on highly reflective surfaces without introducing an independent response-calibration sequence. The complete branch-and-feedback control logic is summarized in Figure 4.

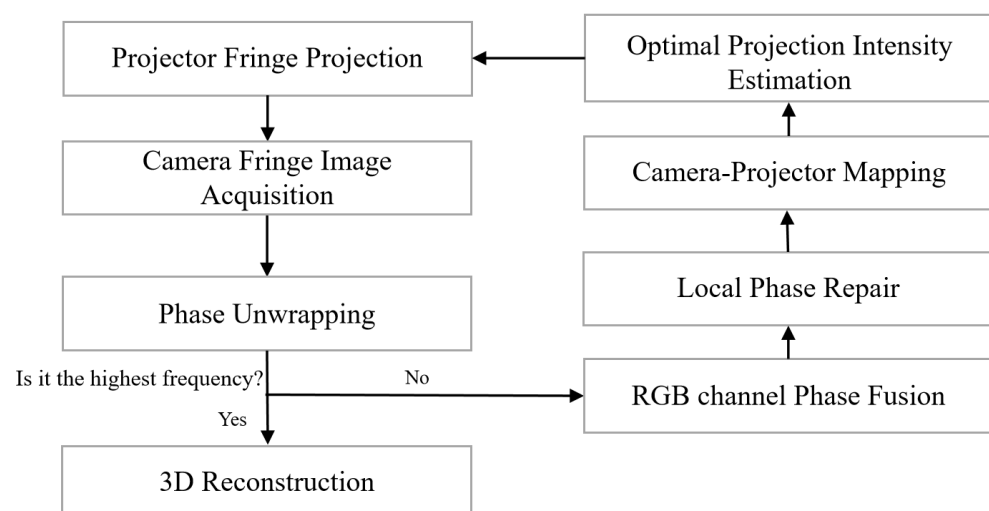


Figure 4. Flowchart of the progressive adaptive fringe projection algorithm.

3. Experiments and Results

The experimental system consists of a DLP4710EVM-LC digital light processing projector (Texas Instruments Incorporated, Dallas, TX, USA), a DFK 23GP031 color industrial camera (The Imaging Source Europe GmbH, Bremen, Germany), and a computer. The pro-

jector and camera have resolutions of 1920×1080 pixels and 2592×1944 pixels, respectively. During each measurement, the camera exposure time, gain, object pose, and ambient illumination remain fixed, and the same camera–projector calibration parameters are used for three-dimensional reconstruction. Unless otherwise specified in the exposure-time evaluation in Section 3.2, the camera exposure time is $1/6$ s. The measured objects are a titanium-alloy aerospace blade with highly reflective regions and a white plaster bust with complex facial geometry. Four-step phase-shifting fringe patterns at low, medium, and high frequencies are projected along the same direction, with fringe period numbers of 1, 16, and 128, respectively. The saturation threshold is set to the camera upper gray level of 255, and the target captured gray level used for adaptive intensity prediction is $I_{\text{target}}^c = 240$. Figure 5 shows the experimental setup and the placement of the aerospace blade. The camera and projector are mounted on the same frame, while the object is placed on an optical table and remains stationary.

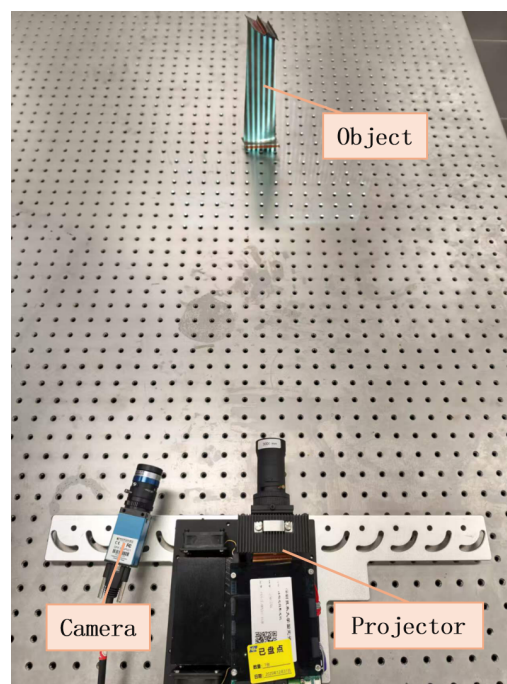


Figure 5. Experimental setup for measuring the highly reflective aerospace blade. The blade, camera, and projector are labeled in the photograph.

3.1. Validation of Adaptive Fringe Projection and Phase Optimization

To verify the effectiveness of camera-response estimation and adaptive projection-intensity calculation, a representative pixel at $(x, y) = (1220, 1582)$ is selected from a highly reflective region of the blade. Figure 6a shows the response fitted from the low-frequency data and the resulting medium-frequency projection intensity. Figure 6b shows the response fitted jointly from the low- and medium-frequency data and the resulting high-frequency projection intensity. At this representative pixel, the unsaturated samples acquired during the standard phase-shifting sequence provide a reliable local response estimate. The calculated projection intensities remain below the onset of saturation, providing a basis for suppressing saturation in the fringe patterns at the next frequency.

This pixel is prone to saturation in the low-frequency four-step phase-shifting sequence. After the predicted intensity is used to generate the adaptive fringe patterns, the gray levels captured at the medium- and high-frequency stages fall within the valid response range of the camera. Stage-wise response fitting therefore provides a suitable projection intensity for the next frequency and yields new unsaturated samples, allowing the response model

to be updated progressively during measurement. Figure 7 further evaluates the practical effect of response fitting and intensity prediction from the global distribution of saturation.

Figure 7 presents the projected patterns and their saturation distributions by row. Row (1) shows the first projected fringe pattern in the four-step phase-shifting sequence at each stage, while row (2) shows the pixelwise saturation count across the corresponding four captured images. Columns (a), (b), and (c) represent the low-, medium-, and high-frequency stages, respectively. The low-frequency fringe pattern in Figure 7(1a) is used to obtain the initial phase and the camera–projector coordinate correspondence. At this stage, saturated pixels remain concentrated in the highly reflective region, as shown in Figure 7(2a). After the local response estimated from the low-frequency data is used to generate the medium-frequency adaptive fringe patterns, the local projection amplitude is selectively reduced, and the saturated area in Figure 7(2b) contracts markedly. The medium-frequency measurements further update the intensity prediction, leaving only a small number of isolated saturated pixels at the high-frequency stage, as shown in Figure 7(2c). These results show that the progressive update suppresses overexposure through local intensity control while preserving fringe contrast outside the highly reflective region.

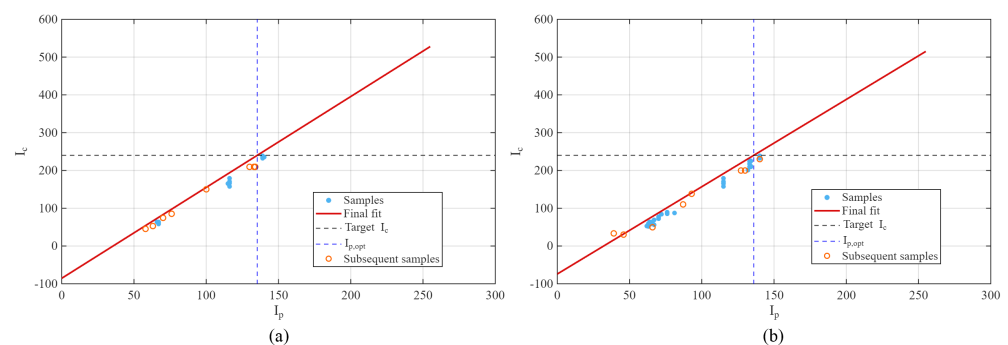


Figure 6. Pixel-response fitting at pixel (1220,1582) for adaptive projection-intensity calculation. (a) Low-frequency response fitting and medium-frequency projection-intensity calculation; (b) joint low- and medium-frequency response fitting and high-frequency projection-intensity calculation. The blue samples are used for fitting, the orange samples are subsequently acquired unsaturated samples, the fitted line represents the estimated local response, and the dashed lines indicate the target captured intensity and the predicted projector intensity. Both projected and captured intensities are expressed as 8-bit gray levels (0–255).

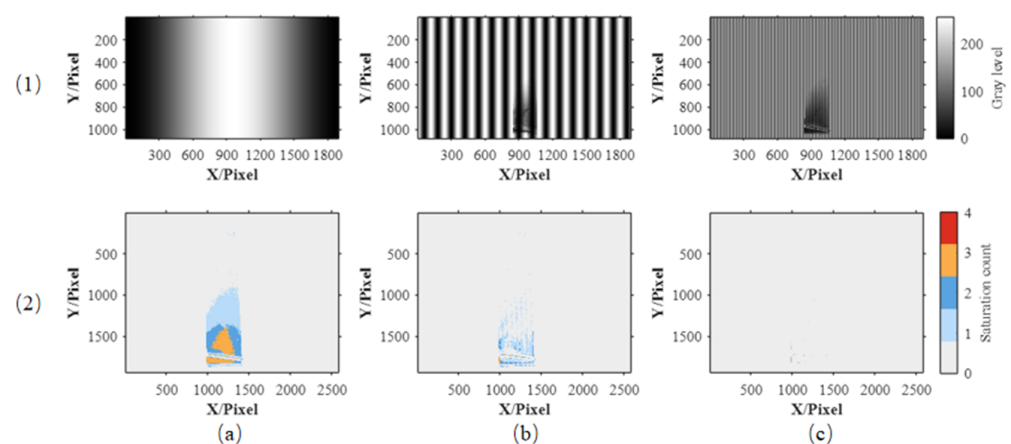


Figure 7. Progressive adaptive projection results. Rows: (1) the first projected fringe of the four-step phase-shifting sequence, displayed as 8-bit projector gray level (0–255), and (2) the pixelwise saturation count in the four captured images, displayed in frames per pixel (0–4). Columns: (a) low-frequency, (b) medium-frequency, and (c) high-frequency stages.

The low-frequency phase provides the basis for subsequent phase unwrapping, coordinate mapping, and intensity prediction; therefore, local errors in this phase can propagate to later stages. The phase optimization evaluated in Figure 8 comprises two consecutive operations: Quality-Guided RGB Phase Fusion followed by Local Phase Repair. Hereafter, these two operations are collectively referred to as phase optimization. Figure 8 compares the absolute low-frequency phase residuals before and after phase optimization relative to the 24-step reference. Before phase optimization, the residual is concentrated around the lower highly reflective portion of the blade. After phase optimization, the residual is substantially reduced and the RMSE decreases from 0.1038 rad to 0.0129 rad. This comparison therefore evaluates the overall phase-optimization process rather than either constituent operation in isolation.

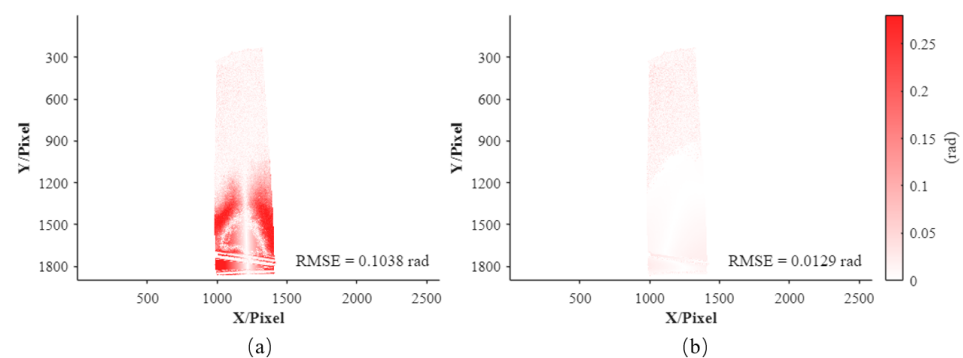


Figure 8. Absolute low-frequency phase residuals relative to the 24-step phase-shifting reference. (a) Residual before phase optimization; (b) residual after phase optimization. The color bars and RMSE values are expressed in radians (rad).

Taken together, these results validate two coupled components of the proposed method. Phase optimization provides a stable low-frequency phase for phase unwrapping and coordinate mapping. Progressive intensity prediction then uses the updated measurements to further reduce saturation at subsequent frequencies. Together, these components mitigate the accumulation of saturation-induced errors during multifrequency phase unwrapping and three-dimensional reconstruction.

3.2. Exposure-Time Evaluation on the Aerospace Blade

The sensitivity of the proposed method to camera exposure time was evaluated using the same highly reflective aerospace blade shown in Figure 5. Measurements were performed using 1/6 s, 1/9 s, and 1/12 s exposures under otherwise identical conditions. Figure 9 shows the corresponding captured low-frequency fringes. The saturated highlight is largest at 1/6 s and progressively contracts as the exposure time decreases, providing three different initial saturation conditions for evaluating the proposed method. Table 1 reports the phase RMSE, point-cloud RMSE, missing ratio, reconstructed point count, and use of the degradation strategy during the two adaptive transitions.

The filtered reference point cloud defines the points expected within the common reconstruction ROI. For each reference point p_i^{ref} , d_i is defined as the minimum Euclidean distance from that point to the evaluated reconstructed point cloud $\mathcal{P}_{\text{eval}}$. A reference point is classified as missing when $d_i > \tau$. Let N_{ref} be the number of filtered reference points in the ROI and N_{miss} the number satisfying this condition. The missing ratio is defined as $R_{\text{miss}} = N_{\text{miss}}/N_{\text{ref}}$, where $\tau = 0.5$ mm. The ratio values reported in the tables are expressed as percentages. The 0.5 mm threshold provides a common submillimeter acceptance tolerance for all methods and exposure settings. It distinguishes reference

points that have a nearby reconstructed counterpart from points that are absent or substantially displaced, while avoiding an exact-coordinate requirement between independently sampled point clouds. Point-cloud RMSE is calculated in the opposite nearest-neighbor direction, from reconstructed points to the reference surface, and therefore measures the geometric error of the available reconstructed points. RMSE can remain low even when part of the reference region is not reconstructed; the missing ratio captures this point loss by evaluating the reverse reference-to-reconstruction correspondence. The two metrics are therefore reported together.

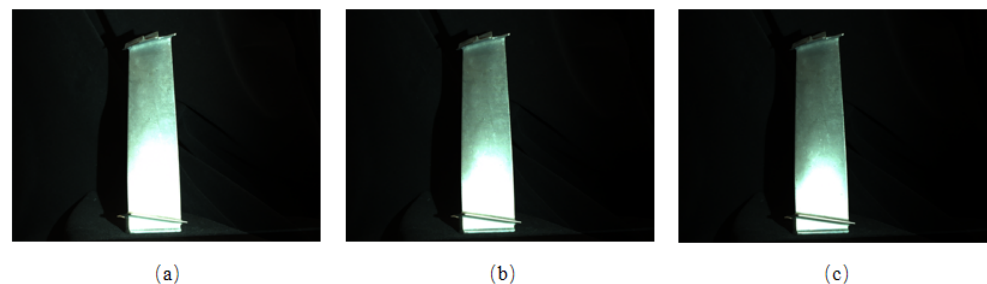


Figure 9. Captured low-frequency fringe of the aerospace blade at different exposure times: (a) 1/6 s, (b) 1/9 s, and (c) 1/12 s.

For each adaptive transition, the candidate mask defines the valid camera-plane pixels whose projection intensities are to be optimized. Let N_{valid} be the number of candidate pixels and N_{fit} be the number for which the local response is directly fitted successfully from valid projected/captured gray-level pairs. Pixels without a successful direct fit (e.g., owing to insufficient valid samples or an unreliable fit) use the median $I_{\text{opt}}^{\text{P}}$ estimate from reliable neighboring pixels to initialize the next-stage projection intensity; this operation does not modify the final reconstructed phase. Accordingly, the degradation-strategy ratio is defined as $R_{\text{deg}} = N_{\text{deg}}/N_{\text{valid}}$, where $N_{\text{deg}} = N_{\text{valid}} - N_{\text{fit}}$ is the number of candidate pixels that require compensation through the degradation strategy. Thus, R_{deg} measures the proportion of optimized candidate pixels that cannot directly yield $I_{\text{opt}}^{\text{P}}$ through local response fitting and require subsequent completion by the degradation strategy; it is neither the fraction of the whole camera image nor the fraction of saturated pixels.

Across the three exposure times, the proposed method maintains phase RMSE values of 0.001641–0.0018664 rad, point-cloud RMSE values of 0.306–0.381 mm, and missing ratios of 0.197%–0.362% on the aerospace blade, demonstrating stable measurement accuracy and low point loss under different exposure settings. The degradation-strategy ratios remain below 10% in both adaptive transitions. For every exposure time, the ratio decreases from the low-to-medium transition to the medium-to-high transition, showing that the progressive accumulation of valid unsaturated gray-level pairs reduces reliance on degradation compensation at the subsequent stage. These results demonstrate the robustness of the proposed method to exposure-time variation within the evaluated range.

Table 1. Performance of the proposed method on the highly reflective aerospace blade at different exposure times.

Exposure	Phase RMSE (rad)	PC RMSE (mm)	Missing Ratio (%)	Reconstructed Points	Degradation Ratio L→M (%)	Degradation Ratio M→H (%)
1/6 s	0.0018664	0.38055	0.362	594,228	9.314	6.747
1/9 s	0.0016410	0.32604	0.302	596,333	8.638	5.416
1/12 s	0.0016540	0.30586	0.197	596,956	8.945	4.730

Note: Phase RMSE is calculated relative to the 24-step phase-shifting reference. L, M, and H denote the low-, medium-, and high-frequency stages, respectively.

3.3. Comparative Evaluation on the Aerospace Blade and White Plaster Bust

The evaluated methods include conventional fringe projection profilometry, the saturated-fringe restoration method proposed by Wei et al., the adaptive digital fringe projection method proposed by Lin et al., and the proposed method. The conventional method, Wei's method, and the proposed method each use 12 images, comprising four-step phase-shifting sequences at low, medium, and high frequencies. In addition to the 12 adaptive fringe patterns required for the final measurement, Lin's method uses seven uniform-gray images and 12 maximum-intensity prescan fringe patterns, resulting in a total of 31 images. For each object, all methods were evaluated using the same 1/6 s exposure time, object pose, camera–projector calibration parameters, reconstruction ROI, and reconstruction pipeline. For all methods, the phase obtained using 24-step phase shifting serves as the ground truth.

The quantitative evaluation uses the entire reconstructed point clouds after removal of non-finite points and statistical-outlier removal (30 nearest neighbors; points whose mean neighbor distance exceeds the global mean plus one standard deviation are rejected). The phase RMSE is calculated from the phase difference with the 24-step reference over common finite phase pixels. The point-cloud RMSE is the one-way nearest-neighbor three-dimensional distance from the evaluated filtered point cloud to the filtered reference point cloud. The missing ratio is calculated over the common reconstruction ROI from the reference-to-reconstruction nearest-neighbor distances defined above, using the same 0.5 mm threshold for all methods. Thus, point-cloud RMSE quantifies the geometric error of the reconstructed points, whereas the missing ratio quantifies the fraction of reference-region points without a sufficiently close reconstructed counterpart.

The captured fringes, phase maps, and three-dimensional point clouds obtained by the four methods are compared on the same highly reflective aerospace blade. Identical display ranges and color scales are used for all phase maps and point clouds to prevent visualization-scale differences from affecting the comparison. Figure 10 compares the measurement results obtained by the four methods on the same aerospace blade. Rows (1)–(4) correspond to the conventional method, Wei's method, Lin's method, and the proposed method, respectively, while columns (a)–(c) show the captured high-frequency fringe, recovered absolute phase, and reconstructed point cloud. The fringe captured by the conventional method exhibits pronounced clipping in the lower part of the blade, as shown in Figure 10(1a). This clipping produces extensive phase anomalies and a continuous missing region in the point cloud in Figure 10(1c). Wei's method alleviates some phase errors by restoring the intensities of the saturated fringes, but panels (2b) and (2c) of Figure 10 show that substantial distortion and point-cloud gaps remain in the deeply saturated region. Both Lin's method and the proposed method reduce the incident intensity in highly reflective regions through adaptive projection. Their phase results in panels (3b) and (4b) and reconstructed point clouds in panels (3c) and (4c) of Figure 10 exhibit substantially better phase continuity and spatial coverage than those obtained by the first two methods.

To further examine the applicability of the method to a nonmetallic object with complex geometry, a white plaster bust was measured using the same experimental protocol. For this object, the phase and point-cloud metrics were calculated in the common manually selected ROI. Figure 11 shows the captured high-frequency fringes, recovered absolute phases, and reconstructed point clouds. The row and column conventions are identical to those in Figure 10: rows (1)–(4) correspond to the conventional method, Wei's method, Lin's method, and the proposed method, respectively, and columns (a)–(c) show the captured fringe, recovered phase, and reconstructed point cloud. The proposed method preserves the facial shape and local geometric details while substantially reducing the phase discontinuities and point-cloud distortions observed in the conventional and fringe-restoration results.

Table 2 summarizes the quantitative results for both objects. On the blade, the proposed method achieves the lowest phase RMSE (0.0018664 rad), point-cloud RMSE (0.38055 mm), and missing ratio (0.362%). In the white plaster bust ROI, it also achieves the lowest phase RMSE (0.0098678 rad), point-cloud RMSE (0.74535 mm), and missing ratio (1.125%). These results indicate that the proposed method provides high measurement accuracy and low missing ratios for both metallic and nonmetallic objects while retaining the 12-image acquisition sequence.

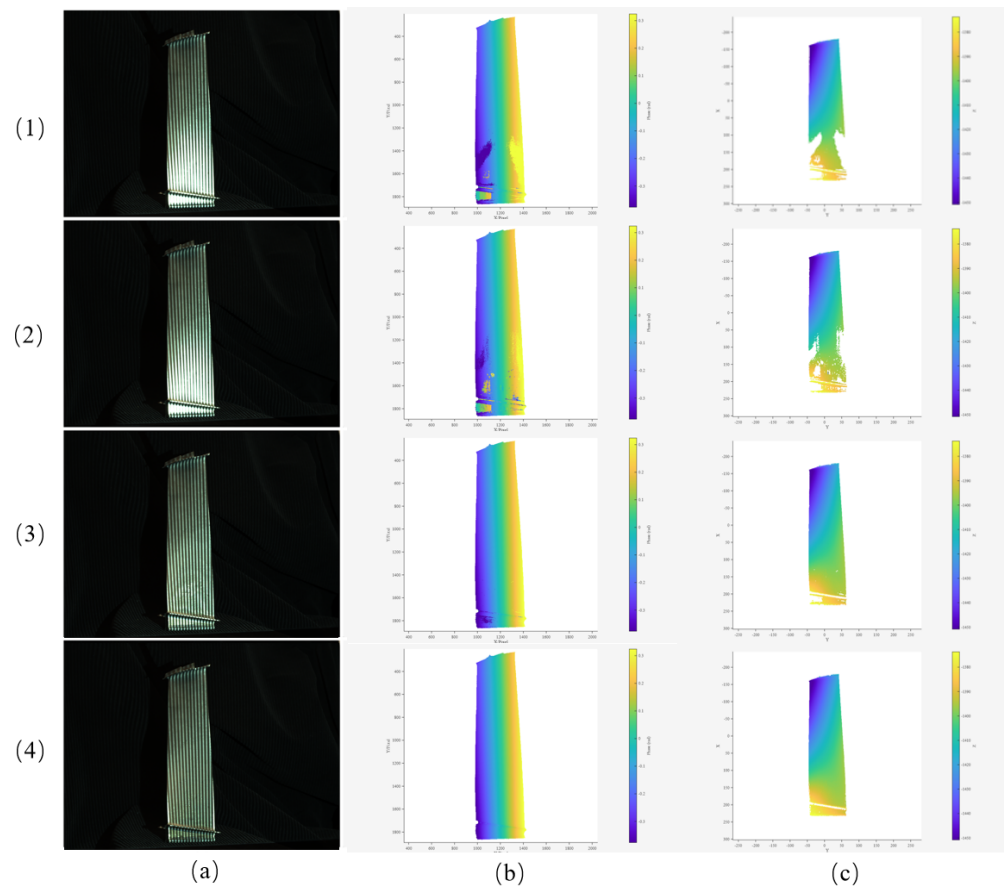


Figure 10. Comparative measurement results for the highly reflective aerospace blade. Rows: (1) conventional method, (2) Wei's method, (3) Lin's method, and (4) proposed method. Columns: (a) captured high-frequency fringe, displayed as 8-bit camera gray level (0–255), (b) recovered absolute phase, with color bars in radians (rad), and (c) reconstructed point cloud, with color bars in millimeters (mm).

Table 2. Comparison of quantitative measurement results for the blade and white plaster bust at a 1/6 s exposure time.

Method	Images	Blade			White Plaster Bust		
		Phase RMSE (rad)	PC RMSE (mm)	Missing Ratio (%)	Phase RMSE (rad)	PC RMSE (mm)	Missing Ratio (%)
Conventional	12	0.1303	85.520	14.041	0.17593	76.392	24.869
Wei's method	12	0.11353	42.934	10.864	0.1803	82.125	27.196
Lin's method	31	0.042676	10.332	1.939	0.024837	6.2736	1.498
Proposed method	12	0.0018664	0.38055	0.362	0.0098678	0.74535	1.125

Note: PC RMSE denotes the point-cloud root mean square error. The 24-step phase-shifting result is used as the phase reference. White plaster bust metrics are evaluated in the common ROI.

As shown in Figures 10 and 11, both adaptive projection methods recover measurements over most of the evaluated surfaces, while the proposed method maintains stable

phase continuity and low point loss. Because the proposed method uses only the images acquired during the standard multifrequency phase-shifting measurement and requires neither additional uniform-gray calibration nor a maximum-intensity prescan, it achieves a favorable balance between measurement accuracy and acquisition efficiency. Compared with Lin's method, the proposed method reduces the number of required images by 61.3%, which directly improves acquisition efficiency under the same camera–projector synchronization rate.

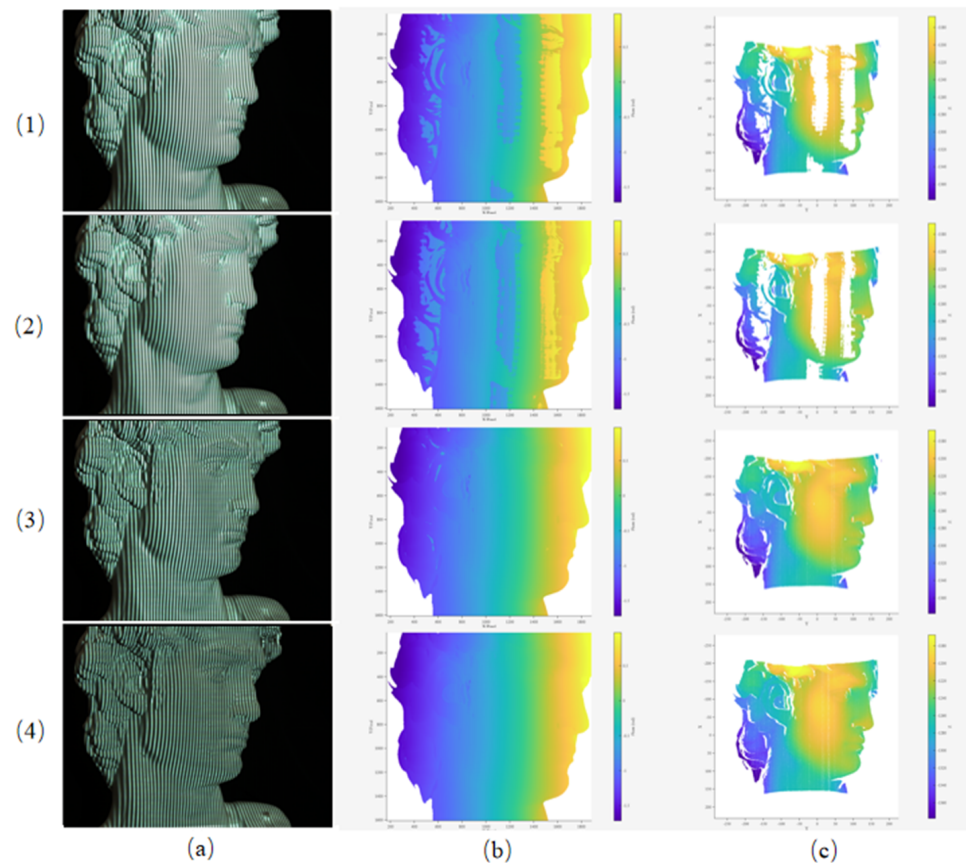


Figure 11. Comparative measurement results for the white plaster bust. Rows: (1) conventional method, (2) Wei's method, (3) Lin's method, and (4) proposed method. Columns: (a) captured high-frequency fringe, displayed as 8-bit camera gray level (0–255), (b) recovered absolute phase, with color bars in radians (rad), and (c) reconstructed point cloud, with color bars in millimeters (mm).

4. Discussion

The experimental results demonstrate that reliable camera–projector correspondence is a key prerequisite for progressive adaptive fringe projection. In conventional FPP, intensity saturation in highly reflective regions distorts the phase and affects phase unwrapping, projector-coordinate decoding, and triangulation. If this distorted phase is directly used to generate adaptive fringe patterns, the estimated projection intensity may be assigned to an incorrect projector region, even when the numerical intensity estimate itself is reasonable. The proposed method addresses this problem by first performing quality-guided RGB phase fusion and then applying local phase repair only to the marked saturated regions. In this way, the phase in highly reflective regions is improved while the originally reliable surrounding phases remain unchanged. The repaired phase supports both phase unwrapping and camera–projector correspondence rather than replacing the final high-frequency measurement phase. Therefore, the method improves adaptive intensity placement without smoothing or artificially reconstructing the final three-dimensional shape.

The second important factor is the progressive update of the local response relationship across frequency stages. Conventional adaptive projection methods usually estimate the camera response and projector mapping from independent calibration or prescanning images. In contrast, the proposed method extracts paired projected and captured gray levels from the phase-shifting fringe patterns already used in the standard measurement sequence. The low-frequency stage provides an initial mapping and a first set of valid response samples. The medium-frequency adaptive fringes reduce local saturation and supply additional unsaturated samples, which further refine the local response model for high-frequency projection. As illustrated by the progressive contraction of the saturated area in Figure 7, this process converts the measurement result of one frequency stage into improved imaging conditions for the next stage. As a result, phase optimization, coordinate mapping, response estimation, and projection-intensity updating are organized into a continuous measurement loop rather than separated into preprocessing and final measurement steps.

Although the low-frequency phase provides the initial basis for phase unwrapping, camera–projector mapping, and response estimation, the proposed method does not rely on a single low-frequency phase result alone. Its robustness in severe high-reflection regions is improved by quality-guided RGB phase fusion, local phase repair of the remaining multichannel-saturated regions, and progressive response updating from the low- to medium- and high-frequency stages. Therefore, the low-frequency phase serves as the initial support for subsequent processing rather than the sole determinant of the final reconstruction. The final 3D reconstruction is performed using the high-frequency phase captured under the progressively optimized projection intensity.

The comparison with existing HDR-FPP strategies further clarifies the role of the proposed method. Compared with conventional FPP, the proposed method actively regulates the incident intensity before image acquisition, thereby reducing the irreversible loss of fringe information caused by deep saturation. Compared with saturated-fringe restoration methods, such as Wei’s method [15], the proposed method does not rely only on post-acquisition recovery of clipped waveforms. Instead, it repairs the phase and updates the projection intensity so that subsequent fringe patterns are captured within the valid response range of the camera. Compared with classical adaptive projection methods, such as Lin’s method [19], the proposed method retains the acquisition-side advantage of adaptive projection but removes the need for uniform-gray calibration and maximum-intensity prescanning. The image counts and error results in Table 2 therefore indicate a more efficient balance between HDR measurement accuracy and image-acquisition cost.

The improvement in phase accuracy and the improvement in final point-cloud accuracy are related but not strictly proportional. The proposed method primarily reduces saturation-induced phase distortion and improves the continuity of the phase used for camera–projector correspondence and final reconstruction. After phase-to-3D conversion, however, the point-cloud RMSE is also affected by the calibrated camera–projector geometry, triangulation sensitivity, the spatial location of the evaluated points, residual correspondence errors, outliers, and the nearest-neighbor distance used for point-cloud comparison. A small phase error at different image locations may correspond to different spatial errors after reconstruction. Therefore, a substantial reduction in phase RMSE does not necessarily produce the same proportional reduction in point-cloud RMSE. The proposed method should thus be interpreted as improving phase reliability, adaptive intensity placement, and the missing ratio, while the final point-cloud accuracy remains jointly constrained by phase quality, calibration accuracy, and the phase-to-3D mapping model.

The proposed method is implemented on a conventionally calibrated camera–projector FPP system, but its geometric calibration is not modified in this work. Phase demodu-

lation, quality-guided RGB phase fusion, and local phase repair are completed in the camera image plane and do not directly depend on the geometric calibration parameters. The subsequent camera–projector coordinate correspondence is obtained by matching the repaired camera-plane phase to the known phase distribution of the projector-plane fringe patterns, as defined by Equations (7) and (8). Consequently, projected/captured gray-level-pair extraction and placement of the adaptive intensity template depend on the quality of this phase-derived correspondence rather than on the intrinsic or extrinsic calibration parameters. Geometric calibration enters only during the final conversion of the high-frequency phase into 3D coordinates; calibration errors therefore propagate mainly through the triangulation model to the reconstructed point-cloud coordinates and affect the final geometric accuracy. In the comparative experiments, all evaluated methods use the same calibration parameters, object pose, reconstruction ROI, and reconstruction pipeline. The reported intermethod differences thus mainly reflect saturation suppression and progressive adaptive fringe projection rather than differences in calibration conditions. The method does not eliminate geometric calibration error, and reliable calibration remains a prerequisite for accurate 3D reconstruction; a controlled parameter-perturbation study will be considered in future system-level evaluation.

Exposure time is another important factor that affects the performance of the proposed method. In the experiments, the exposure time and camera gain are kept fixed during the low-, medium-, and high-frequency stages so that the extracted projected/captured gray-level pairs correspond to a consistent local radiometric response. If the exposure time is too long, highly reflective regions may become saturated over a large area in the initial low-frequency stage, leaving too few unsaturated samples for RGB phase fusion, local response estimation, and reliable adaptive intensity prediction. If the exposure time is too short, the modulation in weakly reflective regions may decrease, and the reduced signal-to-noise ratio may degrade phase precision. Therefore, the initial exposure should keep most normal and low-reflectance regions within the effective camera dynamic range while retaining usable nonsaturated samples around highly reflective regions. Nevertheless, the aerospace-blade experiment shows that the proposed method maintains low phase RMSE, point-cloud RMSE, and missing ratio at all three tested exposure times. The degradation-strategy ratio remains small and consistently decreases at the medium-to-high transition, indicating that progressive sample accumulation improves direct response fitting and reduces dependence on degradation compensation.

It should also be clarified that the median-filtered neighboring estimate used in the progressive adaptive fringe projection stage is not a phase-optimization operation. Local phase repair, which is the second step of phase optimization, is performed by local quadratic surface fitting from reliable neighboring phase samples, whereas the median estimate is used only when fewer than two valid gray-level pairs are available for local response fitting. In such cases, the degradation strategy provides an initial estimate of the optimal projection intensity for the next frequency stage. Since the response model is progressively updated when new unsaturated samples are acquired at later stages, this strategy mainly affects the initialization of local projection intensity rather than directly determining the final phase. Its reliability may decrease when a large saturated region lacks sufficient neighboring valid gray-level samples.

The current implementation has several limitations and application requirements. First, the local phase-repair strategy assumes that the phase in the saturated region is locally continuous and can be estimated from nearby reliable samples. If a large saturated region crosses sharp geometric discontinuities or lacks sufficient valid neighboring pixels, the local quadratic fitting result may become less reliable. Second, the progressive response update requires the object, camera, projector, exposure setting, and illumination conditions to

remain stable during the low-, medium-, and high-frequency stages. Motion or illumination changes between stages may affect both phase processing and gray-level pairing. Third, when all color channels are severely saturated over a large area, the available phase and gray-level information may still be insufficient for reliable repair and response estimation. Future work will focus on improving the robustness of the repair model near discontinuities, extending the method to more complex highly reflective surfaces, and evaluating its performance in faster online measurement scenarios.

5. Conclusions

This paper proposed a phase-optimization-guided progressive adaptive fringe projection method for HDR three-dimensional measurement of highly reflective surfaces. The method embeds phase optimization and adaptive projection-intensity estimation into the standard multifrequency phase-shifting measurement sequence. Quality-guided RGB phase fusion first uses complementary RGB-channel phase information to reduce unreliable phase regions, and Local Phase Repair is then applied only to the remaining saturated regions to obtain a stable phase for phase unwrapping and camera-projector correspondence. Based on this optimized phase and the resulting correspondence, known projected gray levels and unsaturated captured gray levels already available in the current phase-shifting sequence are reused to estimate the local response and generate adaptive fringes for the next frequency stage.

The experimental results on the highly reflective aerospace blade and white plaster bust confirmed the effectiveness of the proposed method. Quality-guided RGB phase fusion and local phase repair provide stable phase information for the progressive adaptive fringe projection stages. At a 1/6 s exposure, the proposed method achieved phase/point-cloud RMSEs of 0.0018664 rad and 0.38055 mm on the blade, and 0.0098678 rad and 0.74535 mm in the white plaster bust ROI. Across the 1/6 s, 1/9 s, and 1/12 s tests on the aerospace blade, the method maintained low phase RMSE, point-cloud RMSE, and missing ratio, while the degradation-strategy ratio decreased at the subsequent adaptive transition. These results support the robustness of the progressive update mechanism to exposure-time variation. Compared with conventional FPP and saturated-fringe restoration, the proposed method significantly improved phase continuity and reduced point loss. It retained high accuracy and low missing ratios while using only the standard 12-image multifrequency phase-shifting sequence, without additional uniform-gray calibration or maximum-intensity prescanning.

By progressively updating the phase, valid response samples, and projection intensity from low to high frequencies, the proposed method suppresses saturation-induced phase distortion without additional projected or captured images, auxiliary calibration, or extra optical hardware. The method therefore provides an efficient HDR-FPP solution for highly reflective surface measurement and has potential for high-speed industrial online inspection.

Author Contributions: Conceptualization, H.T. and H.C.; methodology, H.T. and Y.D.; software, H.T.; validation, H.T.; formal analysis, H.T. and Y.D.; investigation, H.T.; resources, H.C.; data curation, H.T.; writing—original draft preparation, H.T., Y.D. and C.P.; writing—review and editing, Y.D., S.X., Z.C., Y.C. and H.C.; visualization, Y.D. and C.P.; project administration, S.X., H.P. and H.C.; supervision, H.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data and code supporting this study will be made available by the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

FPP	Fringe projection profilometry
HDR	High dynamic range
RMSE	Root mean square error

References

1. Zuo, C.; Feng, S.; Huang, L.; Tao, T.; Yin, W.; Chen, Q. Phase shifting algorithms for fringe projection profilometry: A review. *Opt. Lasers Eng.* **2018**, *109*, 23–59. [\[CrossRef\]](#)
2. Xu, J.; Zhang, S. Status, challenges, and future perspectives of fringe projection profilometry. *Opt. Lasers Eng.* **2020**, *135*, 106193. [\[CrossRef\]](#)
3. Gai, S.; Da, F.; Dai, X. Novel 3D measurement system based on speckle and fringe pattern projection. *Opt. Express* **2016**, *24*, 17686–17697. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Zhu, J.; Zhou, P.; Su, X.; You, Z. Accurate and fast 3D surface measurement with temporal-spatial binary encoding structured illumination. *Opt. Express* **2016**, *24*, 28549–28563. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Qi, Z.; Wang, Z.; Huang, J.; Xing, C.; Gao, J. Error of image saturation in the structured-light method. *Appl. Opt.* **2018**, *57*, A181–A188. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Feng, S.; Zhang, L.; Zuo, C.; Tao, T.; Chen, Q.; Gu, G. High dynamic range 3D measurements with fringe projection profilometry: A review. *Meas. Sci. Technol.* **2018**, *29*, 122001. [\[CrossRef\]](#)
7. Zhang, S.; Yau, S.-T. High dynamic range scanning technique. *Opt. Eng.* **2009**, *48*, 033604. [\[CrossRef\]](#)
8. Rao, L.; Da, F. High dynamic range 3D shape determination based on automatic exposure selection. *J. Vis. Commun. Image Represent.* **2018**, *50*, 217–226. [\[CrossRef\]](#)
9. Wu, K.; Tan, J.; Xia, H.L.; Liu, C.B. An exposure fusion-based structured light approach for the 3D measurement of a specular surface. *IEEE Sens. J.* **2021**, *21*, 6314–6324. [\[CrossRef\]](#)
10. Li, J.; Guan, J.; Chen, X.; Le, X.; Xi, J. Exposure map fusion for precise 3-D reconstruction of high dynamic range surfaces. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 5022911. [\[CrossRef\]](#)
11. Zhang, S. Rapid and automatic optimal exposure control for digital fringe projection technique. *Opt. Lasers Eng.* **2020**, *128*, 106029. [\[CrossRef\]](#)
12. Salahieh, B.; Chen, Z.; Rodriguez, J.J.; Liang, R. Multi-polarization fringe projection imaging for high dynamic range objects. *Opt. Express* **2014**, *22*, 10064–10071. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Zhu, Z.; You, D.; Zhou, F.; Wang, S.; Xie, Y. Rapid 3D reconstruction method based on the polarization-enhanced fringe pattern of an HDR object. *Opt. Express* **2021**, *29*, 2162–2173. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Suresh, V.; Wang, Y.; Li, B. High-dynamic-range 3D shape measurement utilizing the transitioning state of a digital micromirror device. *Opt. Lasers Eng.* **2018**, *107*, 176–181. [\[CrossRef\]](#)
15. Wei, H.; Li, H.; Liu, J.; Deng, G.; Zhou, S. A method for suppressing saturation-induced errors in fringe projection profilometry by fringe restoration assisted via Euler formula-based method and intersection points. *IEEE Trans. Instrum. Meas.* **2024**, *73*, 5031816. [\[CrossRef\]](#)
16. Waddington, C.; Kofman, J. Analysis of measurement sensitivity to illuminance and fringe-pattern gray levels for fringe-pattern projection adaptive to ambient lighting. *Opt. Lasers Eng.* **2010**, *48*, 251–256. [\[CrossRef\]](#)
17. Li, D.; Kofman, J. Adaptive fringe-pattern projection for image saturation avoidance in 3D surface-shape measurement. *Opt. Express* **2014**, *22*, 9887–9901. [\[CrossRef\]](#) [\[PubMed\]](#)
18. Chen, C.; Gao, N.; Wang, X.; Zhang, Z. Adaptive pixel-to-pixel projection intensity adjustment for measuring a shiny surface using orthogonal color fringe pattern projection. *Meas. Sci. Technol.* **2018**, *29*, 055203. [\[CrossRef\]](#)
19. Lin, H.; Gao, J.; Mei, Q.; He, Y.; Liu, J.; Wang, X. Adaptive digital fringe projection technique for high dynamic range three-dimensional shape measurement. *Opt. Express* **2016**, *24*, 7703–7718. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Liu, Y.; Fu, Y.; Cai, X.; Zhong, K.; Guan, B. A novel high dynamic range 3D measurement method based on adaptive fringe projection technique. *Opt. Lasers Eng.* **2020**, *128*, 106004. [\[CrossRef\]](#)
21. Cai, X.; Xu, R.; Li, H.; Wang, Y.; Lu, R. High-reflective surfaces shape measurement technology based on adaptive fringe projection. *Sens. Actuators A Phys.* **2022**, *347*, 113916. [\[CrossRef\]](#)

22. Zhang, M.; Chen, C.; Xie, L.; Zhang, C. Accurate measurement of high-reflective surface based on adaptive fringe projection technique. *Opt. Lasers Eng.* **2024**, *172*, 107820. [[CrossRef](#)]
23. Zheng, R.; Li, L.; Wan, M.; Zhang, W.; Yu, L. Automatic optimization of projection intensity for high dynamic range 3D surface measurement. *Opt. Lasers Eng.* **2024**, *177*, 107888. [[CrossRef](#)]
24. Zhang, L.; Chen, Q.; Zuo, C.; Feng, S. High dynamic range 3D shape measurement based on the intensity response function of a camera. *Appl. Opt.* **2018**, *57*, 1378–1386. [[CrossRef](#)] [[PubMed](#)]
25. Cai, Z.; Liu, X.; Li, A.; Tang, Q.; Peng, X.; Gao, B.Z. Phase-3D mapping method developed from back-projection stereovision model for fringe projection profilometry. *Opt. Express* **2017**, *25*, 1262–1277. [[CrossRef](#)] [[PubMed](#)]
26. Lv, S.; Kemaio, Q. Modeling the measurement precision of fringe projection profilometry. *Light Sci. Appl.* **2023**, *12*, 257. [[CrossRef](#)] [[PubMed](#)]
27. Zhang, P.; Zhong, K.; Li, Z.; Zhang, B. Hybrid-quality-guided phase fusion model for high dynamic range 3D surface measurement by structured light technology. *Opt. Express* **2022**, *30*, 14600–14614. [[CrossRef](#)] [[PubMed](#)]
28. Xu, B.; Qu, S.; Li, J.; Deng, Z.; Li, H.; Zhang, B.; Zhang, G.; Liu, K. Quaternary categorization strategy for reconstructing high-reflectivity surface in structured light illumination. *Sensors* **2023**, *23*, 9740. [[CrossRef](#)] [[PubMed](#)]

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