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**Supplementary information**

# Physics-informed neural network enabled high-fidelity compressive phase-shifting fringe projection profilometry

Bozhang Cheng, Yunhua Yao, Yu He, Mengdi Guo, Hongmei Ma, Dalong Qi, Yuecheng Shen, Lianzhong Deng, Zhenrong Sun, Shian Zhang

**1.Study on Hyperparameter Sensitivity of PINN-CPSFPP**

To evaluate the influence of the regularization weights in the proposed physics-informed reconstruction framework, we performed a systematic ablation study on a static "Happy Easter" plaster relief. The profile reconstructed using conventional ten-step phase-shifting profilometry was treated as the ground truth, and RMSE and SSIM were calculated to quantitatively assess the reconstruction performance. The reconstructed first striped images and height maps are presented in **Figure S1**, where the rows and columns correspond to different TV and Hessian regularization weights, respectively. When both regularization terms are absent, the reconstruction suffers from obvious artifacts, resulting in a high RMSE of 2.53 mm and a low SSIM of 0.68. Introducing only Hessian regularization improves the reconstruction only when a relatively large weight is applied, whereas moderate TV regularization significantly stabilizes the reconstruction. In particular, when $\lambda_{\text{Hessian}} = 0$ and $\lambda_{\text{TV}}$ ranges from 0 to 0.06, the reconstructed 3D profile exhibits severe discontinuities, leading to a reduction in the overall height of the object. Based on this analysis, $\lambda_{\text{TV}} = 0.04$ and $\lambda_{\text{Hessian}} = 0.06$ were selected as a balanced parameter setting for the reconstruction of the "Happy Easter" plaster relief.

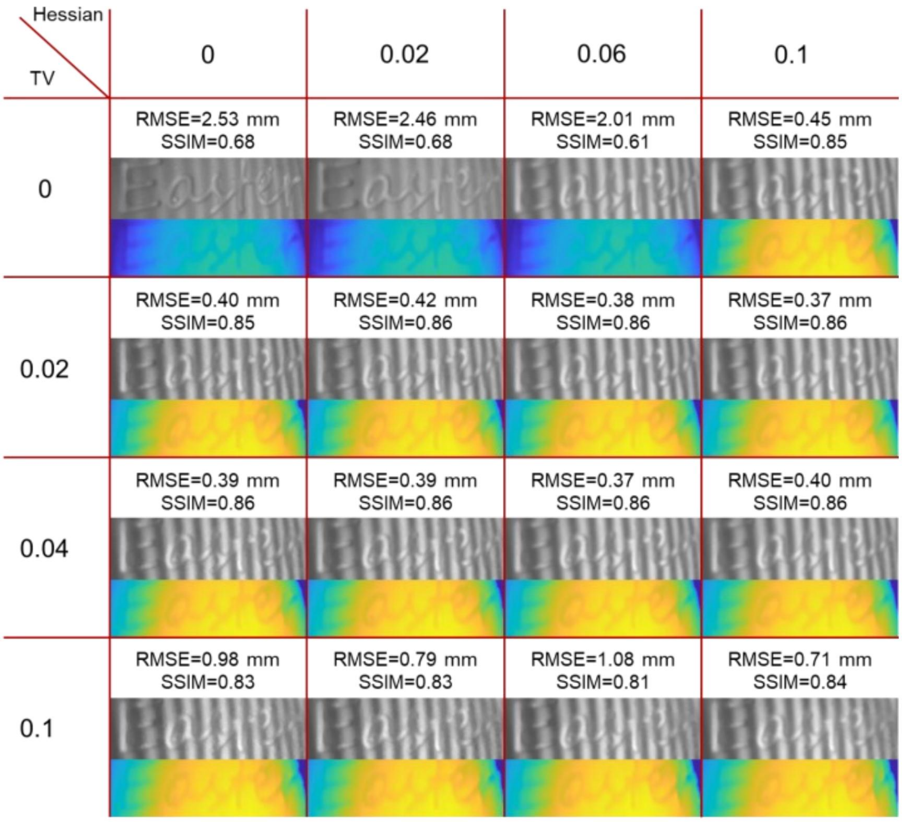


**Figure S1.** Ablation study on hyperparameter sensitivity of PINN-CPSFPP. PINN: physics-informed neural network; CPSFPP: compressive phase-shifting fringe projection profilometry.

## 2.Comparison of ADMM and PINN Frameworks with Both TV and Hessian Regularizations

To demonstrate the superiority of PINN framework against previous ADMM framework, we conducted a fair comparison using the “Happy Easter” plaster relief with both TV and Hessian regularization. As to the termination conditions of the ADMM iterative algorithm, we employ a five-stage denoiser strategy with a total of 200 iterations. The first three stages utilize TV denoiser, with weights set to 1.0, 0.5, and 0.2, respectively, and each stage runs for 40 iterations. The last two stages employ Hessian denoiser, with weights set to 2.0 and 1.0, respectively, and each stage runs for 30 iterations. This multi-stage denoising strategy achieves a favorable hyperparameter configuration within the ADMM framework, however, the comparative analysis against the PINN algorithm still reveals that its reconstruction accuracy remains limited, with an RMSE of 0.97 mm and SSIM of 0.82. The result is shown in **Figure S2.**

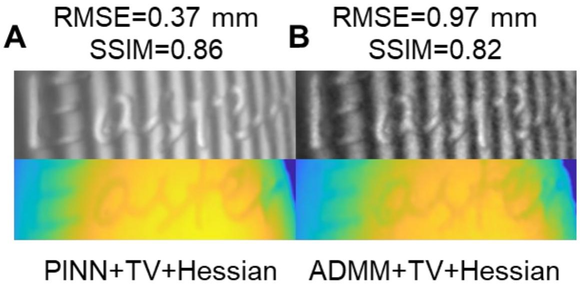


**Figure S2.** Reconstruction results using different frameworks combined with TV and Hessian denoisers. (A) The PINN framework; (B) The ADMM framework. TV: total variation; ADMM: alternating direction method of multipliers; RMSE: root mean square error; SSIM: structural similarity index measure; PINN: physics-informed neural network.

## 3.Computational Time of PINN-CPSFPP

The reconstructions of PINN-CPSFPP were performed in an environment of Python 3.7.16, NumPy 1.21.5, Matplotlib 3.5.3 and Scikit-image 0.19.2 on a compute server equipped with Intel i9-10920X CPU, 192 GB RAM and RTX 3090-24 GB GPU. Hessian and TV were employed as the denoisers. The iterations were set to be 4,000, and the execution time for different compressed measurements are detailed in **Table S1**, which is strongly correlated with the image dimensions.

**Table S1.** Pixel size and execution time of different compressed measurements.

| Compressed measurement | “Happy Easter” plaster | Corn-shaped plaster | Shell-cracked dinosaur statue | Thin membrane |
|---|---|---|---|---|
| Size (pixels) | 1,020 × 970 | 1,000 × 940 | 1,020 × 970 | 450 × 425 |
| Time (s) | 1,486 | 1,397 | 1,481 | 396 |

**4.Quantitative Evaluation of The Reconstruction Accuracy of PINN-CPSFPP**

To quantitatively evaluate the reconstruction accuracy of PINN-CPSFPP, a spherical shell was measured. A spherical shell with a base diameter of approximately 35.9 mm and a height of about 11.2 mm was cut from a white table tennis ball of 40 mm diameter. The sample was measured by the CPSFPP system under a compression ratio of nine. The theoretical spherical profile was calculated according to the measured geometric parameters and used as the reference. **Figure** S3A presents the photograph of the spherical shell sample. **Figure** S3B shows the reconstructed 3D profile obtained by PINN-CPSFPP. And **Figure** S3C compares the reconstructed height distribution with the theoretical values along the central row of the spherical shell. The reconstructed profile agrees well with the true spherical curve, and the corresponding error remains within a small range, indicating ideal height accuracy, as shown in **Figure** S3D. These results confirm that PINN-CPSFPP can reliably recover surfaces and preserve accurate 3D geometry.

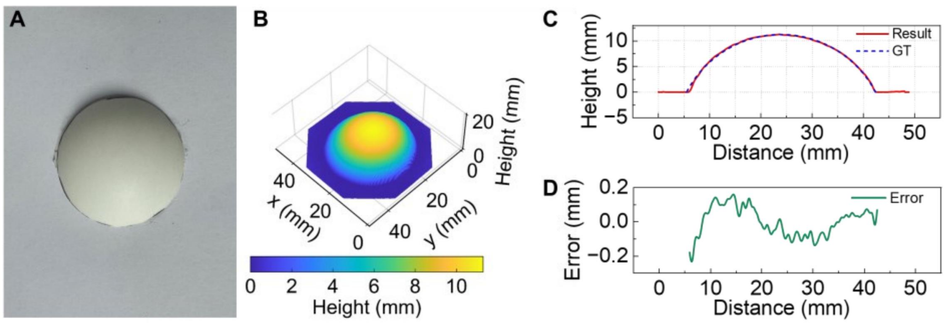


**Figure S3.** Quantitative evaluation of the reconstruction accuracy of PINN-CPSFPP. (A) Photograph of the spherical shell; (B) Reconstructed height map of the spherical shell obtained via PINN-CPSFPP; (C) Comparison between the reconstructed height profile and the ground truth along the center of the spherical shell; (D) Spatial distribution of the height error between the reconstructed result and the ground truth. PINN: physics-informed neural network; CPSFPP: compressive phase-shifting fringe projection profilometry.

See Visualization 1 for more details of motion inspections by PINN-CPSFPP.