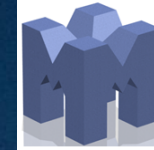


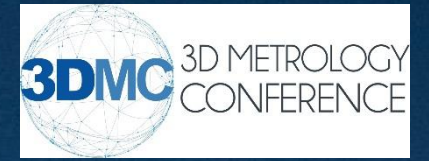


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**MANUFACTURING
METROLOGY TEAM**



Aachen, Germany, 16 – 18 September 2025

Single-Shot Composite Fringe Projection Profilometry for Real-Time Dynamic 3D Measurement

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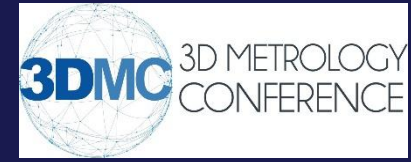
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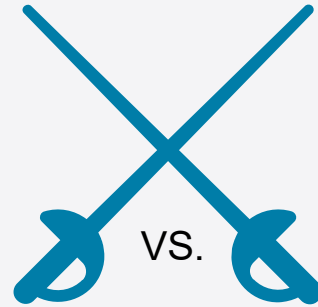


Fringe Projection Profilometry



3 s +

Traditional fringe
projection profilometry

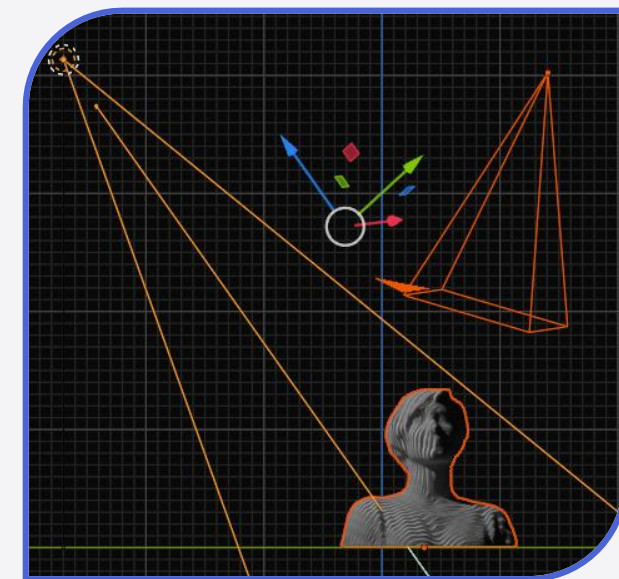
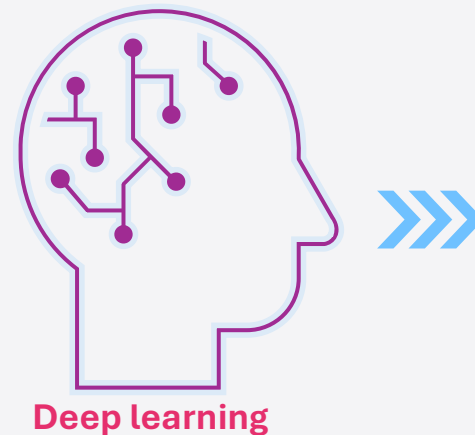


0.2 s

Real-time fringe projection
profilometry



- Introduction & Motivation
- Methodology
 - Composite Fringe Pattern
 - U-Net Network
 - Uncertainty Evaluation
- Experiments
 - Data Collection
 - Model Training
 - Validation & Analysis
- Conclusion

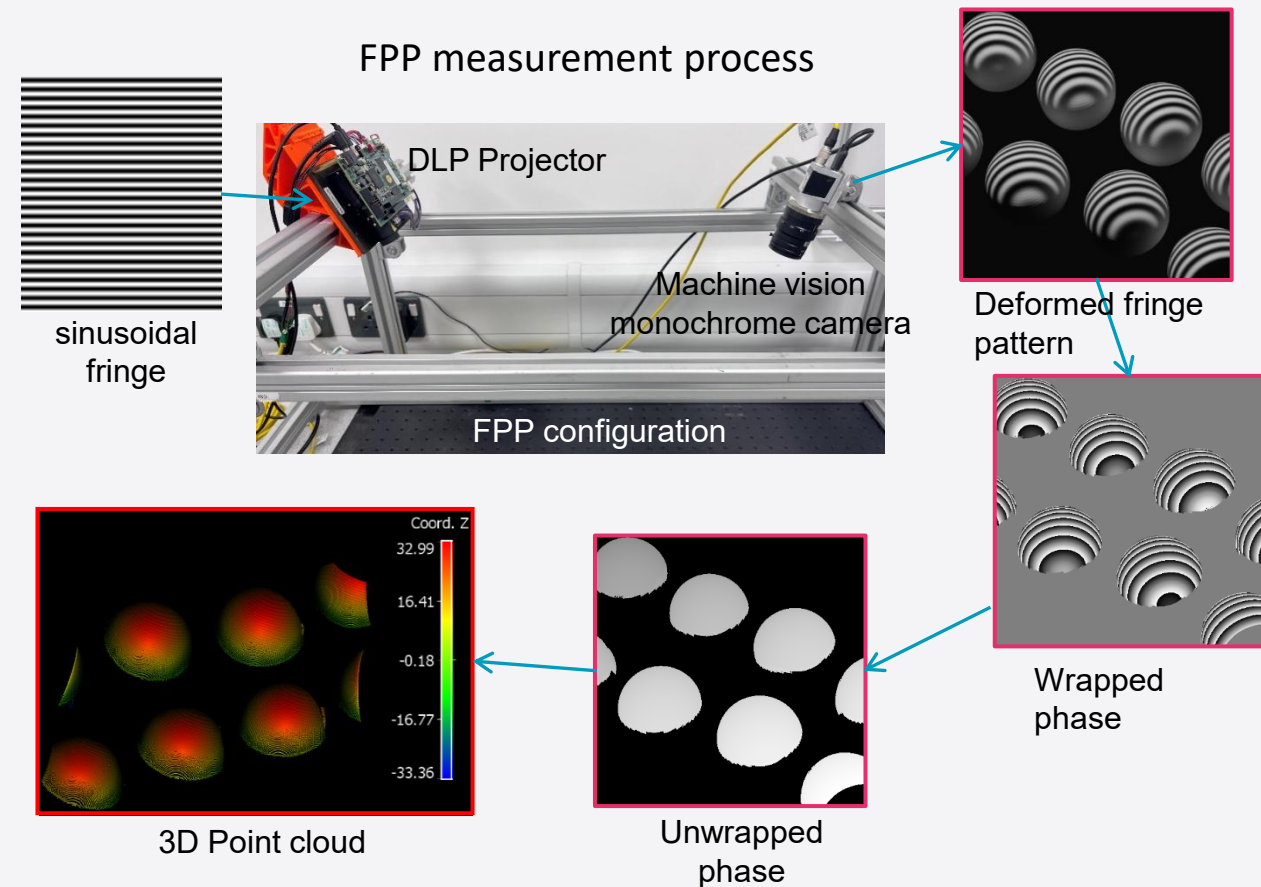




Introduction & Motivation

Fringe projection profilometry (FPP), also known as structured light profilometry, is a non-contact measurement method that reconstructs an object's 3D shape by projecting sinusoidal fringes onto its surface, and then capturing the deformed fringe patterns with a camera. The phase of the fringe pattern can then be reconstructed into a 3D point cloud using calibration data.

Applications	Advantages	Disadvantages
Industrial Inspection	Non-Contact Measurement	Sensitivity to Surface Characteristics
Medical Imaging	High Resolution and Accuracy	High algorithmic complexity
Robotic Vision	Low Cost	Low measurement speed
Cultural Heritage Preservation	Full Field Measurement	





Introduction & Motivation

There are two main factors that determine the 3D measurement speed of FPP:

1. The performance of hardware devices.
2. The number and coding strategy of projected patterns required by the software algorithms.

The speed of hardware devices

	refresh rate (frames · s ⁻¹)	exposure time (μs)
Projector	4,225 (1-bit binary) / 120 (8-bit grey)	235 (+230)
High-speed Camera	≥ 120	1×10 ⁴ - 3×10 ⁴

	CPU	GPU	RAM
Computer	Intel i9-13900K	RTX 4080 / 4090	32GB

The number of patterns required of the software algorithms

	Number of patterns	Accuracy	Need machine learning?
PSP-binary (Defocus) + Gray code	$3 + \log_2 M$	✓✓✓✓	No
PSP-binary (Defocus)	3	✓	No
Speckle image	1	✓✓	No
FTP	1	✓	No
FTP-composite fringe	1	✓✓	No
Color composite fringe	1	✓✓	Yes / No
Single sinusoidal fringe	1	✓✓	Yes
FPP-composite fringe	1	✓✓✓	Yes

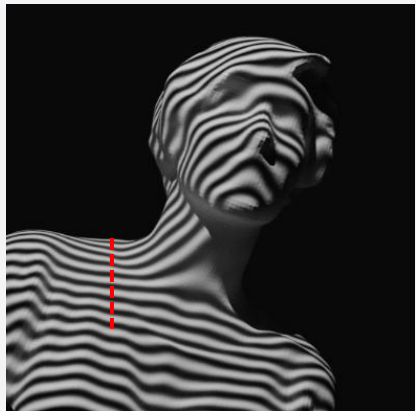
Phase-shifting profilometry (PSP)
 Fourier transform profilometry (FTP)
 M: the number of fringe periods



Introduction & Motivation

From an algorithmic view: Why real-time measurement is challenging in FPP?

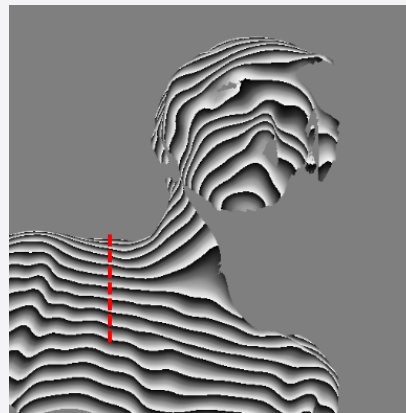
Fringe pattern



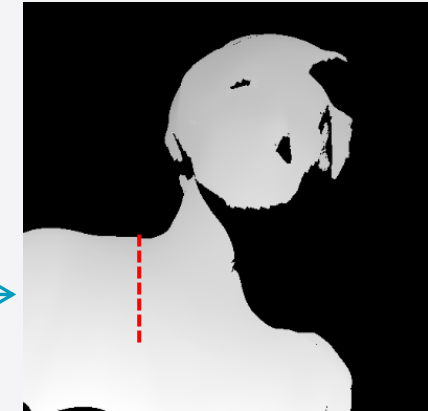
$$\phi(x, y) = \arctan \frac{\sum_{n=1}^N I_n(x, y) \sin(\delta_n)}{\sum_{n=1}^N I_n(x, y) \cos(\delta_n)}$$

$$= \arctan \frac{N(x, y)}{D(x, y)}$$

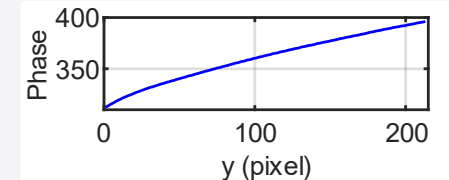
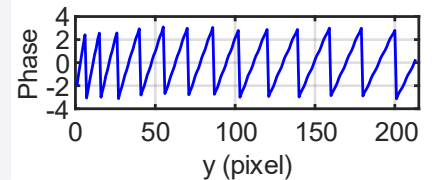
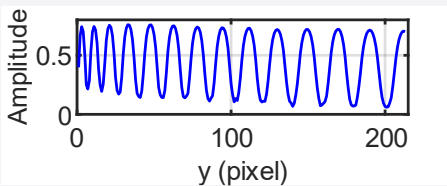
Wrapped phase



Unwrapped phase



Time domain
(Multi-Frequency Phase Unwrapping)



Phase-Unwrapping Approaches Used in FPP

Approach	Number of patterns	Accuracy
Spatial domain	3+	✓✓
Frequency domain	1	✓
Time domain	6+	✓✓✓✓
Machine learning	1	✓✓✓

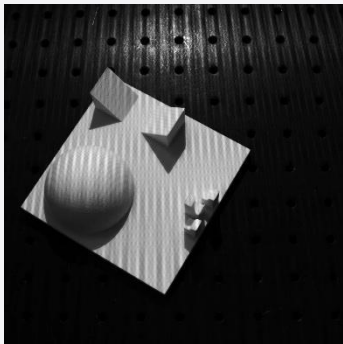


Introduction & Motivation

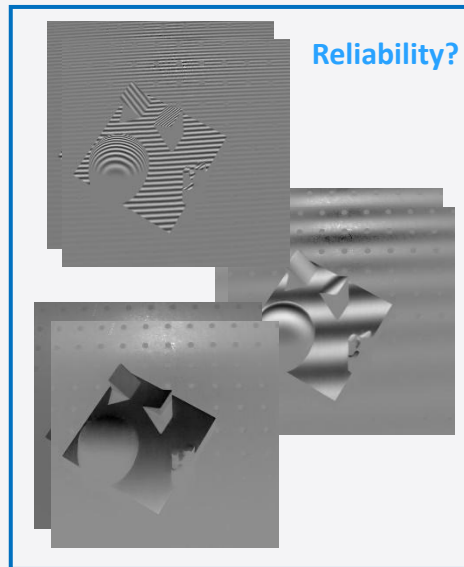
How much confidence can we place in the predicted results?

Are the predicted results reliable?

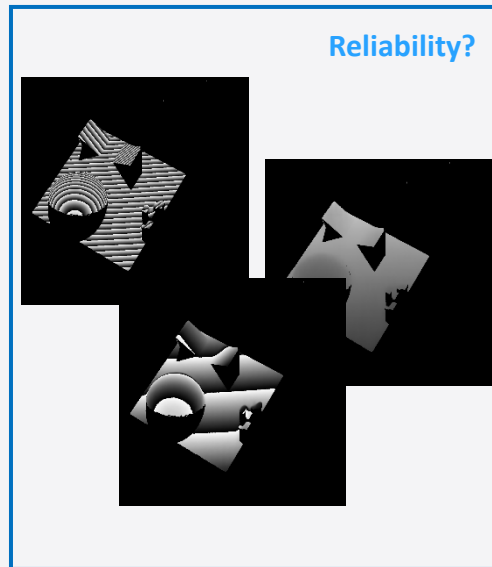
Deep Learning



Fringe pattern



Reliability?



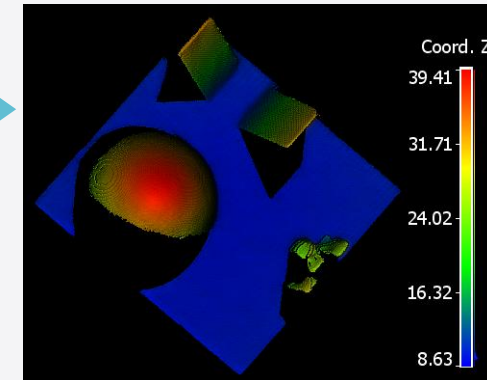
Reliability?



Reliability?



Reliability?



3D point cloud

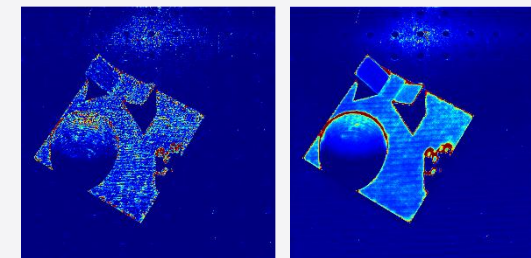


Predictions



Evaluation is only possible with ground truth

Ground Truth ?

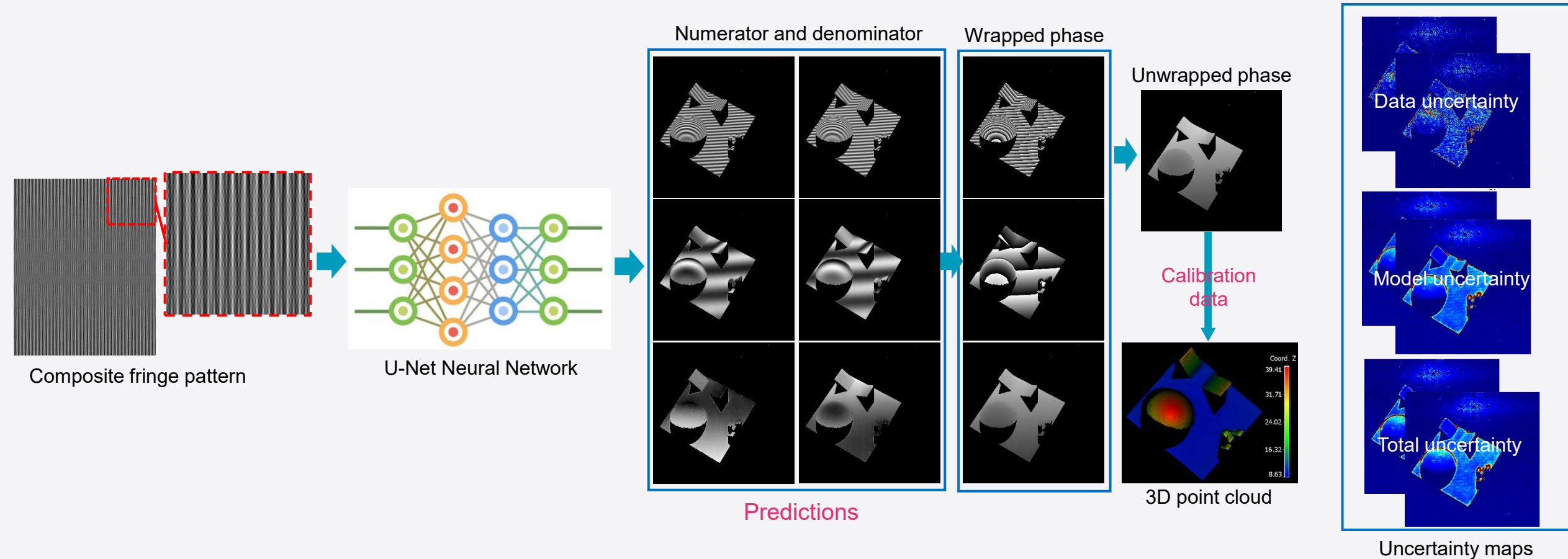


Uncertainty maps



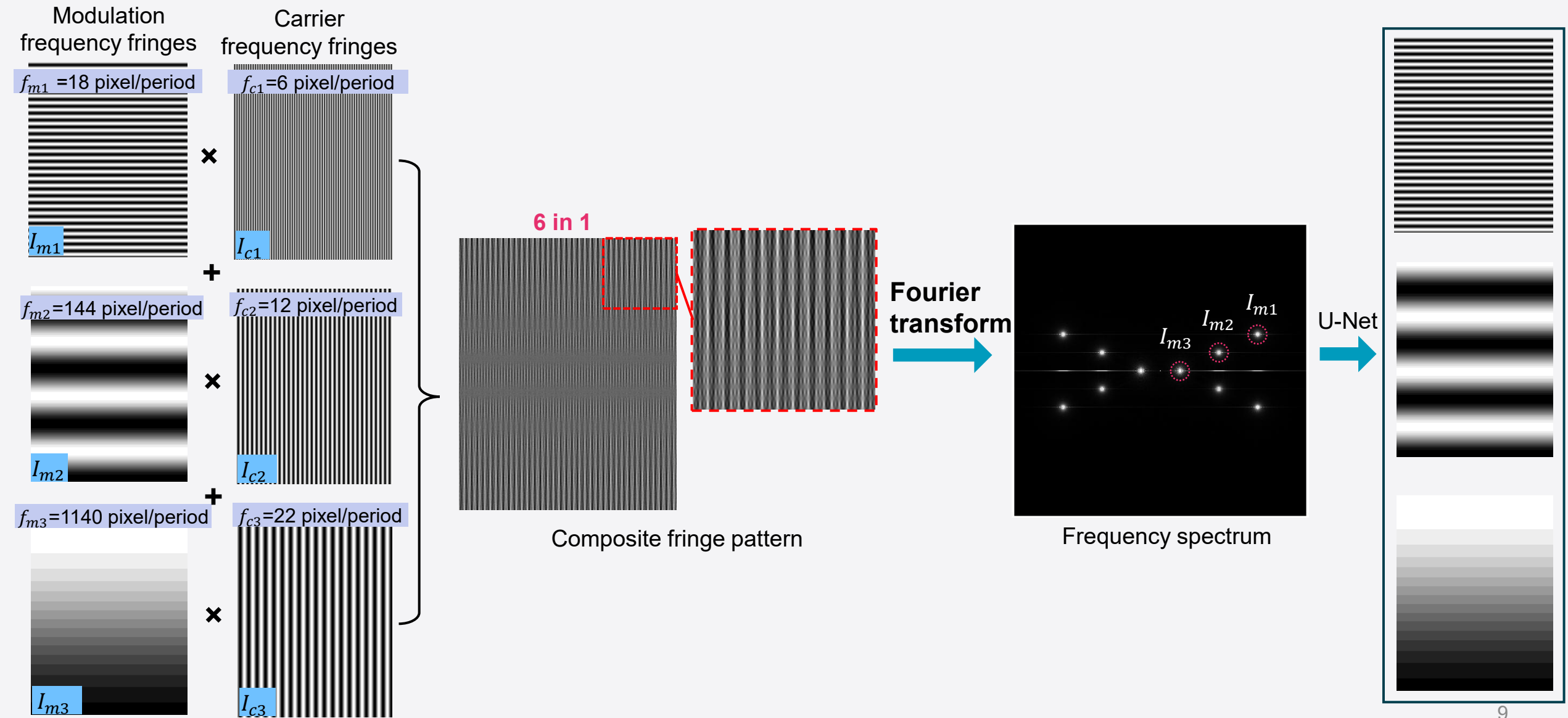
Method

In this work, we propose a **deep learning-based** multi-frequency phase unwrapping method using a novel **single composite fringe pattern**, which also outputs **uncertainty maps** to estimate the confidence of predictions.





Method: Composite Fringe Pattern

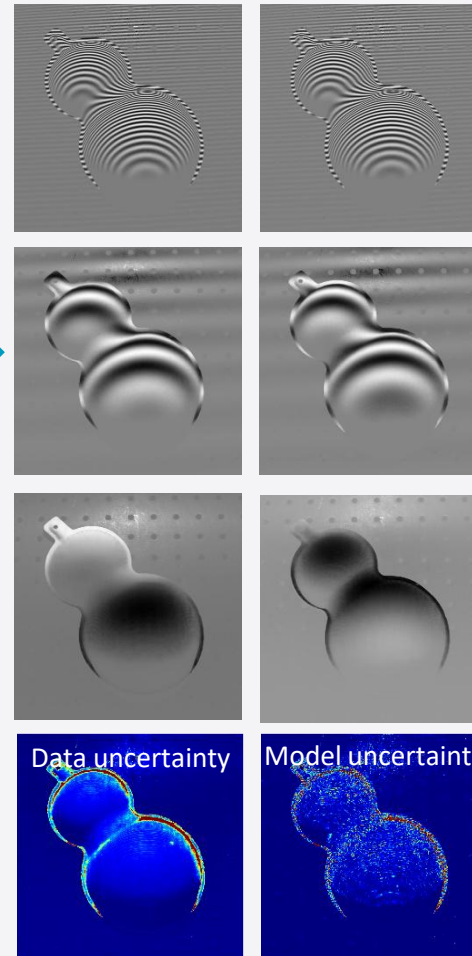
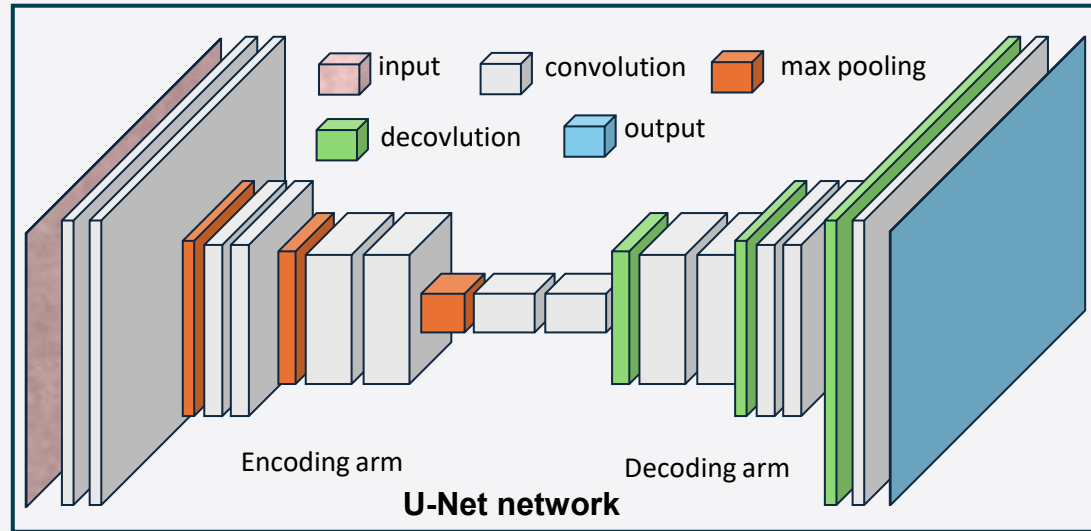




Method: U-Net Network

Standard U-Net loss: Mean Squared Error (MSE)

Limitation: The network does not output or learn the uncertainty of each pixel



U-Net Architecture Overview	Component	Configuration
	Encoder Channels	1 → 64 → 128 → 256 → 512
	Bottleneck Channel	1024
	Decoder Channels	512 → 256 → 128 → 64 → 1
	Output Channels	4 (N & D & Uncertainty)
	Activation Function	ReLU (hidden layers), Tanh (output layer)
	Skip Connections	Yes (between encoder & decoder at each stage)

Alternative loss: Gaussian Negative Log-Likelihood (NLL)

Data uncertainty: Arises from observation noise, inherent ambiguity, or measurement errors.

Snapshot Ensemble: Save model weights at multiple training stages

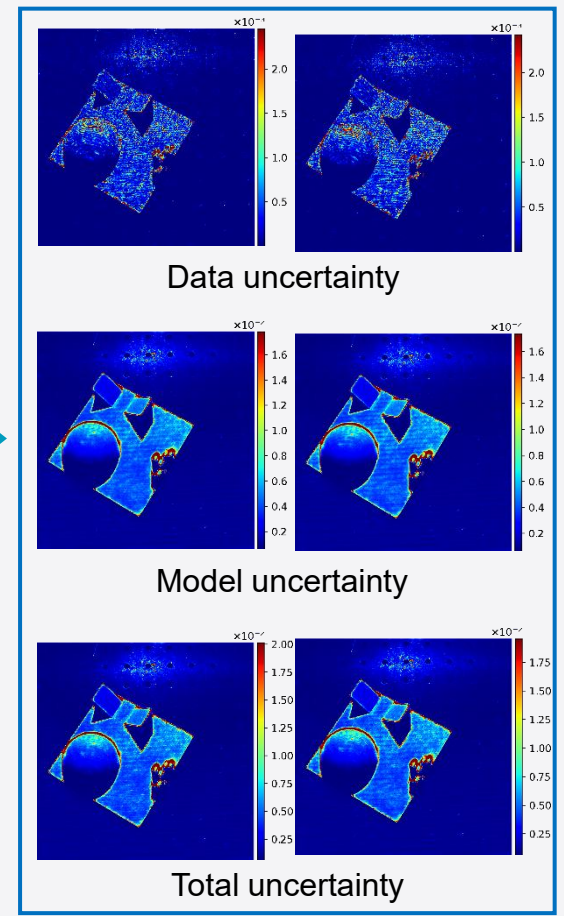
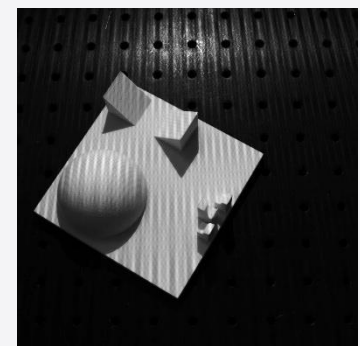
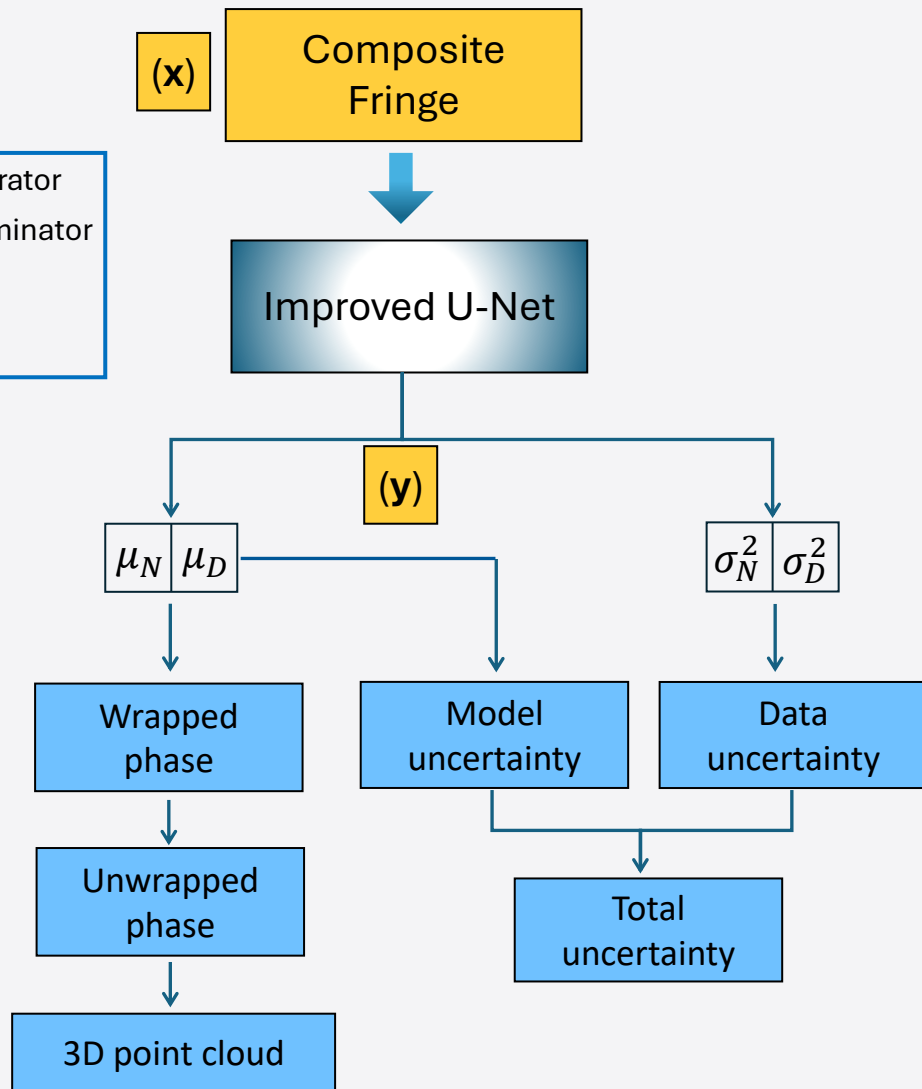
Model uncertainty: Stems from the model's limited knowledge of the data distribution, e.g., insufficient or incomplete training data, leading to multiple plausible parameter solutions

Uncertainty maps



Method: Uncertainty Evaluation

μ_N : predicted mean of the numerator
 μ_D : predicted mean of the denominator
 σ_N^2 : variance of the numerator
 σ_D^2 : variance of the denominator

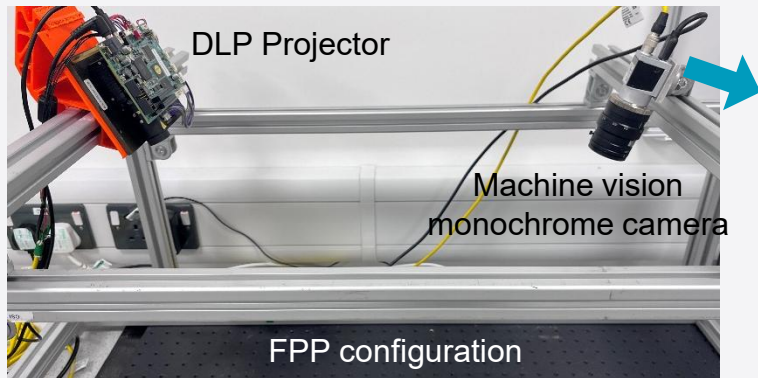


Uncertainty maps

Workflow of the improved u-net combined with composite FPP



Experiments: Data collection

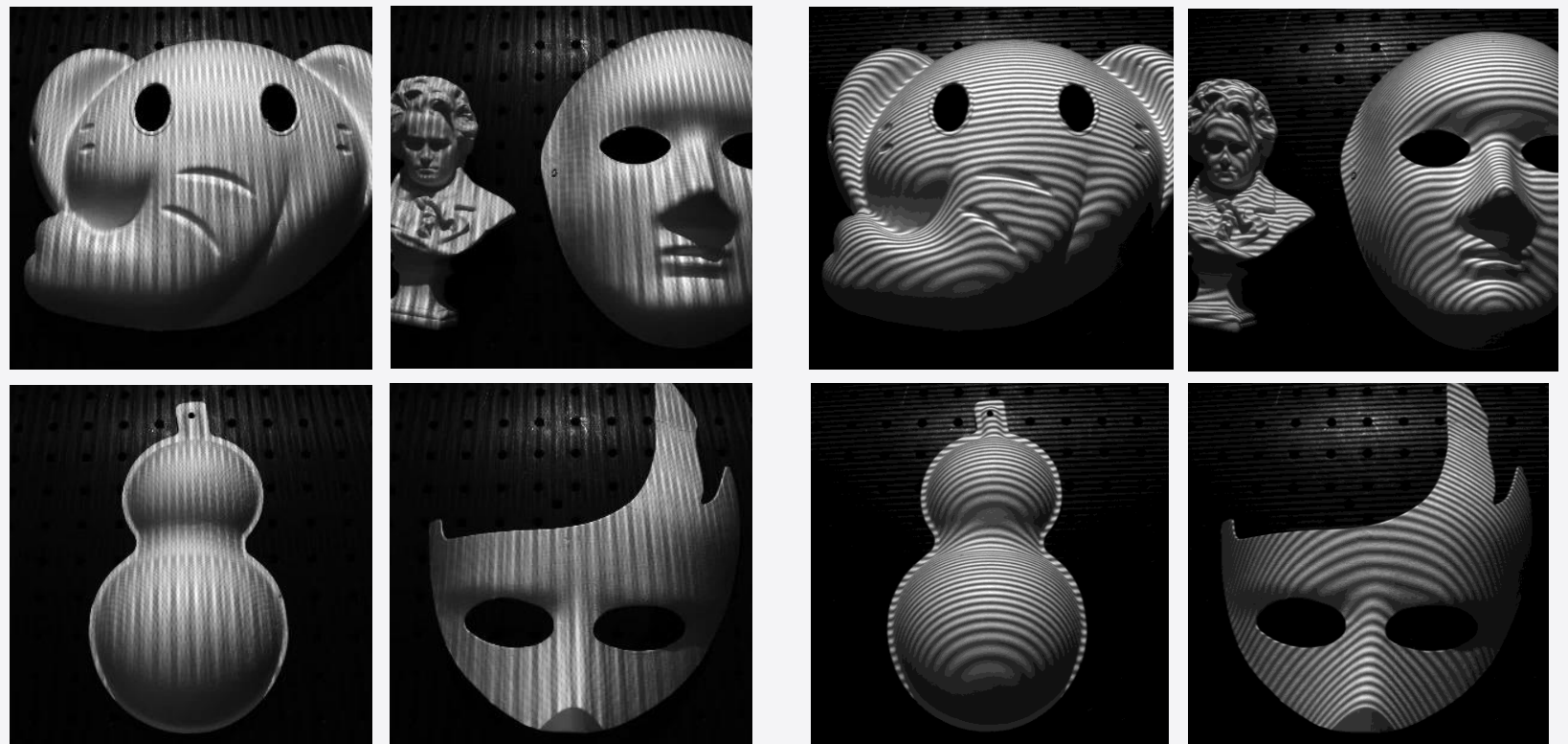


Number of images	$985 \times (21+1) = 21670$
Collection Time	5 days
Exposure time t_c and t_p (projector and camera)	50 ms
Period time	110 ms

$$\text{period time} = \max(t_c, t_p) + t_{\text{capture}}$$

$$t_{\text{capture}} = t_{\text{margin}} + t_{\text{buffer}} > \frac{1}{\text{FPS}_c} = 58.8 \text{ ms}$$

Training dataset



Input

Ground truth
(numerator only)

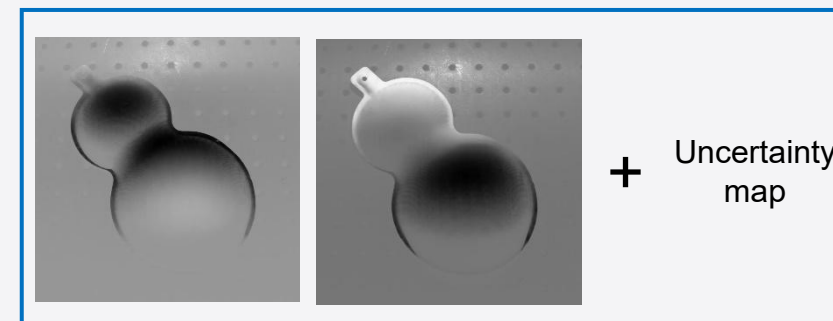
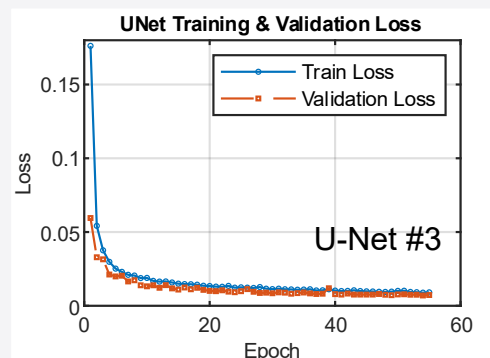
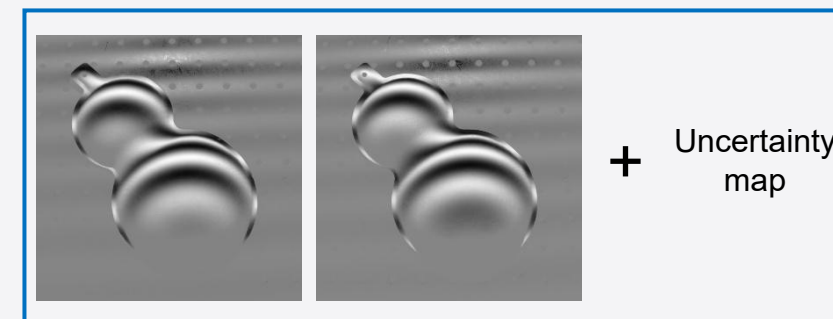
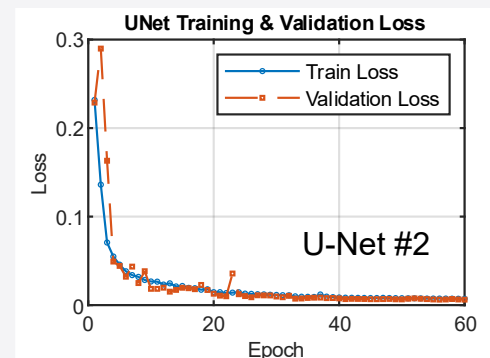
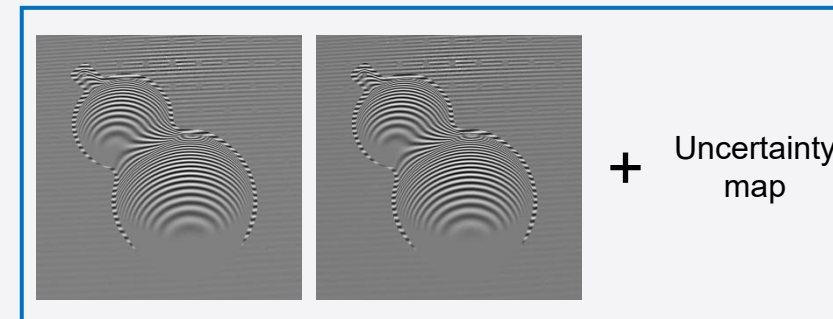
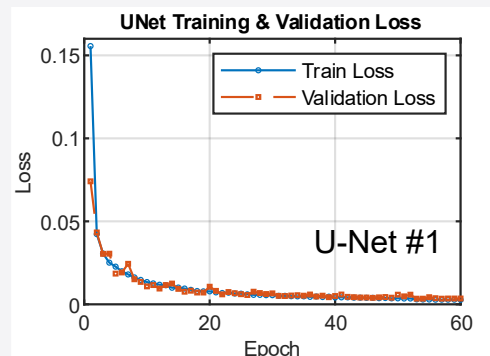


Experiments: Model training

Dataset details	Image size	912×912
	Number of samples	985
	Training & validation ratio	8:1

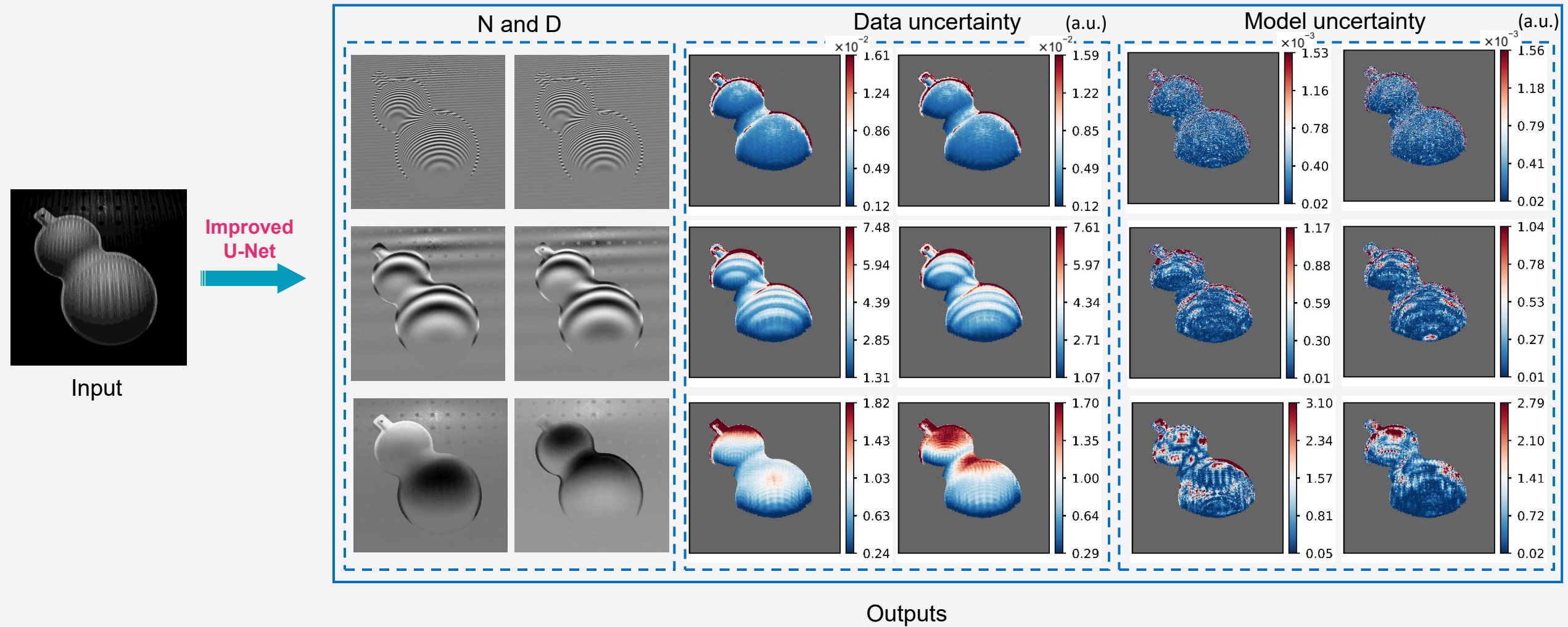
System configuration	Computer	Lenovo ThinkStation P3 Tower
	CPU	Intel® Core™ i9-13900K processor
	GPU	NVIDIA GeForce RTX 4070 (12 GB GDDR6X)
	OS	Windows 10 Enterprise 64-bit

Parameter	Value	Explanation
Batch size	4	Samples per iteration
Num epochs	60	Max training epochs
Learning rate	5e-4	Initial learning rate
loss function	MSE and NLL	Measures prediction error of the model



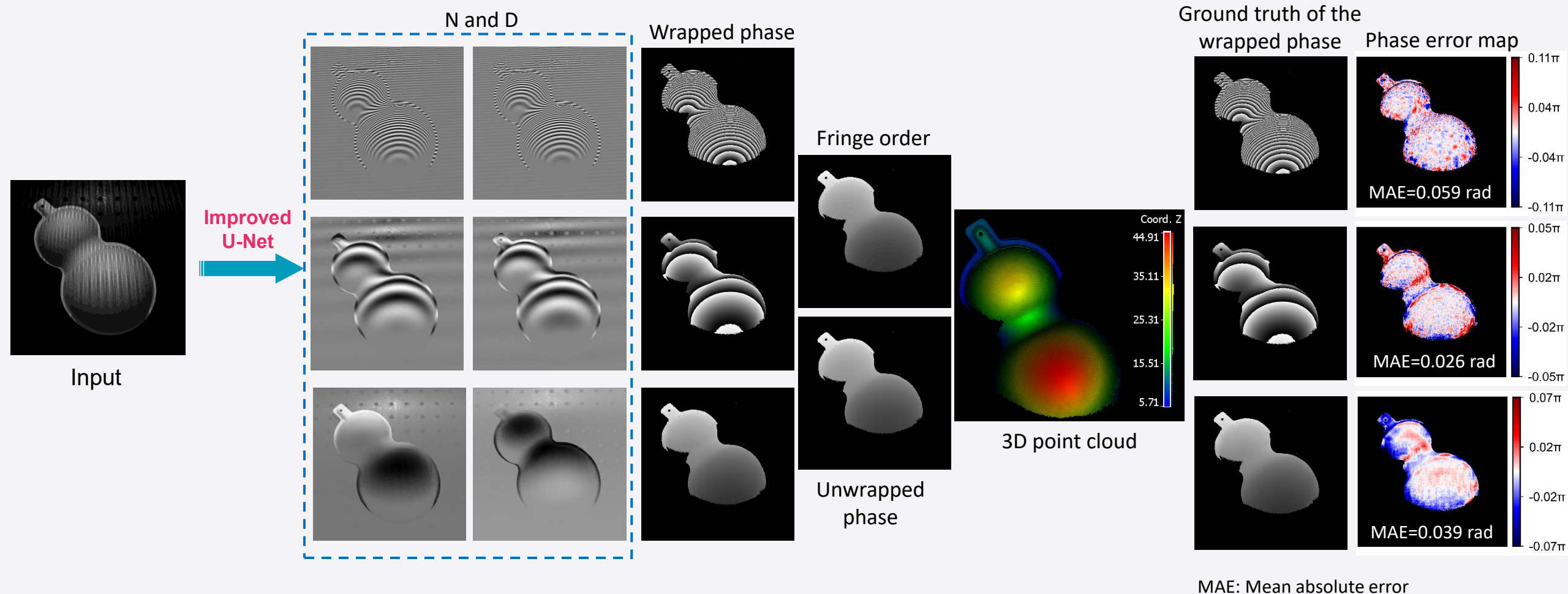


Experiments: Validation & Analysis



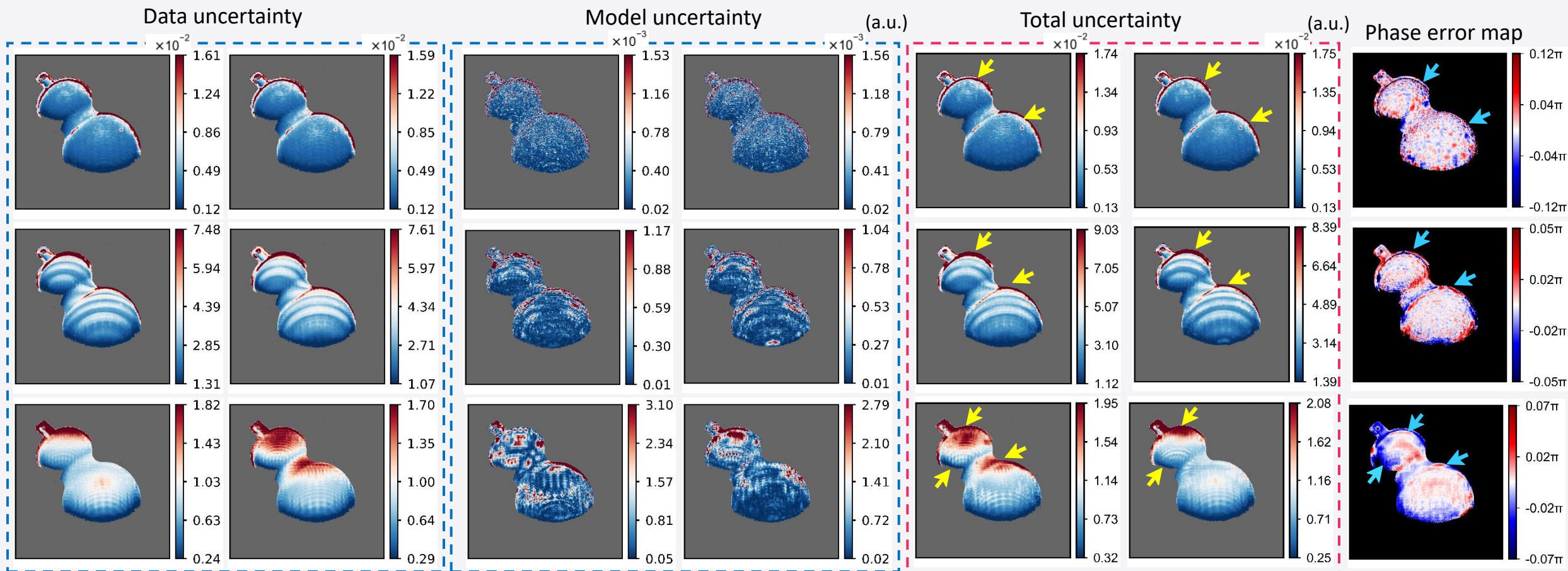


Experiments: Validation & Analysis



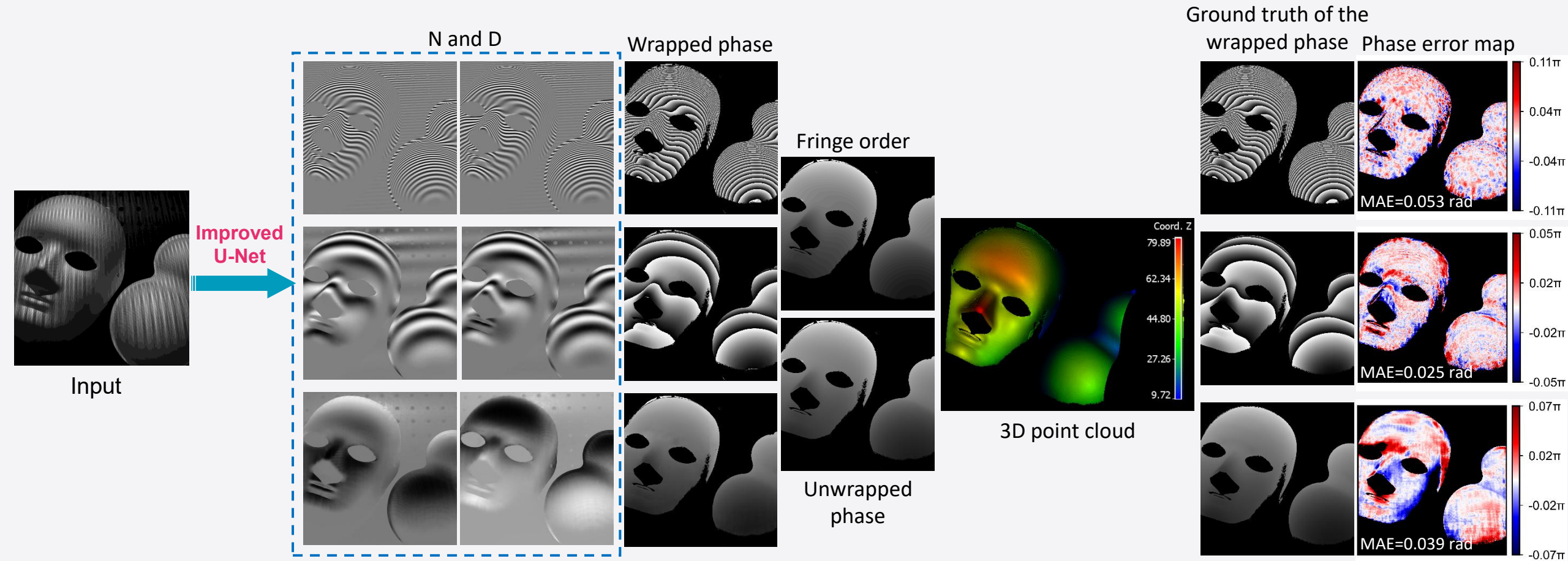


Experiments: Validation & Analysis



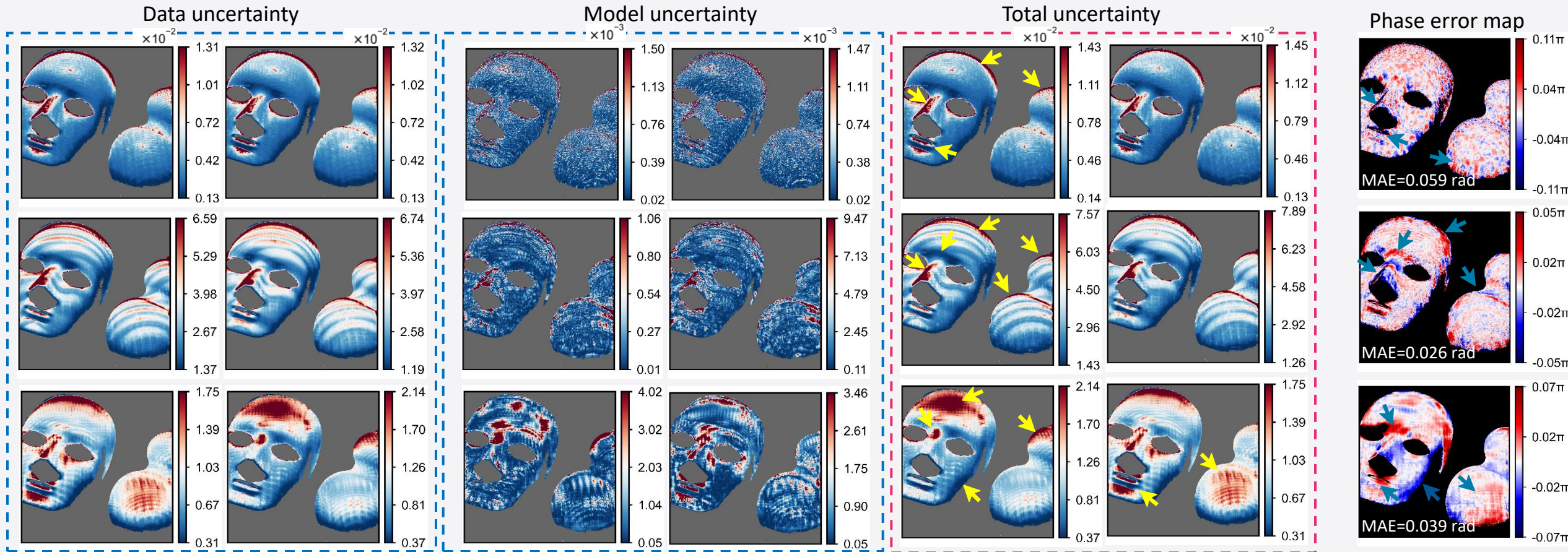


Experiments: Validation & Analysis



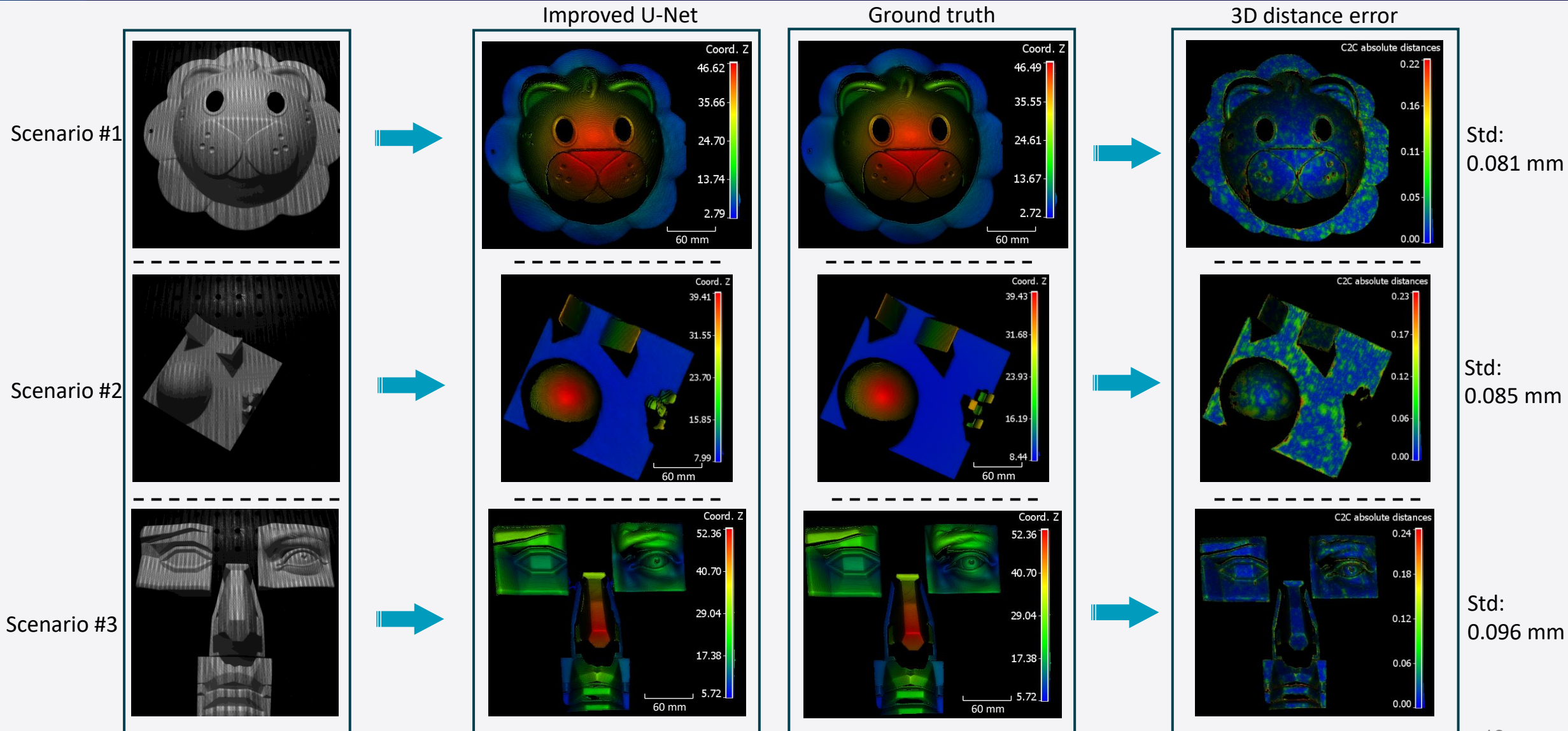


Experiments: Validation & Analysis





Experiments: Validation & Analysis





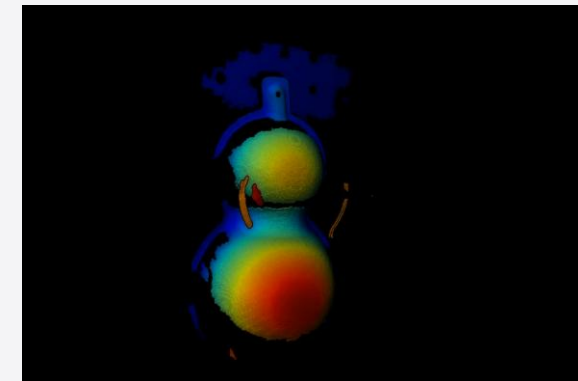
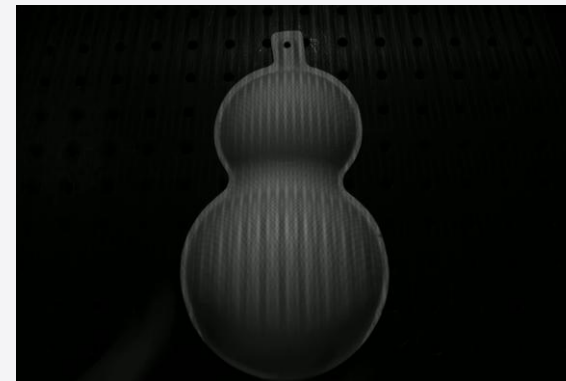
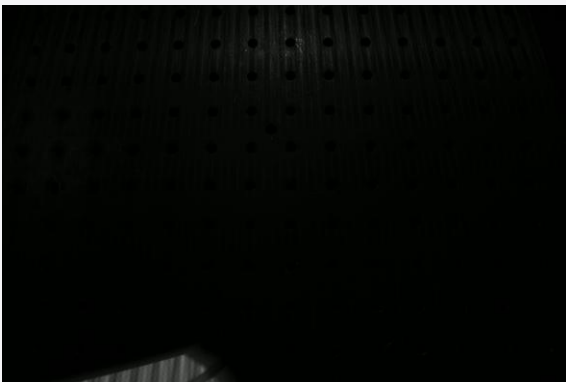
Experiments: Validation & Analysis

	Exposure time
Projector (t_p)	25 ms
Camera (t_c)	25 ms

Period time	300 ms
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	Exposure time
Projector (t_p)	25 ms
Camera (t_c)	25 ms

Period time	200 ms
--------------------	--------





Current contributions:

- **Composite multi-frequency fringe design**
Generated a composite fringe pattern that simultaneously encodes six spatial frequencies, providing three independent wrapped-phase maps for robust phase unwrapping.
- **Single-shot U-Net pipeline**
Trained a customised U-Net to regress the numerators and denominators of the three wrapped phases directly from the composite image, enabling real-time 3D reconstruction.
- **Uncertainty evaluation**
Replaced the traditional loss function with Gaussian NLL and incorporated Snapshot Ensemble, which enabled the improved U-Net to generate an uncertainty map for estimating prediction confidence.

Future work:

- Enhance the resolution of the U-Net model.
- Reduce fringe order errors to improve the accuracy of the unwrapped phase by designing different frequencies or adopting alternative solutions.
- Develop an digital twin of the FPP setup for collecting the synthetic data for model training.

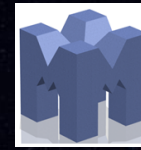


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