# Fusion-Based Digital Image Correlation Framework for Strain Measurement

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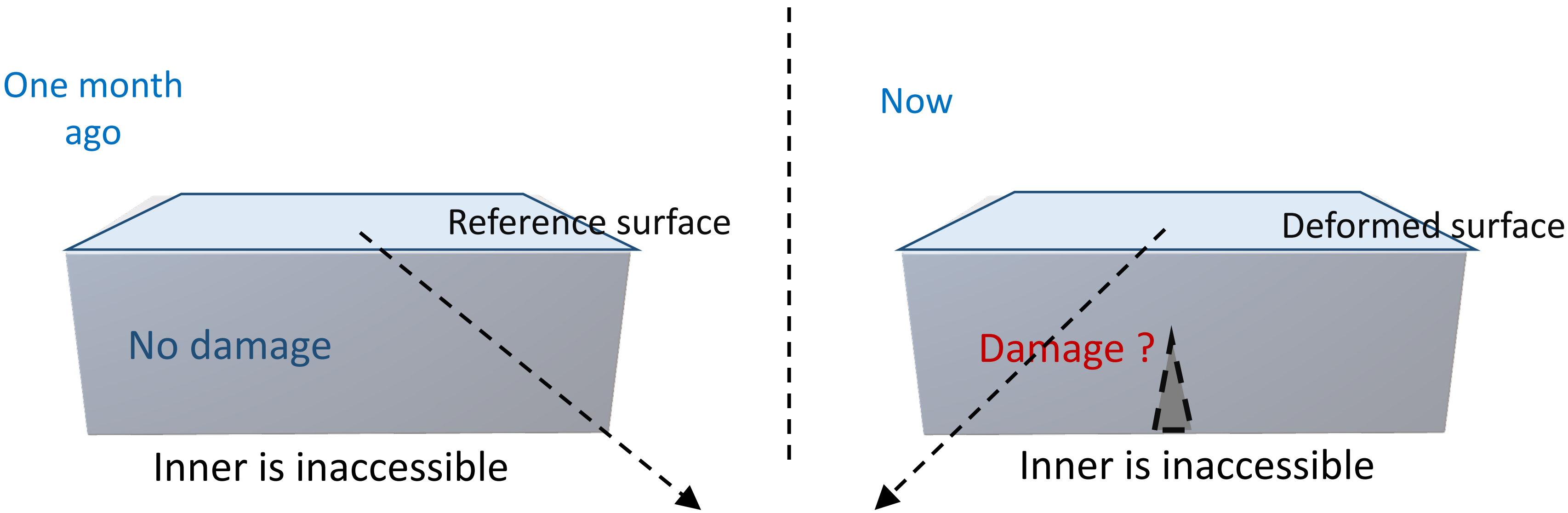
# Motivation: Strain Measurement of Materials

- Strain measurement is required in various applications: damage detection, stress intensity estimation [1].




No damage → strain is same
With damage → strain is different

[1] Bing Pan, Kemao Qian, Huimin Xie, and Anand Asundi. Two-dimensional digital image correlation for in-planedisplacement and strain measurement: a review.Measurement science and technology, 20(6):062001, 2009

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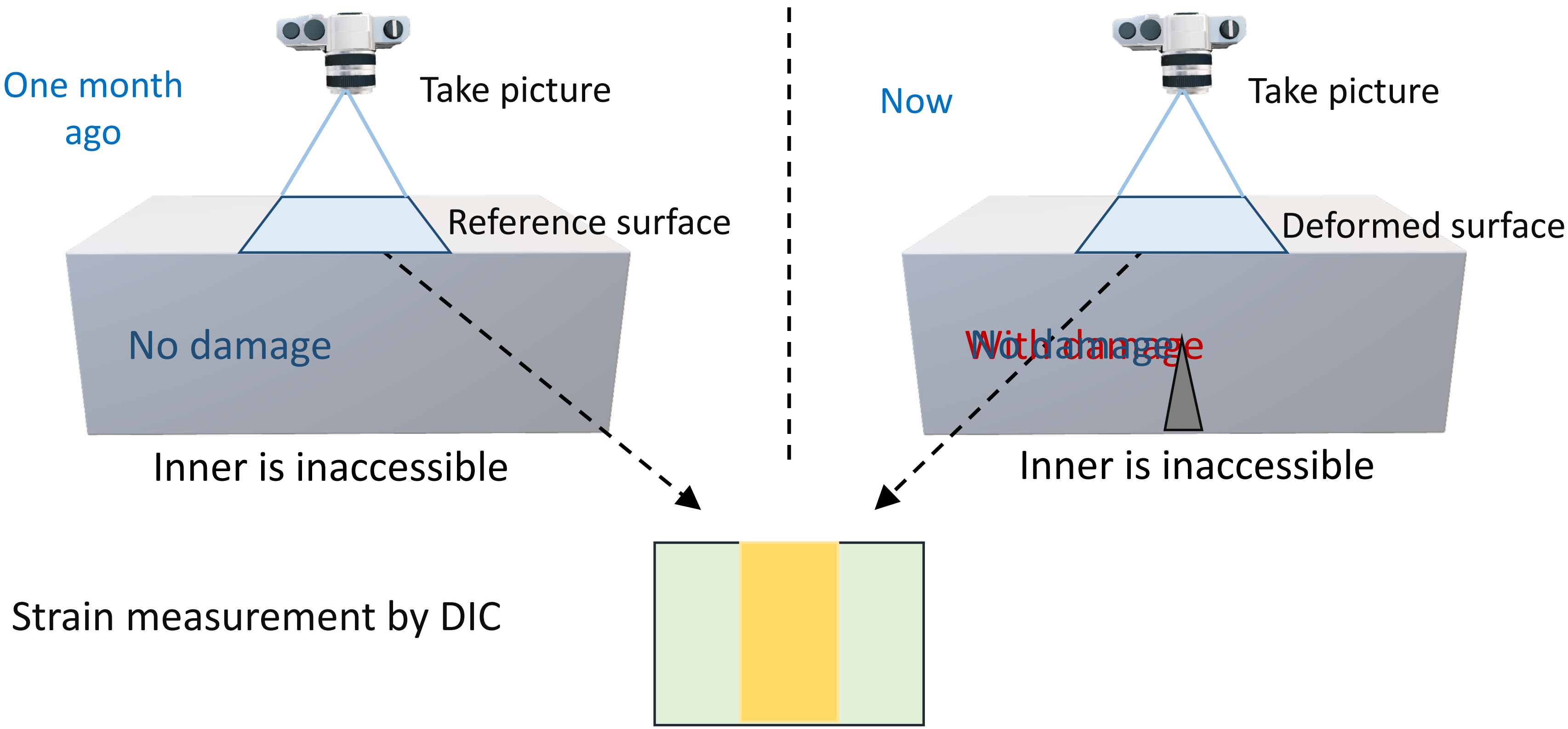
# Motivation: Strain Measurement of Materials

- Non-contact optical technologies:
  - Interferometric: holography interferometry.
  - Non-interferometric: digital image correlation (DIC).




[1] Bing Pan, Kemao Qian, Huimin Xie, and Anand Asundi. Two-dimensional digital image correlation for in-planedisplacement and strain measurement: a review.Measurement science and technology, 20(6):062001, 2009

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# Challenges

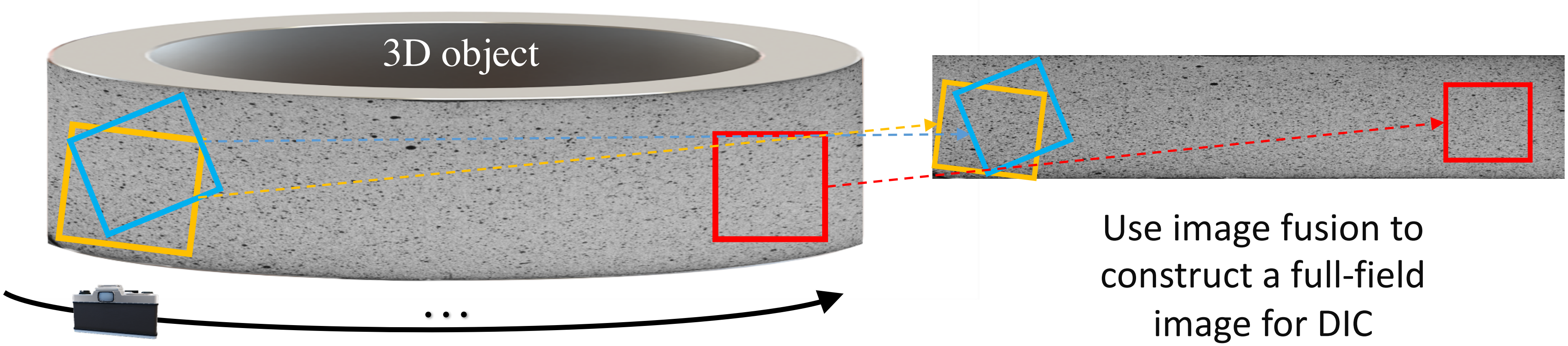
Goal : strain measurement on a curved surface of a large three-dimensional (3D) object.

Challenges :

1. Curved surfaces:
   – Classical 2D DIC is limited to planar surfaces.
2. Difficulty of experimental source and setup:
   – 3D DIC usually need multi-cameras or markers on surface.
3. Large size of the object:
   – Single image can't cover full-field with high-resolution for reasonable DIC results.
   – Images may have blur.

# Novelty of Our Framework

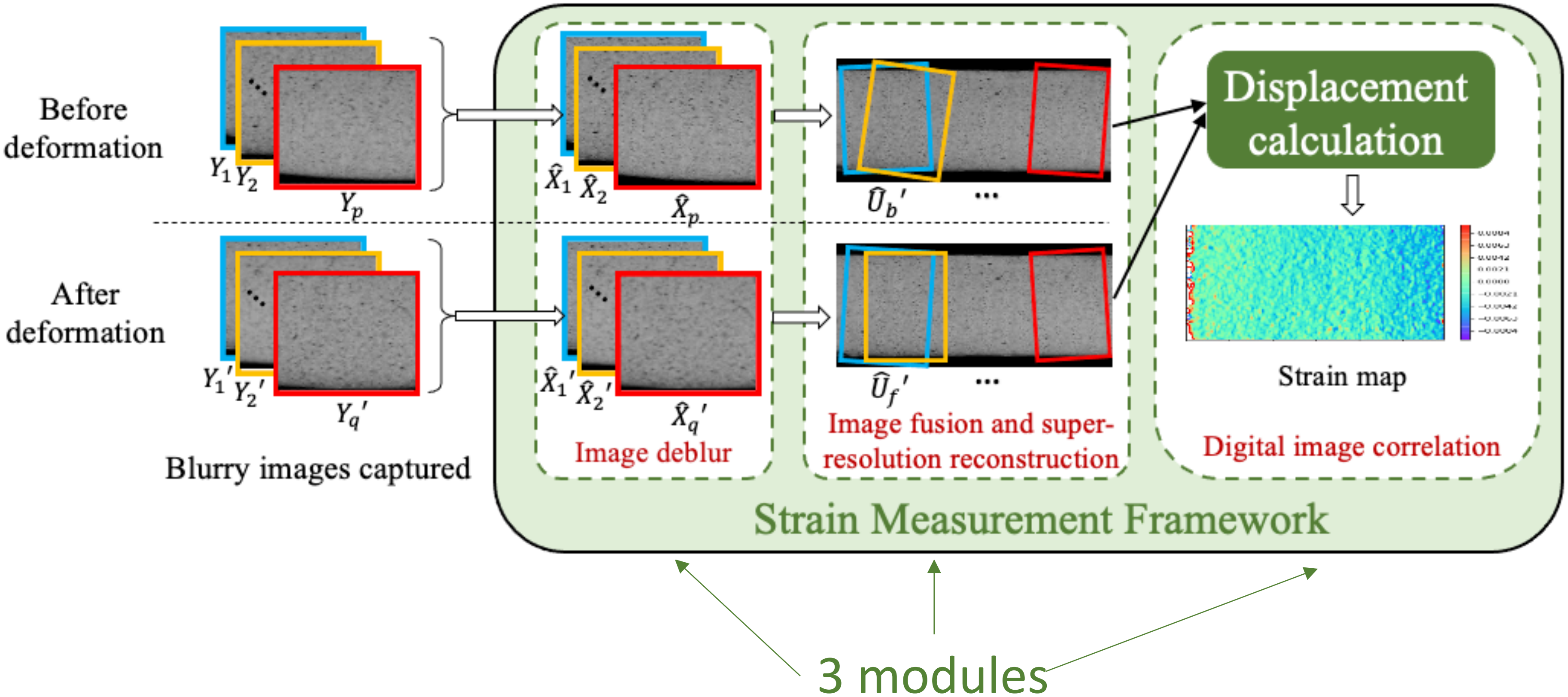
| Challenges | Solution of our framework |
|---|---|
| 1. Curved surfaces | Unfold the curved 3D surface to 2D. |
| 2. Difficulty of experimental source and setup | Simple experiment setup:<br>One single camera (such as Google pixel 3).<br>No operation on the 3D surface. |
| 3. Large size of the object | Incorporate image fusion principle into the framework. |




Use image fusion to construct a full-field image for DIC

# Framework Pipeline

- We propose an end-to-end fusion-based DIC framework consisting of image deblur, image fusion and DIC modules.



# Presentation Pipeline

- Camera image simulation process
- The proposed DIC framework
  - Image deblur module
  - Image fusion and super-resolution reconstruction module
  - Digital Image Correlation module

# Camera Image Simulation Process

- Model parameters:
  - 3D object cylinder: radius = 500mm, height = 80mm.
  - Camera moving trajectory radius: 540 mm (close to the surface).
  - Camera image resolution: 500 * 600 pixels.

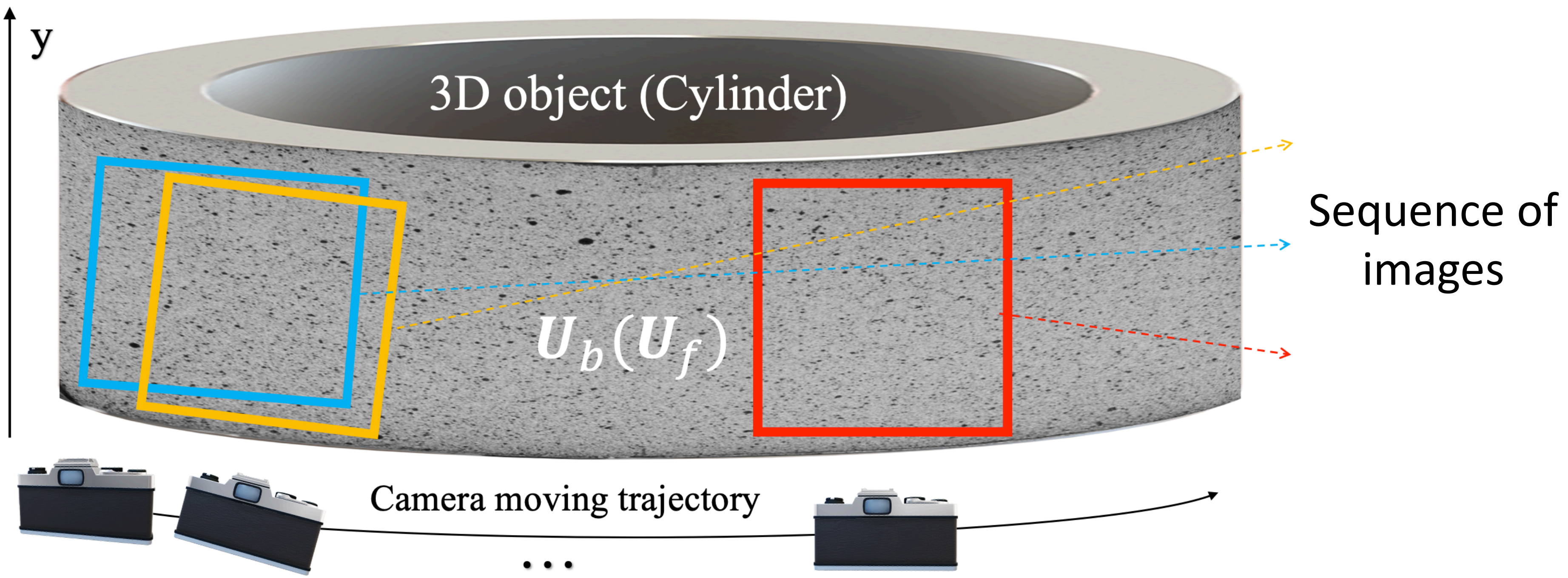
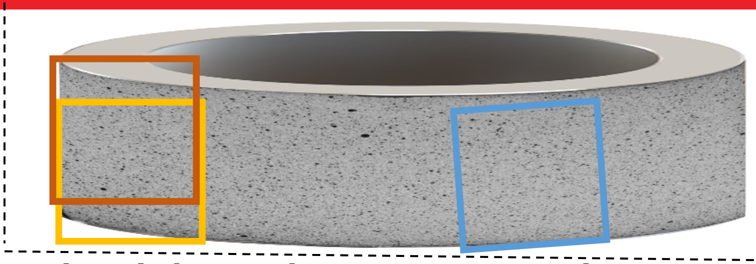
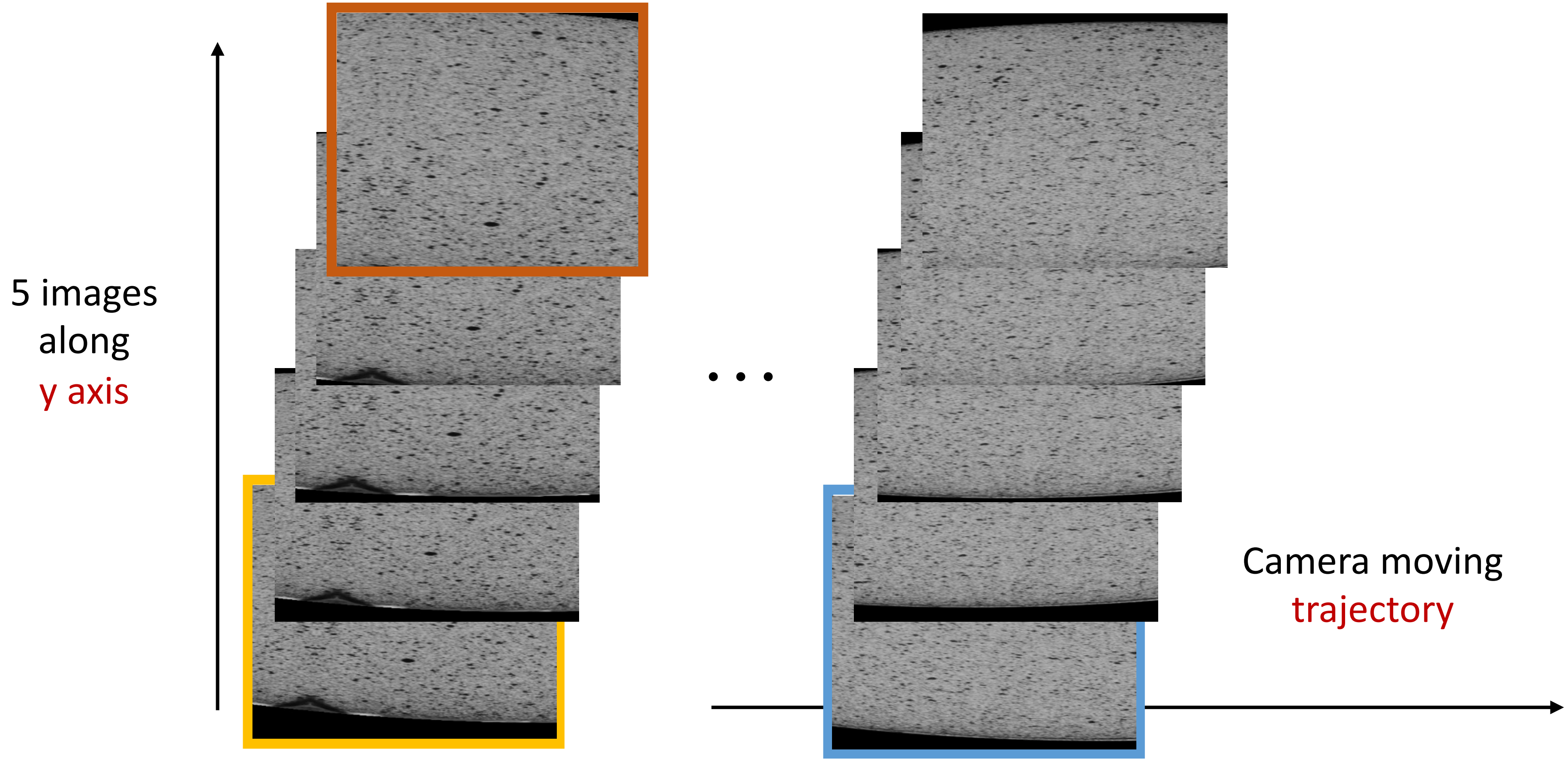



Image Acquisition Process

# Blurred Camera Image Examples



- Random camera pose: images are captured with unknown random perturbation.
- For surface before or after deformed: 160 images in total.



# Presentation Pipeline

- Camera image simulation process
- The proposed DIC framework
  - Image deblur module
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# Image Deblur Problem Formulation

- Goal: recover the sharp images $\{\boldsymbol{X}_i\}$ and blur kernel $\boldsymbol{K}$ by the blurred observations $\{\boldsymbol{Y}_i\}$.

$$\boldsymbol{Y}_i = \boldsymbol{K} \circledast \boldsymbol{X}_i, \quad i = 1, 2, \cdots, p.$$

  - $\circledast$ : the circulant convolution operator
- Assumptions: the blur kernel is a truncated Gaussian with radius $r_g$ and unknown standard deviation $\sigma$:
  - $C_1$: normalization term

$$\boldsymbol{K}(x, y) = \begin{cases} \frac{1}{C_1} \exp\left(\frac{-(x^2+y^2)}{2\sigma^2}\right) & \sqrt{x^2+y^2} \leqslant r_g \\ 0 & \sqrt{x^2+y^2} > r_g, \end{cases}$$

# Image Deblur Approach

- Step1: initialize the Gaussian blur kernel $\boldsymbol{K}$ with Wiener filter [2] by minimizing the normalized sparsity loss [1] in the region of $\sigma$ :

$$\boldsymbol{K}_0 = \underset{\boldsymbol{K}}{\operatorname{argmin}} \sum_{i=1}^{L} \frac{\left\|\nabla_x \overline{\boldsymbol{X}}_i(\boldsymbol{K}, \boldsymbol{Y}_i)\right\|_1}{\left\|\nabla_x \overline{\boldsymbol{X}}_i(\boldsymbol{K}, \boldsymbol{Y}_i)\right\|_2} + \frac{\left\|\nabla_y \overline{\boldsymbol{X}}_i(\boldsymbol{K}, \boldsymbol{Y}_i)\right\|_1}{\left\|\nabla_y \overline{\boldsymbol{X}}_i(\boldsymbol{K}, \boldsymbol{Y}_i)\right\|_2},$$

  - $\overline{\boldsymbol{X}}_i(\boldsymbol{K}, \boldsymbol{Y}_i) = Wiener(\boldsymbol{K}, \boldsymbol{Y}_i)$ : the filtered image of $\boldsymbol{Y}_i$ with kernel $\boldsymbol{K}$.
  - $\nabla_x$,$\nabla_y$ :the derivatives in the $x, y$ directions respectively.
  - $L$: the total number of the utilized blurred observation images.

[1] Krishnan, Dilip, Terence Tay, and Rob Fergus. "Blind deconvolution using a normalized sparsity measure." CVPR 2011. IEEE, 2011.
[2] Rafael C Gonzalez, Richard E Woods, et al. Digital image processing, 2002

# Image Deblur Approach

- Step 2: blind deconvolution: image reconstruction using the initialization blur kernel $\boldsymbol{K}_0$ by adding Total variation (TV) regularization [1]:

$$\min_{\boldsymbol{K},\{\boldsymbol{X}_i\}} \sum_{i=1}^{p} \left( \frac{\beta}{2} \|\boldsymbol{Y}_i - \boldsymbol{K} \circledast \boldsymbol{X}_i\|_F^2 + \underbrace{\sum_{j=1}^{m \cdot n} \|\boldsymbol{D}_j \boldsymbol{X}_i\|_2}_{\text{TV}} \right) + \boldsymbol{I}_{\mathcal{G}}(\boldsymbol{K}),$$

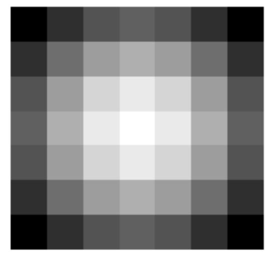
  - $\boldsymbol{I}_{\mathcal{G}}(\cdot)$: indicator to ensure $\boldsymbol{K}$ is a truncated Gaussian.
  - $\beta$ : noise weight depending on the noise of $\boldsymbol{Y}_i$.
  - $\boldsymbol{D}_j$: the derivative of $\boldsymbol{X}_i \in \mathbb{R}^{m \times n}$ at pixel $j$ in both $x$ and $y$ directions.

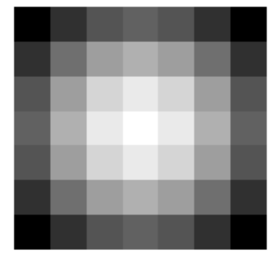
[1] Tao, Min, Junfeng Yang, and Bingsheng He. "Alternating direction algorithms for total variation deconvolution in image reconstruction." *TR0918, Department of Mathematics, Nanjing University* (2009).

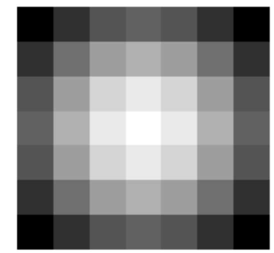
# Image Deblur Results

| Blur kernel parameters | Ground truth | Estimation for reference image | Estimation for deformed image |
|---|---|---|---|
| $\sigma$ | 3.0 | 3.0 | 3.05 |

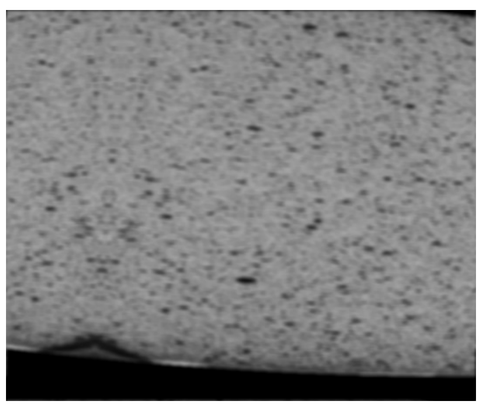
Step1: blur kernel initialization result







Step2: sharp image estimation $\hat{X}_i$



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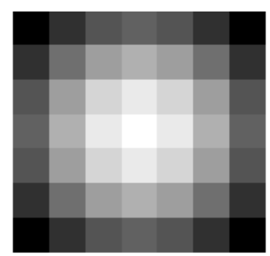
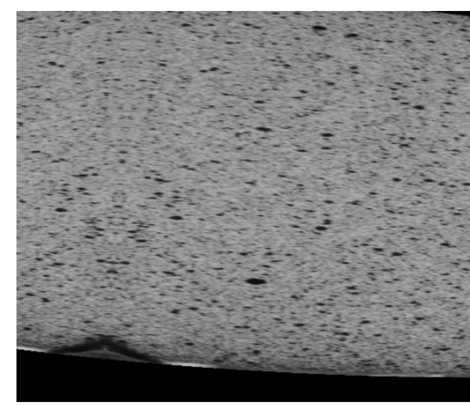


$\circledast$



$Y_i$ $K$ $\hat{X}_i$

# Presentation Pipeline

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# Pinhole Camera Model

- Pinhole camera model:

$$\begin{bmatrix} \boldsymbol{x} \\ 1 \end{bmatrix} = \frac{1}{v} \boldsymbol{P}_s \begin{bmatrix} \boldsymbol{R} & \boldsymbol{T} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{u} \\ 1 \end{bmatrix} = \frac{1}{v} \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \boldsymbol{R} & \boldsymbol{T} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_u \\ y_u \\ z_u \\ 1 \end{bmatrix},$$

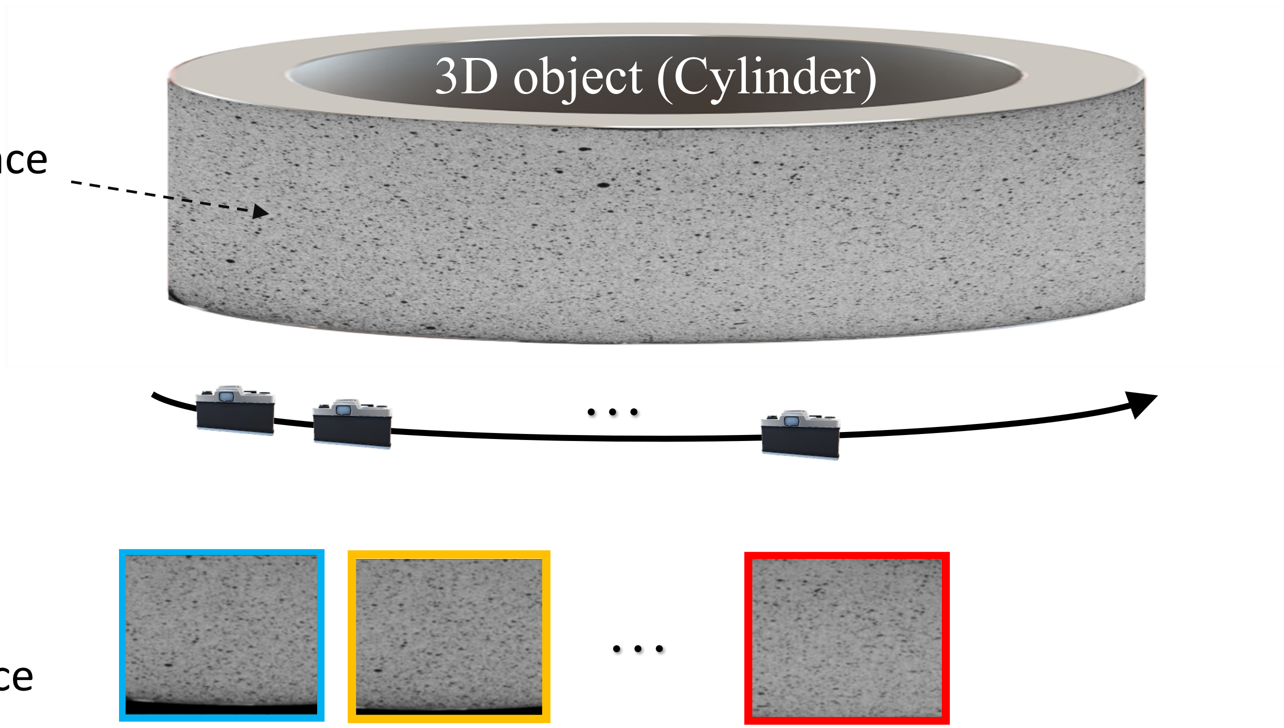
  - $\boldsymbol{R} \in \mathbb{R}^{3\times 3}, \boldsymbol{T} \in \mathbb{R}^3$: the unknown rotation and translation (depend on the camera pose).
  - $\boldsymbol{P}_s$: the known perspective matrix of the camera.
  - $\boldsymbol{u} = [x_u, y_u, z_u]^\top$: a pixel $\boldsymbol{u}$ on the 3D object surface.
  - $\boldsymbol{x} = [x, y]^\top$ : the pixel position on the camera focal plane.
  - $f$ is the focal length, $v$ is a pixel-dependent normalization term.

With camera pose, we can project the pixel $\boldsymbol{x}$ in camera plane back to 3D object surface with known 3D geometry.

# Image Fusion and Super-Resolution Reconstruction

- Goal: reconstruct the super-resolution full-field surface on the 3D object and unfold it to a 2D image.

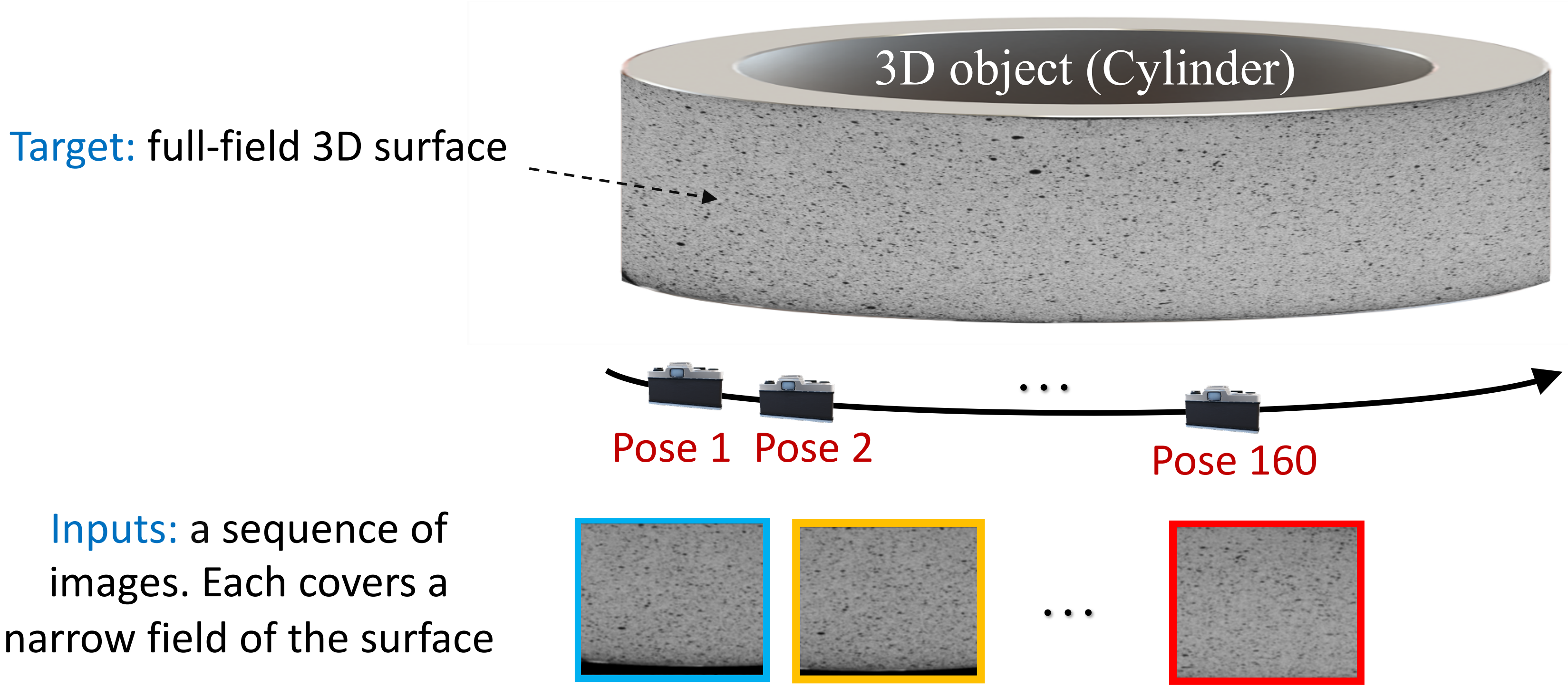
Target: full-field 3D surface




Inputs: a sequence of images. Each covers a narrow field of the surface

# Image Fusion and Super-Resolution Reconstruction

- Goal: reconstruct the super-resolution full-field surface on the 3D object and unfold it to a 2D image.
  - Step1: estimate all the unknown camera poses $(R, T)$ of these images.



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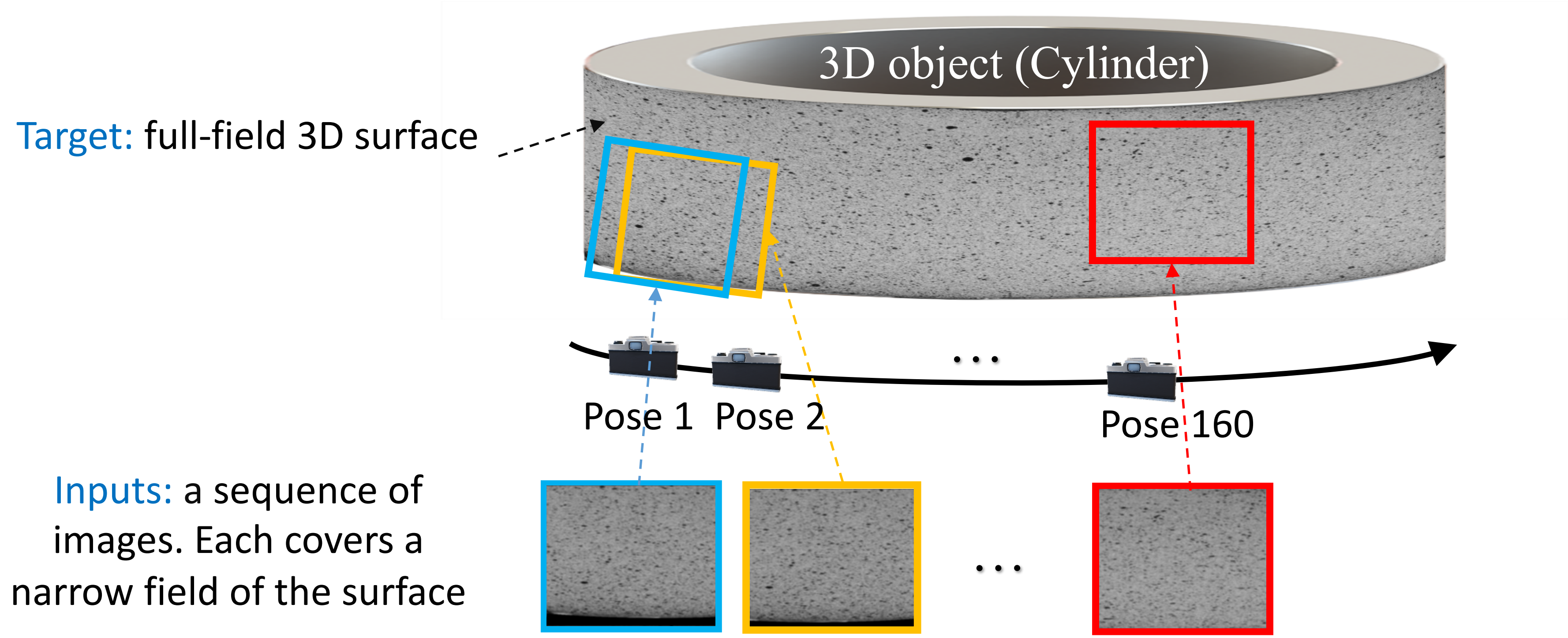
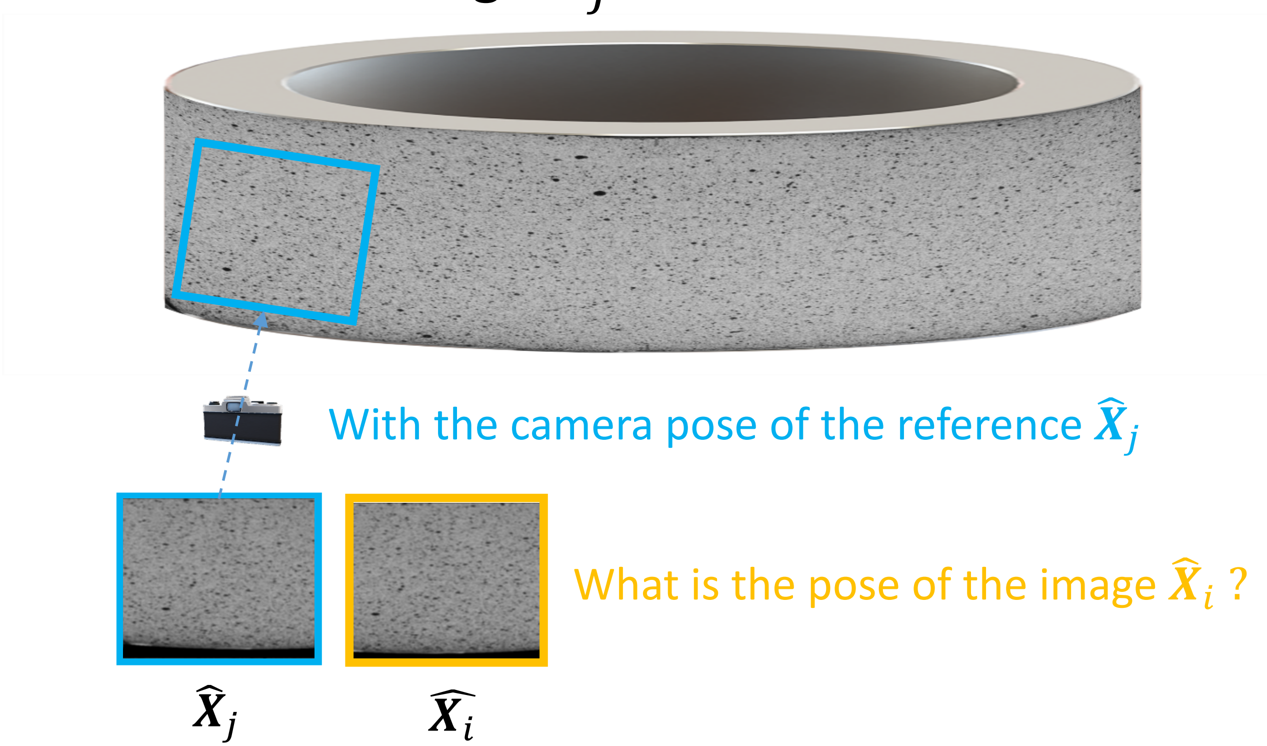
# Image Fusion and Super-Resolution Reconstruction

- Goal: reconstruct the super-resolution full-field surface on the 3D object and unfold it to a 2D image.
  - Step1: estimate all the unknown camera poses $(R, T)$ of these images.
  - Step2: project all pixels of images back to the 3D surface for fusion and interpolate it to get unfolded 2D image.



# Step 1: formulation of camera pose estimation

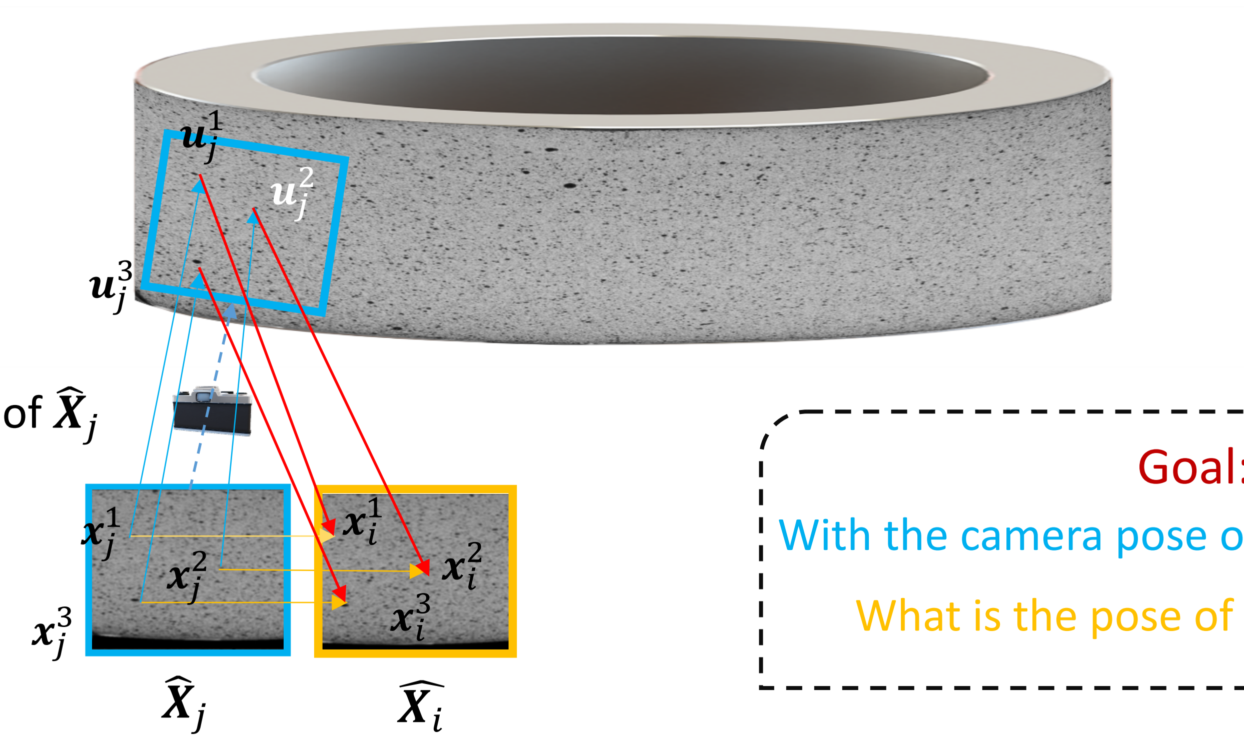
- Inputs:
  - Deblurred sequence of images $\{\hat{\boldsymbol{X}}_i\}$ from the former module.
  - 3D object geometry.
  - The pose of the first image $\hat{\boldsymbol{X}}_1$ is known as reference.
- Goal: solve the subproblems: estimate the pose of each $\hat{\boldsymbol{X}}_i$, with the pose of a reference image $\hat{\boldsymbol{X}}_j$ .



# Step 1: camera pose estimation of $\widehat{\boldsymbol{X}}_i$

- Problem decoupling:
  - Find a set of matching SIFT feature points $\mathcal{A}_{(j,i)} = \{(\boldsymbol{x}_j^m, \boldsymbol{x}_i^m)\}$
  - Project $\{\boldsymbol{x}_j^m\}$ to the 3D surface $\{\boldsymbol{u}_j^m = \left[x_{u_j}^m, y_{u_j}^m, z_{u_j}^m\right]^\mathsf{T}\}$
  - Perspective-n-point problem (PnP): estimate the camera pose of $\widehat{\boldsymbol{X}}_i$ using the 3D-2D matching points $\mathcal{M}_{(j,i)} = \{(\boldsymbol{u}_j^m, \boldsymbol{x}_i^m)\}$

Use the pose of $\widehat{\boldsymbol{X}}_j$




Goal:

With the camera pose of the image $\widehat{\boldsymbol{X}}_j$

What is the pose of the image $\widehat{\boldsymbol{X}}_i$ ?

# Step 1: camera pose estimation: PnP problem

- Solve PnP by proposed RWLM: use Levenberg Marquardt algorithm (LM) to solve the re-weighted nonlinear least squares:

$$\min_{\boldsymbol{h}} g(\boldsymbol{h}|\mathcal{M}_{(j,i)}) = \sum_{(\boldsymbol{u}_j^m,\boldsymbol{x}_i^m)\in\mathcal{M}_{(j,i)}} w_m \left\| \hat{\boldsymbol{x}}_i(\boldsymbol{u}_j^m, \boldsymbol{h}) - \boldsymbol{x}_i^m \right\|_2^2,$$

$$\text{s.t. } \boldsymbol{R}\boldsymbol{R}^\top = \boldsymbol{I},$$

  - $\boldsymbol{h} \in R^{9\times 1}$ : Reparameterized by $\boldsymbol{R}, \boldsymbol{T}$.
  - $\hat{\boldsymbol{x}}_i(\boldsymbol{u}_j^m, \boldsymbol{h})$: the projection result from the 3D point $\boldsymbol{u}_j^m$ to the camera focal plane $\widehat{\boldsymbol{X}}_i$ with respect to the camera pose $\boldsymbol{h}$.
  - $w_m = \dfrac{1}{\left\| \hat{\boldsymbol{x}}_i(\boldsymbol{u}_j^m, \boldsymbol{h}) - \boldsymbol{x}_i^m \right\|_2^\alpha}$ : the inverse of the measurement error for the m-th feature.

## Step 1: camera pose estimation: PnP

- Refined method RRWLM:
  - Initial the camera poses using the results from the former RWLM:

$$\min_{\boldsymbol{h}} g(\boldsymbol{h}|\boxed{\mathcal{M}_{(j,i)}}) = \sum_{(\boldsymbol{u}_j^m, \boldsymbol{x}_i^m)\in \boxed{\mathcal{M}_{(j,i)}}} w_m \left\| \hat{\boldsymbol{x}}_i(\boldsymbol{u}_j^m, \boldsymbol{h}) - \boldsymbol{x}_i^m \right\|_2^2 .$$

  - Estimate the camera pose of $\widehat{\boldsymbol{X}}_i$ with others fixed iteratively:

$$\min_{\boldsymbol{h}} g(\boldsymbol{h}|\boxed{\bigcup_{j\in\mathcal{L}_i} \mathcal{M}_{(j,i)}}) = \sum_{(\boldsymbol{u}_j^m, \boldsymbol{x}_i^m)\in \boxed{\bigcup_{j\in\mathcal{L}_i} \mathcal{M}_{(j,i)}}} w_m \left\| \hat{\boldsymbol{x}}_i(\boldsymbol{u}_j^m, \boldsymbol{h}) - \boldsymbol{x}_i^m \right\|_2^2 .$$

  - $\mathcal{L}_i = \{l | l < i, \hat{\boldsymbol{X}}_l \bigcap \hat{\boldsymbol{X}}_i \neq \boldsymbol{0}\}$: the index set of images overlapping with $\widehat{\boldsymbol{X}}_i$.

Utilize more feature points from previous reference images instead of only one $\widehat{\boldsymbol{X}}_j$

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# Image Fusion and Super-Resolution Reconstruction Results

- Comparisons with existing PnP state-of-art methods:
  - Pose error metric is: $\left\| \left[ \hat{R} - R, \hat{T} - T \right] \right\|_2$ .
  - $\hat{U}'_b, \hat{U}'_f$ : image stitching results of the surface before and after deformed.

| Method | Average pose error | | PSNR of $\hat{U}'_b$ and $\hat{U}'_f$ | |
|---|---|---|---|---|
| | $\{\hat{X}_i\}_{i=1}^{160}$ | $\{\hat{X}_i\}_{i=1}^{10}$ | $\{\hat{X}_i\}_{i=1}^{160}$ | $\{\hat{X}_i\}_{i=1}^{10}$ |
| **LHM** | 40.67 | 0.15 | 11.86 | 30.63 |
| **EPnP+GN** | 34.23 | 0.18 | 11.91 | 30.63 |
| **OPnP+LM** | 29.35 | 0.12 | 12.53 | 30.67 |
| **RWLM** | 0.22 | 0.08 | 28.09 | 27.84 |
| **RRWLM** | 0.13 | 0.07 | 30.18 | 30.74 |

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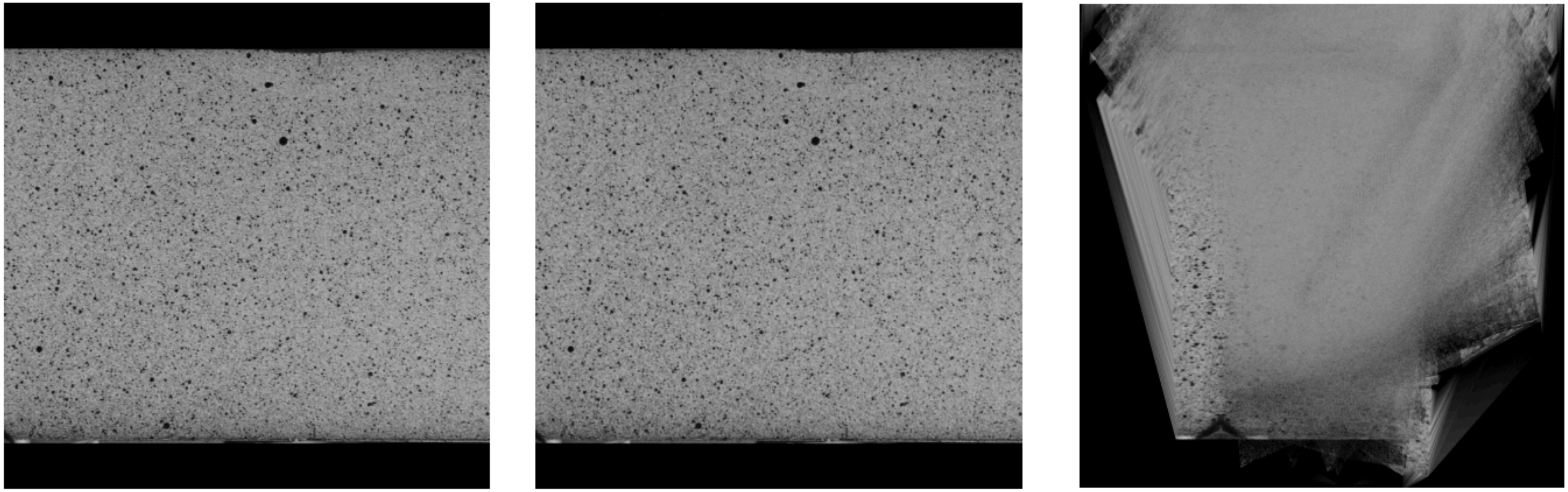
# Image Fusion and Super-Resolution Reconstruction Results

- Comparisons with existing PnP state-of-art methods: using all the 160 images in each sequence.



(a) $\boldsymbol{U}_b$ (b) $\hat{\boldsymbol{U}}_b'$ by **RRWLM** (c) $\hat{\boldsymbol{U}}_b'$ by **OPnP + LM**

# Presentation Pipeline

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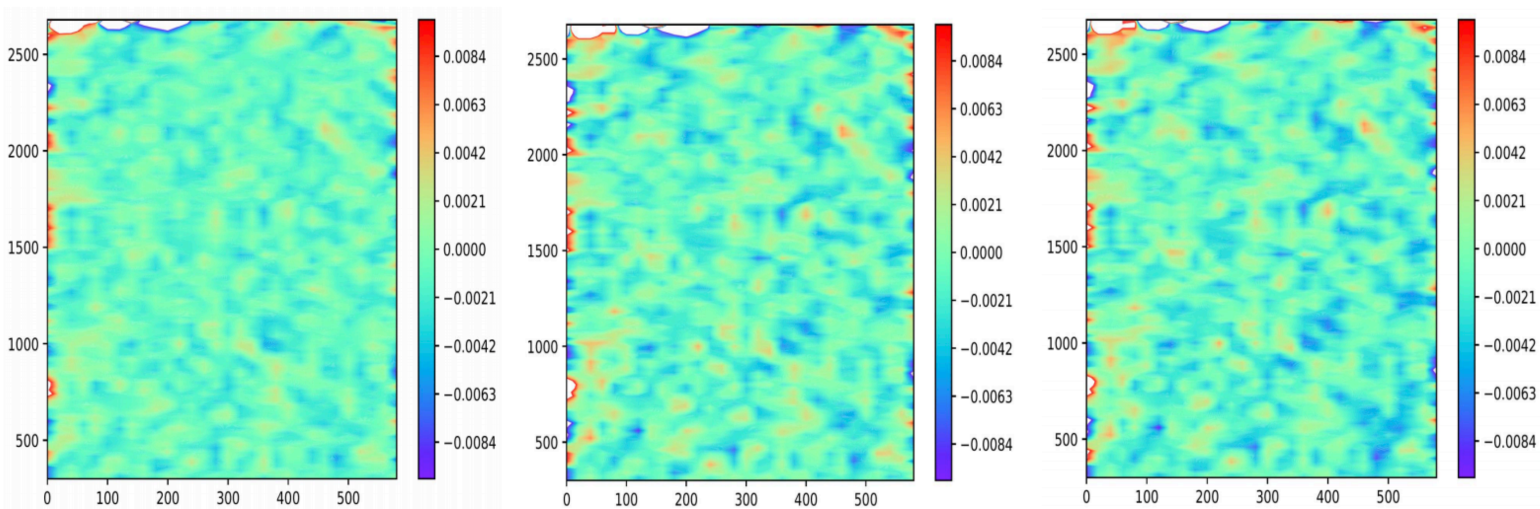
# DIC Module Results

- DIC: Strain measurement in region of interest (ROI): track and compute the displacements of the feature points between the image before ($\hat{U}_b'$) and after deformation ($\hat{U}_f'$).
- The result for the ROI covered by the first 10 images in each sequence for $\hat{U}_b', \hat{U}_f'$:

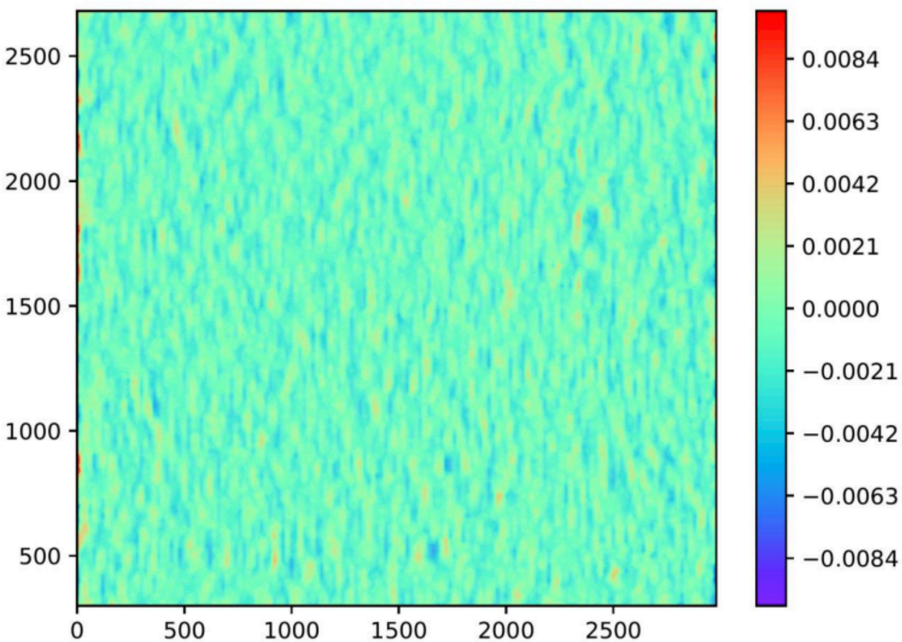



(a) True strain (b)**RRWLM** (c) **OPnP+ LM**

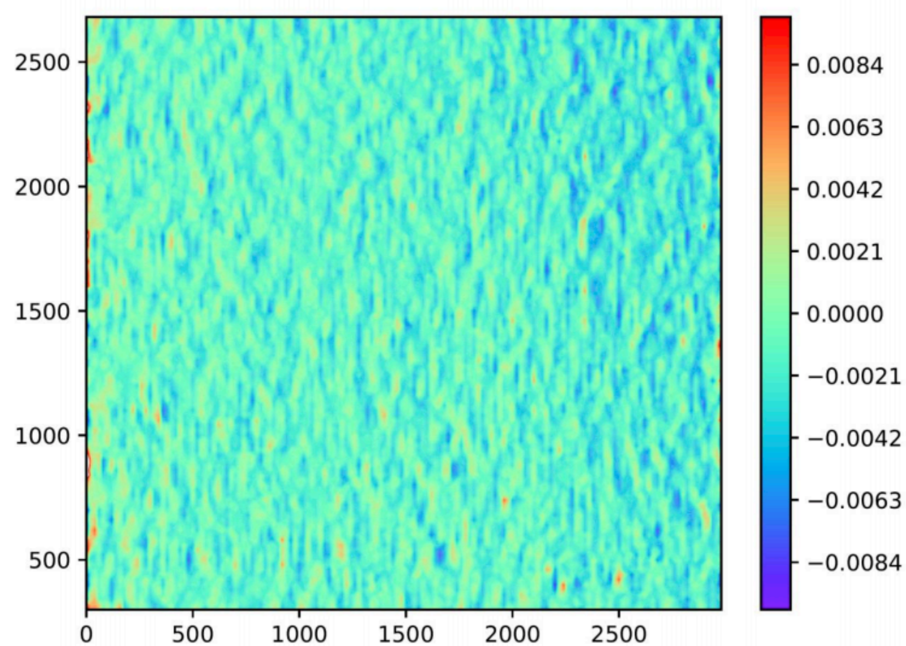
However, the covered region is too small.

# DIC Module Results

- The result for the ROI covered by all 160 images:
  - Baseline is not applicable.




(a) Strain using $\boldsymbol{U}_b$ and $\boldsymbol{U}_f$




(b) Strain via **RRWLM** fusion

# Conclusion

- We propose an end-to-end fusion-based DIC framework for 2D strain measurement along curved surfaces of large 3D objects:
  - Extend the applications for 2D DIC to curved surfaces in large size.
  - Introduce a general pipeline for future works consisting deblurring, image fusion and super-resolution reconstruction, and DIC modules.
- We incorporate image fusion principle into strain measurement framework:
  - The proposed method for the essential PnP problem achieves better image fusion results with comparisons to prior works and meets the stringent requirement for DIC based strain measurement.

# Thank you for listening!

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