Measuring Distortion Strength with Dewarping Diffusion Models in Anomaly Detection

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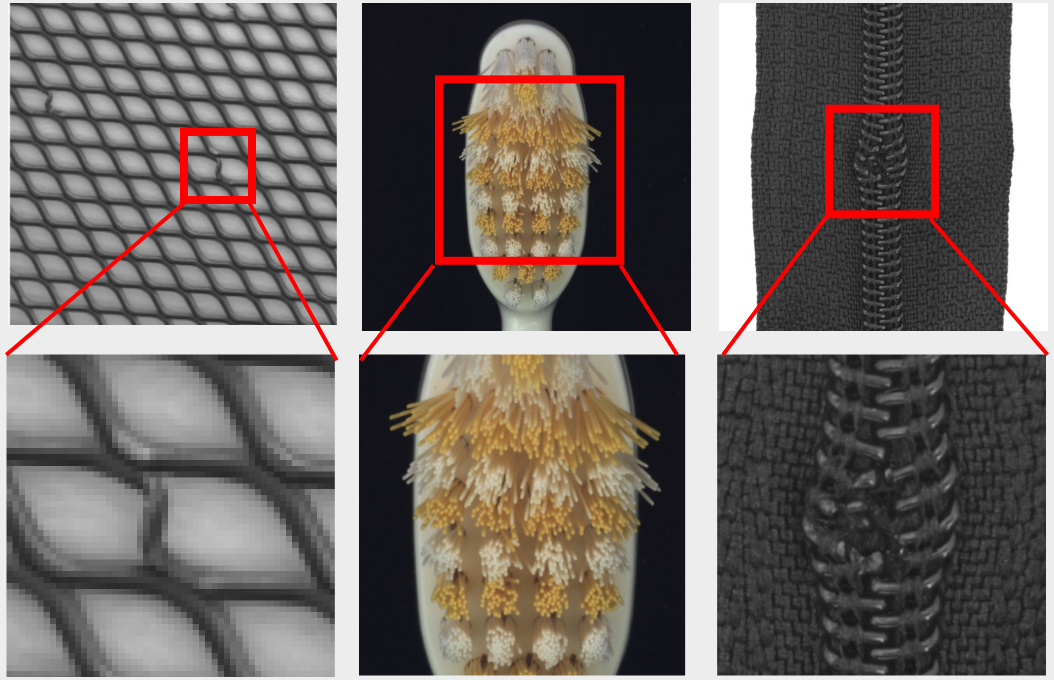
Background: Anomaly Detection

A process for detecting defects in the production lines

Examples of physical distorted defects

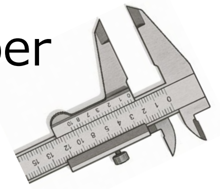
Local distortion caused by external force



Distorted strengths (degrees) are often measured to classify defects.

small ⟷ large

Caliper



3D scanner

Source: Keyence

Background: Image-Based Anomaly Detection

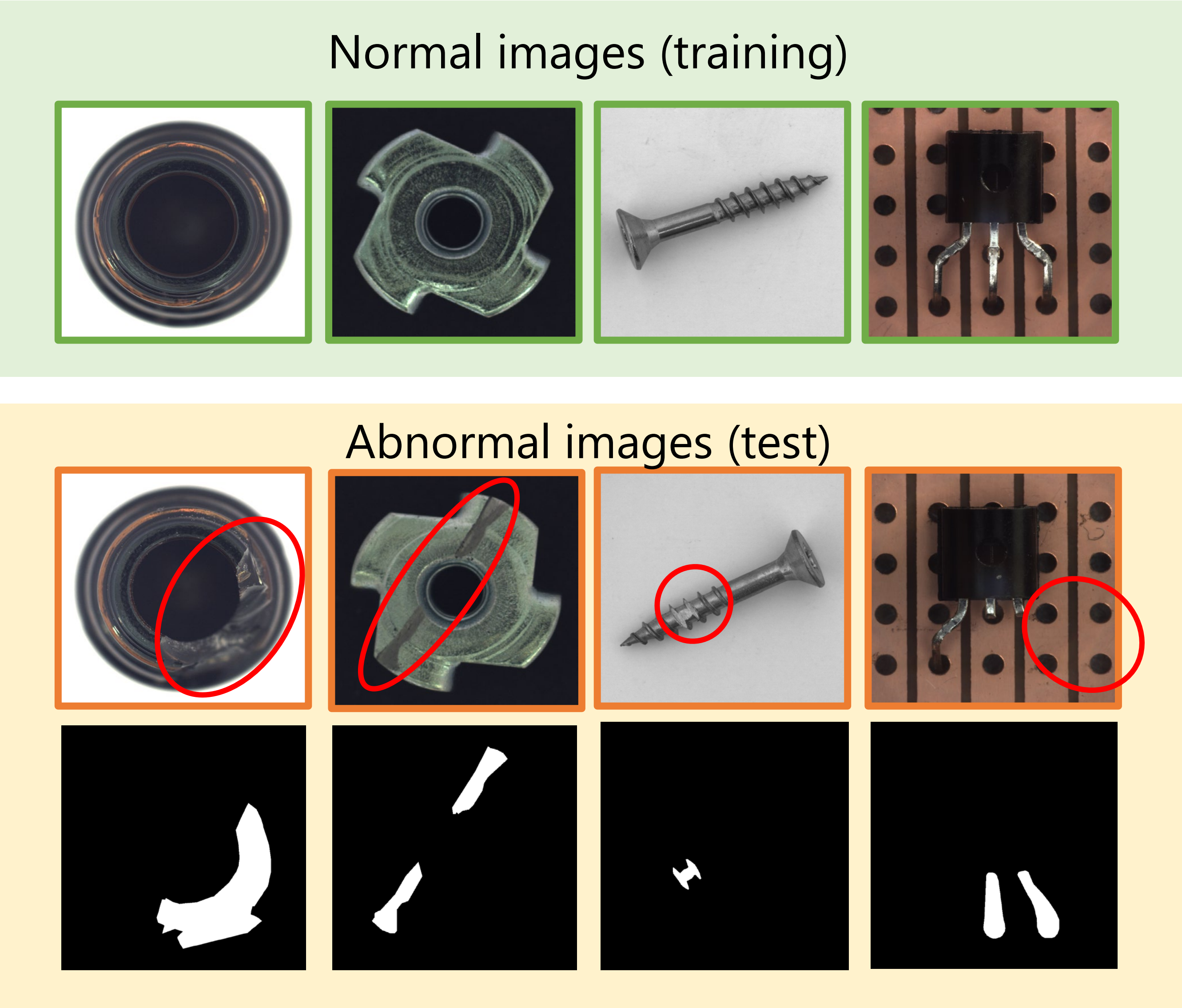
Task

To automatically identify defect regions in product images

Constraints

Only normal images are available at training time due to the limited number of defect images.

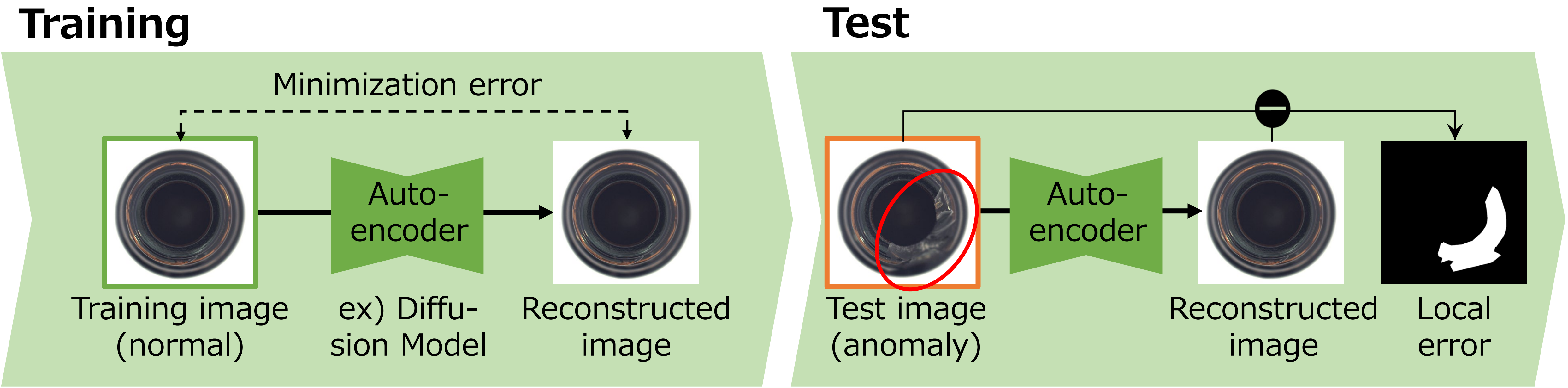
→ <u>Need to construct anomaly detectors by training normal images.</u>



Reconstruction-Based Approaches

Based on an image autoencoder trained with normal images, defect regions are detected by local reconstruction error.

[e.g., V. Zavrtanik+, ICCV’21; H. Zhang+, arxiv’23]



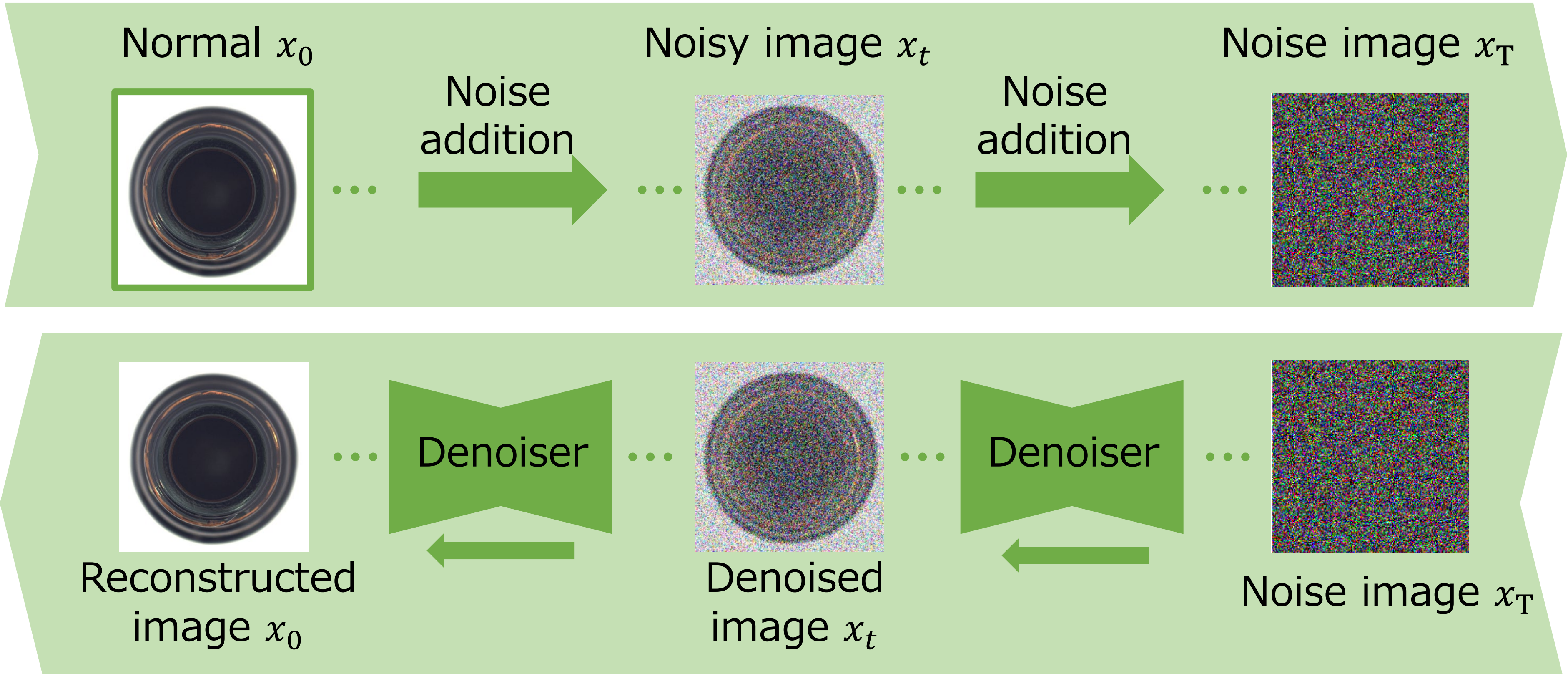
An image autoencoder is trained with only normal images.

Under the hypothesis that reconstruction for unlearned defect region fails, local defect regions are identified.

Diffusion Models [J. Ho+, Neurips'20]

Generative models that mimic inverse diffusion process

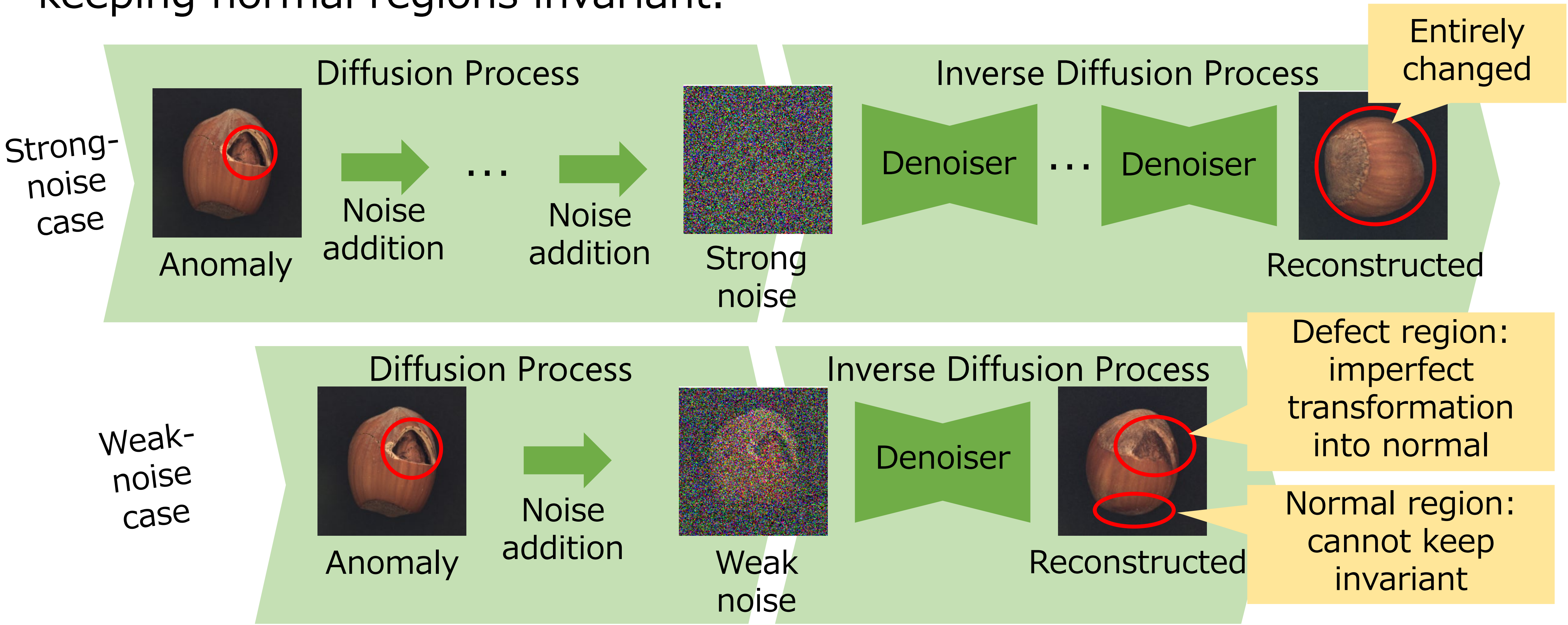
Diffusion process: incremental noise superposition



Inverse Diffusion Process: step-by-step denoising

Issues of Diffusion Model-Based Anomaly Detection

Sometimes struggles to change defect regions into normal ones with keeping normal regions invariant.

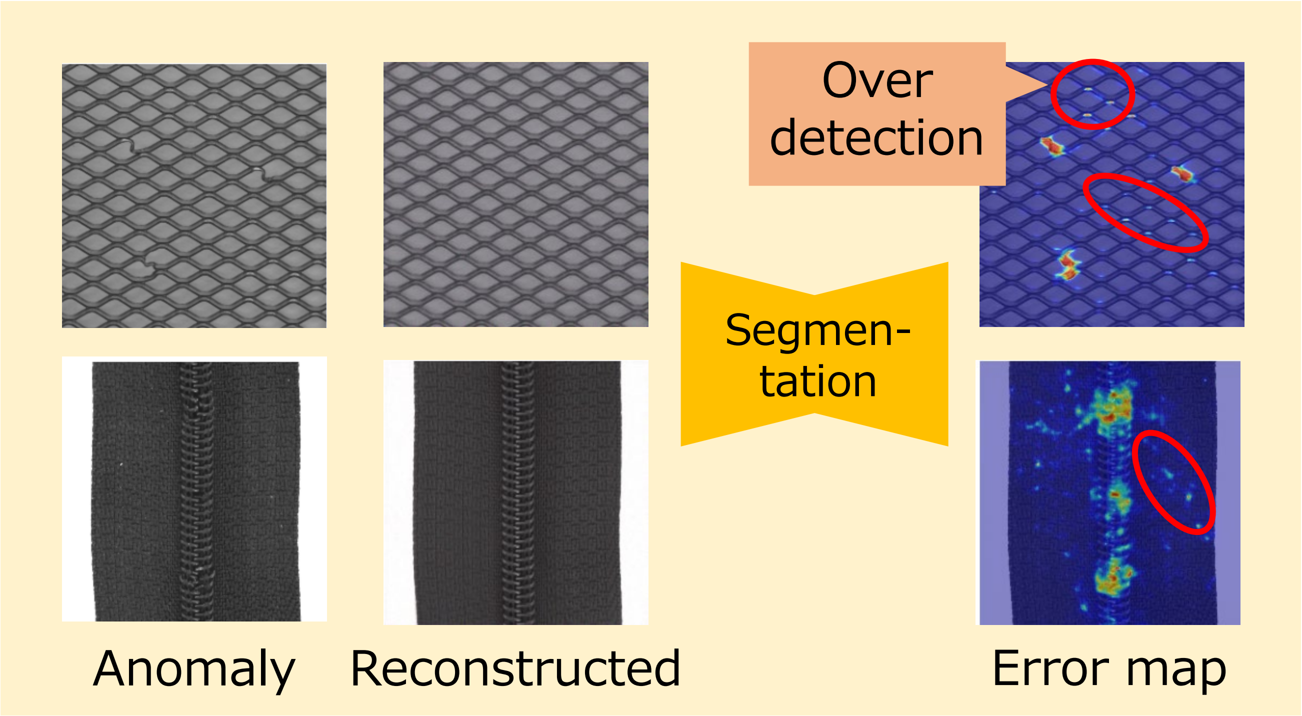


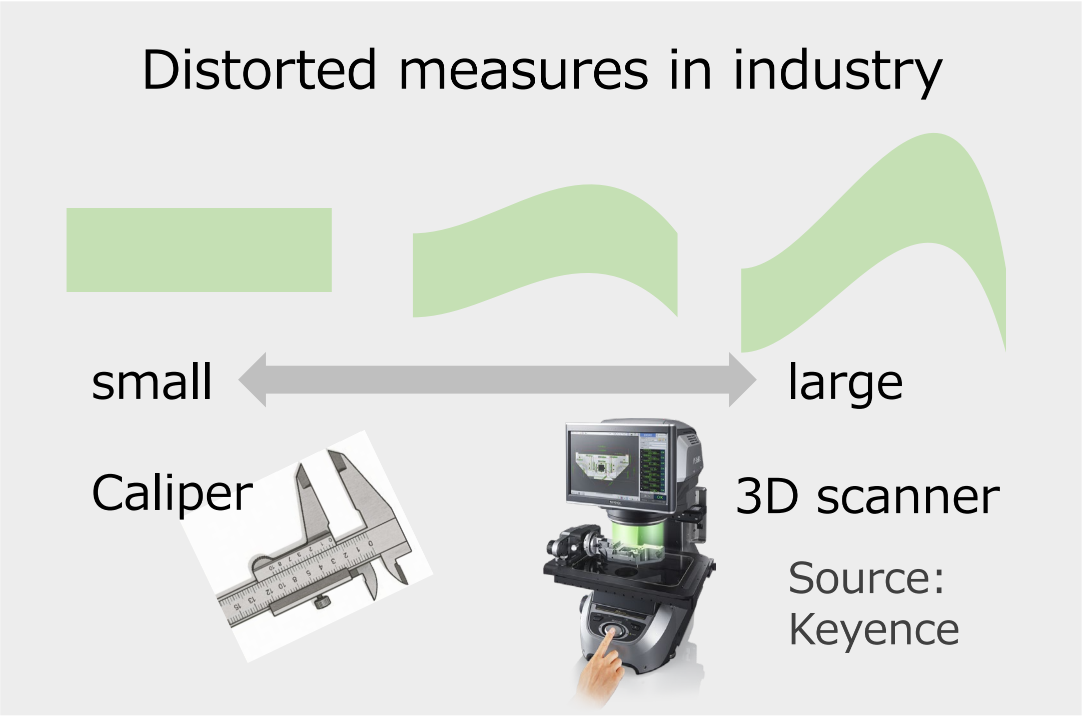
Issues of Diffusion Model-Based Anomaly Detection

Case of DiffuionAD [H. Zhang+, arxiv’23]

☹ Tendency of over detection due to imperfect reconstruction

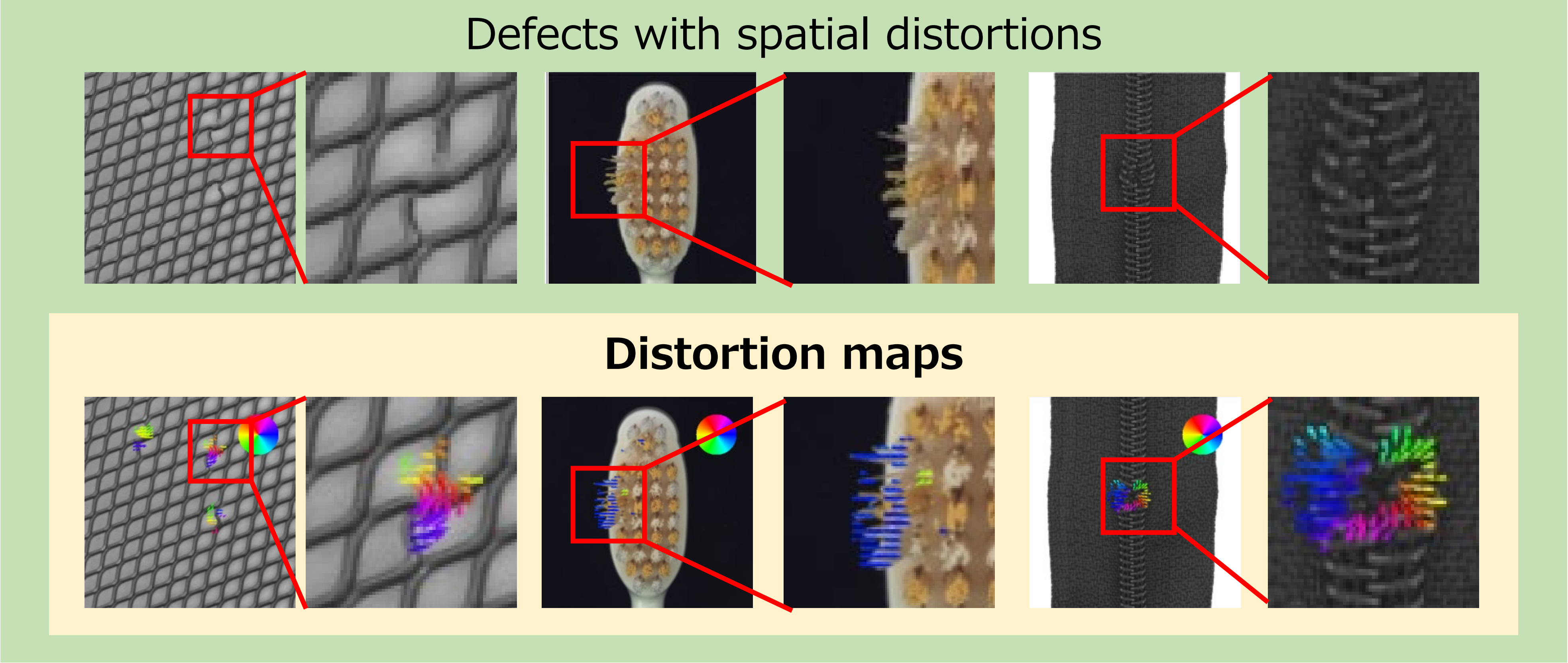
☹ Unclear relationship from the distortion measures adopted in industry





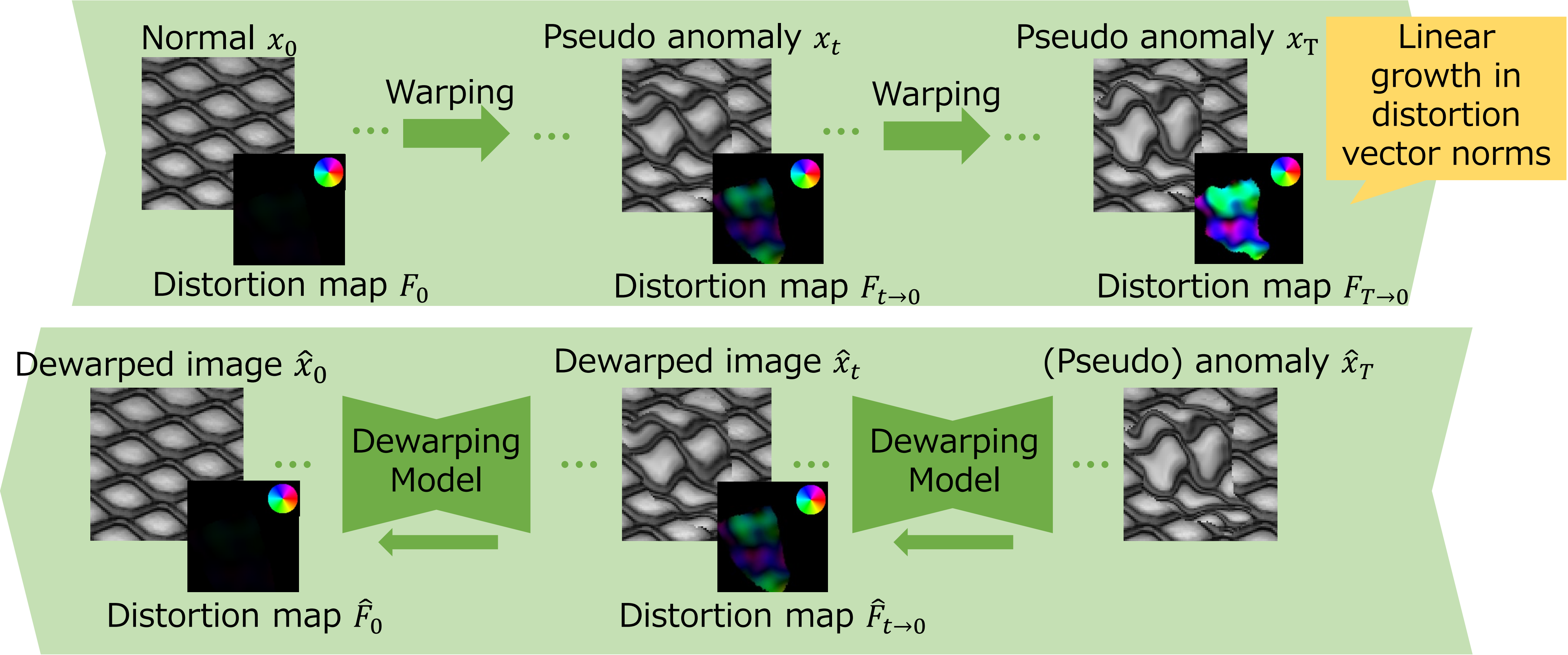
Aim of Our Research

- Approximately infers distortion strengths for anomaly samples
- No noise is added at test time



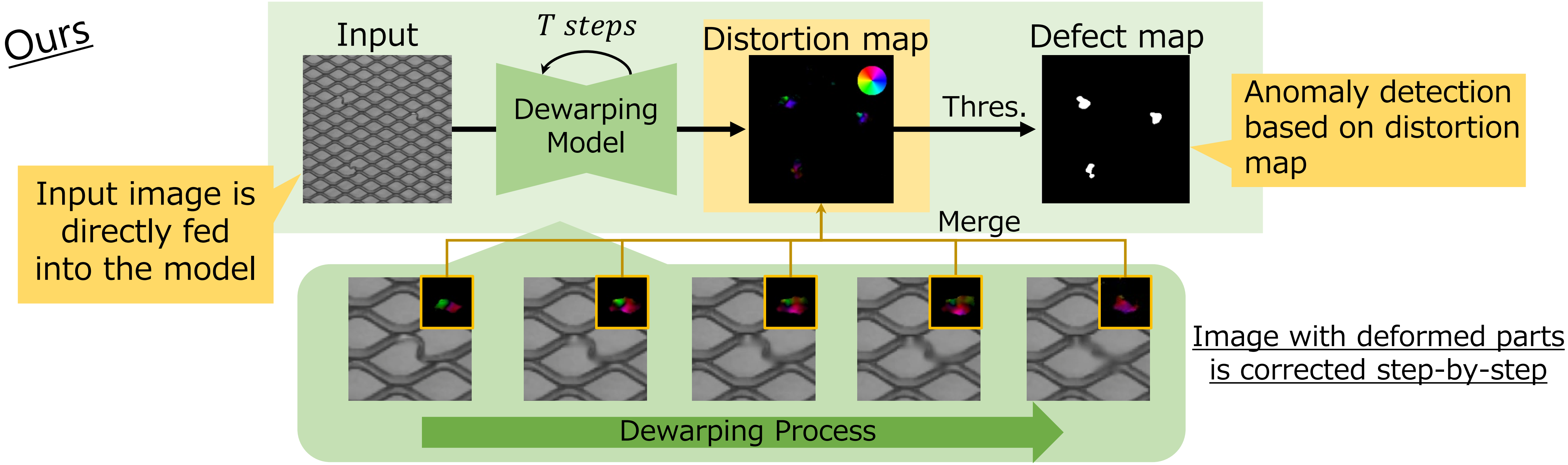
DiffuDewarp: Warping-Based Diffusion Model for Anomaly Detection

Diffusion Process: Step-by-step random warping mimicking spatial distortions



Inverse Diffusion Process: Step-by-step dewarping for time reversal

DiffuDewarp: Requiring No Noise at Test Time



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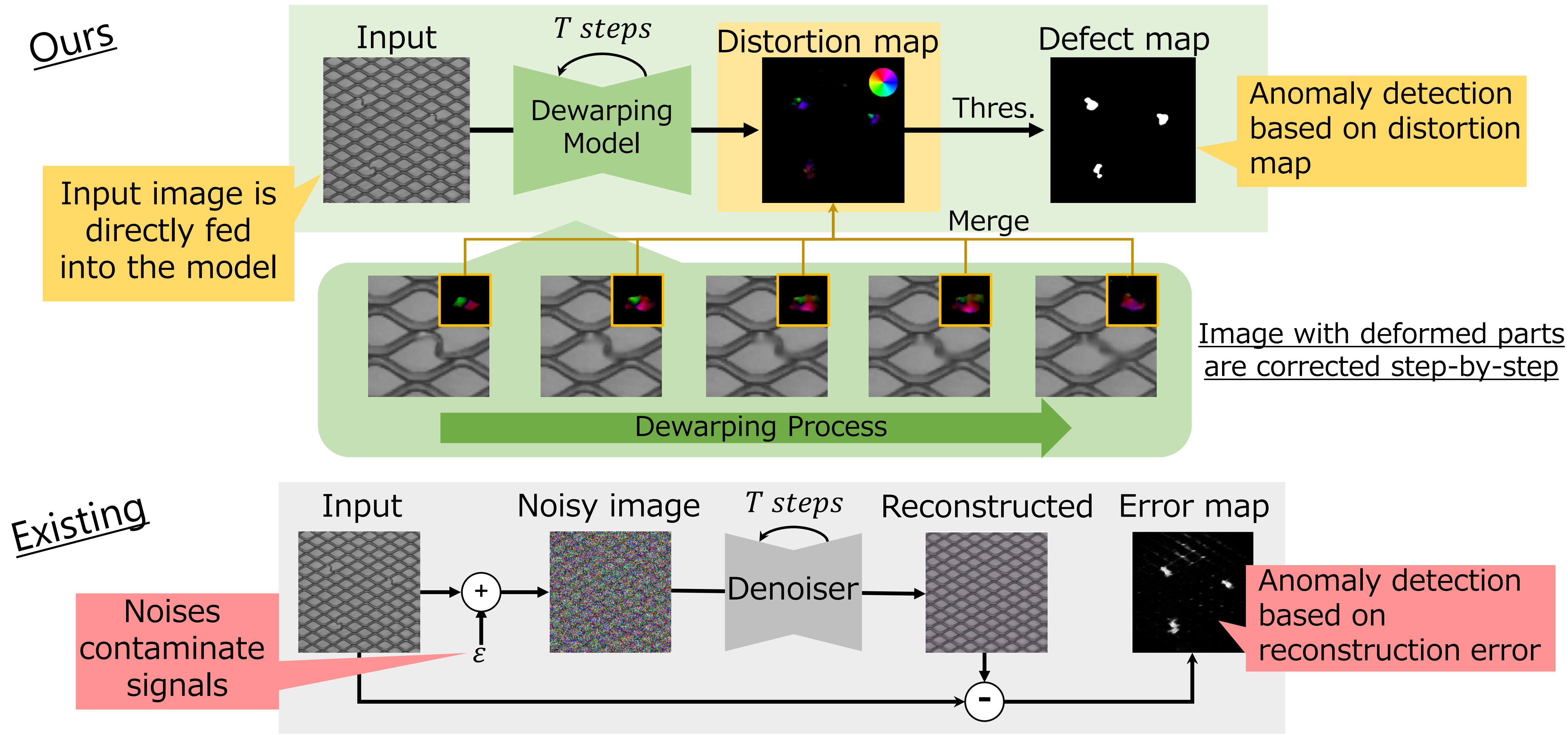
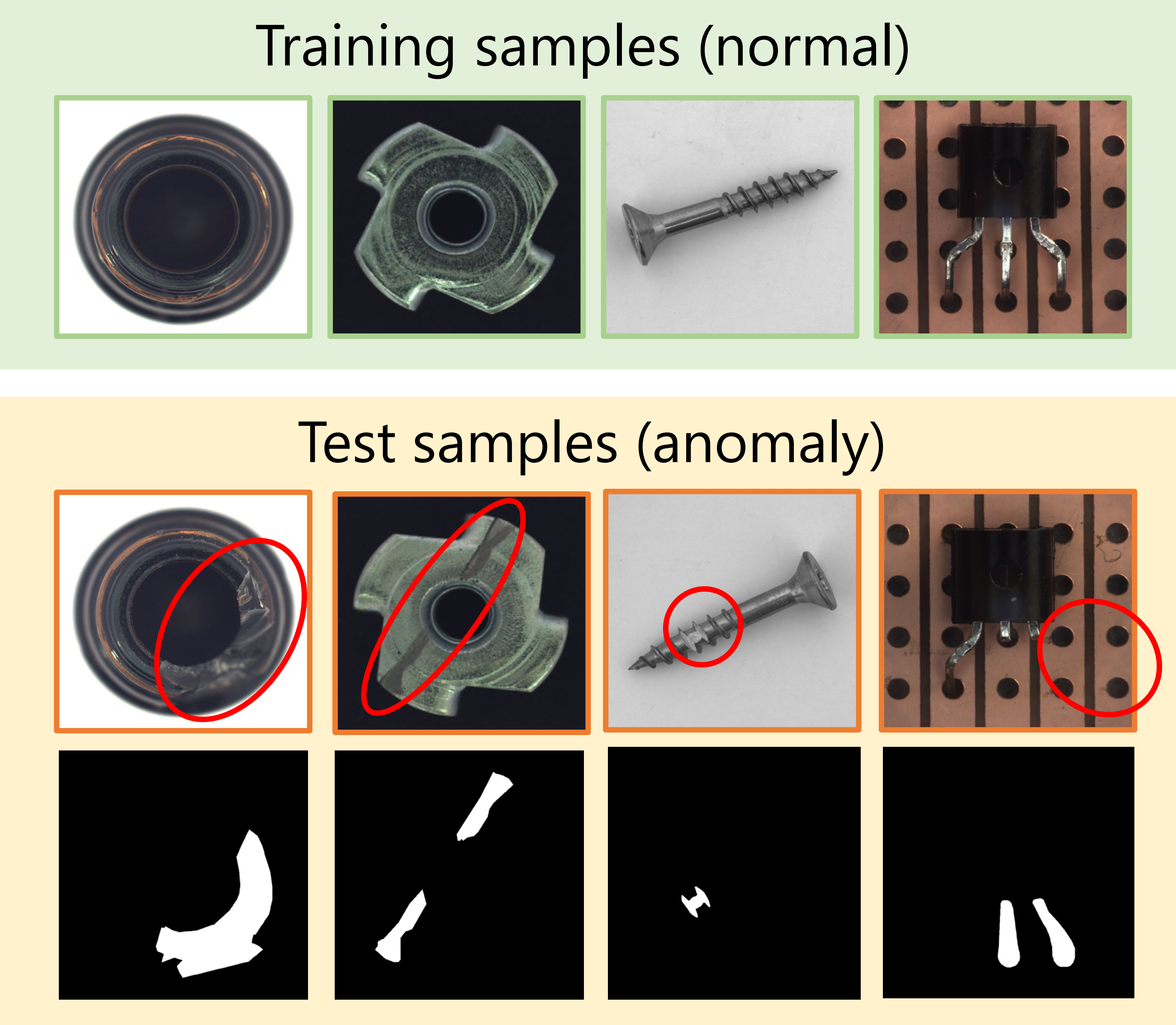


Evaluation Settings

Dataset

MVTec AD [P. Bergmann+, CVPR2019]
- Training set:
  - 100-300 normal images / category
- Test set:
  - ~100 normal & defect images / category



Model constructions

Constructed category-wise Diffusion Models with U-Net architecture

Metric

Pixel level AUROC
(Area under the ROC curve)

3 Evaluation Scenarios

1. We evaluate categories where defects are caused mainly by spatial distortions ('Grid', 'Toothbrush', 'Zipper').

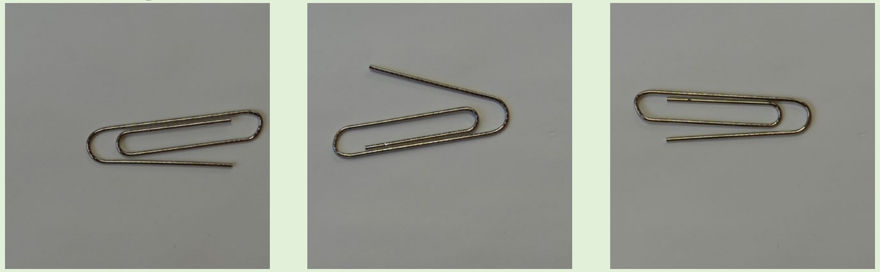
2. We evaluate categories where defects are caused by spatial distortion and discoloration ('Screw', 'Carpet', 'Leather', 'Wood').

3. We evaluate distortion strength prediction accuracy on our AnoClip dataset.

1 'Grid', 'Toothbrush', 'Zipper'

2 'Screw', 'Carpet', 'Leather', 'Wood'

3 Our AnoClip dataset for distortion strength prediction evaluation



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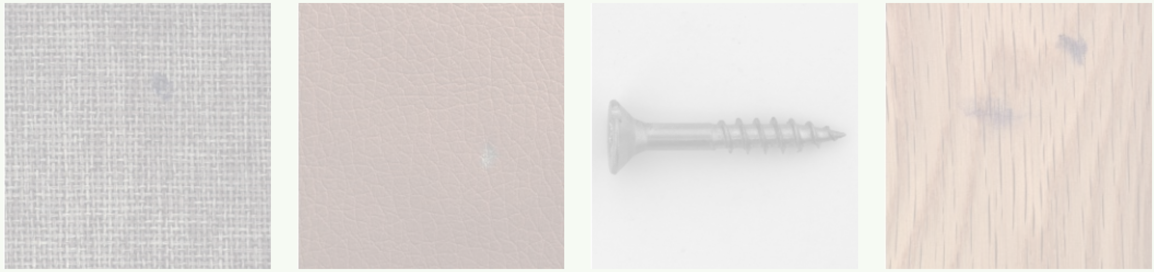

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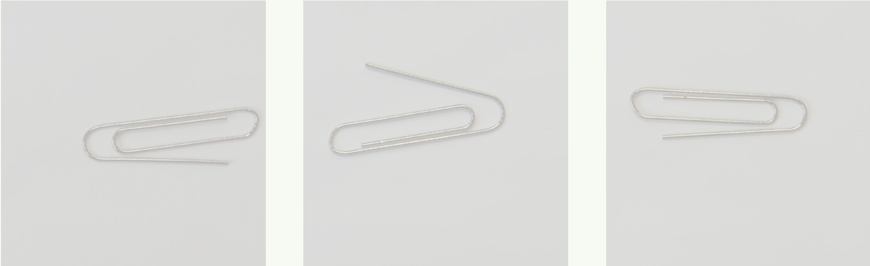


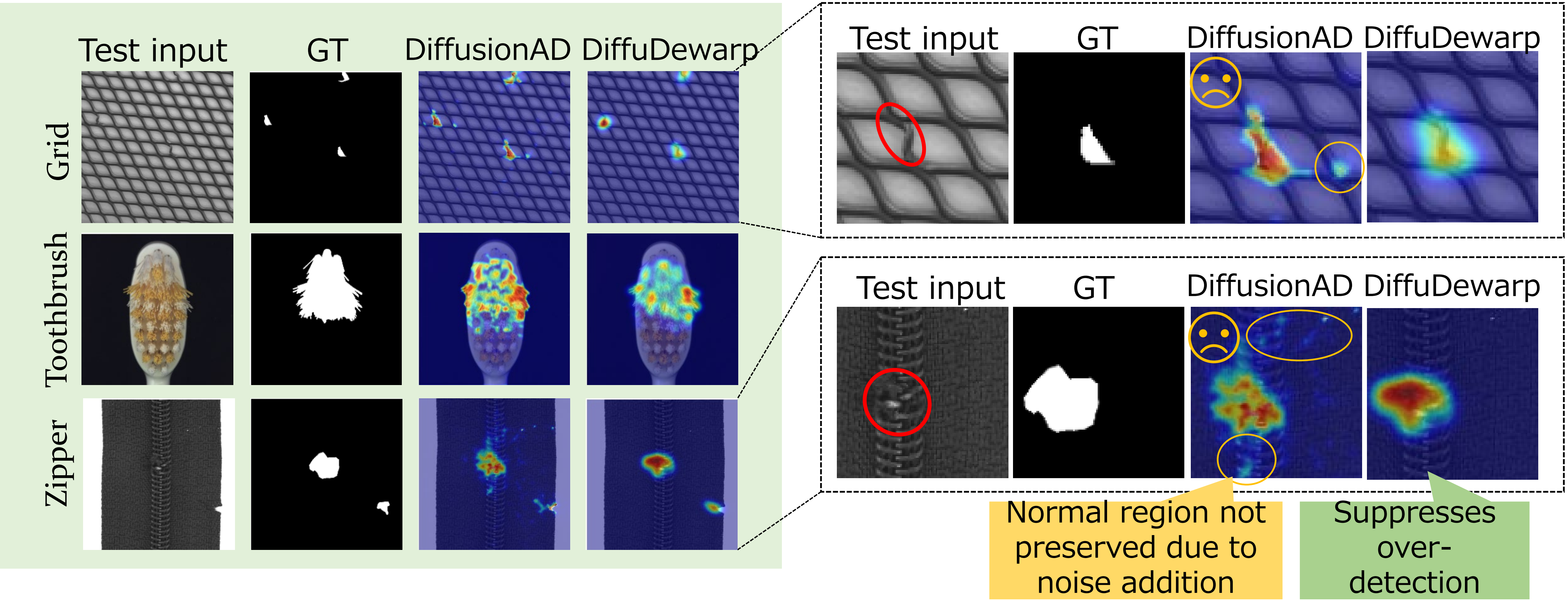
Quantitative Results (AUROC[%]↑)

Without a need of segmentation network, our DiffuDewarp outperforms DiffAD, TransFusion, DiffusionAD, AnomDiff, DDAD, and MDPS on average.

	With segmentation network			Without segmentation network			
	DiffAD Zhang+ ICCV'23	TransFusion Fucka+ ECCV'25	DiffusionAD Zhang+ arxiv'23	AnomDiff Lu+ ICCV'23	DDAD Mousakhan+ arxiv'23	MDPS Wu+ IJCAI'24	**DiffuDewarp (ours)**
Grid	**99.7**	99.4	**99.7**	99.1	99.4	99.4	99.4
Tooth brush	99.2	97.6	98.8	98.9	98.7	98.8	**99.3**
Zipper	99.0	98.5	99.2	97.6	98.2	98.5	**99.4**
Ave	99.3	98.5	99.2	98.5	98.8	98.9	**99.4**

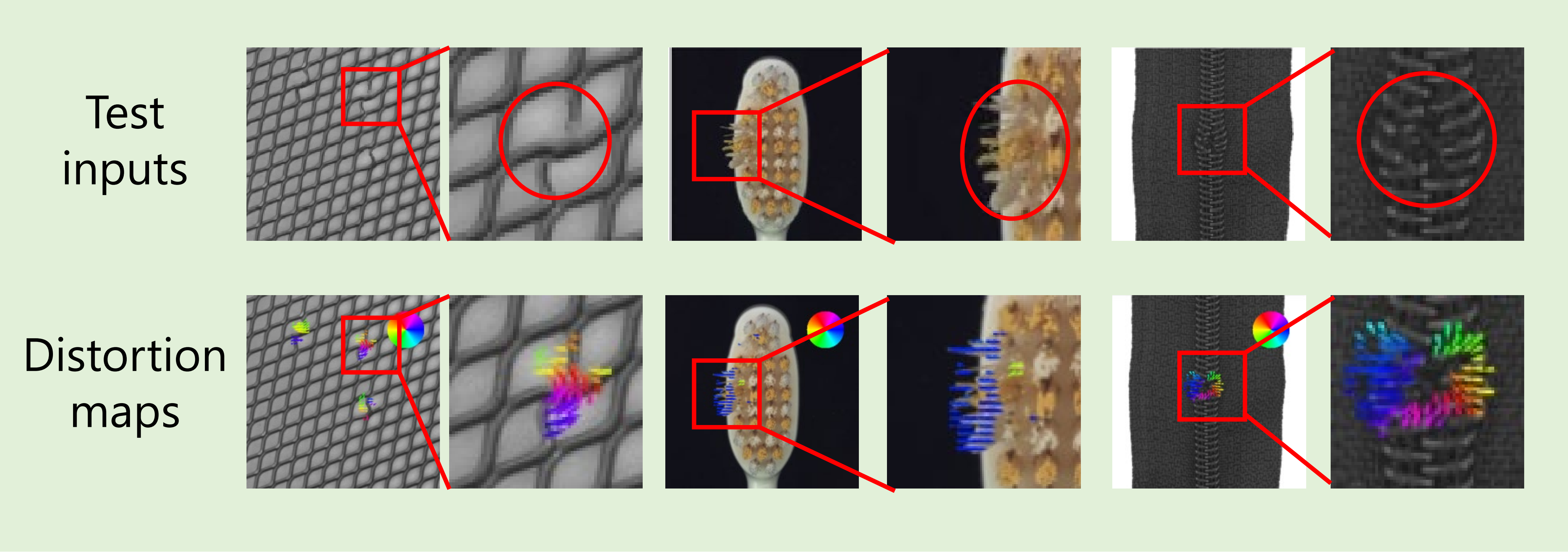
Qualitative Results (1/2)

Our DiffuDewarp well suppresses over-detection without a need of segmentation network, thanks to noise-free inference.



Qualitative Results (2/2)

DiffuDewarp computes distortion maps containing local displacement vectors.



Summary

<u>Aim</u>

To develop an anomaly detector
- approximately infers distortion strengths for anomaly samples
- no noise is added at test time

<u>Method</u>

DiffuDewarp based on local warping mimicking local spatial distortion

<u>Results</u>

✓ DiffuDewarp outperforms existing diffusion-based anomaly detectors.

✓ Computed distortion maps well approximate physical distortions.