Few-Shot Anomaly-Driven Generation for Anomaly Classification and Segmentation

Guan Gui[1], Bin-Bin Gao[1], Jun Liu, Chengjie Wang and Yunsheng Wu

Tencent YouTu Lab

AnoGen Code

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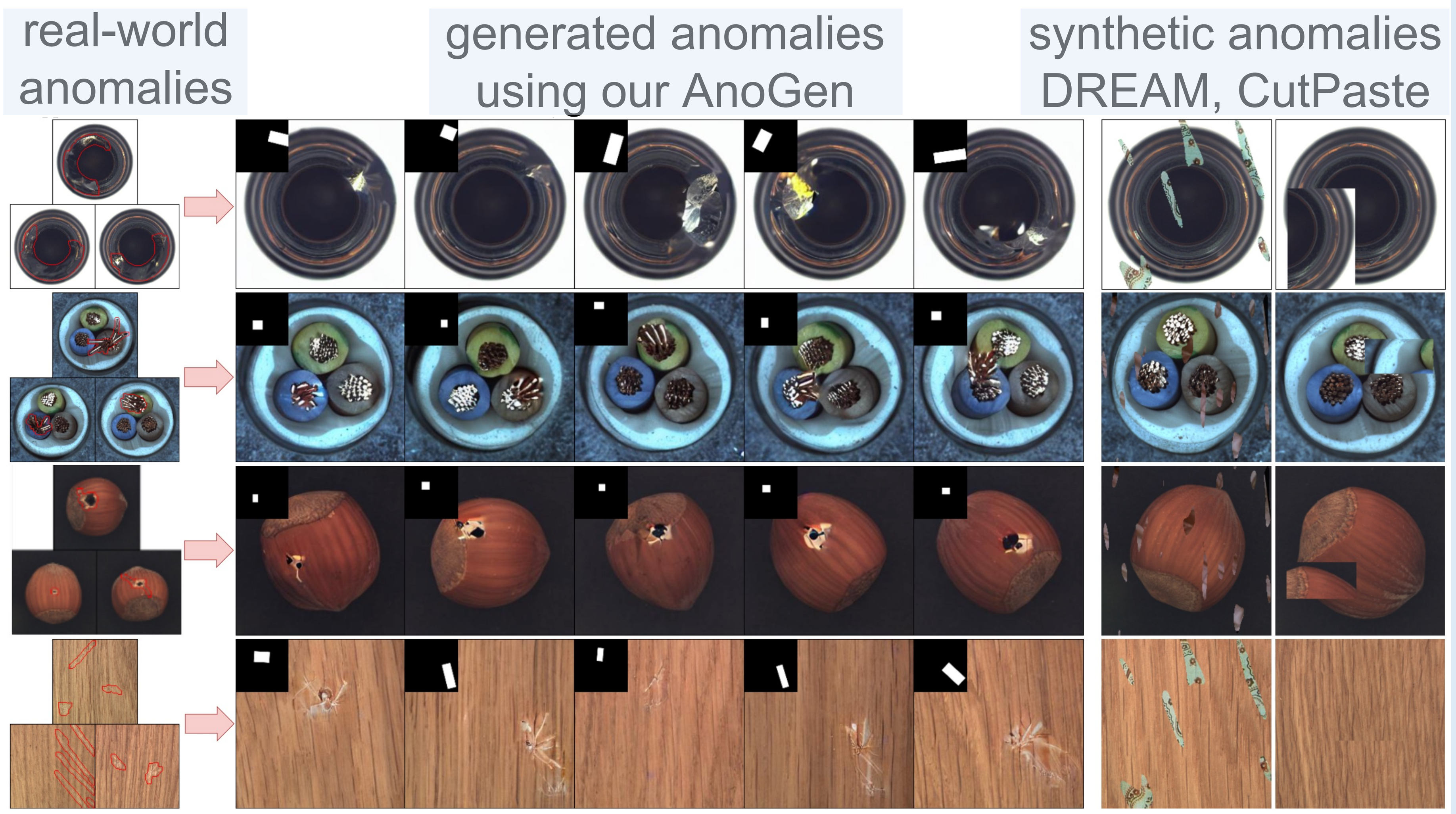
1. Introduction

Anomaly Detection Challenges

Challenge 1: The anomaly data in the real-world is extremely scarcity, making the AD tasks highly challenging.

- ✓ Most unsupervised learning methods perform poorly in anomaly segmentation due to the lack of discriminative guidance from anomaly data.
- ✓ Recent works, e.g., DRAEM, CutPaste, and SimpleNet, attempt to synthesize anomalies, bringing superior anomaly segmentation performance. However, the improvements are limited because there is a semantic gap between real and synthesized anomalies.



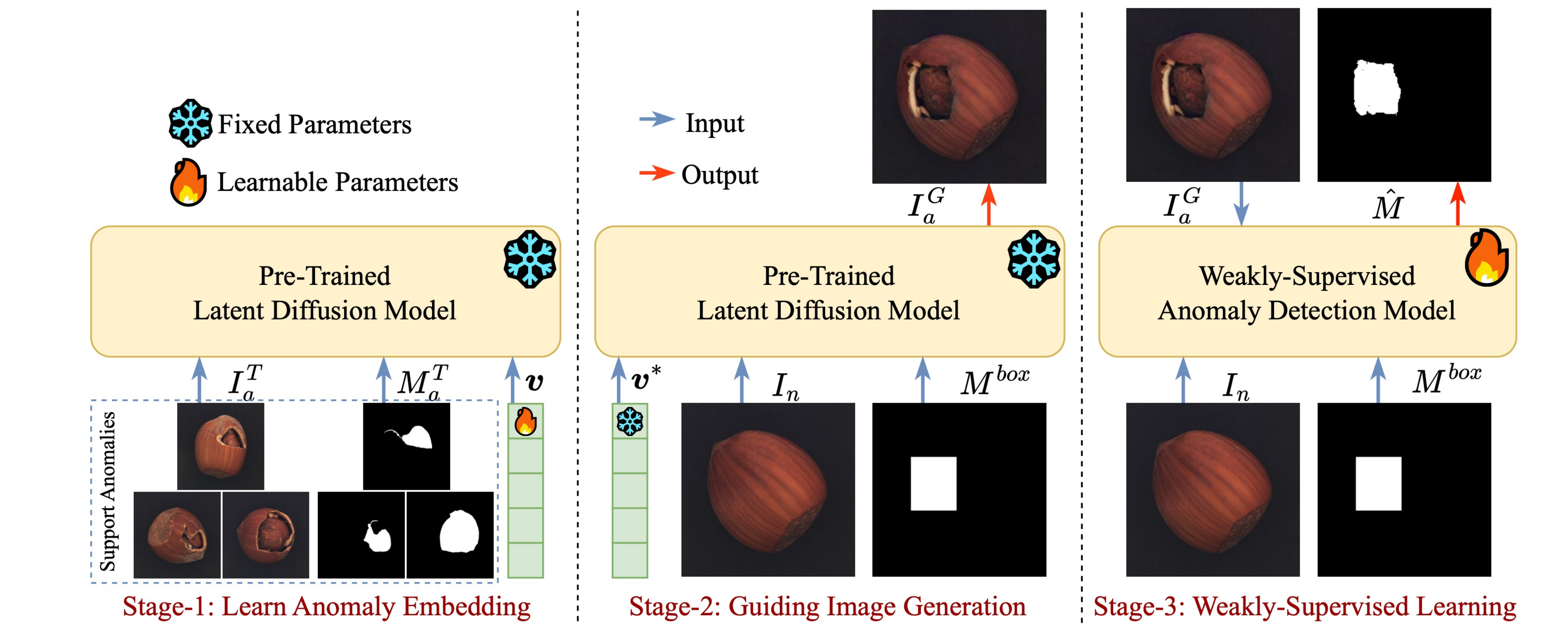
Challenge 2: Generative modes, e.g., GANs and LDMs, achieve remarkable progress in creating realistic and diverse images, but they require a large number of training images.

Challenge 3: It is difficult to obtain accurate defect masks for generated images using generative modes.

Inspiration: How to generate realistic and diverse anomaly images with generative models given only few-shot real anomaly images?

2. Our Method: AnoGen

AnoGen Framework



Stage 1: Learn Anomaly Embedding

Learning anomaly embedding given few–shot anomaly images. Initialize an embedding v to replace the condition embedding in LDM, and then optimize it with real-world anomaly images I_a^T,

$$v^* = \arg\min_{v} L_{LDM}(I_a^T, t, v)$$

Stage 2: Guiding Anomaly Generation

Generating realistic, diverse and controllable anomaly images.

- ✓ randomly sample a normal image I_n, and give a bounding box mask M^{box}
- ✓ freeze the embedding v^* and inject it into the image as a condition
- ✓ at inference, the area within the box will be retained, and the area outside the box will be replaced by the noisy version of I_n

$$z_t = z_n^t \odot (1 - M^{box}) + z_t' \odot M^{box}$$

Stage 3: Weakly-Supervised Anomaly Detection

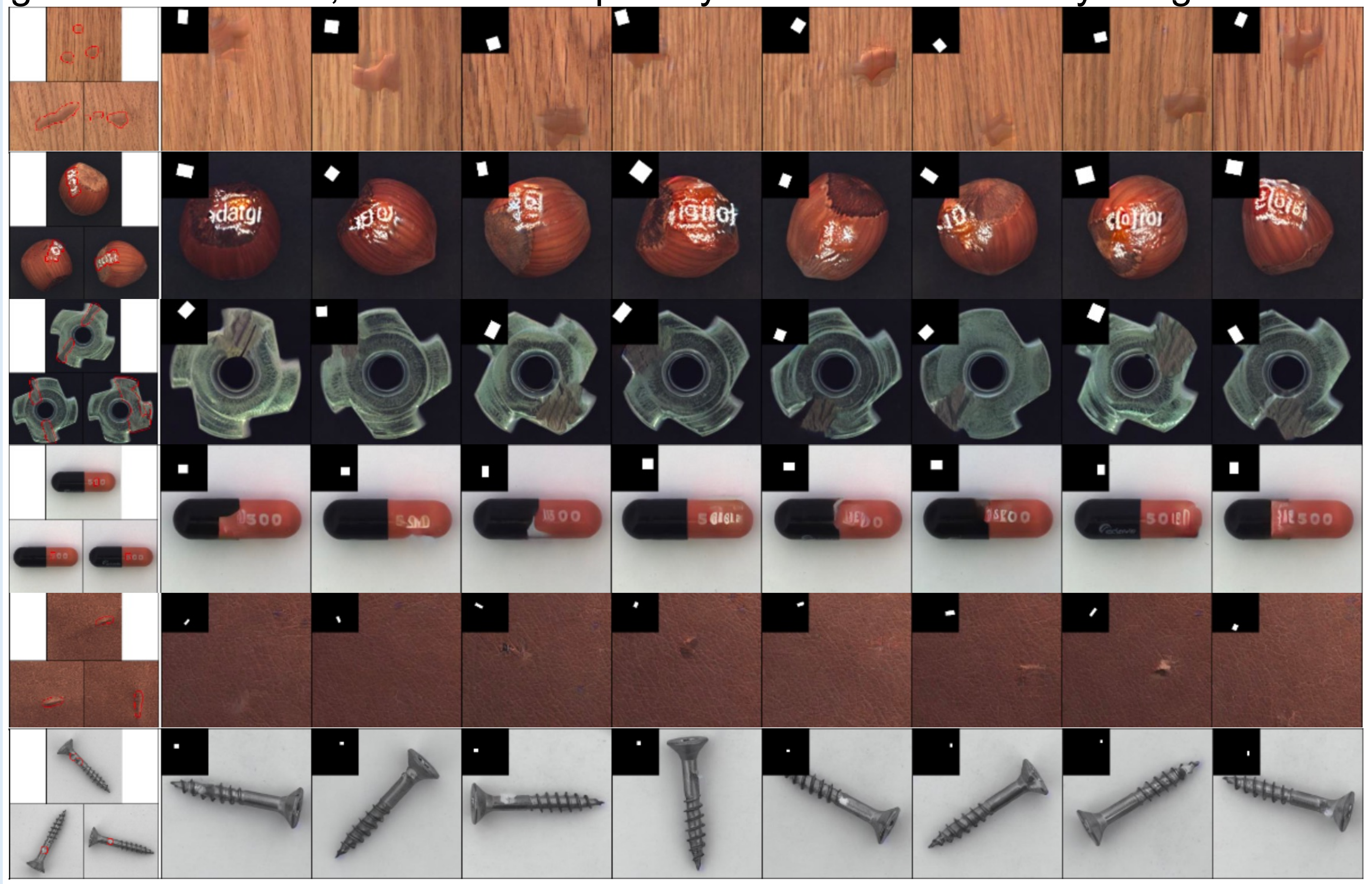
Reducing the confliction of possible normal pixels within the bounding box.

- ✓ For high-confidence normal pixels within the box region, we set their loss to 0;
- ✓ For all pixels out of the box, we use the default segmentation loss;

3. Experiments

3.1 Generated Anomaly Images

By using three real anomaly images as a driving, we have successfully generated diverse, realistic and spatially controllable anomaly images.



3.2 Comparisons on Anomaly Classification and Segmentation

Metrics		CS-FLow	PaDim	PatchCore	RD4AD	DRAEM	**AnoGen**	DeSTSeg	**AnoGen**
Image	AU-ROC	97.5	91.2	97.8	98.7	97.1	**98.7** (1.6 ↑)	98.3	**98.8** (0.5 ↑)
	AU-PR	97.7	94.2	98.8	97.8	98.5	**99.5** (1.0 ↑)	99.4	**99.6** (0.2 ↑)
Pixel	AU-ROC	93.4	96.9	97.5	93.9	96.8	**98.1** (1.3 ↑)	98.2	**98.8** (0.6 ↑)
	AU-PR	59.6	48.5	61.7	55.4	67.4	**73.2** (5.8 ↑)	76.6	**78.1** (1.5 ↑)

Generated anomalies effectively improve the model performance of both anomaly classification and segmentation tasks simultaneously.

k-shot		1	3	5
Image	AU-ROC	97.7	98.7	98.6
	AU-PR	98.9	99.5	99.5
Pixel	AU-ROC	97.6	98.1	98.2
	AU-PR	70.5.	73.2	73.0

leaning embedding		mask	non-mask
Image	AU-ROC	98.7	97.8
	AU-PR	99.5	98.7
Pixel	AU-ROC	98.1	97.6
	AU-PR	73.2	70.4

support set		1-st set	2-nd set
Image	AU-ROC	98.7	98.5
	AU-PR	99.5	99.1
Pixel	AU-ROC	98.1	97.7
	AU-PR	73.2	71.4