Wavelet-Driven 3D Anomaly Detection with Pose-Agnostic and Sparse-View Supplementary Materials

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Overview

The supplementary material presents the following sections to strengthen the main manuscript:
Sec. A shows more ablation studies.
Sec. B shows more quantitative comparisons.
Sec. C shows more qualitative comparisons.

A. Ablation Study

Table 5 presents the per-category ablation results on the PIAD_synt (20%) dataset, evaluating the effectiveness of each proposed component: SWGM (Structure-aware Wavelet-optimized Gaussian Modeling), WPE (Wavelet-based Pose Estimator), and WDAD (Wavelet Difference-aware Anomaly Detector). Compared to the full model ("All"), the removal of any single component results in a performance decline in both pixel-level and image-level AUROC. Notably, the absence of WPE causes the most substantial drop, reducing the mean image-level AUROC from 82.34 to 78.65, underscoring the critical importance of Wavelet-based matching verification and pose optimization in addressing sparse-view challenges. The complete model consistently outperforms others across most object categories, highlighting the synergistic contributions of all three components.

B. Quantitative Comparison

Quantitative comparison of each category on MAD_sim. Table 1 and Table 2 report the per-category performance of Wave-Pose3D and three state-of-the-art PAD methods (OmniPoseAD [3], SplatPose [1], and PIAD [2]) on the MAD_sim dataset under 10% and 20% sparse-view settings, respectively. Across both configurations, our method consistently achieves the highest average AUROC at both pixel and image levels. Specifically, Wave-Pose3D attains a mean pixel-level AUROC of 94.0 and 95.1 under 10% and 20% settings, outperforming PIAD by 1.6% and 2.1%, respectively. At the image level, our approach yields 64.6 and 69.1 average AUROC, showing clear improvements over the best-performing baseline PIAD (60.2 and 64.5). Notably, our method achieves the highest scores in the majority of object categories (e.g., Gorilla, Pig, Bear, Scorpion), demonstrating its robustness in both fine-grained anomaly localization and holistic detection, even under severe view sparsity.

Quantitative comparison of each category on PIAD_synt. Table 3 and Table 4 show per-category results on the PIAD_synt dataset under 10% and 20% sparse-view settings. Across both configurations, Wave-Pose3D consistently outperforms OmniPoseAD, SplatPose, and PIAD on both pixel-level and image-level AUROC. At 10% sparsity, our method achieves a mean pixel AUROC of 96.3 and image AUROC of 73.2, surpassing the best baseline (PIAD) by 1.1% and 5.8%, respectively. When increasing to 20% views, Wave-Pose3D further improves to 97.8 (pixel) and 82.3 (image), ranking first in most categories and demonstrating strong robustness and generalization under limited view conditions.

C. Qualitative comparison

Figure 1 shows a qualitative comparison with PIAD in a 20% sparse setting. It can be seen that our method can predict more accurate poses, reconstruct accurate and anomaly-free objects, and ultimately obtain precise positioning results.

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Objects	P_AUROC				I_AUROC			
	OmniPoseAD (NeurIPS23)	SplatPose (CVPRW24)	PIAD (CVPR25)	Wave-Pose3D Ours	OmniPoseAD (NeurIPS23)	SplatPose (CVPRW24)	PIAD (CVPR25)	Wave-Pose3D Ours
01Gorilla	88.1	91.1	92.5	**95.2**	51.9	53.9	50.2	**57.7**
02Unicorn	90.2	90.8	92.6	**95.5**	52.6	52.5	53.4	**69.4**
03Mallard	92.1	91.2	93.3	**94.4**	59.2	62.2	64.2	**65.6**
04Turtle	91.2	90.8	91.0	**92.4**	55.5	53.7	59.4	**66.1**
05Whale	88.6	89.2	92.0	**93.6**	59.3	63.8	**66.0**	58.9
06Bird	89.4	91.1	92.5	**93.4**	51.4	56.7	53.8	**59.8**
07Owl	91.2	92.3	94.1	**94.7**	55.6	56.2	56.6	**64.4**
08Sabertooth	91.5	91.8	91.0	**93.7**	54.3	58.6	**61.9**	54.5
09Swan	85.4	88.1	92.3	**96.4**	55.6	61.3	62.7	**69.8**
10Sheep	94.3	93.7	**94.9**	94.2	65.3	62.8	62.3	**67.7**
11Pig	91.6	93.7	95.0	**95.9**	59.7	52.6	61.9	**65.5**
12Zalika	87.3	89.6	90.5	**93.6**	60.5	64.9	64.7	**66.8**
13Pheonix	85.7	90.5	**94.2**	92.4	57.6	59.7	62.4	**63.1**
14Elephant	83.1	81.2	83.9	**87.5**	62.4	61.9	64.2	**67.1**
15Parrot	86.2	89.2	90.0	**94.4**	61.3	62.6	**65.3**	59.8
16Cat	89.6	91.4	**95.5**	95.1	56.3	57.4	57.5	**70.3**
17Scorpion	88.2	87.6	89.9	**91.8**	51.6	53.4	62.4	**65.8**
18Obesobeso	90.2	91.6	**96.3**	94.2	52.3	54.6	62.3	**68.4**
19Bear	89.6	91.2	94.6	**95.8**	60.3	62.9	62.3	**67.7**
20Puppy	88.2	89.1	90.9	**94.9**	57.2	56.8	52.1	**63.4**
Mean	89.1	90.3	92.4	**94.0**	57.0	58.4	60.2	**64.6**

Table 1. Quantitative comparison of each category on the MAD_sim (10%) dataset. The best performance is highlighted in **bold**, while the second-best is underlined.

Objects	P_AUROC				I_AUROC			
	OmniPoseAD (NeurIPS23)	SplatPose (CVPRW24)	PIAD (CVPR25)	Wave-Pose3D Ours	OmniPoseAD (NeurIPS23)	SplatPose (CVPRW24)	PIAD (CVPR25)	Wave-Pose3D Ours
01Gorilla	88.3	92.1	93.5	**96.4**	56.9	55.4	57.6	**68.6**
02Unicorn	91.2	90.8	91.7	**96.3**	57.6	53.2	56.8	**76.7**
03Mallard	93.4	93.2	**95.1**	94.6	63.2	64.3	67.6	**68.2**
04Turtle	91.2	90.8	91.0	**93.5**	56.5	54.4	59.4	**68.2**
05Whale	89.4	91.2	93.0	**93.4**	59.3	65.4	**73.7**	66.3
06Bird	90.2	92.1	93.2	**95.3**	58.4	60.3	59.1	**62.8**
07Owl	93.6	92.3	94.9	**96.6**	55.6	54.2	58.5	**65.7**
08Sabertooth	92.5	91.8	93.4	**93.6**	56.3	59.7	**73.3**	61.8
09Swan	86.4	90.1	92.2	**95.5**	59.6	62.3	65.6	**71.2**
10Sheep	95.3	96.7	**97.3**	97.2	65.3	68.5	71.2	**71.6**
11Pig	90.6	93.7	95.7	**96.7**	59.7	54.2	61.3	**68.7**
12Zalika	88.6	89.6	91.0	**94.0**	60.5	62.9	**71.1**	68.4
13Pheonix	86.2	90.5	92.9	**93.2**	59.6	58.3	64.8	**65.5**
14Elephant	85.1	83.2	85.1	**90.8**	62.4	61.2	67.5	**70.0**
15Parrot	87.4	90.2	92.3	**94.7**	64.3	65.3	**66.8**	66.4
16Cat	90.6	93.4	96.3	**97.7**	60.3	58.3	63.2	**70.7**
17Scorpion	89.6	87.6	89.9	**93.7**	53.6	54.9	62.4	**77.7**
18Obesobeso	91.6	92.6	96.3	**97.2**	57.6	56.3	68.1	**74.4**
19Bear	92.6	91.2	94.6	**97.1**	65.3	68.5	64.0	**70.8**
20Puppy	90.1	89.3	91.3	**94.0**	61.2	62.3	57.6	**68.6**
Mean	90.2	91.1	93.0	**95.1**	59.7	60.0	64.5	**69.1**

Table 2. Quantitative comparison of each category on the PIAD_synt (10%) dataset. The best performance is highlighted in **bold**, while the second-best is underlined.

References

[1] Mathis Kruse, Marco Rudolph, Dominik Woiwode, and Bodo Rosenhahn. Splatpose & detect: Pose-agnostic 3d anomaly detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3950–3960, 2024. 1

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[3] Qiang Zhou, Weize Li, Lihan Jiang, Guoliang Wang, Guyue Zhou, Shanghang Zhang, and Hao Zhao. Pad: A dataset and benchmark for pose-agnostic anomaly detection. *Advances in Neural Information Processing Systems*, 36:44558–44571, 2023. 1

Objects	P_AUROC				I_AUROC			
	OmniPoseAD (NeurIPS23)	SplatPose (CVPRW24)	PIAD (CVPR25)	Wave-Pose3D Ours	OmniPoseAD (NeurIPS23)	SplatPose (CVPRW24)	PIAD (CVPR25)	Wave-Pose3D Ours
Axletree	94.3	96.4	97.0	**98.2**	64.4	68.8	73.7	**80.2**
Box	92.8	94.3	**95.7**	**95.7**	63.2	62.3	52.3	**63.7**
Can	96	96.5	97.9	**98.9**	74.5	73.4	84.0	**86.0**
Chain	96.8	98.0	97.9	**98.2**	62.4	61.2	**67.6**	64.6
Gear	93.4	94.3	93.4	**93.7**	57.4	65.4	**70.4**	65.3
Keyring	96.5	97.8	98.8	**98.9**	68.3	71.2	70.3	**76.2**
Motor	89.7	87.8	85.8	**91.6**	50.2	54.3	52.3	**64.6**
Parts	94.3	93.3	94.6	**94.8**	53.9	51.2	60.2	**68.7**
Picker	94.3	93.2	94.1	**94.5**	54.6	56.9	59.9	**65.5**
Section	92.6	96.5	98.8	**99.1**	69.9	73.4	80.7	**85.2**
Shaft	91.3	95.4	98.0	**98.5**	58.7	64.3	63.0	**77.9**
Spray_can	91.1	98.7	99.2	**99.4**	96.5	95.6	99.1	**99.3**
Spring	90.9	94.5	95.9	**97.9**	70.7	73.2	77.0	**80.7**
Sprockets	89.7	92.6	91.4	**95.3**	50.4	58.7	65.2	**78.8**
Amphora	87.6	90.2	**92.5**	92.3	48.9	65.4	54.6	**57.1**
Teapot	90.2	91.1	92.1	**94.4**	45.6	49.9	48.6	**57.9**
Mean	92.6	94.4	95.2	**96.3**	61.9	65.3	67.4	**73.2**

Table 3. Quantitative comparison of each category on the PIAD_synt (10%) dataset. The best performance is highlighted in **bold**, while the second-best is underlined.

Objects	P_AUROC				I_AUROC			
	OmniPoseAD (NeurIPS23)	SplatPose (CVPRW24)	PIAD (CVPR25)	Wave-Pose3D Ours	OmniPoseAD (NeurIPS23)	SplatPose (CVPRW24)	PIAD (CVPR25)	Wave-Pose3D Ours
Axletree	95.2	96.3	98.3	**98.7**	67.6	78.8	83.0	**84.3**
Box	94.1	94.4	96.5	**99.0**	63.4	65.4	58.9	**81.7**
Can	96.6	97.6	98.9	**99.1**	89.2	92.5	**93.5**	93.1
Chain	96.2	97.8	98.2	**98.3**	65.4	67.8	**75.8**	72.6
Gear	91.4	92.1	94.3	**94.8**	78.8	81.1	88.5	**90.3**
Keyring	95.4	97.1	98.9	**99.2**	68.7	71.2	**83.5**	80.8
Motor	90.1	91.2	90.6	**96.8**	61.3	63.2	67.8	**79.6**
Parts	94.4	95.5	95.2	**97.6**	62.6	58.9	68.0	**82.2**
Picker	91.2	92.3	94.9	**96.9**	63.0	53.2	61.0	**75.3**
Section	96.4	97.5	98.9	**99.3**	75.6	77.7	82.1	**92.5**
Shaft	94.3	97.3	**98.9**	98.6	76.5	78.2	**88.4**	79.5
Spray_can	97.6	98.9	99.2	99.5	95.6	97.8	99.1	**99.4**
Spring	94.3	97.4	**98.9**	98.8	71.0	72.2	77.6	**83.8**
Sprockets	91.2	93.9	93.9	**97.2**	67.5	69.8	75.5	**89.0**
Amphora	91.2	92.1	93.5	**94.8**	52.3	54.3	57.9	**62.0**
Teapot	91.3	91.4	92.8	**95.4**	56.7	54.1	45.5	**71.4**
Mean	93.8	95.3	96.4	**97.8**	69.7	71.0	75.4	**82.3**

Table 4. Quantitative comparison of each category on the PIAD_synt (20%) dataset. The best performance is highlighted in **bold**, while the second-best is underlined.

Object	Baseline		w/o SWGM		w/o WPE		w/o WDAD		All	
Axletree	97.3	77.0	**98.7**	84.0	98.4	82.5	**98.7**	**84.9**	**98.7**	84.3
Box	96.7	62.1	98.6	81.1	98.2	66.3	98.5	80.0	**99.0**	**81.7**
Can	98.1	81.7	99.1	90.5	99.1	86.6	98.8	91.9	**99.1**	**93.1**
Chain	97.6	70.4	98.3	**72.8**	**98.7**	86.3	98.2	72.7	98.3	72.6
Gear	94.2	74.9	94.7	83.4	94.7	80.5	94.2	85.2	**94.8**	**90.3**
Keyring	97.7	74.6	99.1	77.6	**99.3**	**85.4**	99.1	74.1	99.2	80.8
Motor	92.1	64.7	96.9	74.7	96.3	74.4	**96.8**	74.4	**96.8**	**79.6**
Parts	95.7	60.1	97.7	79.0	97.4	79.7	**97.8**	78.1	97.6	**82.2**
Picker	94.6	55.8	96.9	70.3	**97.2**	73.0	96.9	68.5	96.9	**75.3**
Section	97.5	85.9	99.2	87.7	99.2	86.3	99.1	89.9	**99.3**	**92.5**
Shaft	97.1	76.4	98.6	76.0	98.5	80.2	**98.6**	**84.3**	**98.6**	79.5
Spray_can	98.4	99.1	99.4	99.3	**99.5**	99.6	99.3	99.3	**99.5**	**99.4**
Spring	97.2	75.8	98.1	81.7	98.8	**86.5**	**99.0**	77.8	98.8	83.8
Sprockets	94.9	77.5	96.4	84.9	96.3	83.7	**97.2**	87.7	**97.2**	**89.0**
Amphora	93.2	61.8	95.1	58.3	**95.0**	57.6	94.4	61.1	94.8	**62.0**
Teapot	91.9	52.4	96.3	64.4	93.6	49.9	**95.8**	**73.3**	95.4	71.4
Mean	95.89	71.89	97.69	80.05	97.51	78.65	97.65	80.2	**97.75**	**82.34**

Table 5. Ablation study on PIAD_synt (20%) with per-category results of the proposed components. The best performance is highlighted in **bold**.

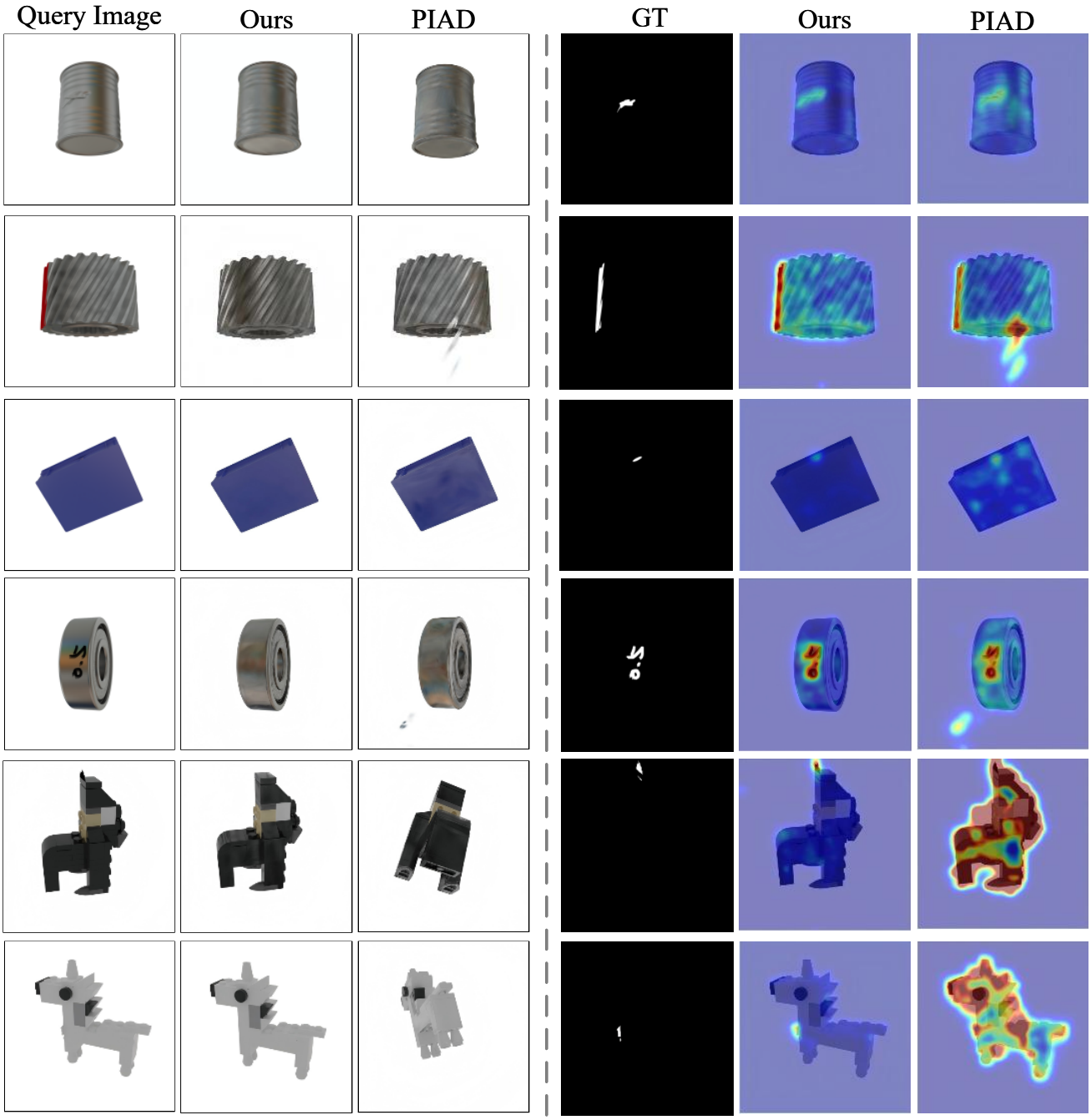

Figure 1. Qualitative visualization of pixel-wise anomaly segmentation compared to the state-of-the-art method PIAD in the 20% sparse view setting.The left side compares the rendered images produced by our method and baselines, while the right side visualizes the corresponding anomaly segmentation results.