JDATT: A JOINT DISTILLATION FRAMEWORK FOR ATMOSPHERIC TURBULENCE MITIGATION AND TARGET DETECTION

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1. INTRODUCTION

- **Problem:** Atmospheric Turbulence severely degrades images with blur, rippling, and noise (*see Figure 1*), hindering both quality and critical object detection tasks.
- **Limitation:** Current deep learning solutions are too computationally complex for real-time use, and handling mitigation and detection separately is inefficient.
- **Our Solution:** JDATT – A Joint Distillation framework that integrates turbulence mitigation and object detection into a single, efficient network for real-time deployment.

Figure 1: Wave-like distortion effect in video.

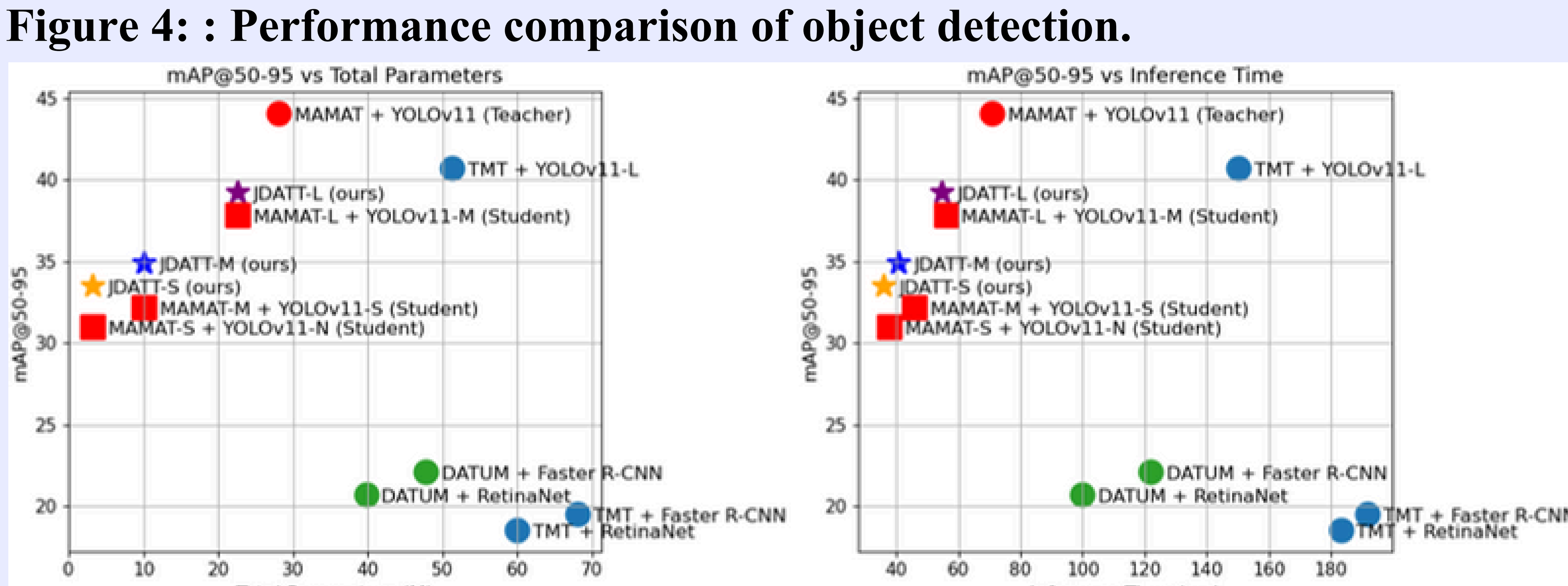
4. RESULTS

- **Superior Performance:** Our joint distillation consistently outperforms separate distillation, achieving higher image quality and detection accuracy for a given model size (*see Table 1 & Figure 3*).
- **Extreme Efficiency:** The JDATT-Small model reduces total parameters by 88.6% compared to the teacher model (*see Figure 4*).
- **Maintained Accuracy:** Despite massive compression, JDATT-Small shows a slight PSNR improvement with only a manageable drop in mAP (*see Table 1*).
- **Enhanced Robustness:** On challenging real-world data, JDATT provides more reliable distortion mitigation and object detection, reducing misses and errors (*see Figure 5*).

Table 1: Performance comparison on distillation models.

Model	param (M)↓	PSNR↑	SSIM↑	mAP (%)↑	Time (ms)↓
MAMAT+YOLOv11-L (Teacher)	2.8+25.3	23.40	0.66	44.11	70.9
Separate Distillation (Students)	0.6+2.6	23.37	0.61	33.18	37.6
Joint Distillation (JDATT-Small)	0.6+2.6	23.43	0.63	33.50	35.7
Joint Distillation (JDATT-Medium)	0.7+9.4	23.56	0.62	34.56	40.7
Joint Distillation (JDATT-Large)	2.5+20.1	23.63	0.64	39.26	54.6

Figure 4: : Performance comparison of object detection.



5 .CONCLUSION

- **Presents JDATT:** The first joint distillation framework unifying turbulence mitigation and object detection.
- **Delivers Efficiency & Performance:** Achieves substantial model compression while maintaining performance comparable to large teacher models.
- **Outperforms Convention:** Consistently beats separate distillation methods.
- **Enables Real-World Deployment:** Provides a practical solution for real-time, robust perception on resource-limited devices.

2. OBJECTIVE

- **Primary Goal:** Develop an end-to-end joint distillation framework that compresses atmospheric turbulence mitigation and target detection models while minimizing performance loss

3. METHODOLOGY

Training Mechanism

- Joint Distillation: Uses frozen expert teachers (MAMAT + YOLOv11) to co-train lightweight student models (*see Figure 2*)
- Bidirectional Feedback: Unified loss enables mutual enhancement
  - Mitigation learns to produce detection-friendly features
  - Detection guides restoration to preserve critical features

Efficient Architecture

- Shallower network structure
- Standard convolutions replace complex ones
- Reduced feature maps and core blocks (*see Figure 2*)

Distillation Strategy

- Feature-level: CWD aligns features, MGD focuses on key regions
- Output-level: KL divergence aligns detection results

Loss Function

- Reconstruction loss (Charbonnier)
- Detection loss (bbox regression + classification)
- Distillation losses (CWD + MGD + KL)

Figure 2: Overview of the proposed JDATT framework.

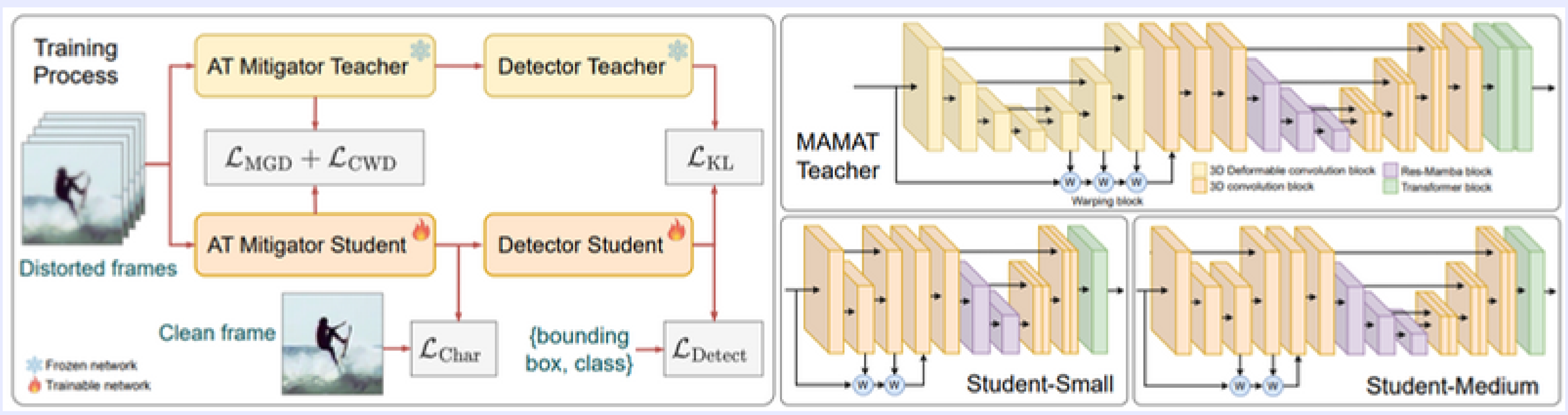


Figure 3: Results on synthetic atmospheric turbulence sequences of varying difficulty levels.

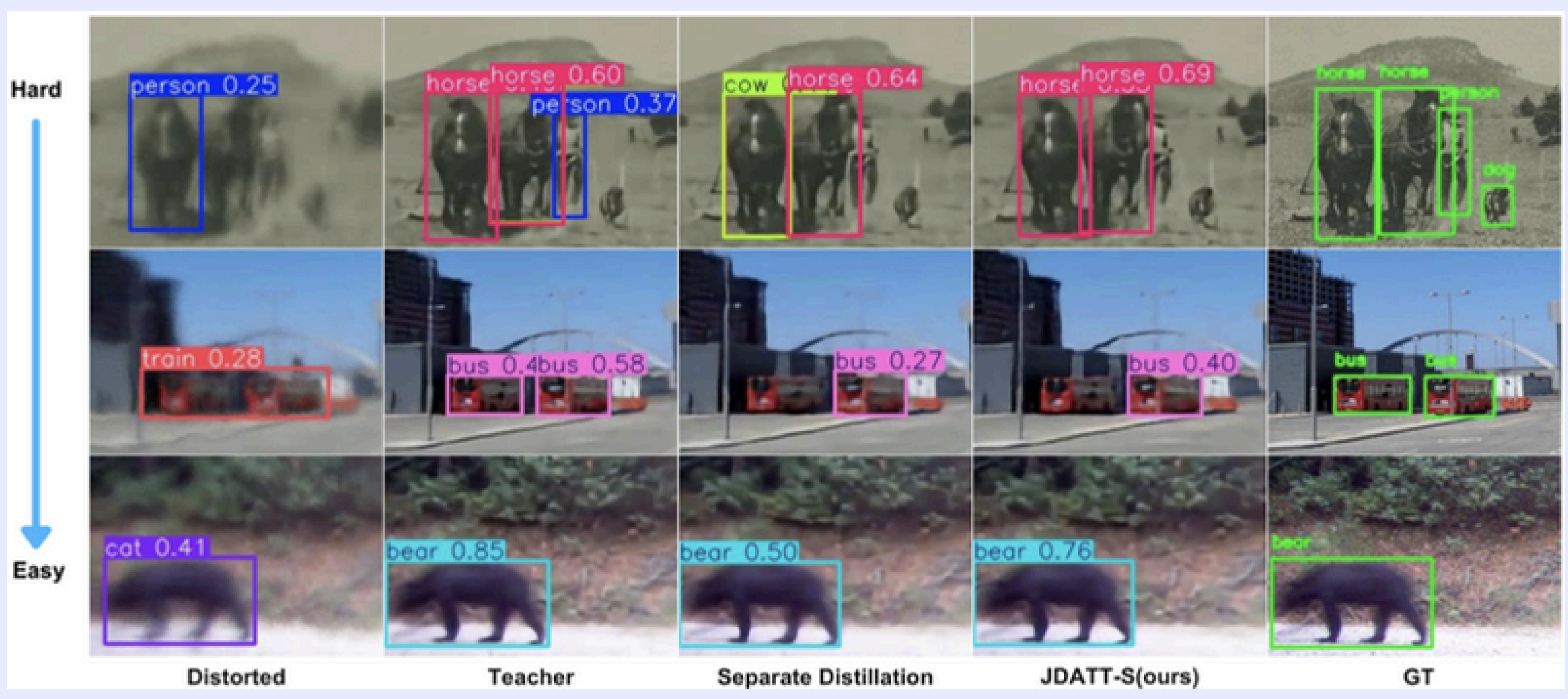


Figure 5: Results on real atmospheric turbulence data.