DMAT: An End-to-End Framework for Joint Atmospheric Turbulence Mitigation and Object Detection

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Abstract

- Atmospheric Turbulence (AT) degrades the clarity and accuracy of surveillance imagery, posing challenges not only for visualization quality but also for object classification and scene tracking. Deep learning-based methods have been proposed to improve visual quality, but spatio-temporal distortions remain a significant issue.
- In this paper, we propose a novel framework that learns to compensate for distorted features while simultaneously improving visualization and object detection.
- This end-to-end training strategy leverages and exchanges knowledge of low-level distorted features in the AT mitigator with semantic features extracted in the object detector.
- Specifically, in the AT mitigator a 3D Mamba-based structure is used to handle the spatio-temporal displacements and blurring caused by turbulence.
- Optimization is achieved through back-propagation in both the AT mitigator and object detector.
- Our proposed DMAT outperforms state-of-the-art AT mitigation and object detection systems up to a 15% improvement on datasets corrupted by generated turbulence.

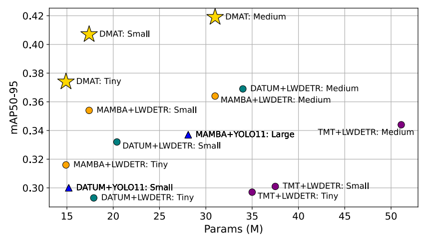


Figure 1. Object detection results for all object sizes and classes of our proposed method (DMAT) compared to individual AT-mitigation and object detection methods.

- Code: https://github.com/pui-nantheera/DMAT
- Dataset: https://zenodo.org/records/17673509

Methods

- Registration module: Incorporating a UNet-like architecture with deformable 3D convolutions. The registration module has a depth scale of 4. Larger kernels are used in the initial layers to provide a wider field of view.
- Enhancement module: Extracting features using 3D convolutions, then being processed in the 3D Mamba-based UNet-like network and simultaneously fed to the object detector.
- Object detection module: Extracting the enhanced features using a ResNet50 backbone, then being flattened and supplemented with positional encoding before being fed into a transformer encoder. We employ cross-stage feature fusion to improve gradient flow between the encoder and decoder.
- Loss functions:
  (1) Reconstruction loss: Charbonnier loss
  (2) Detection loss: L1 for box size and location + the generalized IoU loss + Binary Cross-Entropy loss

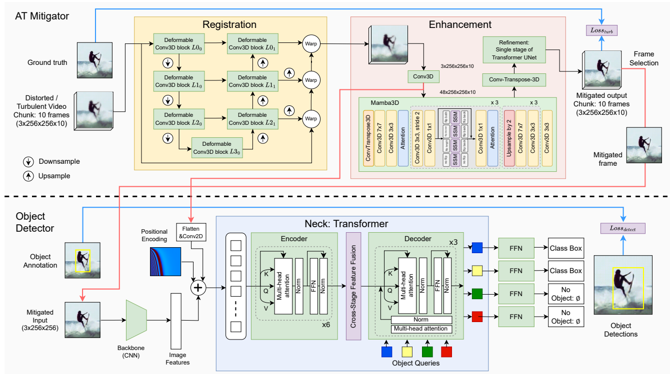


Figure 2. Architecture of the DMAT framework for atmospheric distortion mitigation and object detection.

Synthetic datasets

- AT distortions using the Phase-to-Space (P2S) Transformation
- Static scenes: COCO2017 (1) all 80 classes, (2) Top10, (3) CarPerson
- Dynamic scenes: GOT-10k dataset, Person or Cars, 50-frame clips, In total, 1,761 videos are used for training and 441 for testing

Results

Table 1. Object detection performance.

Mitigator	Detector	Params (M)	Static scenes: All classes, All sizes	Static scenes: All classes, Small	Static scenes: Top 10 classes, All sizes	Static scenes: Top 10 classes, Small	Static scenes: Car and person, All sizes	Static scenes: Car and person, Small	Dynamic scenes: Car and person, All sizes	Dynamic scenes: Car and person, Small
DATUM	YOLO11x	5.8+56.9	0.317	0.060	0.166	0.032	0.291	0.132	0.133	0.013
	DETR-Large	5.8+60.0	0.243	0.100	0.120	0.051	0.216	0.087	0.102	0.007
	LWDETR-Med	5.8+28.2	0.369	0.200	0.231	0.098	0.306	0.140	0.154	0.015
TMT	YOLO11x	22.9+56.9	0.307	0.038	0.168	0.026	0.256	0.092	0.112	0.008
	DETR-Large	22.9+60.0	0.224	0.087	0.129	0.040	0.178	0.052	0.093	0.003
	LWDETR-Med	22.9+28.2	0.344	0.165	0.226	0.088	0.271	0.119	0.126	0.007
MAMBA	YOLO11x	2.8+56.9	0.350	0.037	0.191	0.031	0.292	0.128	0.147	0.011
	DETR-Large	2.8+60.0	0.275	0.097	0.135	0.041	0.217	0.076	0.128	0.008
	LWDETR-Med	2.8+28.2	0.364	0.186	*0.249*	0.105	0.310	0.138	0.167	0.017
DMAT-Tiny (ours)		2.8+12.1	*0.374*	*0.188*	0.214	*0.108*	*0.348*	*0.178*	*0.214*	*0.127*
DMAT-Small (ours)		2.8+14.6	0.407	**0.234**	0.276	0.134	0.373	0.194	0.251	0.143
DMAT-Med (ours)		2.8+28.2	**0.419**	**0.234**	**0.282**	**0.137**	**0.385**	**0.199**	**0.269**	**0.152**

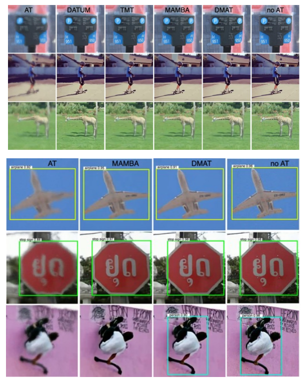


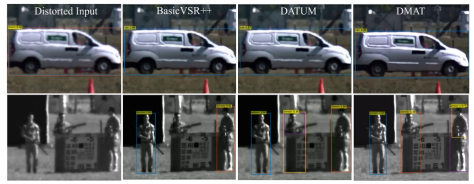
Figure 3. Performance on synthetic AT dataset.

Results

Table 2. Atmospheric turbulence mitigation performance.

AT Mitigation	Static, All: PSNR ↑	Static, All: SSIM ↑	Static, All: LPIPS ↓	Static, Top10: PSNR ↑	Static, Top10: SSIM ↑	Static, Top10: LPIPS↓	Static, CarPerson: PSNR ↑	Static, CarPerson: SSIM ↑	Static, CarPerson: LPIPS↓	Dynamic, CarPerson: PSNR ↑	Dynamic, CarPerson: SSIM ↑	Dynamic, CarPerson: LPIPS↓
AT	20.946	0.512	0.546	20.668	0.513	0.550	20.210	0.488	0.564	22.252	0.591	0.466
DATUM	23.092	0.644	0.356	22.910	0.649	0.343	22.390	0.632	0.360	22.564	0.693	*0.373*
TMT	*23.332*	*0.654*	**0.348**	*23.167*	*0.661*	**0.331**	*22.592*	*0.641*	**0.350**	*22.747*	*0.712*	**0.367**
MAMBA	23.763	0.667	0.378	23.693	0.677	0.360	23.084	0.657	0.380	23.297	0.783	0.379
DMAT (ours)	**23.841**	**0.671**	*0.373*	**23.861**	**0.683**	*0.357*	**23.220**	**0.663**	*0.376*	**23.312**	**0.831**	0.371

Figure 4. Performance on real AT dataset **CLEAR**.



Ablation Study

- Experiment 1: When the AT mitigator is removed, the performance of object detection drops by approximately 50% on average, with an even larger drop for smaller objects.
- Experiment 2: When the object detection module is removed, the performance of AT mitigation drops by up to approximately 1.5% in term of PSNR.
- Experiment 3: When the feature sharing between the two modules is removed, the performance degradation is reduced by up to 1% in terms of PSNR and 2% in terms of mAP.

Conclusions

The main contributions of this paper are summarized as follows.

- A first end-to-end architecture for joint AT mitigation and object detection, **DMAT**.
- Integrating a 3D Mamba-based restoration module with a transformer-based detector.
- New optimized sets of synthetic turbulent videos based on subsets of the COCO and GOT-10k datasets for static and dynamic scenes.

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