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Test-Time Intensity Consistency Adaptation for Shadow Detection

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Outline

- Introduction
- Contributions
- Method
- Results
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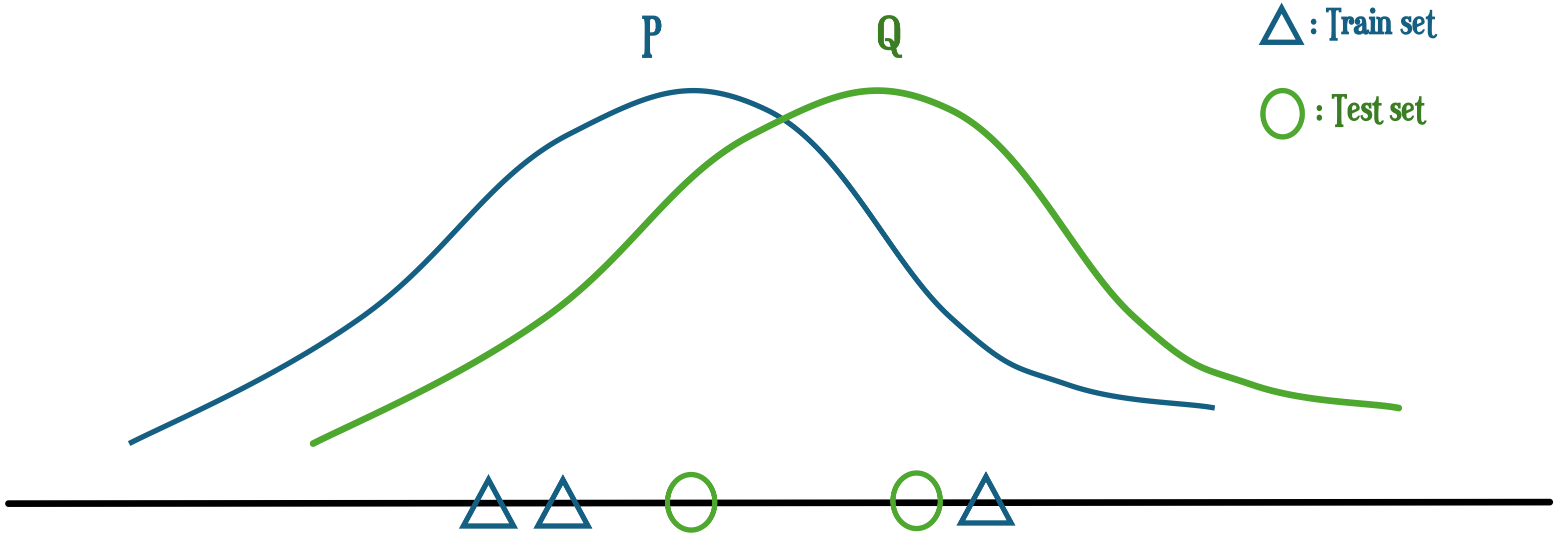
Introduction: Distribution Shifts



- **In theory assumption:** same distribution for training and testing.
- **In real-world samples:** distribution shifts with unseen variants.

Introduction: Intensity Bias

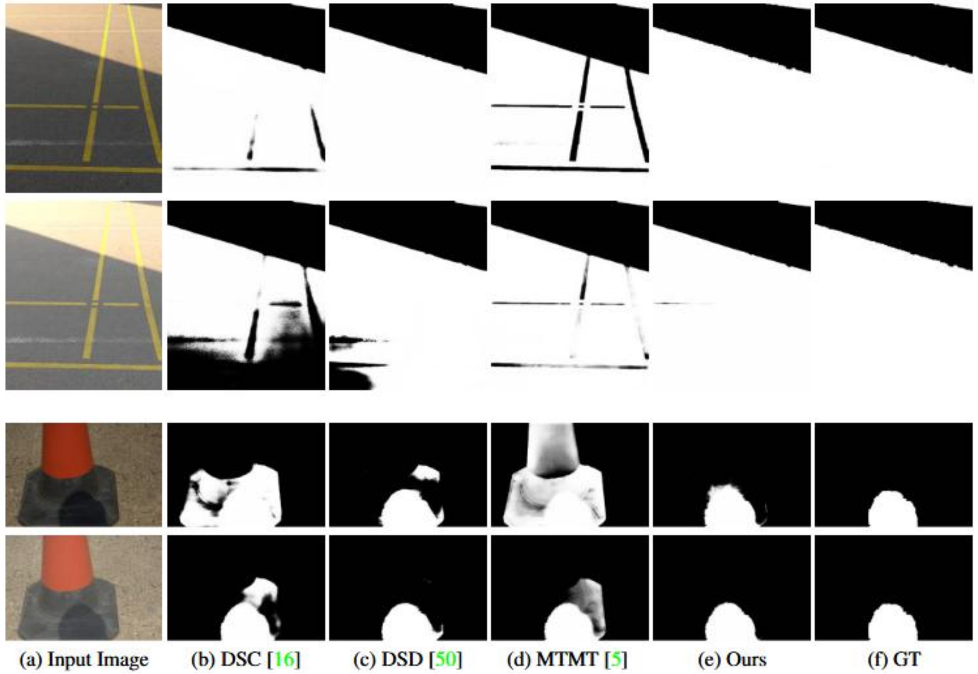


Figure 1. Intensity bias in shadow detection.

Mitigating Intensity Bias in Shadow Detection via Feature Decomposition and Reweighting (Lei Zhu et al. 2021ICCV)

Introduction: Test-Time Adaptation

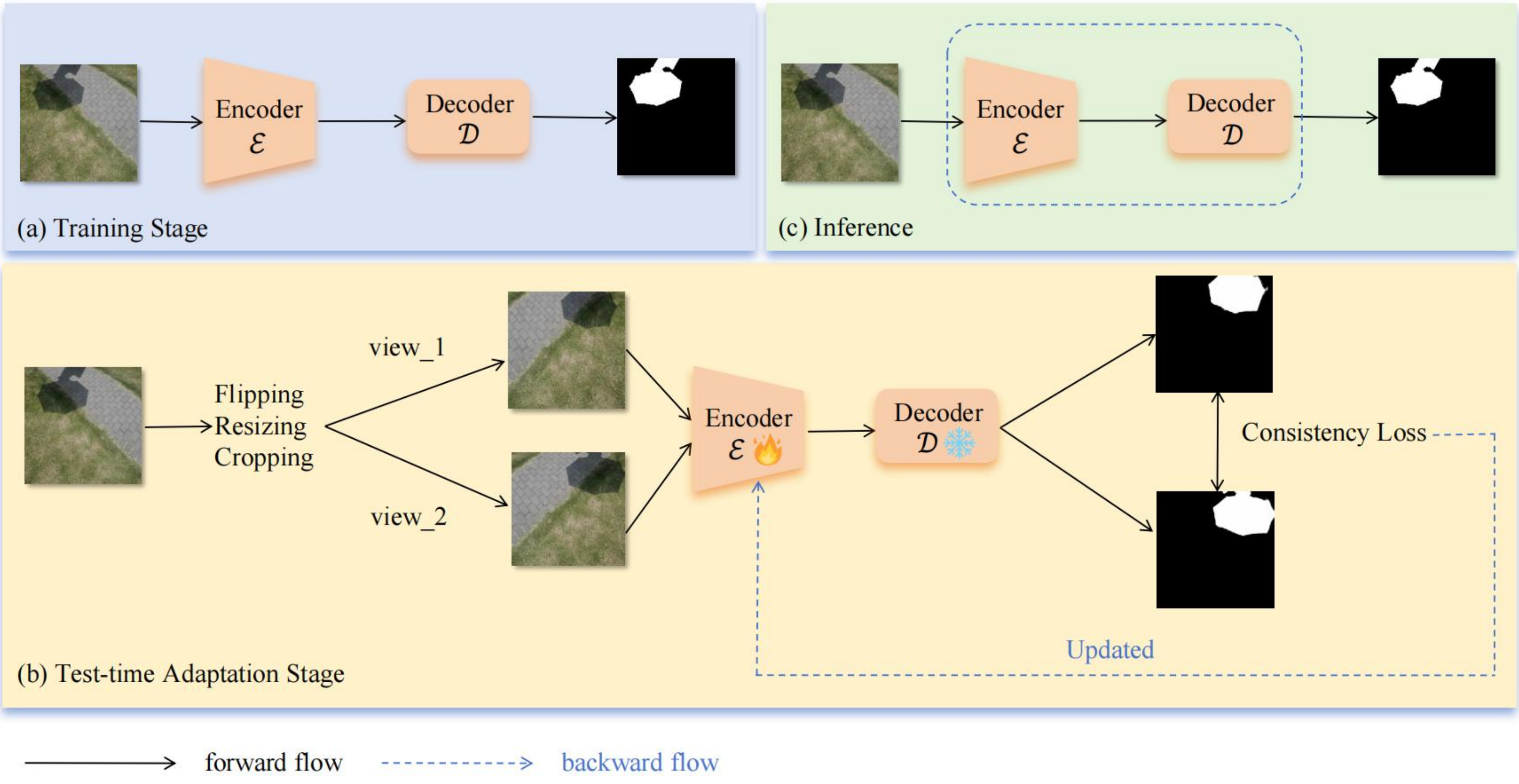
$$\text{standard test error} = \mathbb{E}_Q\,[\ell(x, y);\ \theta]$$

$$\text{TTA test error} = \mathbb{E}_Q\,[\ell(x, y);\ \theta(x)]$$

- Does not include the test distribution set during training.
- The test sample x gives us a hint about Q.
- No fixed model, but adapt at test time.

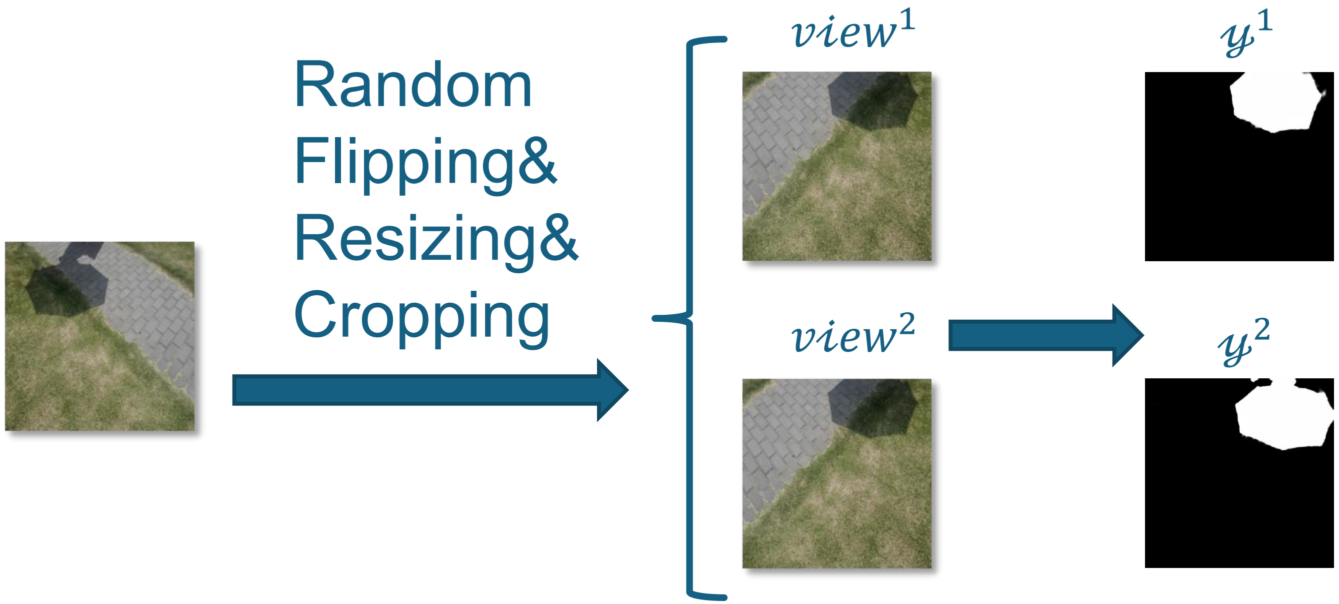
Test-Time Training with Self-Supervision for Generalization under Distribution Shifts (Yu Sun et al. 2020ICML)

Contributions: Our TICA



- TICA framework
- Intensity consistency
- Effectiveness

Method: Intensity Consistency



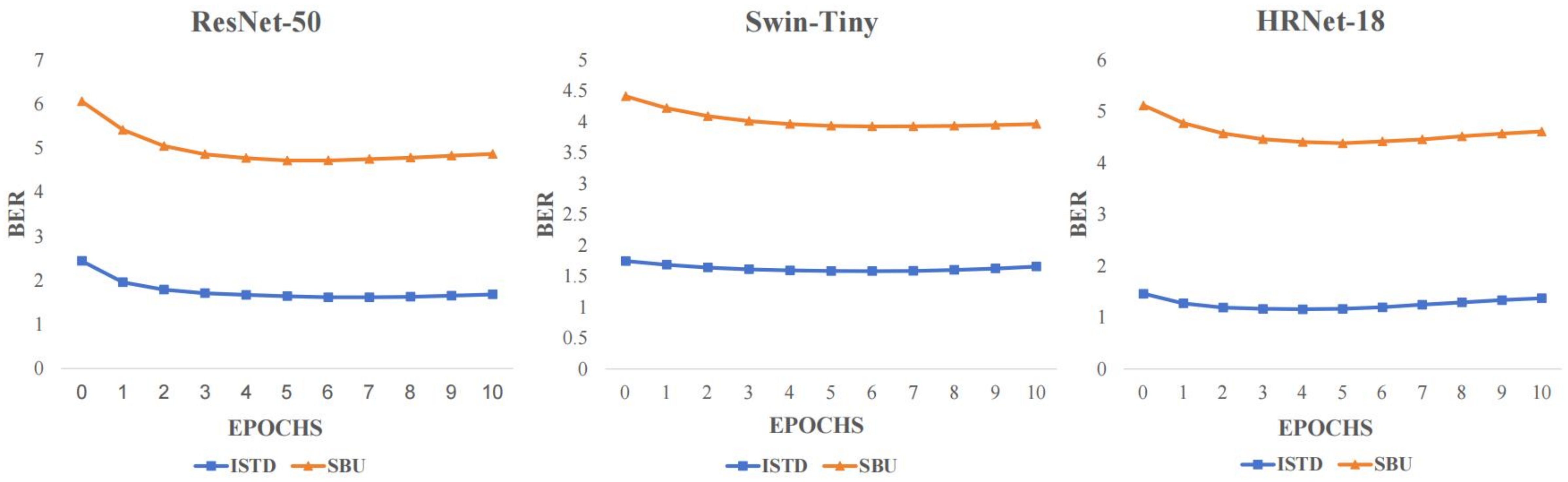
$$\mathcal{L}_{fg} = \mathcal{L}_{KL}(y_i^1, y_i^2), \forall i \in (y^1 \cap y^2) \quad (1)$$

$$\mathcal{L}_{bg} = \mathcal{L}_{KL}(\overline{y_i^1}, \overline{y_i^2}), \forall i \in (\overline{y_i^1} \cap \overline{y_i^2}) \quad (2)$$

$$\mathcal{L}_{tica} = \lambda_{fg}\mathcal{L}_{fg} + \lambda_{bg}\mathcal{L}_{bg} \quad (3)$$

- Intensity consistency on both foreground and background between two augmented images.

Results: TICA Ablation Studies



- The impact of the proposed TICA fluctuates with the number of epochs.

Results: TICA Ablation Studies

Table 1. Ablation study using variable intensity consistency strategy on different backbone models across two public datasets.

	ResNet-50 as Backbone				Swin-Tiny as Backbone				HRNet-18 as Backbone			
	-	FC	BC	both	-	FC	BC	both	-	FC	BC	both
ISTD	2.45	1.93	1.65	**1.64**	1.76	1.96	1.58	**1.59**	1.47	1.43	1.17	**1.17**
SBU	6.07	4.70	4.83	**4.72**	4.44	3.93	3.98	**3.94**	5.14	4.37	4.47	**4.38**

- Ablation studies results of intensity consistency strategy in different backbone (ResNet-50, Swin-Tiny and HRNet-18).

Results: Comparison with SOTA TTA

Table 2. Compare the BER with the SOTA TTA methods for shadow detection.

	ResNet-50 as Backbone					Swin-Tiny as Backbone					HRNet-18 as Backbone				
	-	TENT	ETA	BN	Ours	-	TENT	ETA	BN	Ours	-	TENT	ETA	BN	Ours
ISTD	2.45	1.97	1.82	1.79	**1.64**	1.76	1.97	1.75	1.73	**1.59**	1.47	1.29	1.20	1.20	**1.17**
SBU	6.07	5.46	5.18	5.41	**4.72**	4.44	4.02	4.04	4.32	**3.94**	5.14	5.40	4.93	5.55	**4.38**

- Comparison with SOTA TTA in different backbone (ResNet-50, Swin-Tiny and HRNet-18).

TENT Wang, D., Shelhamer, E., Liu, S., Olshausen, B., Darrell, T.: Tent: Fully test-time adaptation by entropy minimization. In: ICLR (2021)
ETA Niu, S., Wu, J., Zhang, Y., Chen, Y., Zheng, S., Zhao, P., Tan, M.: Efficient test_x0002_time model adaptation without forgetting. In: ICML (2022)
BN Schneider, S., Rusak, E., Eck, L., Bringmann, O., Brendel, W., Bethge, M.: Improving robustness against common corruptions by covariate shift adaptation. NeurIPS (2020)

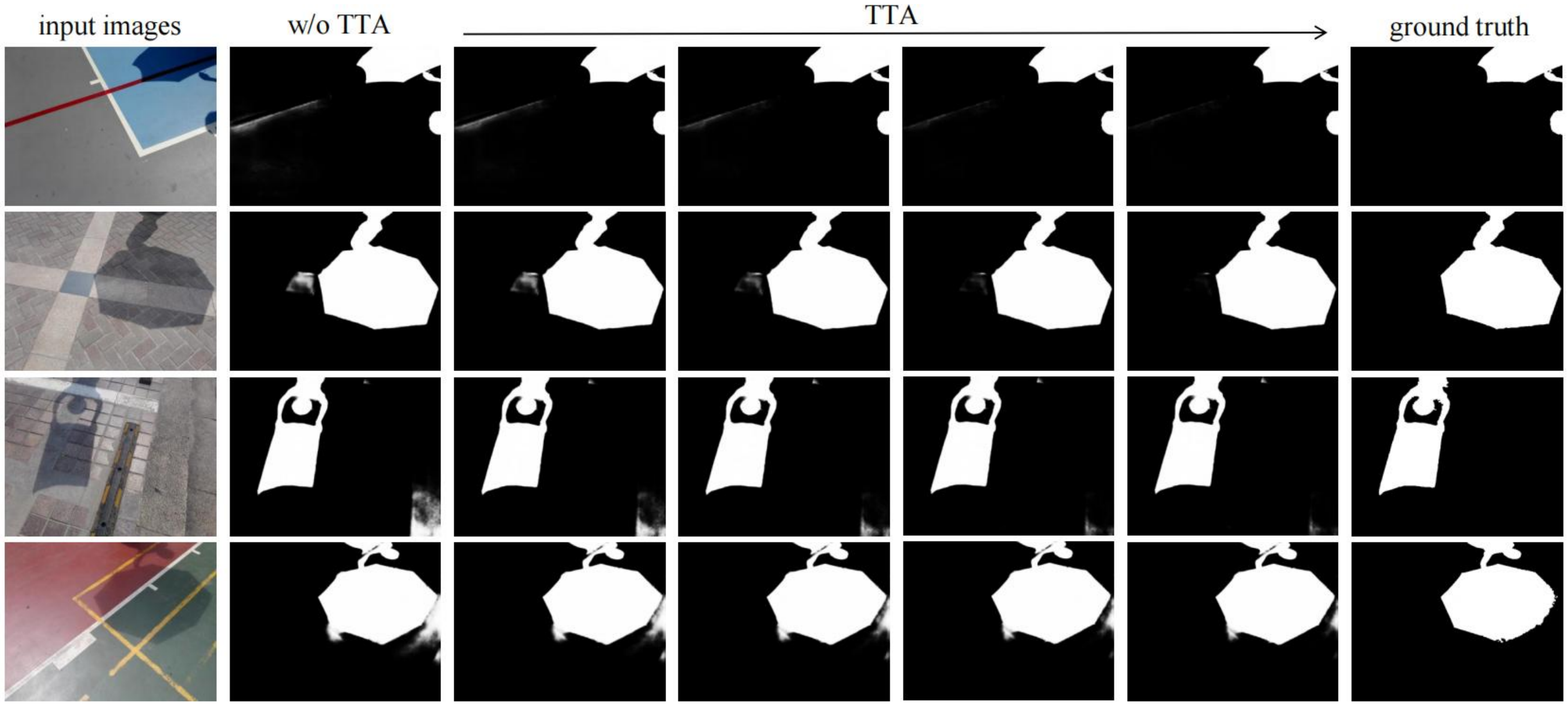
Results: SOTA Shadow Detectors Comparison

Table 3. Comparing our method with the SOTA shadow detectors.

Method	Backbone	ISTD	SBU
DSC [44]	VGG16 [77]	3.42	5.59
DSD [55]	ResNeXt-101 [78]	2.17	3.45
MTMT [65]	ResNeXt-101 [78]	1.72	3.15
FDRNet [42]	EfficientNet-B3 [79]	1.55	**3.04**
FCSDNet [80]	ResNeXt101 [78]	1.69	3.15
Ours	ResNet-50 [71]	1.64	4.72
	Swin-Tiny [72]	1.59	3.94
	HRNet-18 [73]	**1.17**	4.38

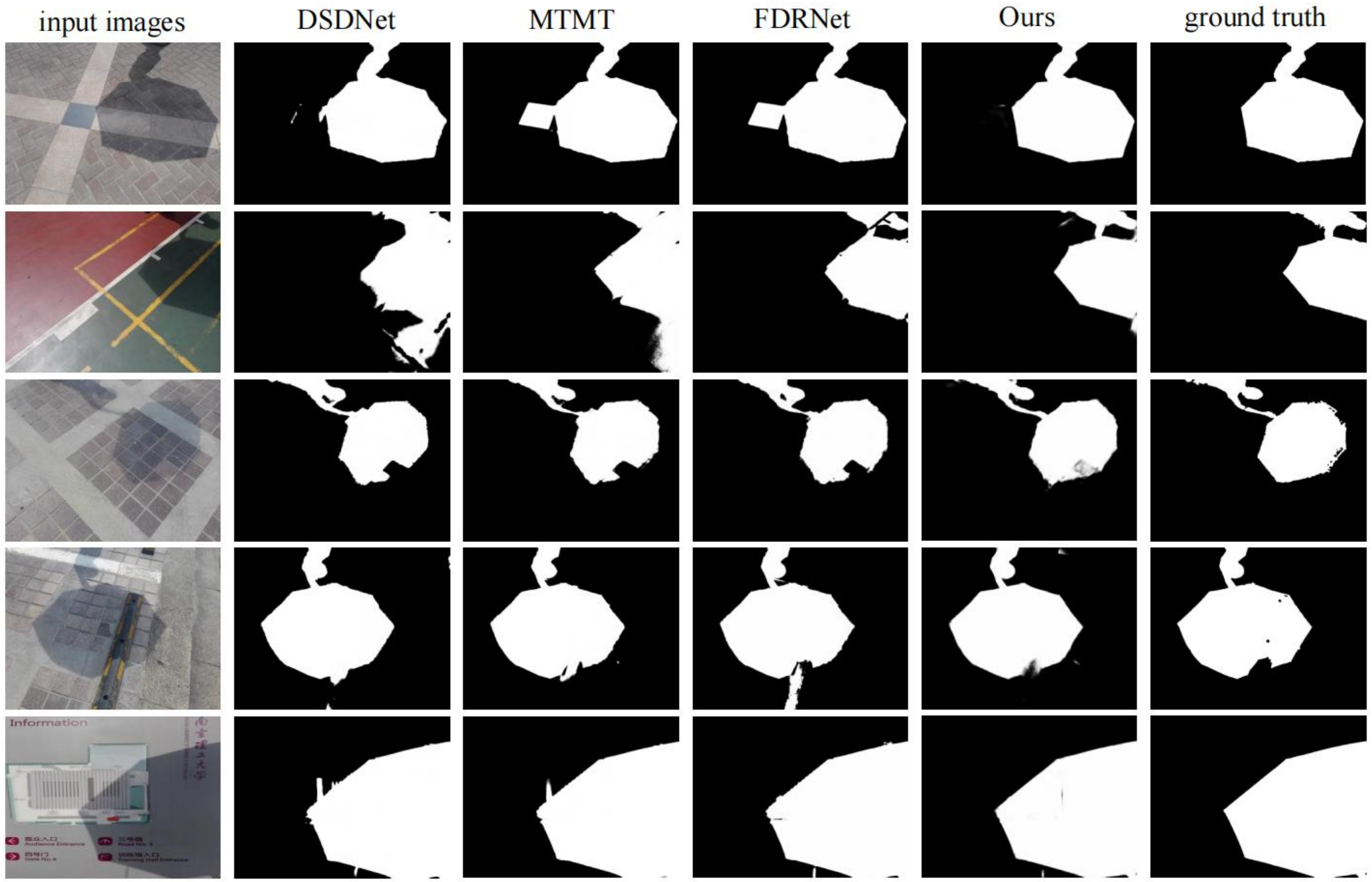
DSC Hu, X., Zhu, L., Fu, C.W., Qin, J., Heng, P.A.: Direction-aware spatial context features for shadow detection. In: CVPR (2018)
DSD Zheng, Q., Qiao, X., Cao, Y., Lau, R.W.: Distraction-aware shadow detection. In: CVPR (2019)
MTMT Chen, Z., Zhu, L., Wan, L., Wang, S., Feng, W.: A multi-task mean teacher for semi-supervised shadow detection. In: CVPR (2020)
FDRNet Zhu, L., Xu, K., Ke, Z.: Mitigating intensity bias in shadow detection via feature decomposition and reweighting. In: ICCV (2021)
FCSDNet Valanarasu, J.M.J., Patel, V.M.: Fine-context shadow detection using shadow re_x0002_moval. In: WACV (2023)

Visualizations: TICA Fine-Tuning



- Qualitative comparison of the fine-tuning results and ground truth for TICA over five epochs.

Visualizations: with SOTA Shadow Detectors



- Visual comparison of other SOTA Shadow Detectors and our method (TICA) against ground truth's shadow mask.

Thank you for listening!

Q & A