



Similarity Min-Max: Zero-Shot Day-Night Domain Adaptation

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Low light hinders both human perception and model performance







Solutions to improve the model's performance in nighttime scenarios:

Day-Night Domain Adaptation:

• Data: labeled daytime + unlabeled nighttime



Labeled daytime data

Unlabeled nighttime data





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Our task, Zero-Shot Day-Night Domain Adaptation:

• Data: labeled daytime data **only**



Labeled daytime data

Motivation





Operator-based [1]

Model-Level: Not robust to complex real-world scenes

[1] Lengyel et al. Zero-Shot Day-Night Domain Adaptation with a Physics Prior. In ICCV, 2021.

Motivation





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[2] Cui et al. Multitask AET with Orthogonal Tangent Regularity for Dark Object Detection. In ICCV, 2021.
[3] Sakaridis et al. Guided Curriculum Model Adaptation for semantic nighttime image segmentation. In ICCV 2019.

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Problem Formulation

- Given a feature extractor F, we hope it to be robust to illumination changes, *i.e., the* daytime image I and its darkened version D(I) should have similar representations.
- Formulation: $\max_{\theta_F} \min_{\theta_D} \operatorname{Sim}(F(I), F(D(I)))$ (1)
- Add regularization to avoid trivial solutions:

 $\max_{\theta_F} \min_{\theta_D} \operatorname{Sim}(F(I), F(D(I))) + \mathcal{R}_D(\theta_D) - \mathcal{R}_F(\theta_F) \quad (2)$

• How to design darkening module D and regularizer R_D , R_F ?

Training Framework

- Image-Level Darkening
 - Regularization (\mathcal{R}_D)
 - Total variance loss
 - Color consistency loss
 - Exposure alignment loss
 - Similarity loss (\mathcal{L}_D^{sim})
 - Cosine similarity





Training Framework

- Image-Level Darkening
- Model-Level Adaptation
 - Regularization (\mathcal{R}_F)
 - Task loss
 - Similarity loss (\mathcal{L}_F^{sim})
 - BYOL loss







Proof of Concept









Proof of Concept





Proof of Concept





Tasks and datasets for evaluation

- Low-Light image classification: CODaN
- Nighttime semantic segmentation: Nighttime Driving, Dark-Zurich
- Visual place recognition: Tokyo 24/7
- Low-Light video action recognition: ARID

Baselines

- Low-light image (video) enhancement
- Zero-shot domain adaptation
- Domain generalization





I. Classification

Method	Top-1 (%)
ResNet-18 [18]	53.32
Low-Light Enhancement	
EnlightenGAN [23]	56.68
LEDNet [63]	57.40
Zero-DCE++ [30]	57.96
RUAS [33]	58.36
SCI [34]	58.68
URetinexNet [56]	58.72
Domain Generalization	
MixStyle [62]	53.12
IRM [1]	54.52
AdaBN [31]	54.25
Zero-Shot Day-Night Domain Adap	otation
MAET† [8]	56.48
CIConv [29]	60.32
Ours	65.87

III. Visual Place Recognition

Method	mAP (%)	
Zero-Shot Day-Night Domain Adaptation		
EdgeMAC [42]	75.9	
U-Net jointly [21]	79.8	
GeM [43]	85.0	
CIConv-GeM [29]	88.3	
Ours-GeM	90.4	
Day-Night Domain Adaptation (night images are available for training)		
U-Net jointly [21]	86.5	
EdgeMAC + CLAHE [21]	90.5	
EdgeMAC + U-Net jointly [21]	90.0	

II. Segmentation

Method	Nighttime Driving	Dark-Zurich
RefineNet [32]	34.3	30.6
Low-Light Enhancer	nent	
EnlightenGAN [23]	25.2	24.9
Zero-DCE++ [30]	32.7	28.3
RUAS [33]	25.1	23.4
SCI [34]	28.6	25.7
URetinexNet [56]	28.1	24.0
LEDNet [63]	27.6	26.6
Domain Generalizati	ion	
AdaBN [31]	37.2	31.1
RobustNet [6]	33.0	34.5
SAN-SAW [38]	28.1	16.0
Zero-Shot Day-Night	t Domain Adaptation	
MAET [8]	28.1	26.4
CIConv [29]	41.2	34.5
Ours	44.9	40.2

IV. Video Action Recognition

Method	Top-1 (%)
I3D [3]	47.02
Low-Light Video Enhancement	
StableLLVE [59]	45.08
SMOID [22]	47.27
SGZ [61]	46.42
Domain Generalization & Zero-Shot Day-Night Domain Adaptation	
AdaBN [31]	46.17
Ours	51.52



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(d) RefineNet

(e) MAET

(f) CIConv



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(a) Query

(b) GeM



III. Low-Light Video Action Recognition





- Task: zero-shot day-night domain adaptation
- Framework: similarity min-max framework
 - A bi-level optimization problem
 - Two-stage training: image-level darkening and model-level adaptation
- **Performance:** state-of-the-art results across multiple downstream tasks.



Thank You

Poster Info: Room Nord, No. 168

Oct. 5th, 10:30-12:30





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