



HalluciDet: Hallucinating RGB Modality for Person Detection Through **Privileged Information** Heitor R. Medeiros, Fidel G. Pena, Masih Aminbeidokhti, Thomas Dubail, Eric Granger, Marco Pedersoli

Introduction & Motivation



Our work investigates image translation for object detection :

- Model adapts from pre-trained RGB to IR.
- Guide the image-to-image translation for the final

Figure 1. IR and RGB images (LLVIP dataset). Images have complementary information; thus, one modality can help the other one.

detection task.



Figure 2. HalluciDet: During training, it is able to train the Hallucination Network with the knowledge from the RGB detector. During the test, it improves the detection of IR.

Image-to-image Benchmark

			AP@50 ↑	
Image-to-image translation	Learning strategy	Test Set (Dataset: LLVIP)		LVIP)
		FCOS	RetinaNet	Faster R-CNN
Blur [10]	-	42.59 ± 4.17	47.06 ± 1.99	63.05 ± 1.96
Histogram Equalization [10]	-	33.10 ± 4.64	36.45 ± 2.02	51.47 ± 4.03
Histogram Stretching [10]	-	38.55 ± 4.25	41.97 ± 1.39	57.69 ± 2.78
Invert [10]	-	53.62 ± 2.07	55.43 ± 2.03	71.83 ± 3.04
Invert + Equalization [10]	-	50.03 ± 2.44	52.57 ± 1.50	68.69 ± 2.73
Invert + Equalization + Blur [10]	-	50.58 ± 2.41	52.62 ± 1.36	68.91 ± 2.74
Invert + Stretching [10]	-	51.48 ± 2.17	52.87 ± 1.80	69.34 ± 3.07
Invert + Stretching + Blur [10]	-	51.54 ± 1.92	52.96 ± 1.80	69.59 ± 2.90
Parallel Combination [10]	-	50.18 ± 2.25	52.52 ± 1.39	68.14 ± 2.98
U-Net [29]	Reconstruction	42.94 ± 4.14	47.35 ± 1.92	63.23 ± 2.03
CycleGAN [39]	Adversarial	22.76 ± 1.94	27.04 ± 4.23	38.92 ± 5.09
CUT [24]	Contrastive learning	19.16 ± 2.10	21.61 ± 2.09	35.17 ± 0.32
FastCUT [24]	Contrastive learning	46.87 ± 2.28	52.39 ± 2.31	67.73 ± 2.14
HalluciDet (ours)	Detection	63.28 ± 3.49	56.48 ± 3.39	88.34 ± 1.50

 Table 1. Comparison of detection over
different methods and HalluciDet.



b) IR - Fine-tuned detections



d) HalluciDet - RGB detections c) FastCUT - RGB detections Figure 3. Different image-to-image on detection task.



c) FastCUT (Faster R-CNN) - Detections of the RGB model on the transformed images.



d) HalluciDet (Faster R-CNN) - Detections of the RGB model on the transformed images.



e) HalluciDet (FCOS) - Detections of the RGB model on the transformed images.



f) HalluciDet (RetinaNet) - Detections of the RGB model on the transformed images.

Figure 5. HalluciDet detections on IR LLVIP dataset over different detectors.

Training Samples, Params. & Fine-Tuning



	No Adaptation	Fine-tuning	HalluciDet		
$\cos 38.52 \pm 0.79$		42.22 ± 1.04	49.18 ± 0.99		
etinaNet	44.13 ± 2.01	47.87 ± 2.21	49.01 ± 4.08		
aster R-CNN	55.85 ± 1.19	61.48 ± 1.55	70.90 ± 1.35		
Table 2. Comparison HalluciDet and Fine-tuning on FLIR dataset.					
		D			
N	Aethod	Params.	AP@50 ↑		
Fast	Aethod er R-CNN	Params. 41.3 M	AP@50 ↑ 84.83		

Table 3. Different Hallucination backbones were evaluated on the LLVIP dataset

Conclusion

We propose a novel approach that leverages privileged information from pre-trained RGB detectors and adapts it for **IR** detection without changing the detector performance on RGB.

✓ HalluciDet uses a straightforward yet powerful image translation network to reduce the domain gap between **IR-RGB** modalities, guided by the proposed hallucination loss function incorporating standard object detection terms.

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