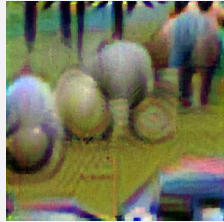


Revisiting Adversarial Patches for Designing **Camera-Agnostic Attacks** against Person Detection

Hui Wei*, Zhixiang Wang*, Kewei Zhang*,
Jiaqi Hou, Yuanwei Liu, Hao Tang, Zheng Wang†
Oct. 10th, 2024

Adversarial Patch

Digital-space

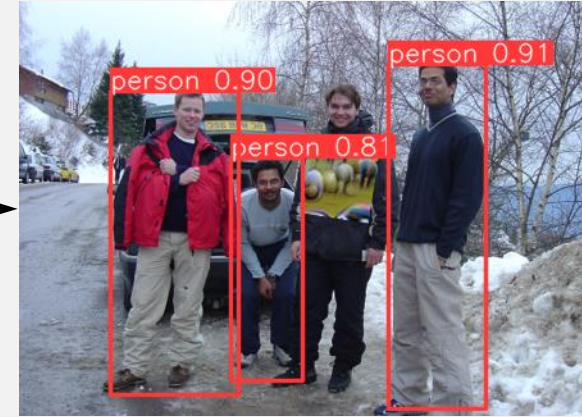


patch

paste



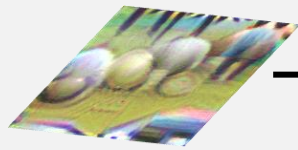
detect



applying a patch to the target person

hiding the target person from the detection model

print



physical patch entity

apply



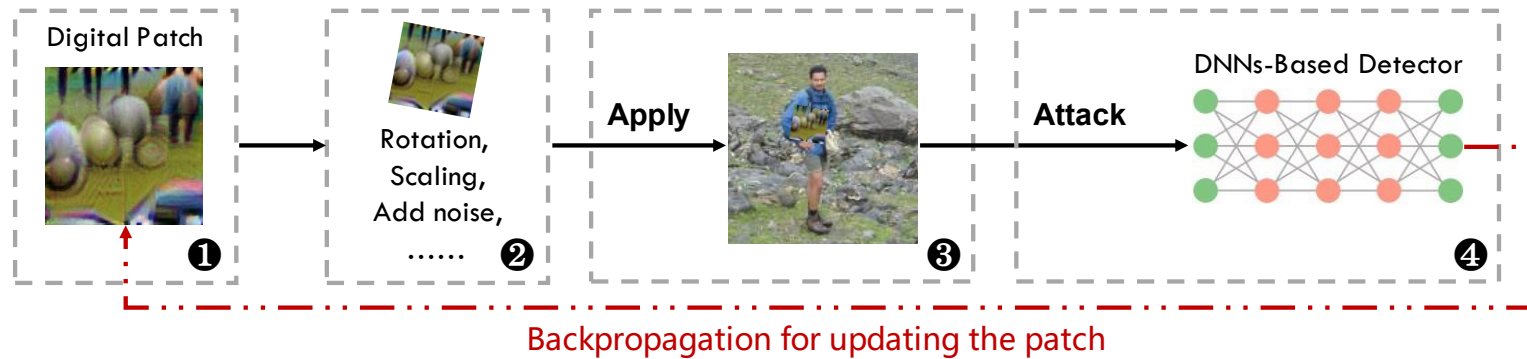
detect



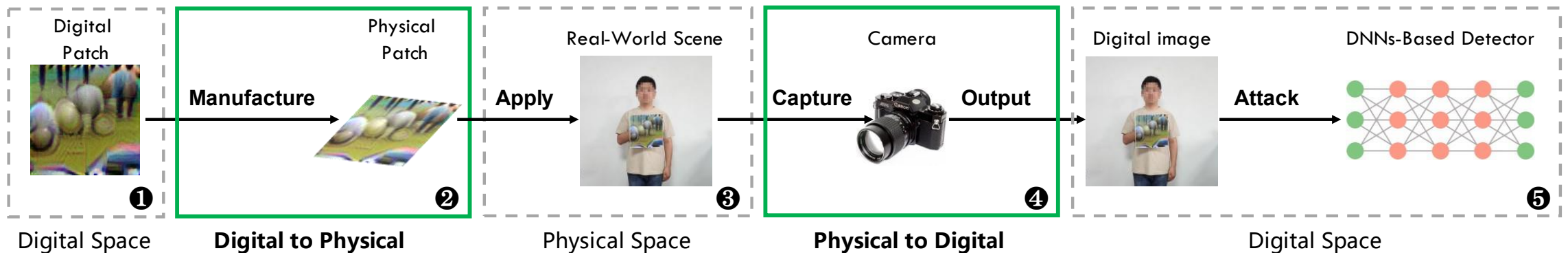
Physical-space

Existing Patch-based Methods

Digital-space

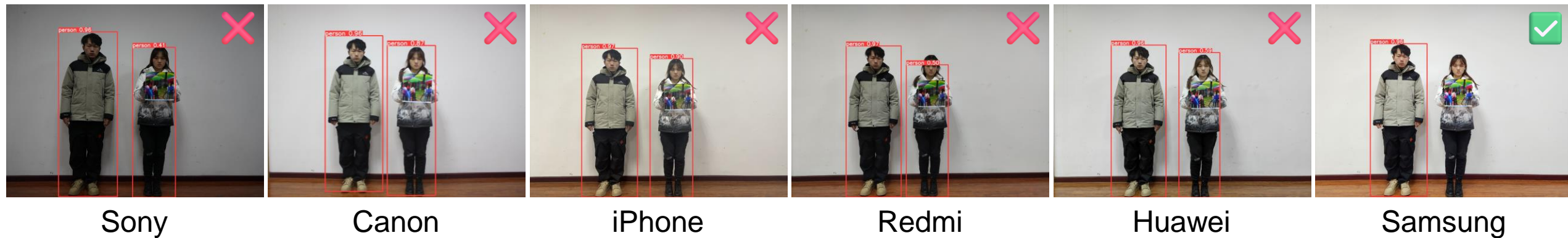


Physical-space

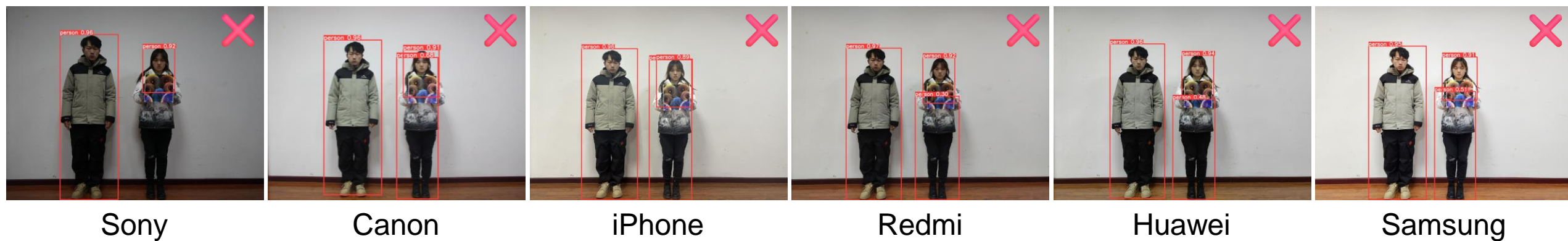


Limitations of Existing Methods

[Thys et al., AdvPatch, 2019]

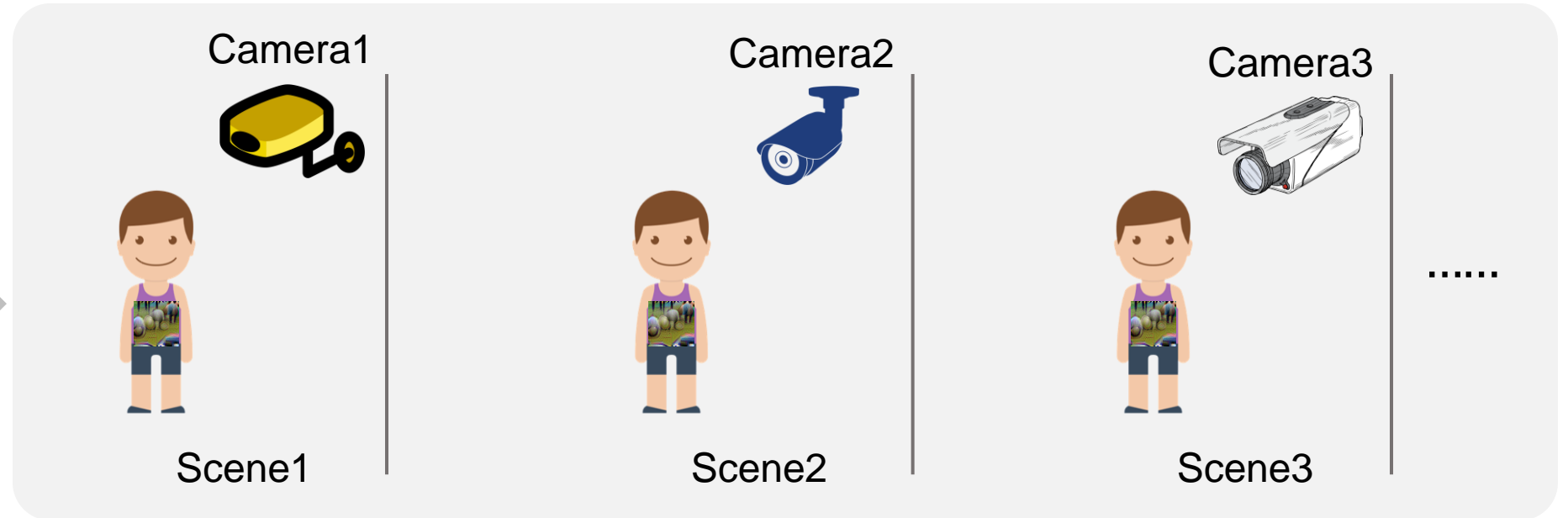


[Huang et al., T-SEA, 2023]



Deployment in the real world

Diverse camera device





Method

Designing Camera-Agnostic Attacks

Problem Definition

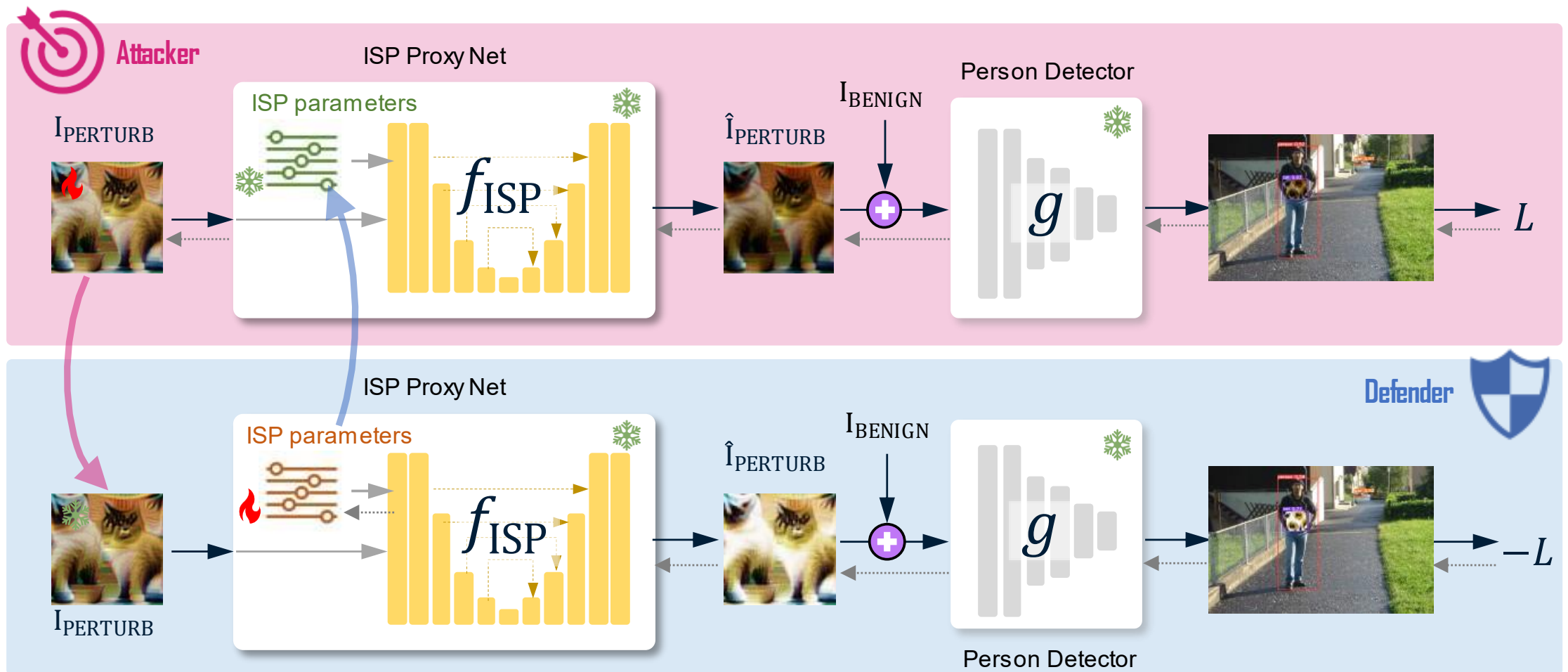
Attack module

$$P^* = \arg \max_i L(f(I_{\text{SCENE}}^i, f_{\text{ISP}}(P; \Theta)), GT),$$

Defense module

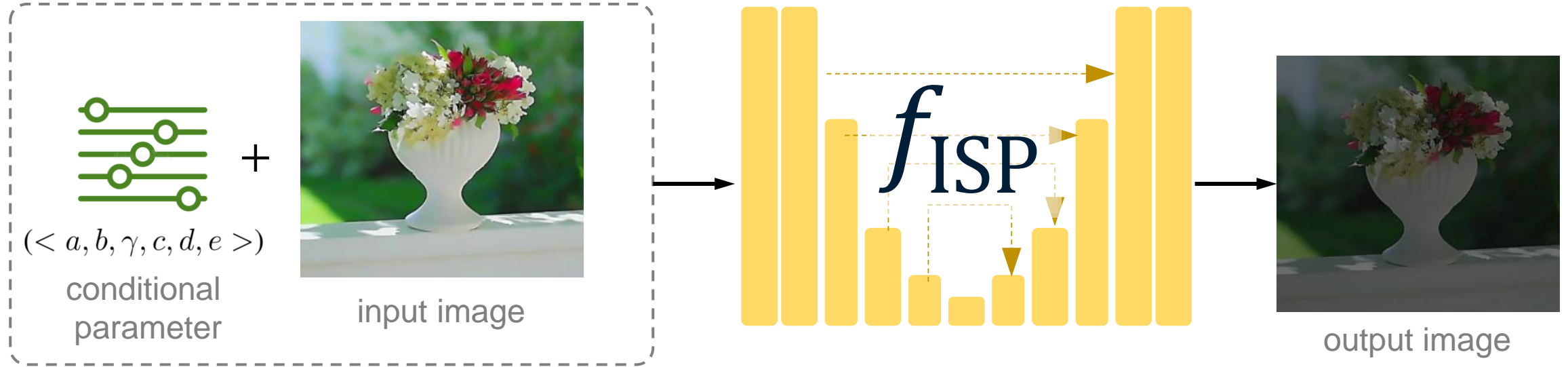
$$\Theta^* = \arg \min_i L(f(I_{\text{SCENE}}^i, f_{\text{ISP}}(P; \Theta)), GT),$$

Overall Framework



Camera ISP Proxy Net

U-Net



Camera ISP Proxy Net

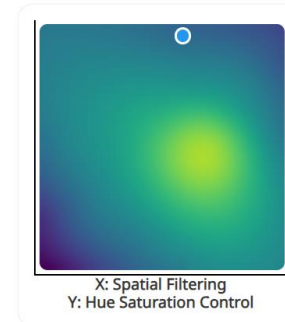
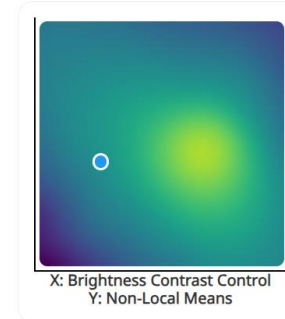
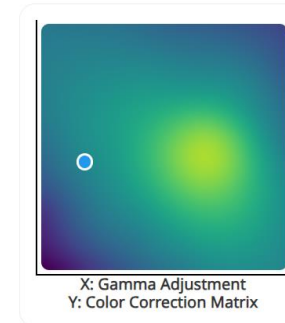
U-Net

(a) Color & Tone Correction

Parameter	Symbol	Value interval	Max
Brightness Contrast Control	a	(64, 256)	2^8
Hue Saturation Control	b	(64, 256)	2^8
Gamma Adjustment	γ	(0.4, 2.0)	2^1
Color Correction Matrix	c	(512, 1024)	2^{10}

(b) Denoising

Parameter	Symbol	Value interval	Max
Spatial Filtering	d	(0.1, 2.0)	2^1
Non-Local Means	e	(1.0, 32.0)	2^5



Optimization

Algorithm 1 The proposed adversarial optimization (Attacker and Defender)

```
1: Given source image  $x \in X$ , targeted person detector  $f$ , and the trained camera ISP network  $f_{\text{ISP}}$ ;  
2: Initialize the adversarial patch  $P$  and input hyperparameters  $\Theta$  of  $f_{\text{ISP}}$ ;  
3: for  $t = 1, 2, \dots, T$  do  
4:   // Optimize the adversarial patch  $P$  to maximize attack effectiveness  
5:   for  $batch = 1, 2, \dots, M$  do  
6:     Sample a batch of data  $x_b$  from  $X$ ;  
7:      $x_{adv} \leftarrow \text{apply}(x_b, P_{\text{ISP}}), P_{\text{ISP}} = f_{\text{ISP}}(P, \Theta)$ ;  
8:      $x_{adv}$  are fed into the person detector  $f$  to obtain predictions and compute the loss;  
9:     Update the adversarial patch  $P$  via Eq. 1;  
10:  end for  
11:  // Optimize input hyperparameters  $\Theta$  to minimize the attack effectiveness  
12:  for  $batch = 1, 2, \dots, M$  do  
13:    Sample a batch of data  $x_b$  from  $X$ ;  
14:     $x_{adv} \leftarrow \text{apply}(x_b, P_{\text{ISP}}), P_{\text{ISP}} = f_{\text{ISP}}(P, \Theta)$ ;  
15:     $x_{adv}$  are fed into the person detector  $f$  to obtain predictions and compute the loss;  
16:    Update the input hyperparameters  $\Theta$  via Eq. 2;  
17:  end for  
18: end for
```

```
python
```

```
total_iterations = 0  
for epoch in range(opt.epochs):  
    for i, (imgs, targets, paths, _) in pbar:  
        if total_iterations % 40 < 20:  
            optimizer_isp.zero_grad()  
            ...  
            ISP_loss.backward()  
            optimizer_isp.step()  
        else:  
            optimizer_patch.zero_grad()  
            ...  
            patch_loss.backward()  
            optimizer_patch.step()  
  
    total_iterations += 1  
...
```

Experiments

Attacking under multiple cameras

Experimental Setup

- **Dataset:** INRIAPerson
- **Compared Methods:** AdvPatch, AdvT-shirt, AdvCloak, NAP, LAP, TC-EGA, and T-SEA.
- **Metrics:** Average Precision (AP%), Attack Success Rate (ASR%)
- **Implementation Details:** two NVIDIA GeForce RTX 3090 GPUs

Digital-space Attacks

Original

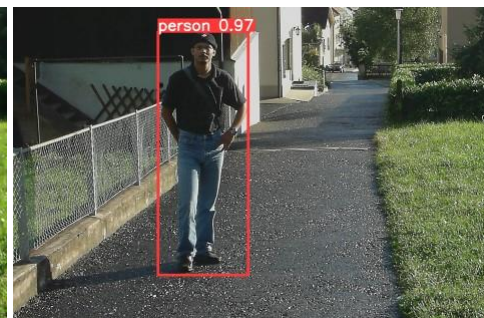
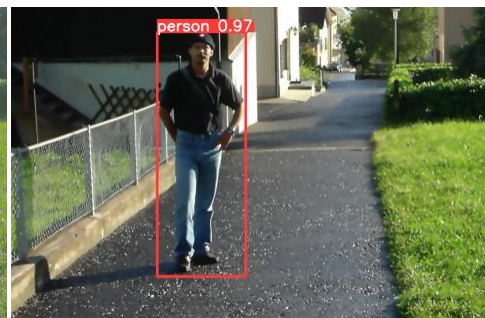
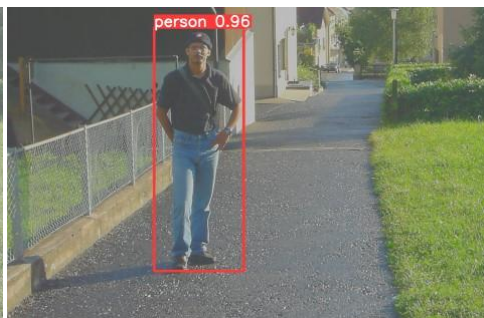
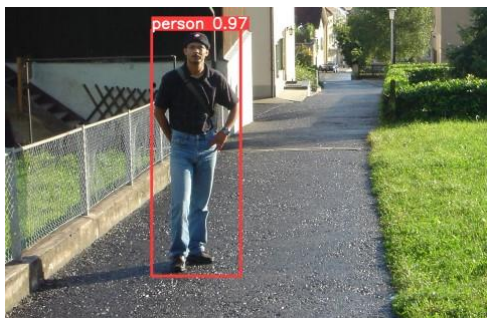
ISP 1

ISP 2

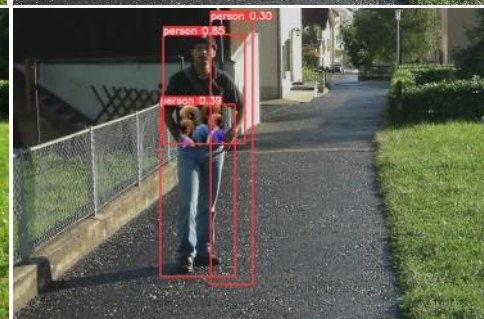
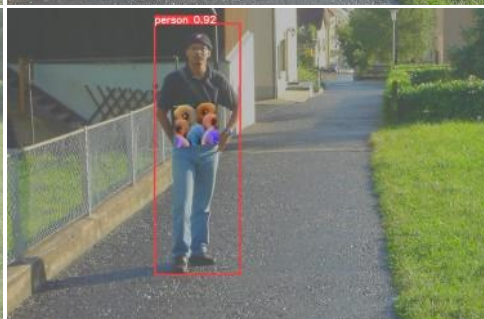
ISP 3

ISP 4

Benign



T-SEA



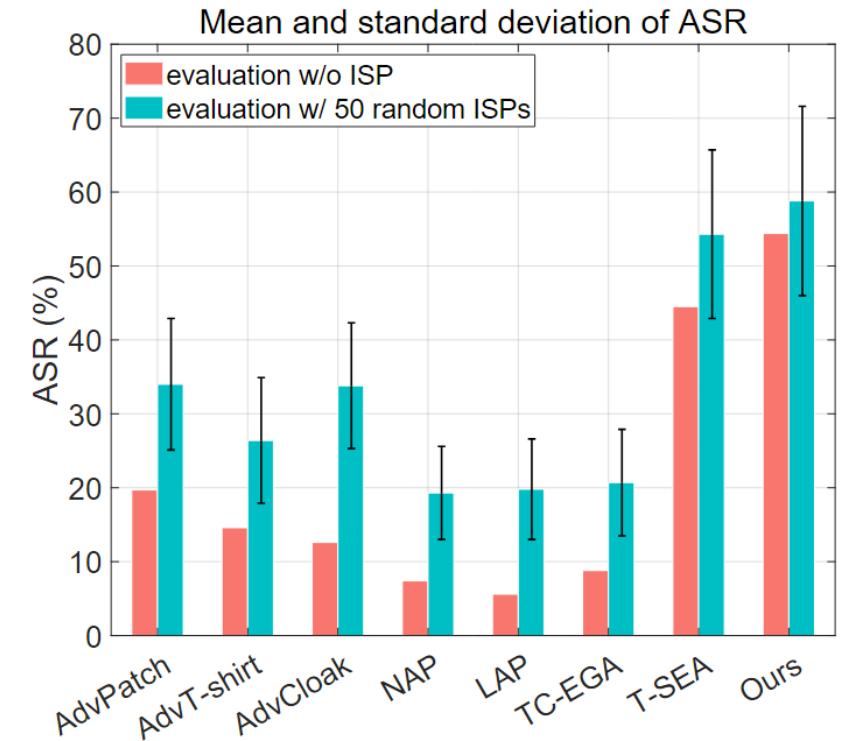
Ours



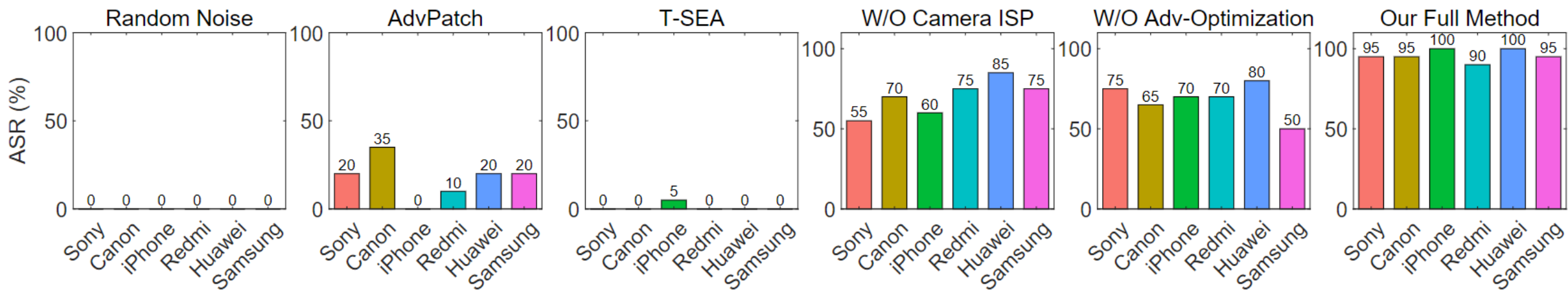
Digital-space Attacks

Quantitative results

Method	Original		ISP 1		ISP 2		ISP 3		ISP 4	
	AP↓	ASR↑	AP↓	ASR↑	AP↓	ASR↑	AP↓	ASR↑	AP↓	ASR↑
	Confidence threshold = 0.001, IoU threshold = 0.6									
Random Noise	81.7	7.3	79.3	14.9	80.2	11.0	79.8	10.9	80.1	8.5
AdvPatch [29]	67.7	19.7	60.4	38.3	65.8	30.4	64.5	28.2	68.6	22.9
AdvT-shirt [35]	76.6	14.6	73.0	21.9	76.1	18.8	71.7	21.2	76.5	14.1
AdvCloak [34]	70.5	12.6	65.3	30.4	68.9	23.7	64.3	25.0	68.6	15.8
NAP [11]	81.3	7.4	76.8	16.9	79.1	12.9	76.5	13.8	80.2	8.8
LAP [28]	81.0	5.6	76.3	17.2	78.6	11.6	77.8	12.1	79.4	10.1
TC-EGA [14]	79.9	8.8	71.3	20.3	76.4	14.4	75.6	17.1	76.8	13.3
T-SEA [15]	21.2	44.5	27.0	53.0	22.8	52.7	26.3	44.7	24.7	47.4
CAP (Ours)	37.7	54.4	24.3	64.5	25.7	73.8	37.8	57.4	31.8	68.2



Physical-space Attacks



Ablation Study

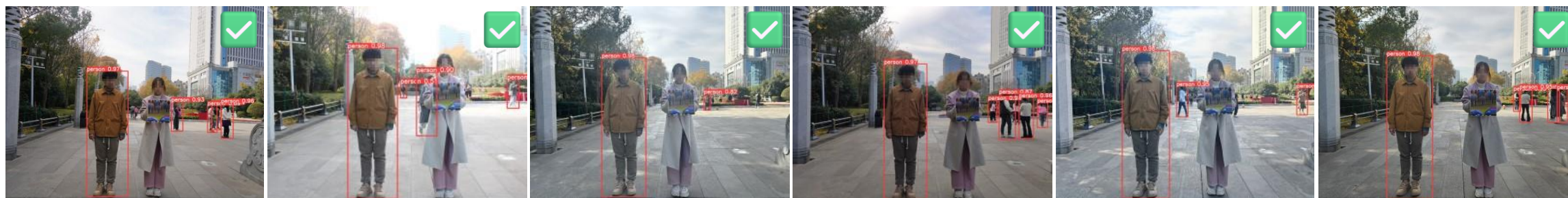
w/o Camera ISP



w/o Adv-Optimize



Our Full Method



Sony

Canon

iPhone

Redmi

Huawei

Samsung

Defense Discussion

Digital-space

Attack method / Defense strategy	Non-attack	CAP*	CAP [†]	CAP
Non-defense	85.0	52.8	45.5	37.7
JPEG compression [6]	84.7	52.7	45.8	36.8
SAC [20]	85.0	56.2	52.2	46.0
Adversarial training-CAP*	84.1	95.7	91.7	94.3
Adversarial training-CAP [†]	84.0	92.6	95.4	92.8
Adversarial training-CAP	84.6	94.2	91.6	96.3

Physical-space

Attack method / Defense strategy	CAP*	CAP [†]	CAP
Non-defense	70.0	68.3	95.8
JPEG compression [6]	90.8	89.2	93.3
SAC [20]	70.0	68.3	95.8
Adversarial training-CAP*	0.0	4.2	1.7
Adversarial training-CAP [†]	5.8	0.0	10.8
Adversarial training-CAP	0.0	4.0	0.0

Future Possibilities

- **Better camera simulation.**
 - Design camera simulator containing lens.
- **More camera devices.**
 - Industrial camera: Sony IMX415, Hikvision DS-2CD2043G1-I ...
- **Extension to black-box models.**
 - YOLOv8, YOLOv10, DETR, ...

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