

Robust VisIntel: A Road towards Robustness of Visual Intelligence



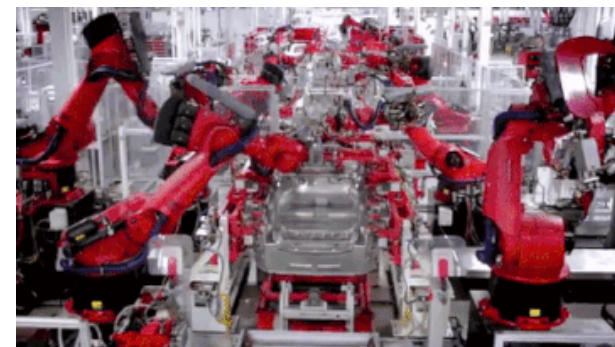
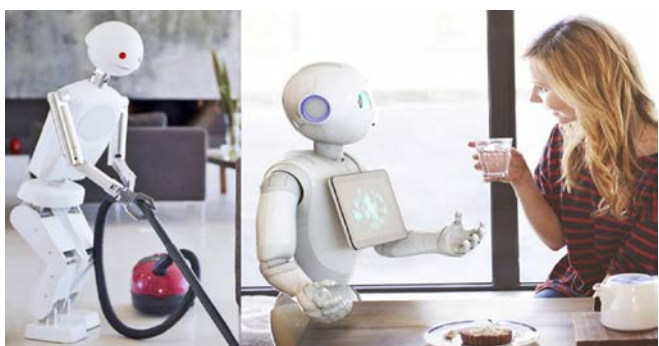
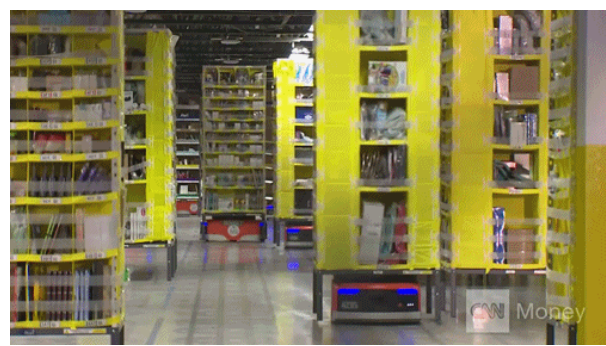
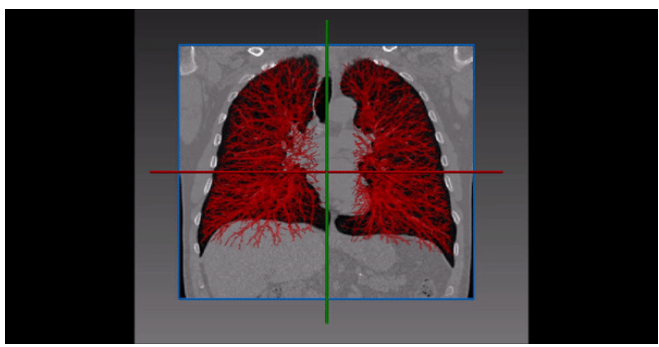
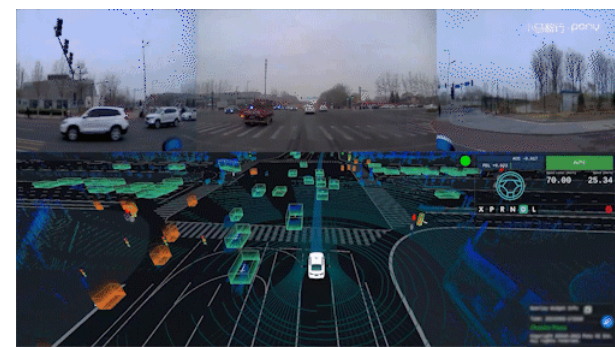
GUO Qing, Scientist, CFAR

tsingqguo@ieee.org

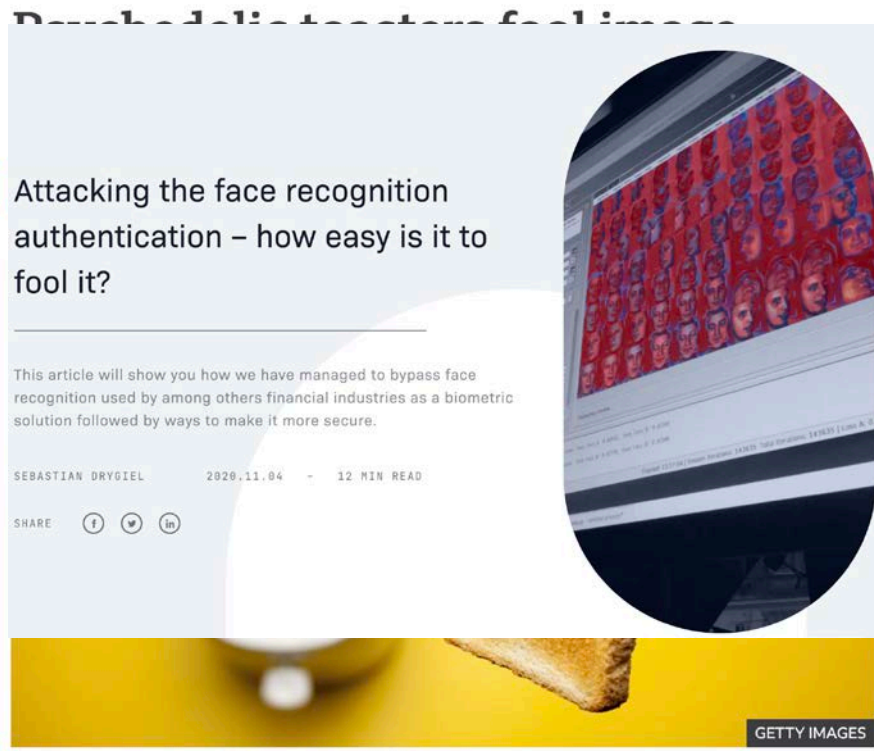
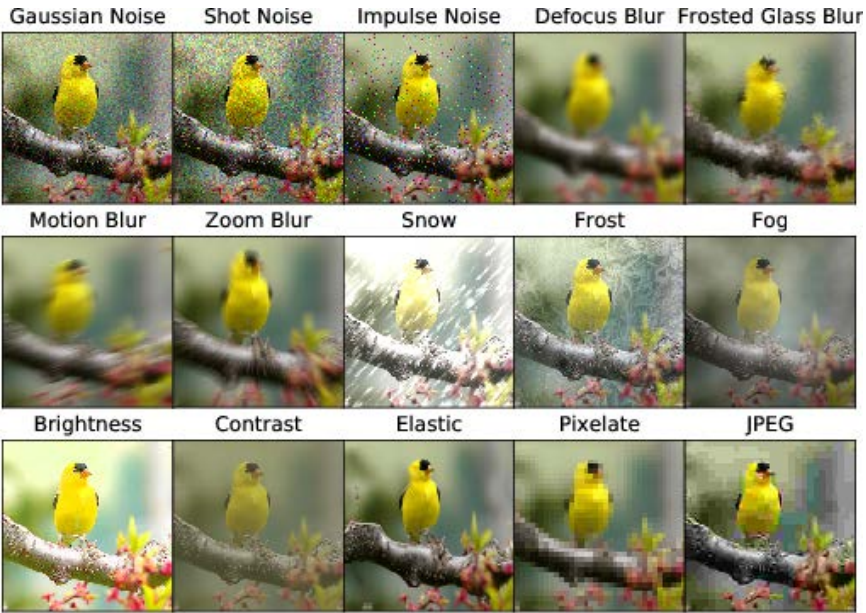
<https://tsingqguo.github.io/>



Visual Intelligence Everywhere



Robustness Issues



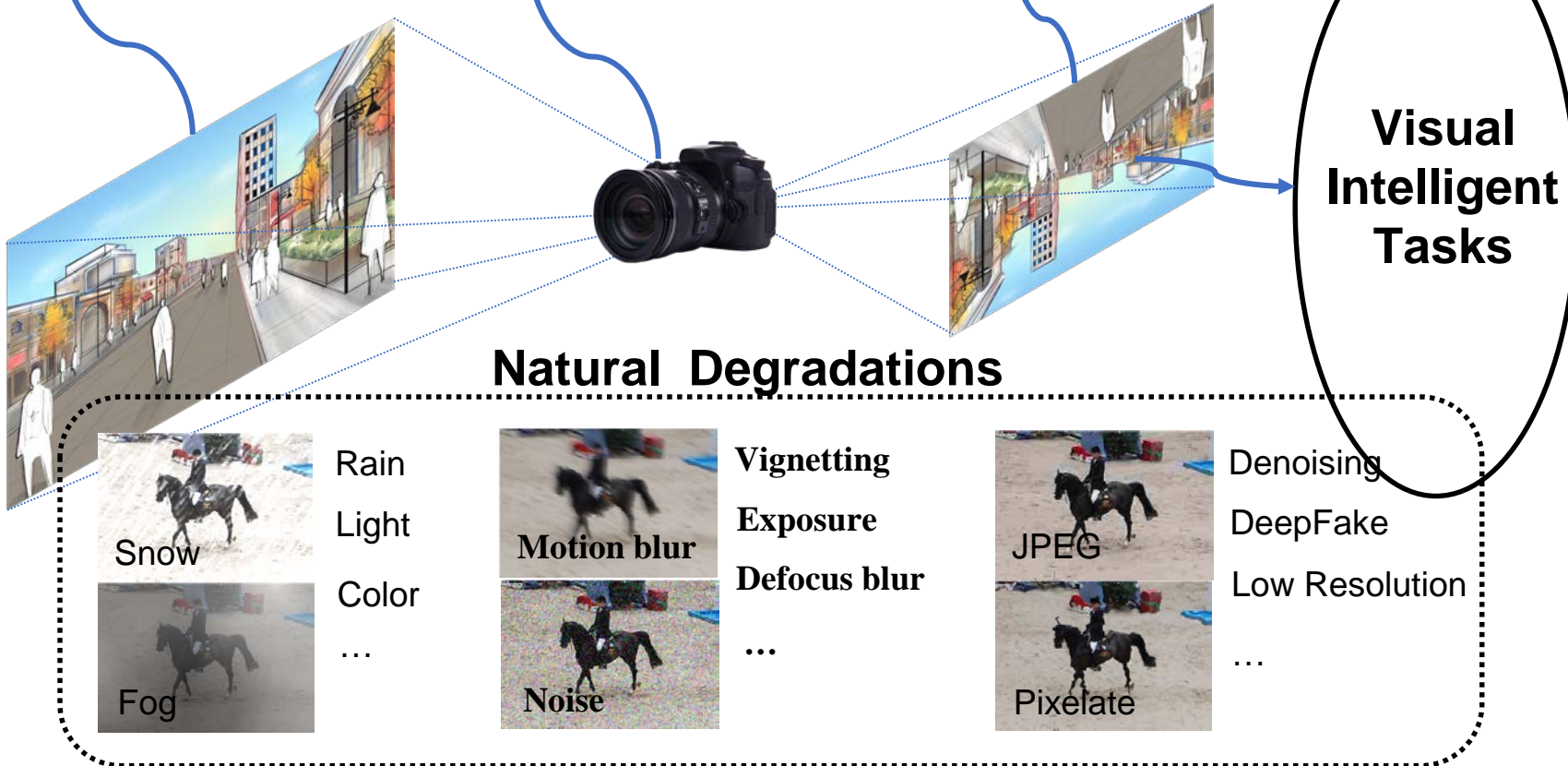
A team of Google researchers has created psychedelic stickers that can fool image recognition software into seeing objects that are not there.

Complex Real-world Scenarios

Scene variations

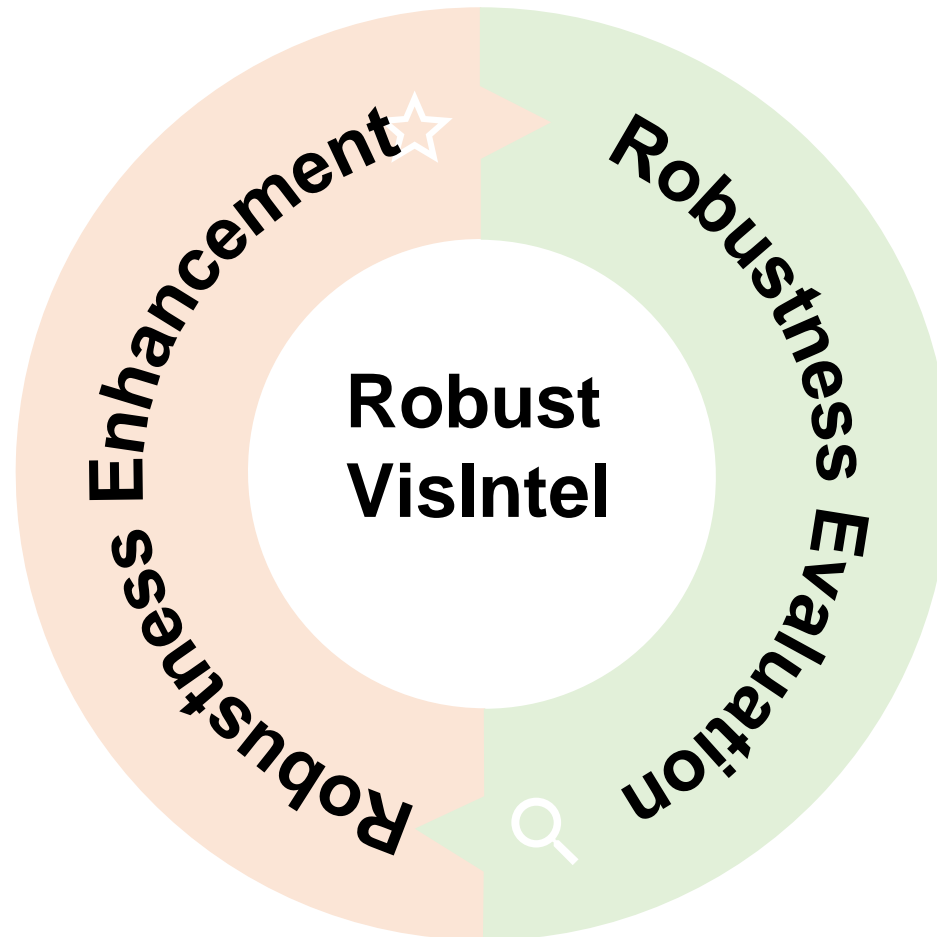
Camera variations

Post modifications



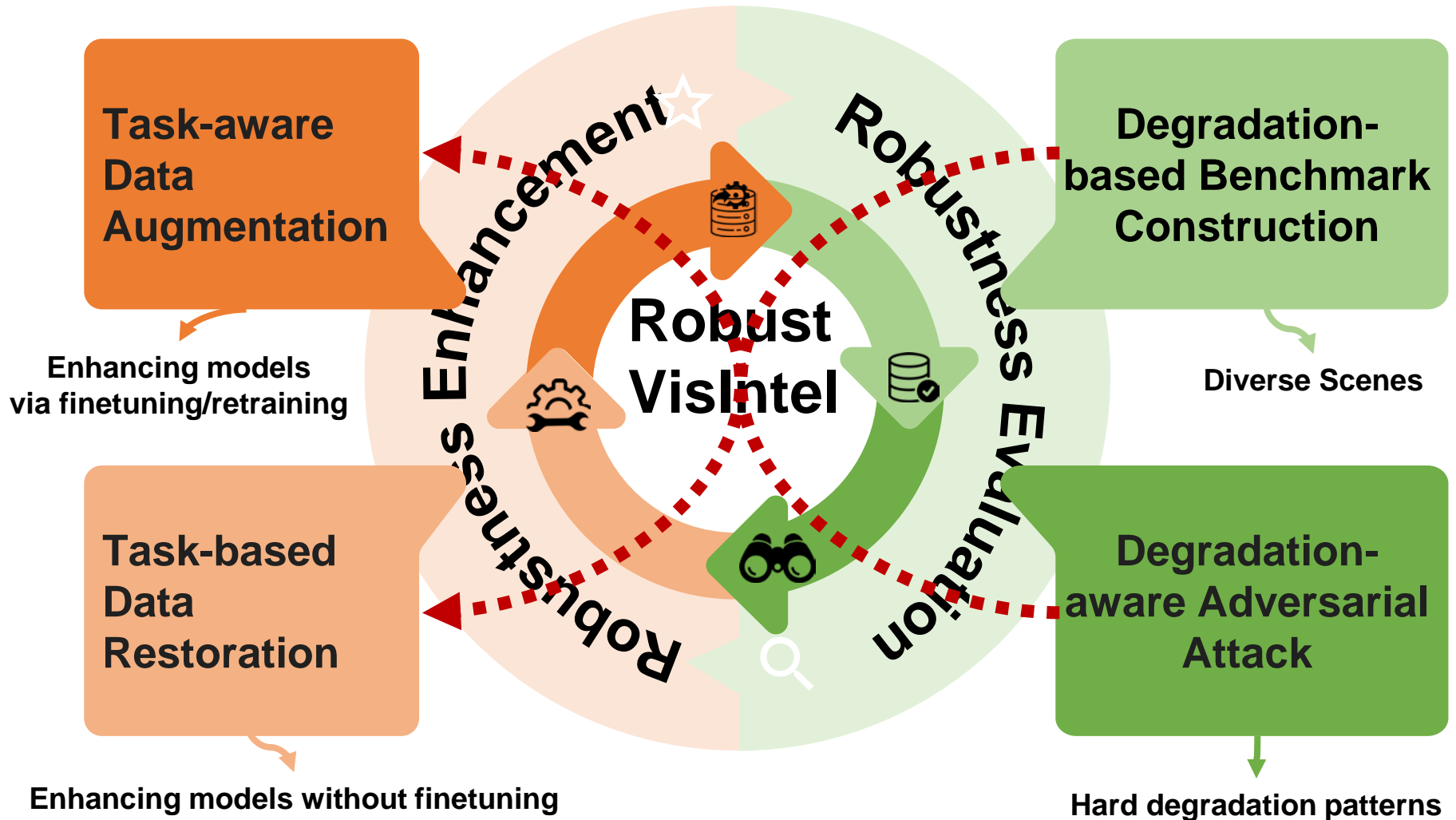
Research Goals

Goal: Robustness Evaluation and Enhancement of Visual Intelligence to Real-world Degradations:



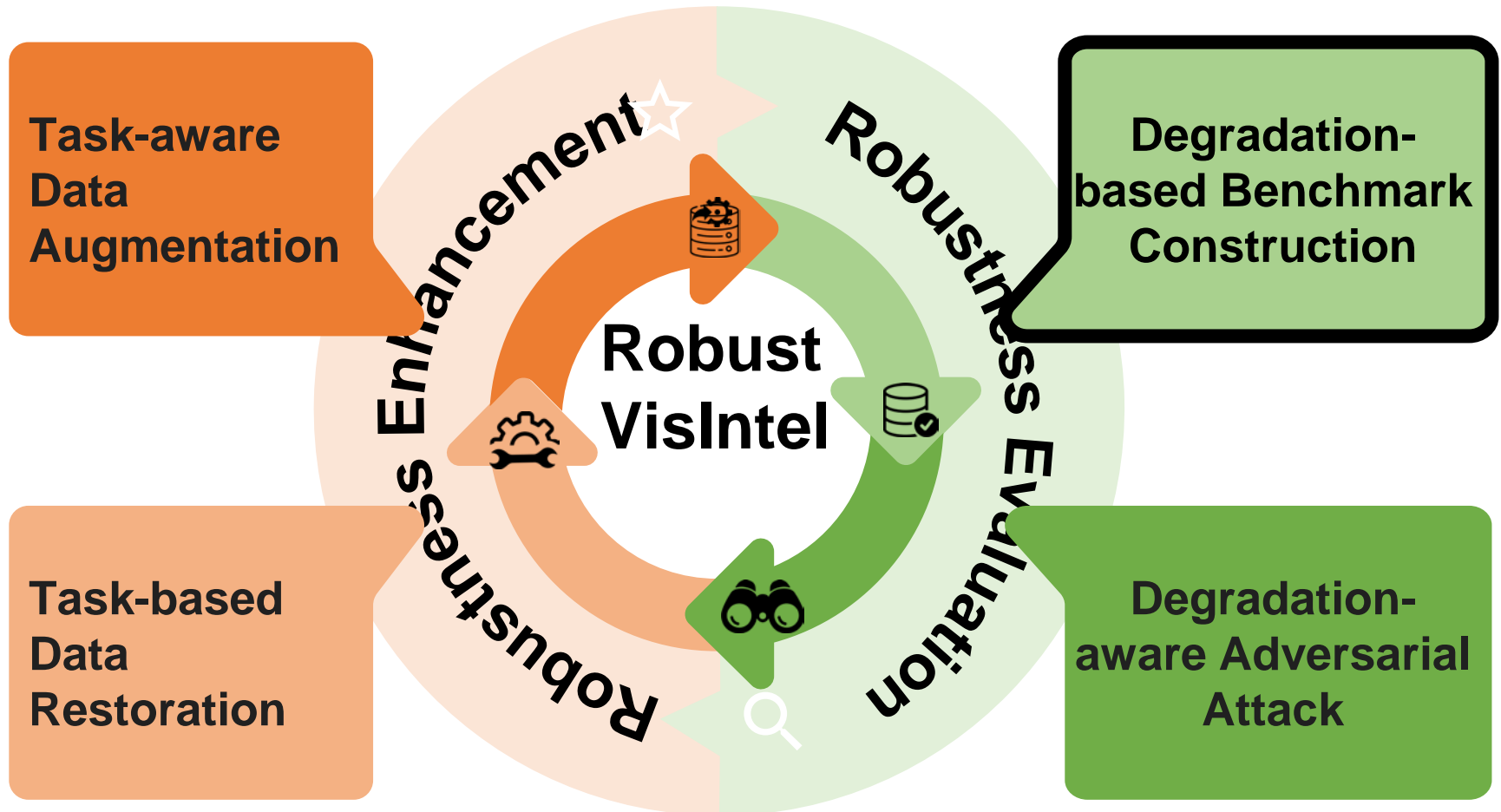
Research Goals

Goal: Robustness Evaluation and Enhancement of Visual Intelligence to Real-world Degradations:



Research Goals

Goal: Robustness Evaluation and Enhancement of Visual Intelligence to Real-world Degradations:



Robustness Evaluation

Blurred Video Benchmark – An Example (TIP' 21)

➤ Motivation

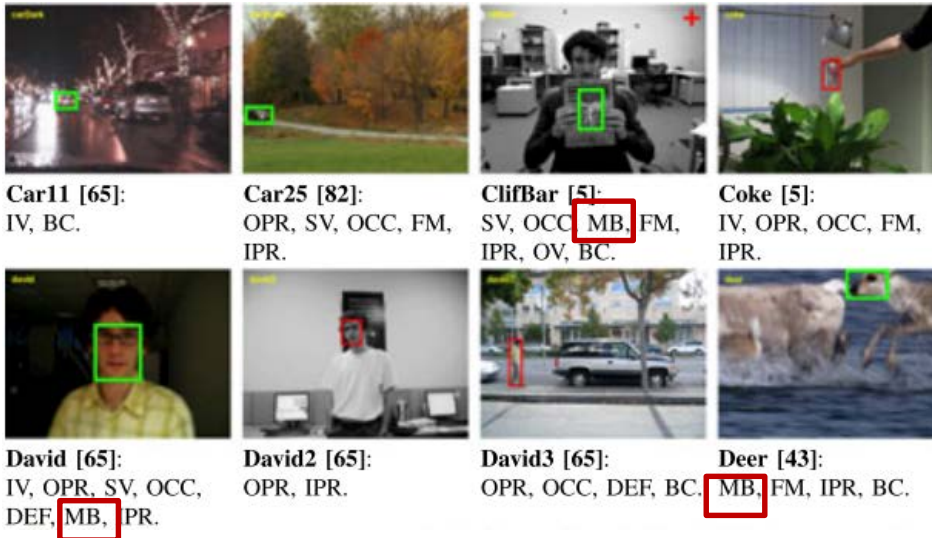
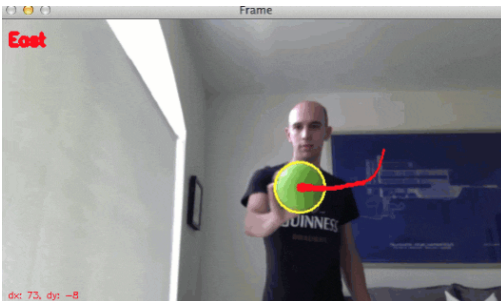


TABLE 2
Annotated Sequence Attributes with the Threshold Values in the Performance Evaluation

Attr	Description
IV	Illumination Variation—The illumination in the target region is significantly changed.
SV	Scale Variation—The ratio of the bounding boxes of the first frame and the current frame is out of range. $[1/t_s, t_s]$, $t_s > 1$ ($t_s = 2$).
OCC	Occlusion—The target is partially or fully occluded.
DEF	Deformation—Non-rigid object deformation.
MB	Motion Blur—The target region is blurred due to the motion of the target or the camera.
FM	Fast Motion—The motion of the ground truth is larger than t_m pixels ($t_m = 20$).
IPR	In-Plane Rotation—The target rotates in the image plane.
OPR	Out-of-Plane Rotation—The target rotates out of the image plane.
OV	Out-of-View—Some portion of the target leaves the view.
BC	Background Clutters—The background near the target has similar color or texture as the target.
LR	Low Resolution—The number of pixels inside the ground-truth bounding box is less than t_r ($t_r = 400$).



- ✗ Cannot exclude other factors during evaluation
- ✗ Cannot evaluate the effects of different blur levels

Y. Wu, J. Lim, and Ming-Hsuan Yang. Object Tracking Benchmark. In IEEE TPAMI, 2015.

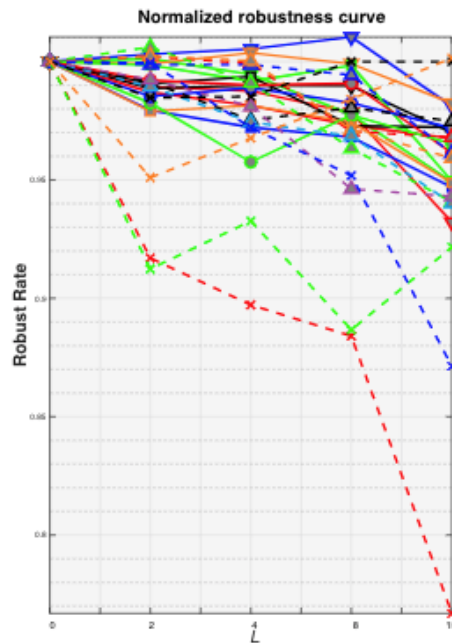
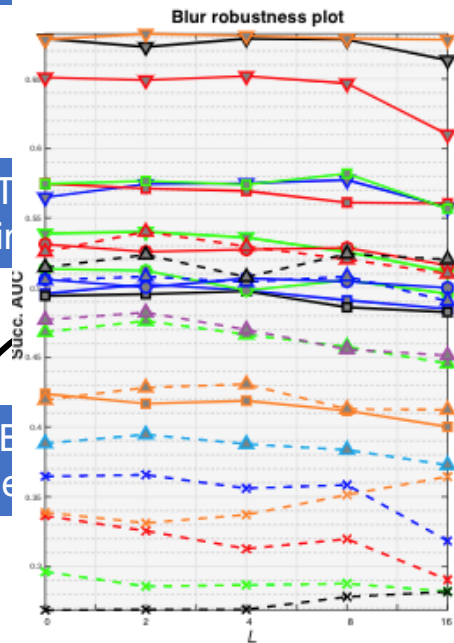
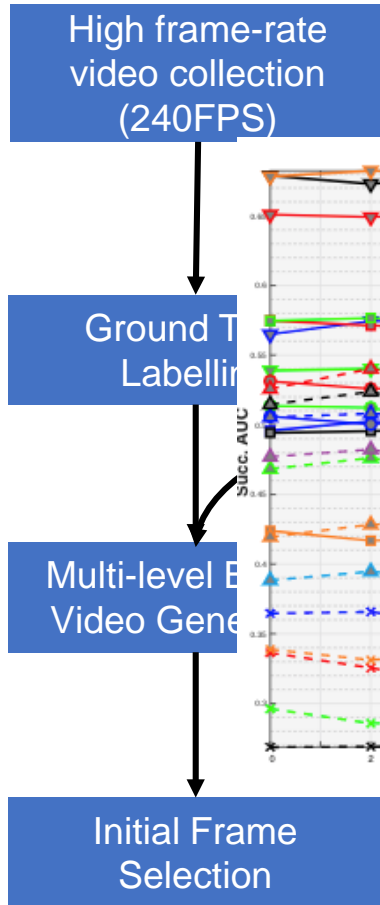
H. Fan, L. Lin, F. Yang, et al. LaSOT: A High-quality Benchmark for Large-scale Single Object Tracking. In CVPR, 2019.

Q. Guo, W. Feng, R. Gao, Y. Liu, and S. Wang. Exploring the Effects of Blur and Deblurring to Visual Object Tracking. In IEEE TIP, 2021

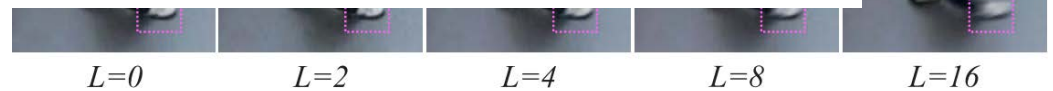
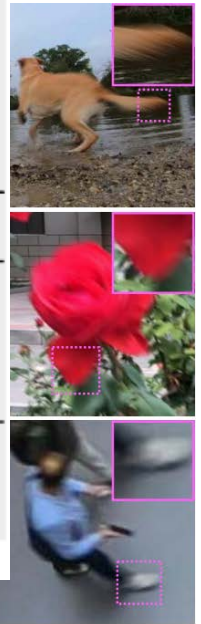
Robustness Evaluation

Blurred Video Benchmark – An Example (TIP' 21)

➤ Construction strategies



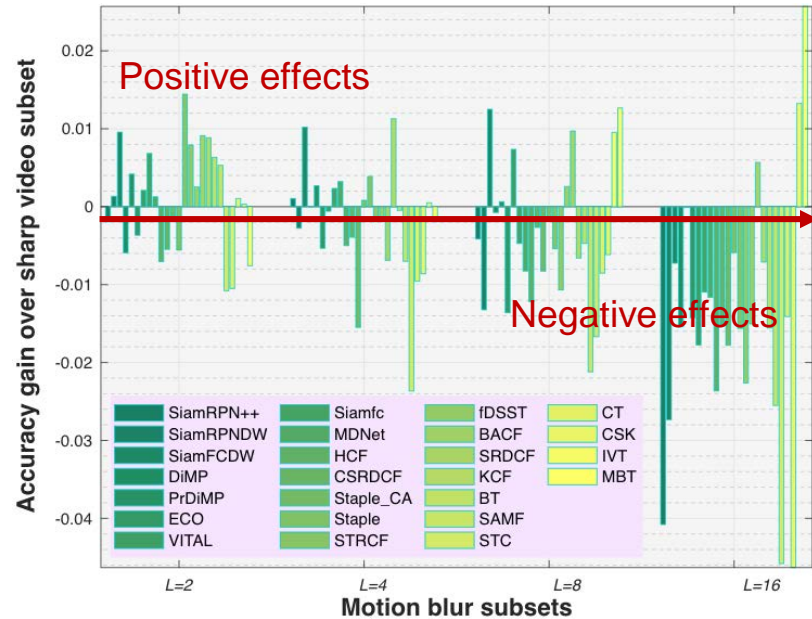
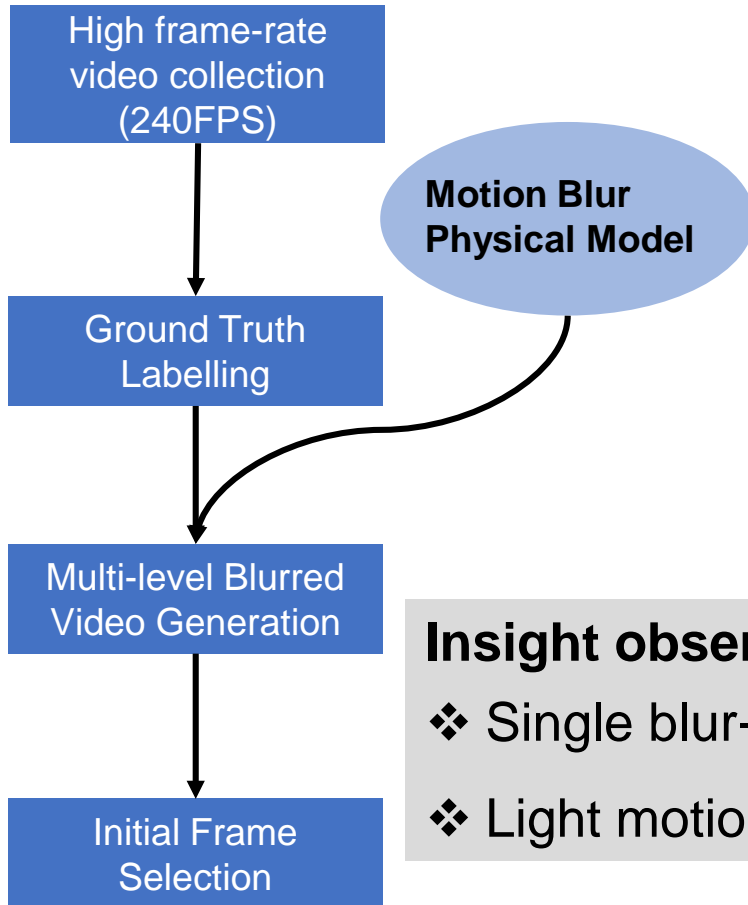
	Avg.AUC	Std.AUC	NRS
SiamRPN++	0.639	0.020	0.972
SiamRPNDW	0.528	0.013	0.981
SiamFCDW	0.571	0.009	1.000
DiMP	0.673	0.007	0.985
PrDiMP	0.680	0.002	0.996
ECO	0.566	0.005	0.977
VITAL	0.572	0.011	0.984
Siamfc	0.494	0.008	0.967
MDNet	0.490	0.007	0.982
HCF	0.412	0.008	0.971
CSRDCF	0.524	0.006	0.984
Staple_CA	0.503	0.007	0.971
Staple	0.503	0.003	0.982
STRCF	0.525	0.013	0.985
IDSSST	0.461	0.013	0.975
BACF	0.503	0.008	0.988
SRDCF	0.519	0.008	0.980
KCF	0.421	0.010	0.983
BT	0.385	0.009	0.968
SAMF	0.465	0.014	0.966
STC	0.312	0.015	0.866
CT	0.285	0.002	0.913
CSK	0.350	0.021	0.949
IVT	0.274	0.007	0.992
MBT	0.346	0.015	0.976



Robustness Evaluation

Blurred Video Benchmark – An Example (TIP' 21)

➤ Some insight observations



Insight observations:

- ❖ Single blur-level videos are not enough.
- ❖ Light motion blur is helpful but heavy blur is harmful.

Robustness Evaluation

Blurred Video Benchmark – An Example (TIP' 21)

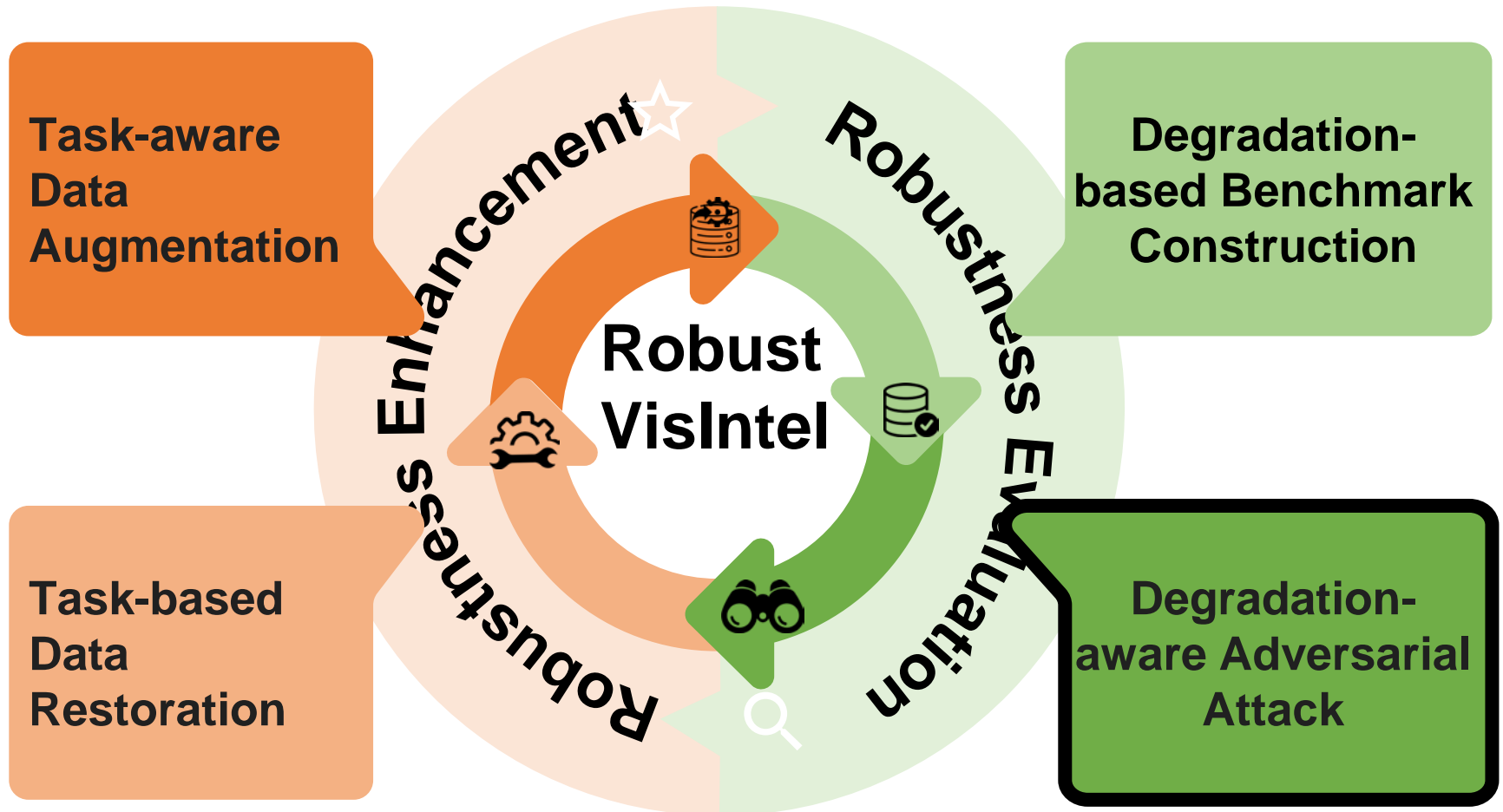
➤ Limitations



✗ Cannot cover the diverse and hard blur patterns.

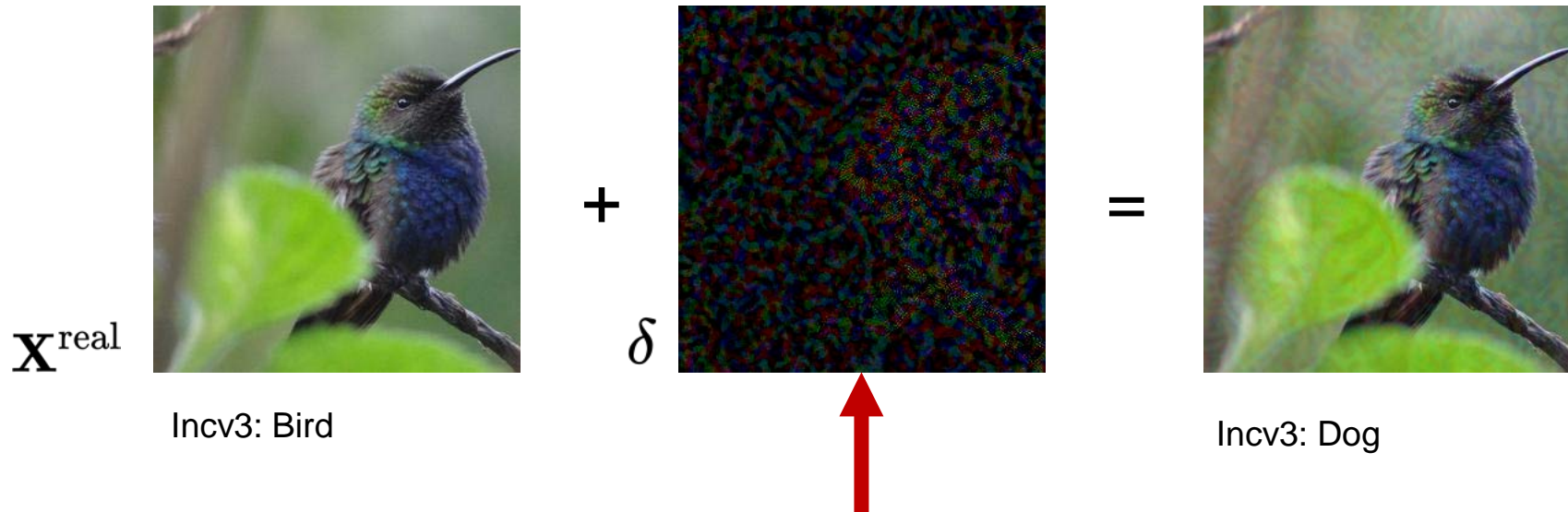
Robustness Evaluation

Goal: Robustness *Evaluation* and *Enhancement* of Visual Intelligence to Real-world Degradations:



Robustness Evaluation

Additive-Perturbation Adversarial Attack

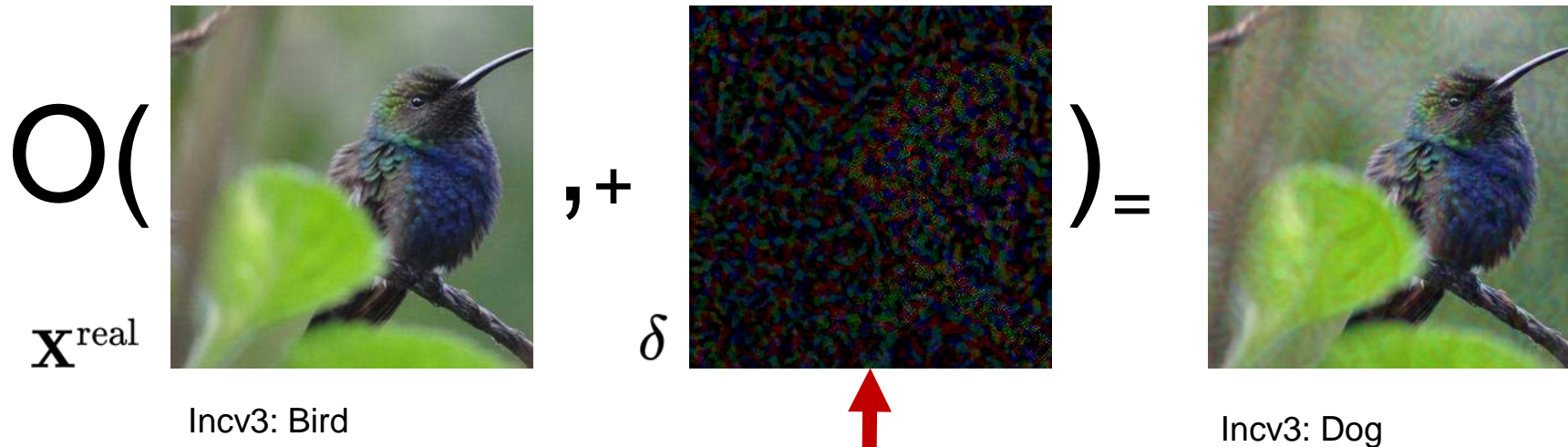


$$\arg \max_{\delta} J(\mathbf{X}^{\text{real}} + \delta, y) \text{ subject to } \|\delta\|_p \leq \epsilon$$

- ✓ **Noise-like adversarial perturbation cannot represent diverse natural degradations in the real world.**

Robustness Evaluation

General Adversarial Attack



$$\arg \max_{\delta} J(O(\mathbf{x}^{\text{real}}, \delta), y) \text{ subject to } \|\delta\|_p \leq \epsilon$$

- ✓ Turning the additive operation to nature degradation-based operations.

Robustness Evaluation

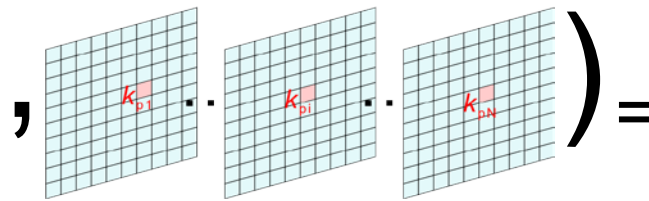
Adversarial Blur Attack (NeurIPS' 20)

Blur (

\mathbf{X}^{real}



Incv3: Bird



Pixel-wise blur kernels



Incv3: Car

$$\mathcal{K} = \{\mathbf{k}_p \mid \forall p \text{ in } \mathbf{X}^{\text{real}}\}$$

$$\arg \max_{\mathcal{K}} J(\{ \sum_{q \in \mathcal{N}(p)} \mathbf{X}_q^{\text{real}} k_{pq} \}, y)$$

$$\text{subject to } \forall p, \|\mathbf{k}_p\|_0 \leq \epsilon,$$

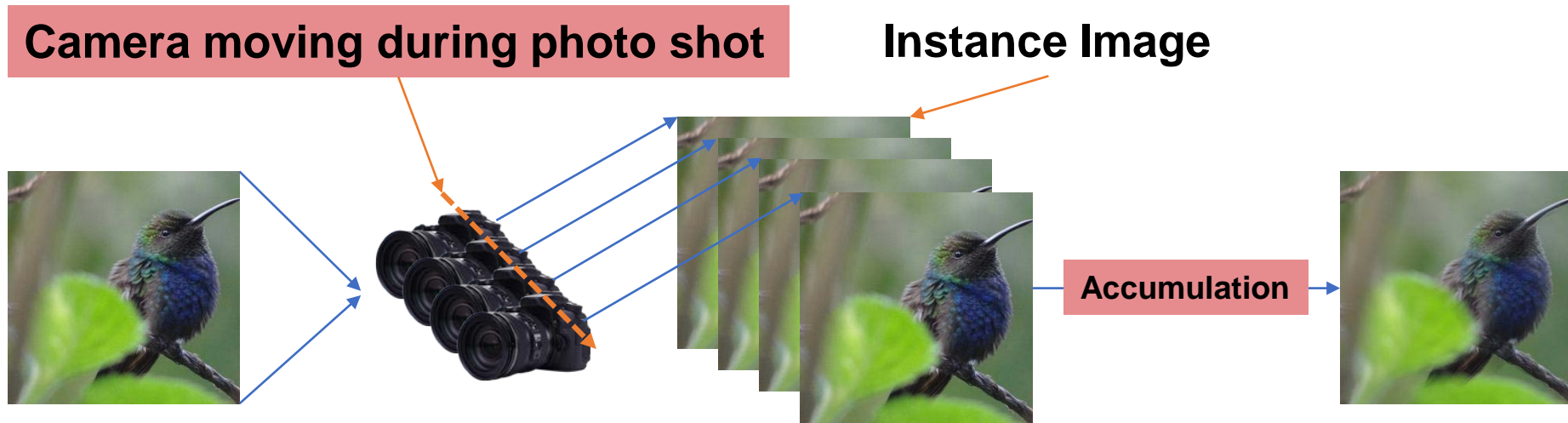
$$\max(\mathbf{k}_p) = k_{pp}, \sum_{q \in \mathcal{N}(p)} k_{pq} = 1,$$



Robustness Evaluation

Adversarial Blur Attack (NeurIPS' 20)

- Physical model of motion blur

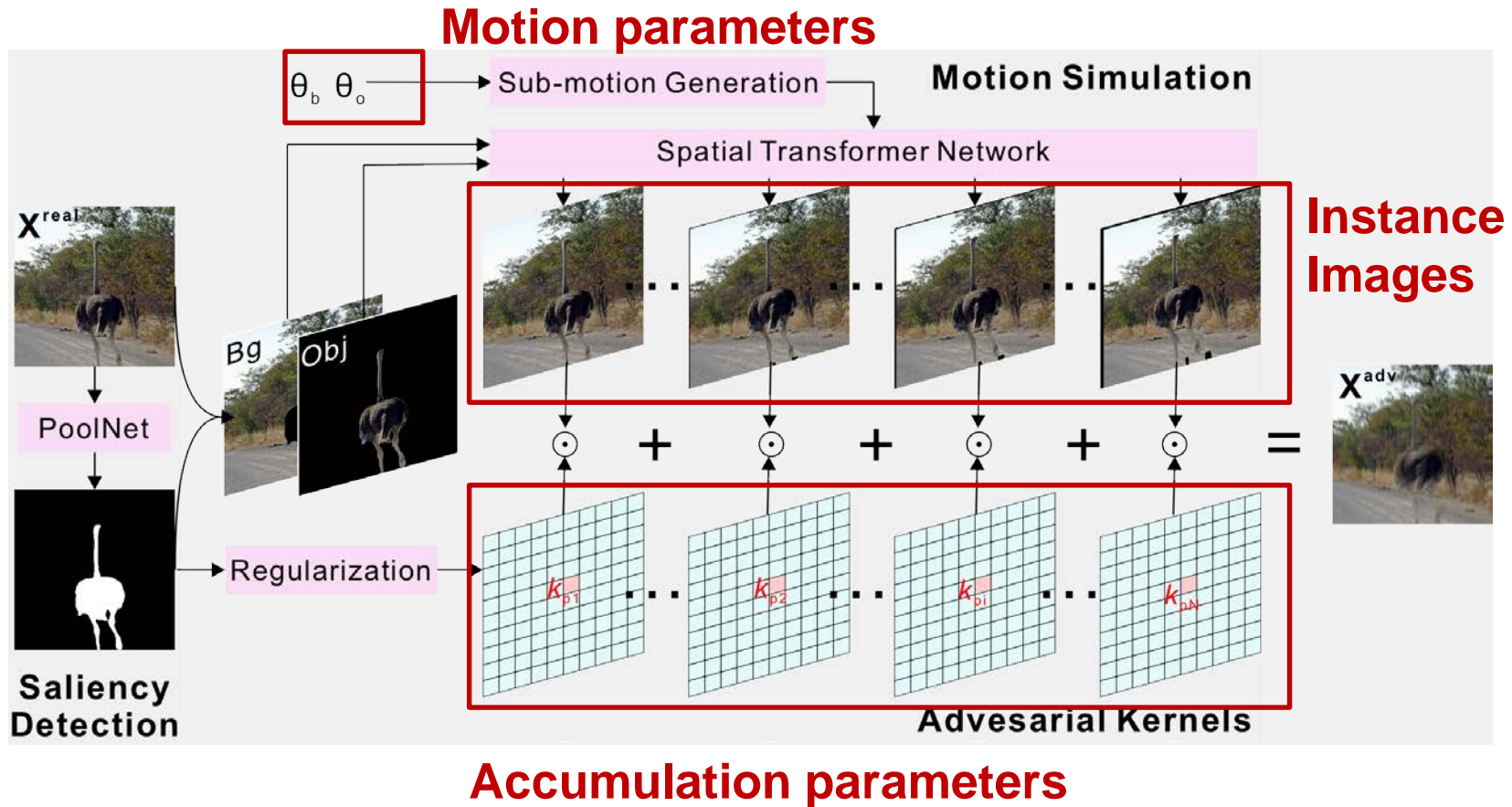


- ✓ Pattern of motion blur is mainly decided by the motion of the camera/object and the accumulation process.

Robustness Evaluation

Adversarial Blur Attack (NeurIPS' 20)

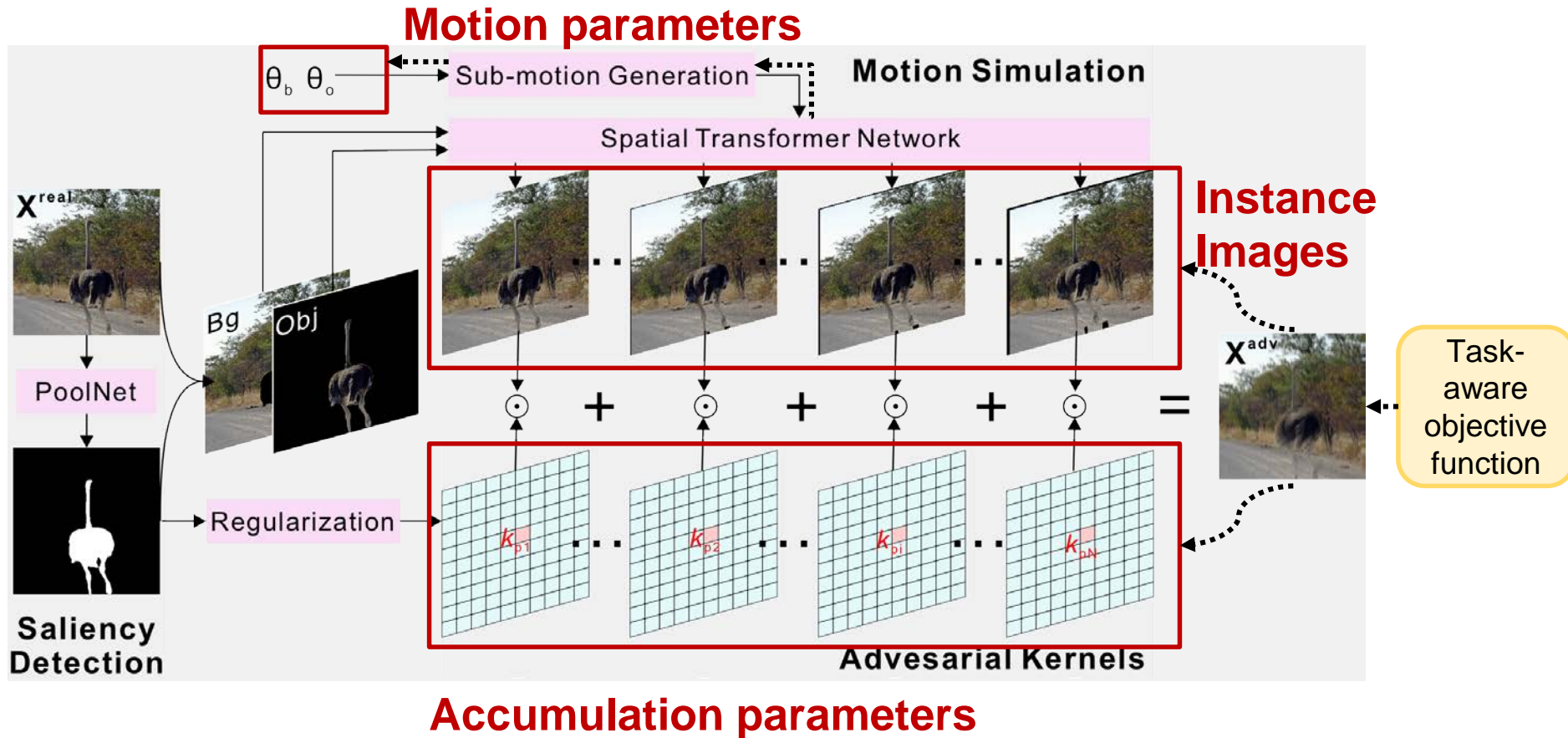
➤ Digital Simulation of motion blur



Robustness Evaluation

Adversarial Blur Attack (NeurIPS' 20)

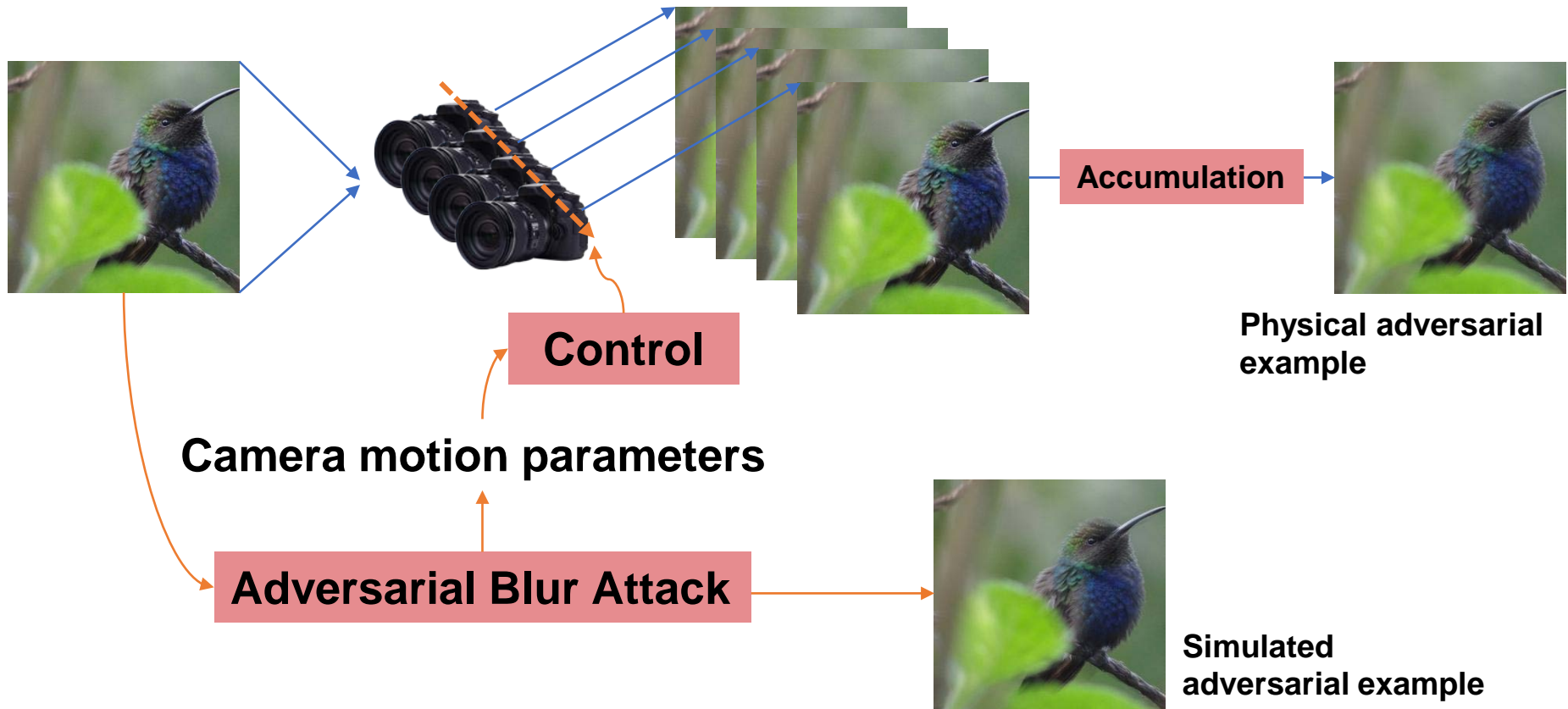
➤ Adversarial motion blur



Robustness Evaluation

Adversarial Blur Attack (NeurIPS' 20)

➤ Physical Adversarial Blur Attack



Robustness Evaluation

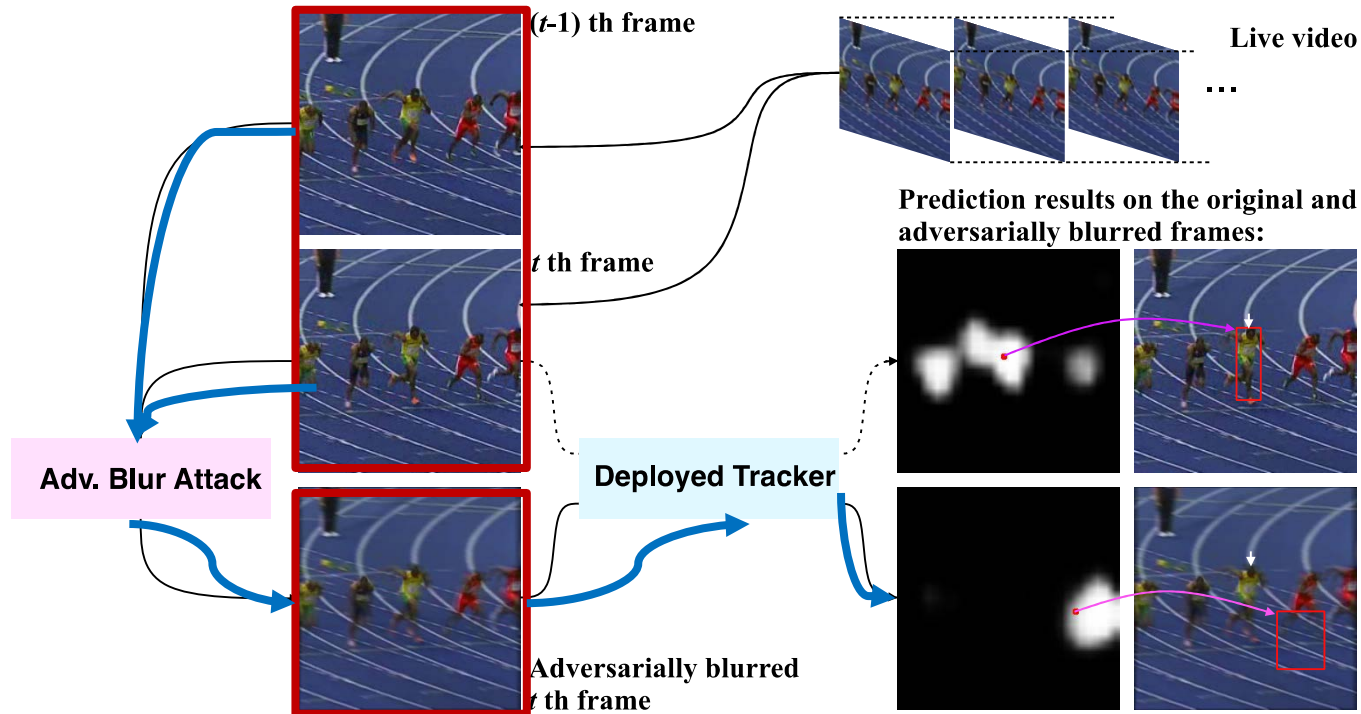
Adversarial Blur Attack (NeurIPS' 20)

➤ Physical Adversarial Blur Attack



Robustness Evaluation

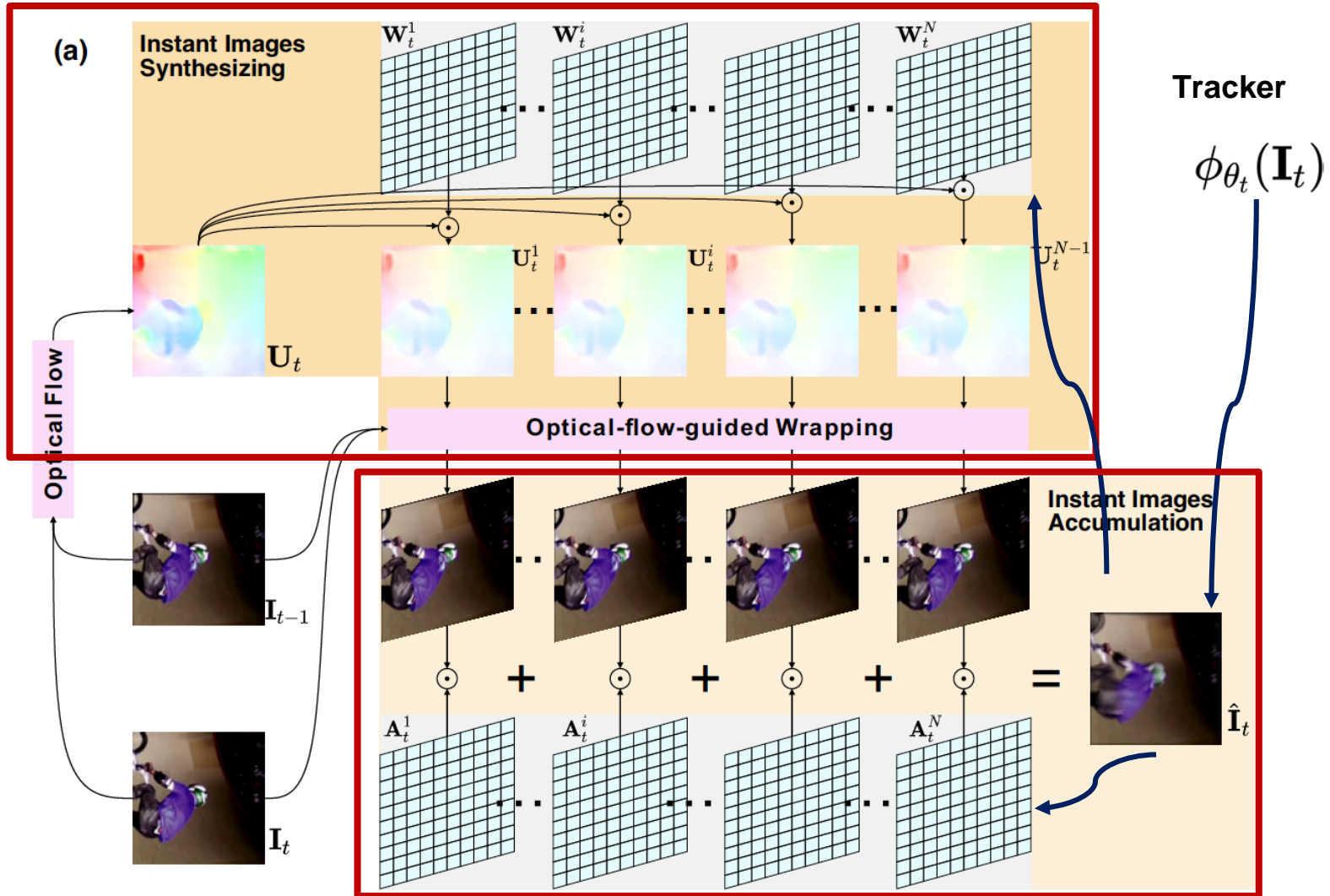
Adversarial Blur Attack against Tracking (ICCV' 21)



- ✓ How to make tuned motion blur keep realistic blur appearance?
- ✓ How to realize efficient adversarial blur attack to adapt the real-time trackers?

Robustness Evaluation

Adversarial Blur Attack against Tracking (ICCV' 21)



Robustness Evaluation

Adversarial Blur Attack against Tracking (ICCV' 21)

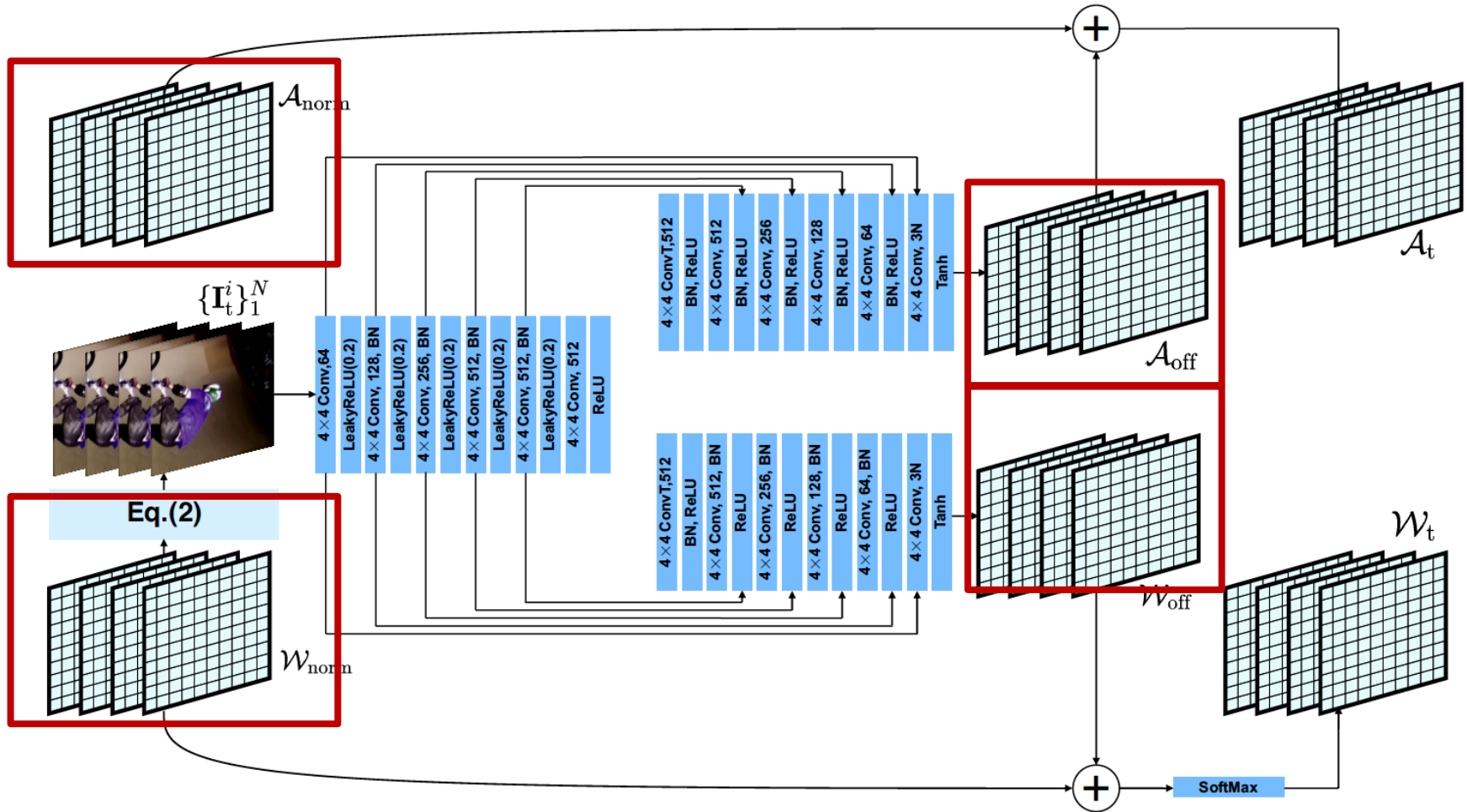


Figure 3: Architecture of JAMANet.

Robustness Evaluation

Adversarial Blur Attack against Tracking (ICCV' 21)

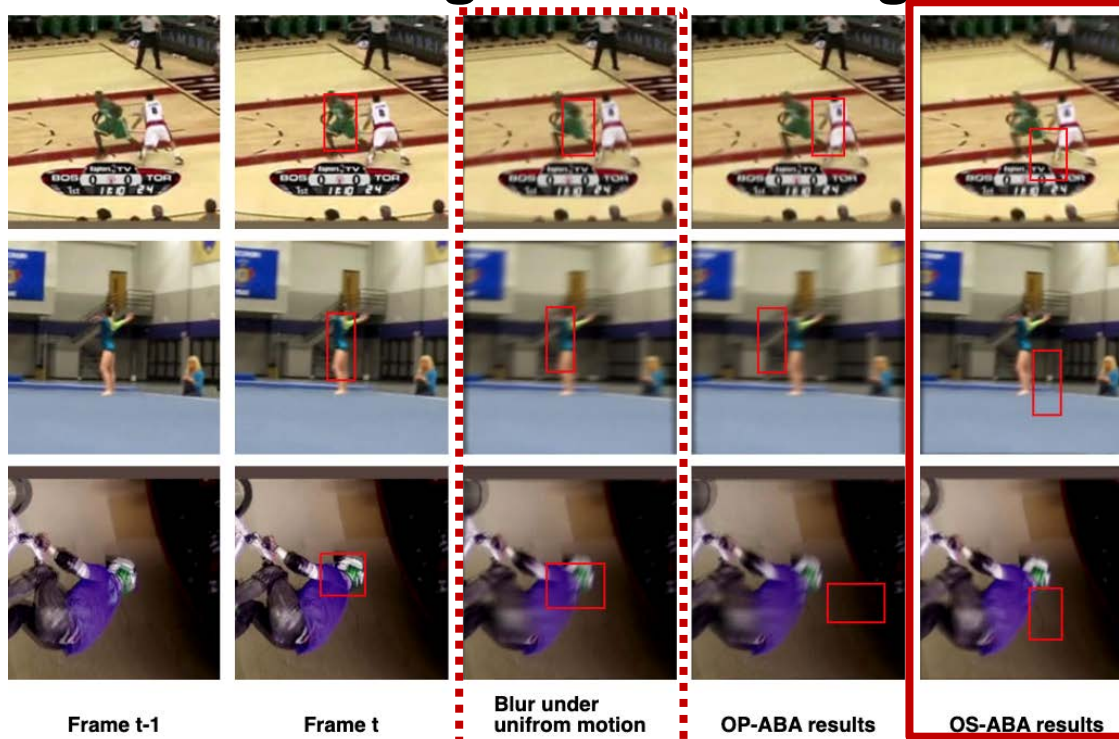


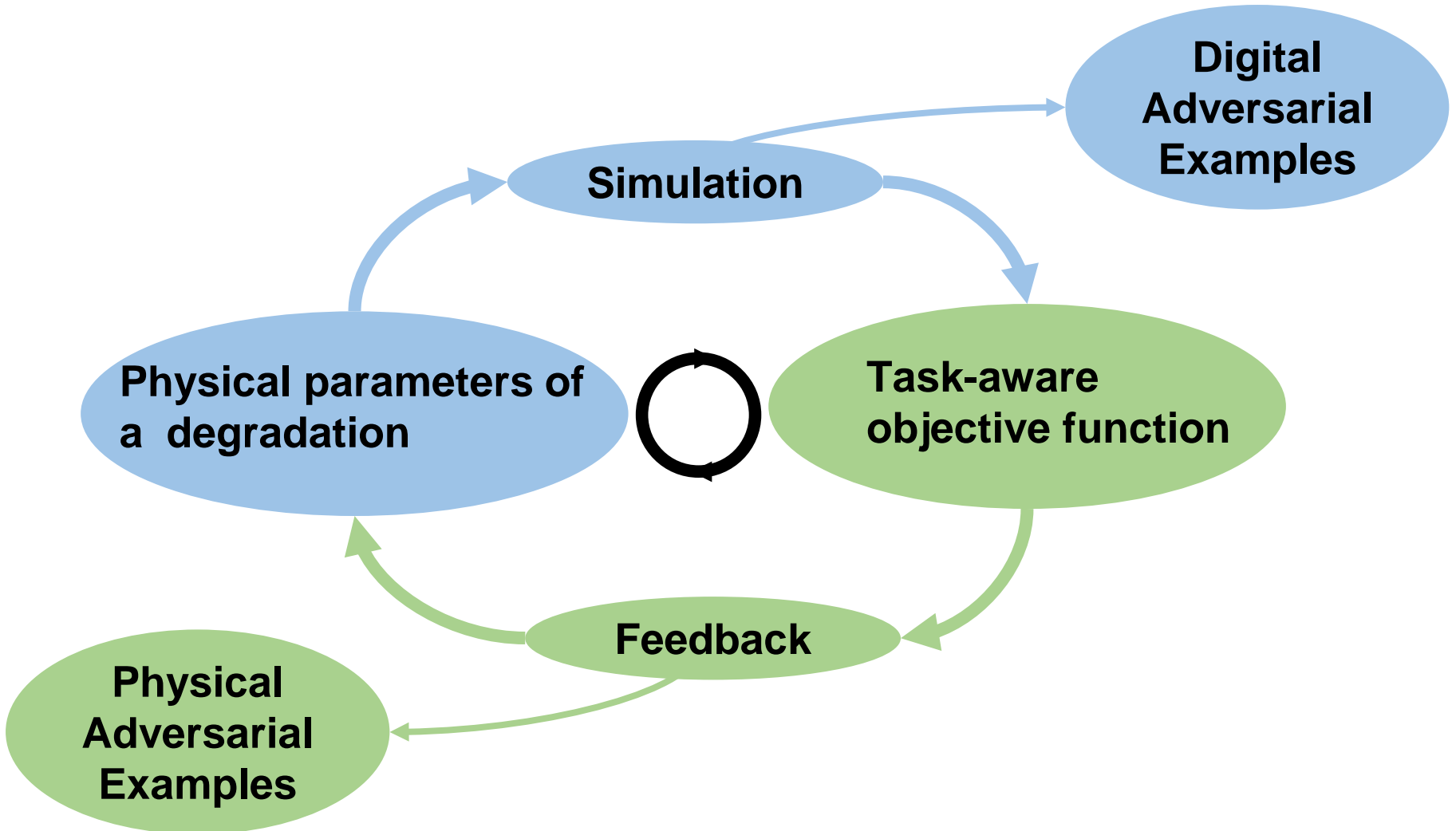
Table 4: Effects of \mathcal{W}_t and \mathcal{A}_t to OP-ABA and OS-ABA by attacking SiamRPN++(ResNet50) on OTB100. The best results are highlighted by red color.

Attackers	Succ. Rate	Succ. Drop \uparrow	Prec.	Prec. Drop \uparrow
Original	66.5	0.0	87.8	0.0
Norm-Blur	65.3	1.2	86.2	1.6
OP-ABA w/o \mathcal{A}_t	51.5	15.0	67.6	20.2
OP-ABA w/o \mathcal{W}_t	40.9	25.6	53.4	34.4
OP-ABA	35.3	31.2	46.1	41.7
OS-ABA w/o \mathcal{A}_t	61.0	5.5	80.8	7.0
OS-ABA w/o \mathcal{W}_t	41.6	24.9	58.3	29.5
OS-ABA	38.4	28.1	55.3	32.5

Robustness Evaluation

Degradation-aware Adversarial Attack

- Generalizing adversarial blur attack to other degradations



Robustness Evaluation

Solution1: Degradation-aware Adversarial Attack

Adversarial
Deformation/Rain/Fog/Relighting Attack (ACMMM'20, IEEE TIFS & TMM)

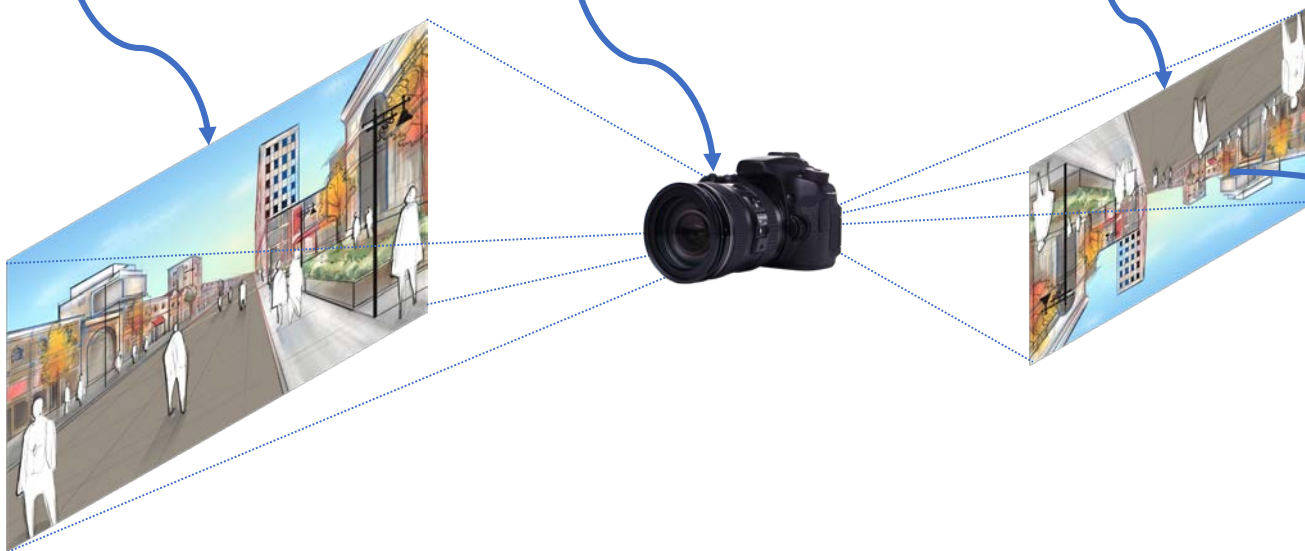
Adversarial
Noise/Vignetting/Exposure Attack (ECCV'20, IJCAI'21, CVPR'22)

Adversarial **Denoising/DeID** Attack (TMM' 21)

Scene variations

Camera variations

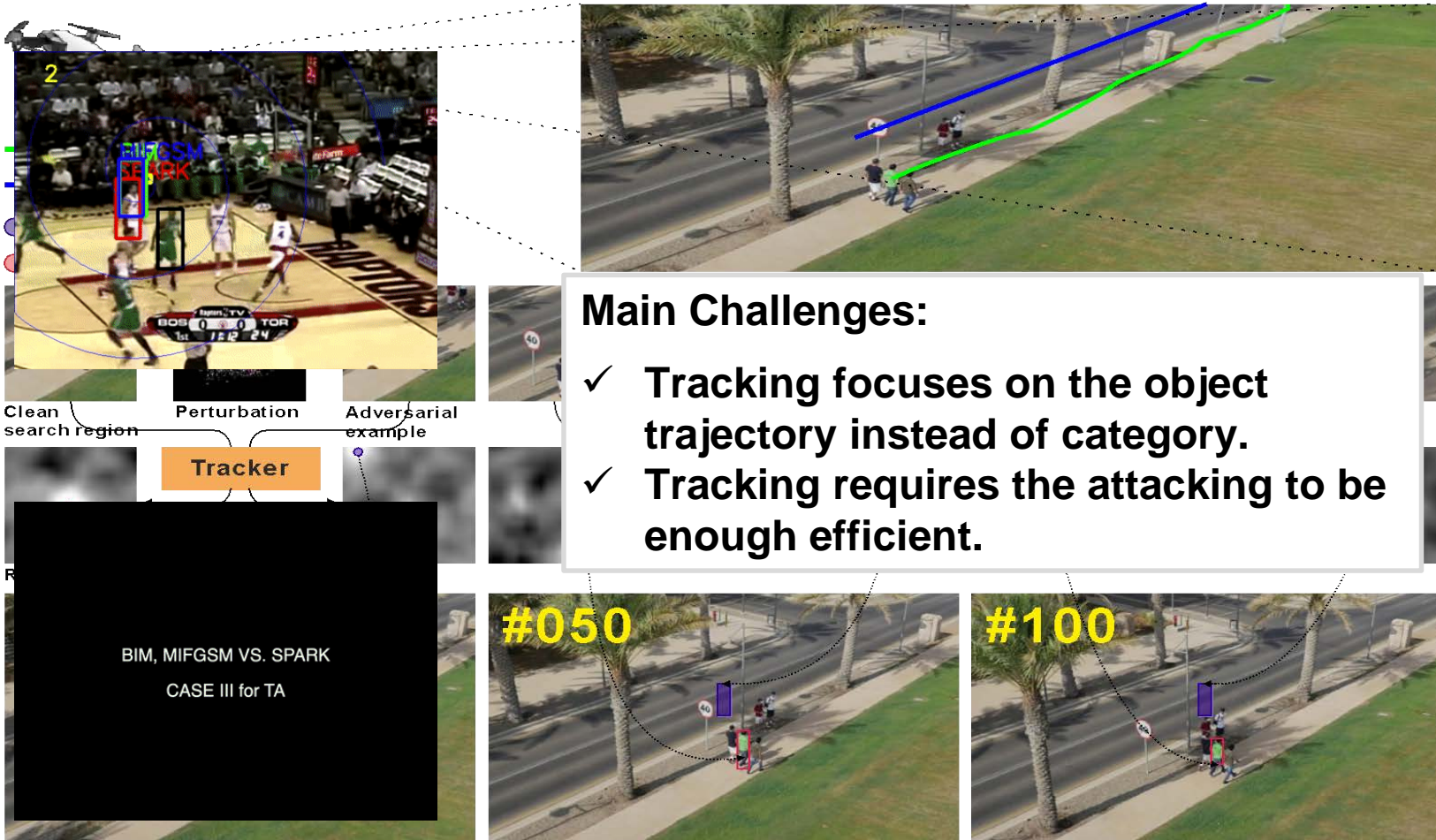
Post modifications



Visual
Intelligent
Tasks

Robustness Evaluation

SPARK - Effects of noise to tracking (ECCV'20)



Clean search region **Perturbation** **Adversarial example**

Tracker

Main Challenges:

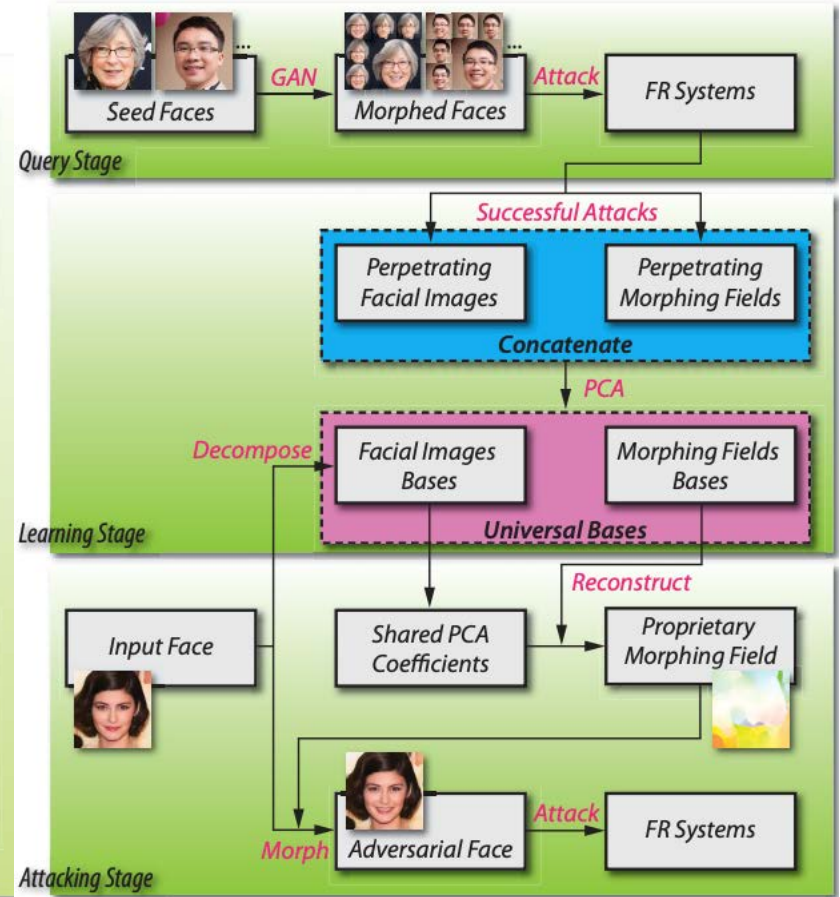
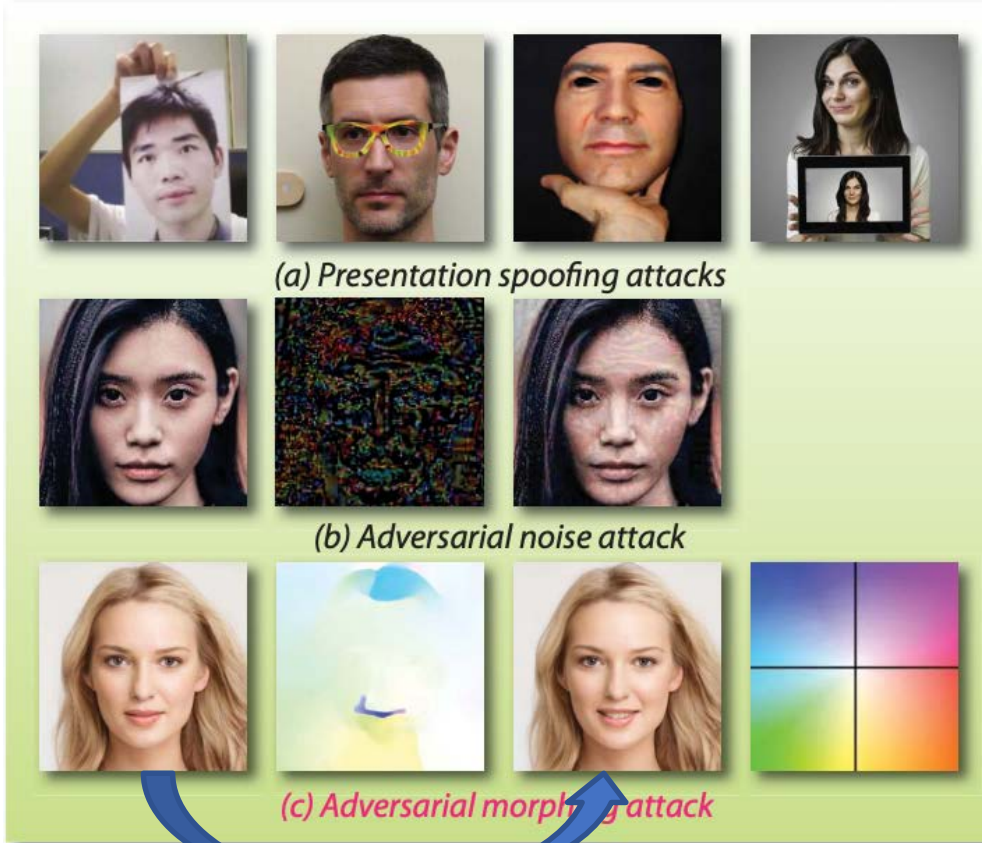
- ✓ Tracking focuses on the object trajectory instead of category.
- ✓ Tracking requires the attacking to be enough efficient.

#050 **#100**

BIM, MIFGSM VS. SPARK
CASE III for TA

Robustness Evaluation

Amora- Effects of deformation to FR (ACM-MM'20)



Robustness Evaluation

AVA - Effects of vignetting to recognition (IJCAI'21)

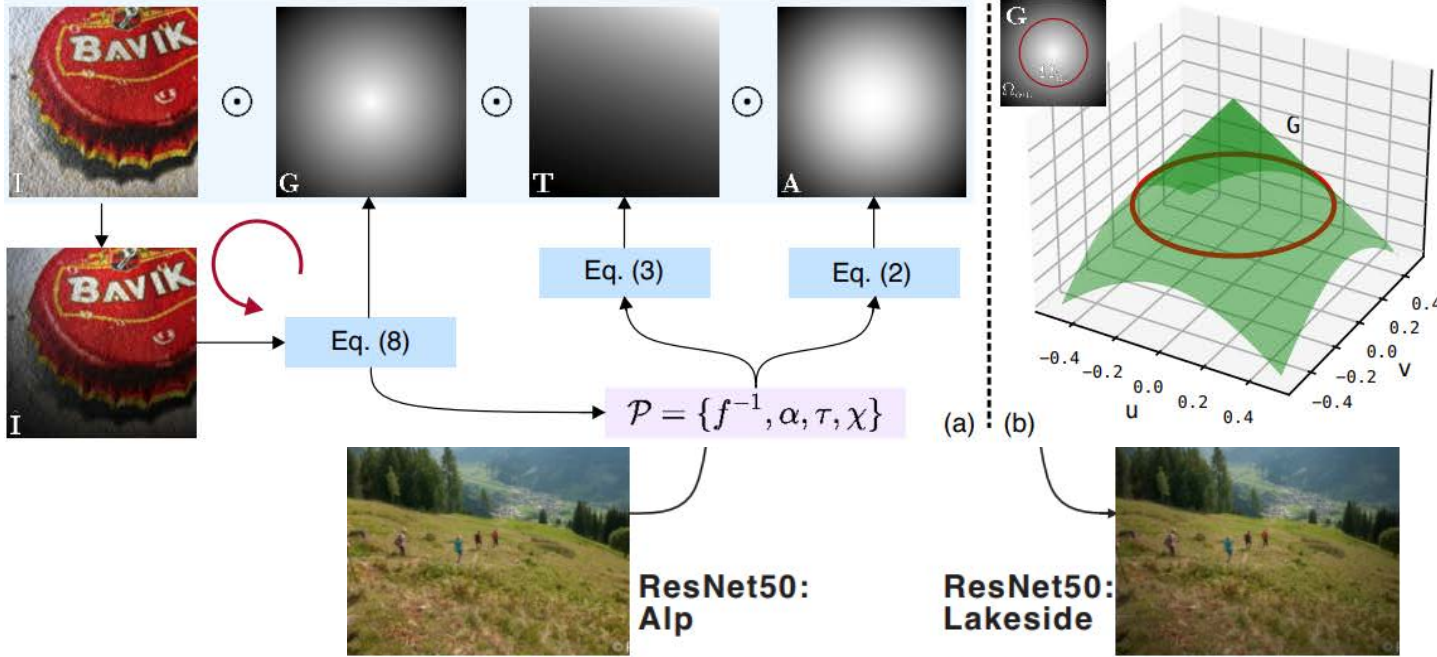


Figure 2: (a) shows the whole process of RA-AVA. (b) shows the 3D surface of the initialized G . The red line is the curve splitting the image to 2 parts, *i.e.*, Ω_{in} and Ω_{out} .

(b) Adversarial Vignetting Examples

Robustness Evaluation

Effects of exposure and noise to CoSOD (CVPR'22)

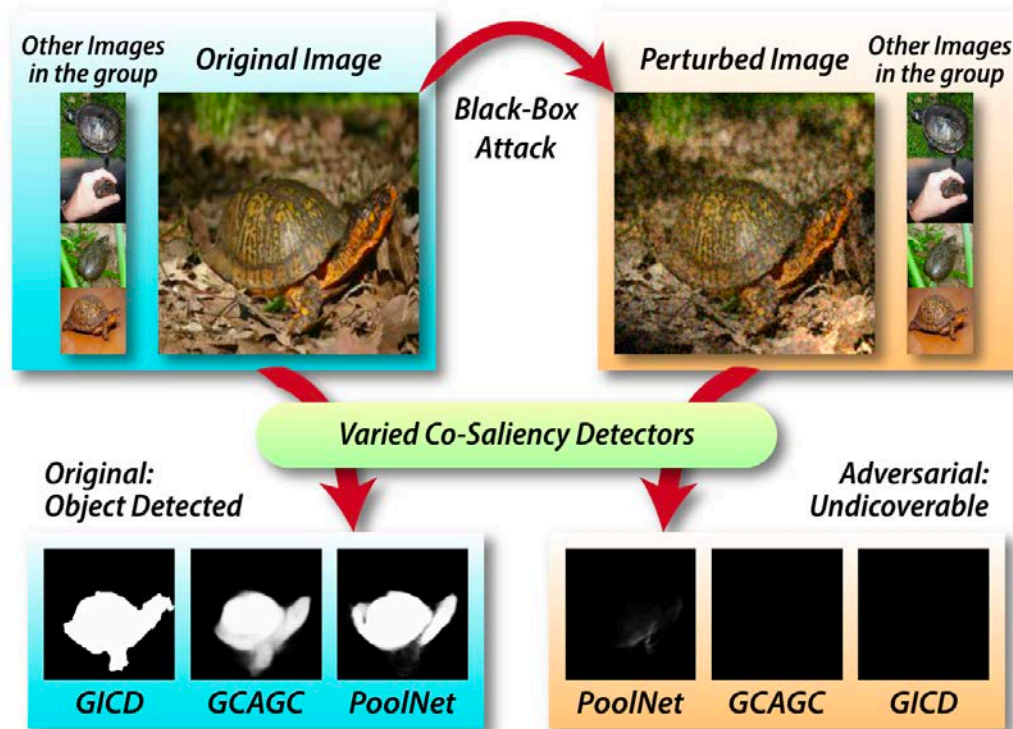
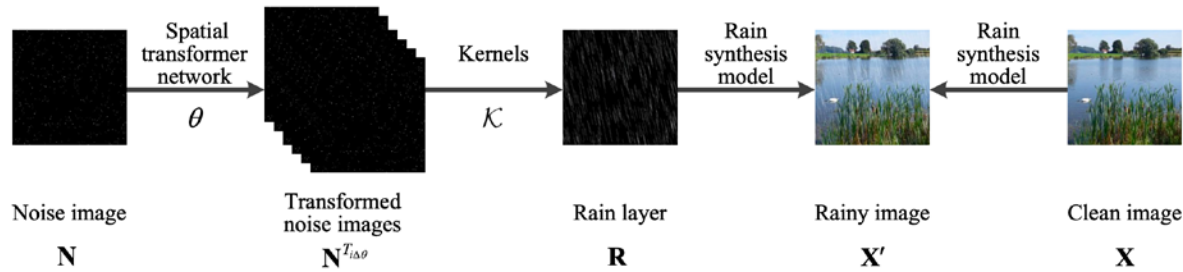


Figure 1: Overall of the novel problem and our solution. We expect the perturbed image to be undiscoverable in an even dynamically growing group of images across multiple CoSOD methods, which is much more challenging and practical in real-world scenarios. Note that our attack is black-box and can be performed without references provided in the group.

Robustness Evaluation

Effects of rain to recog. & detection



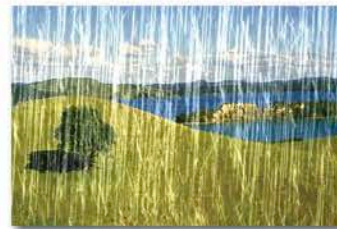
(a) AdvRain-DEV (ours)



(b) AdvRain-COCO (ours)



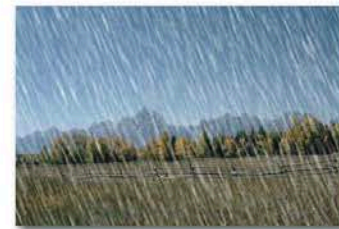
(c) AdvRain-KITTI (ours)



(d) Rain100H



(e) Rain800



(f) Rain1200



(g) Rain1400

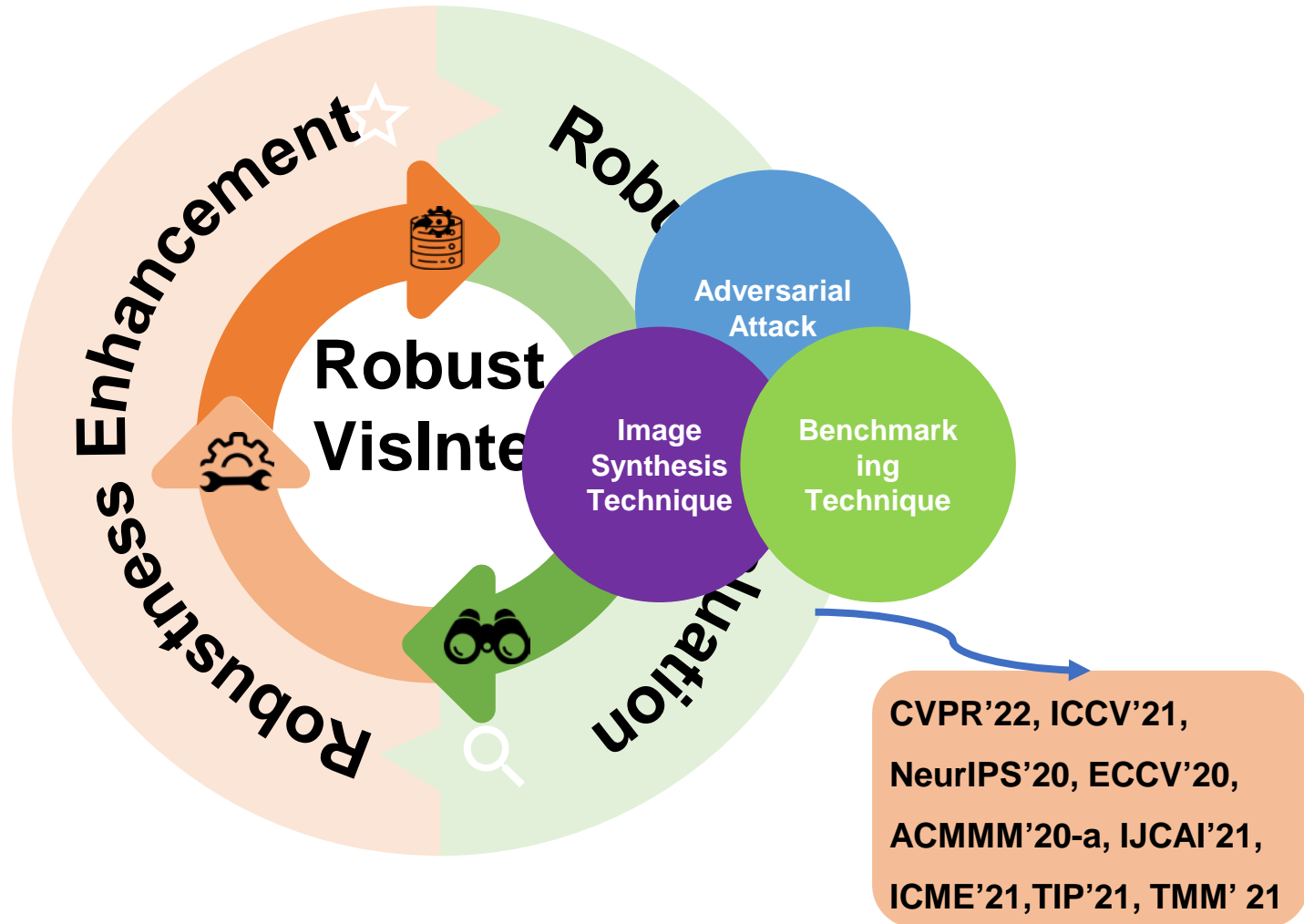


(h) Physics-based Rain Rendering

Figure 4: Comparison of our adversarial rainy images on three datasets (a-c) and other synthesized rainy images from Rain100H (Yang et al. 2017), Rain800 (Zhang, Sindagi, and Patel 2019), Rain1200 (Zhang and Patel 2018), Rain1400 (Fu et al. 2017) and Physics-based Rain Rendering (Halder, Lalonde, and Charette 2019) (d-h).

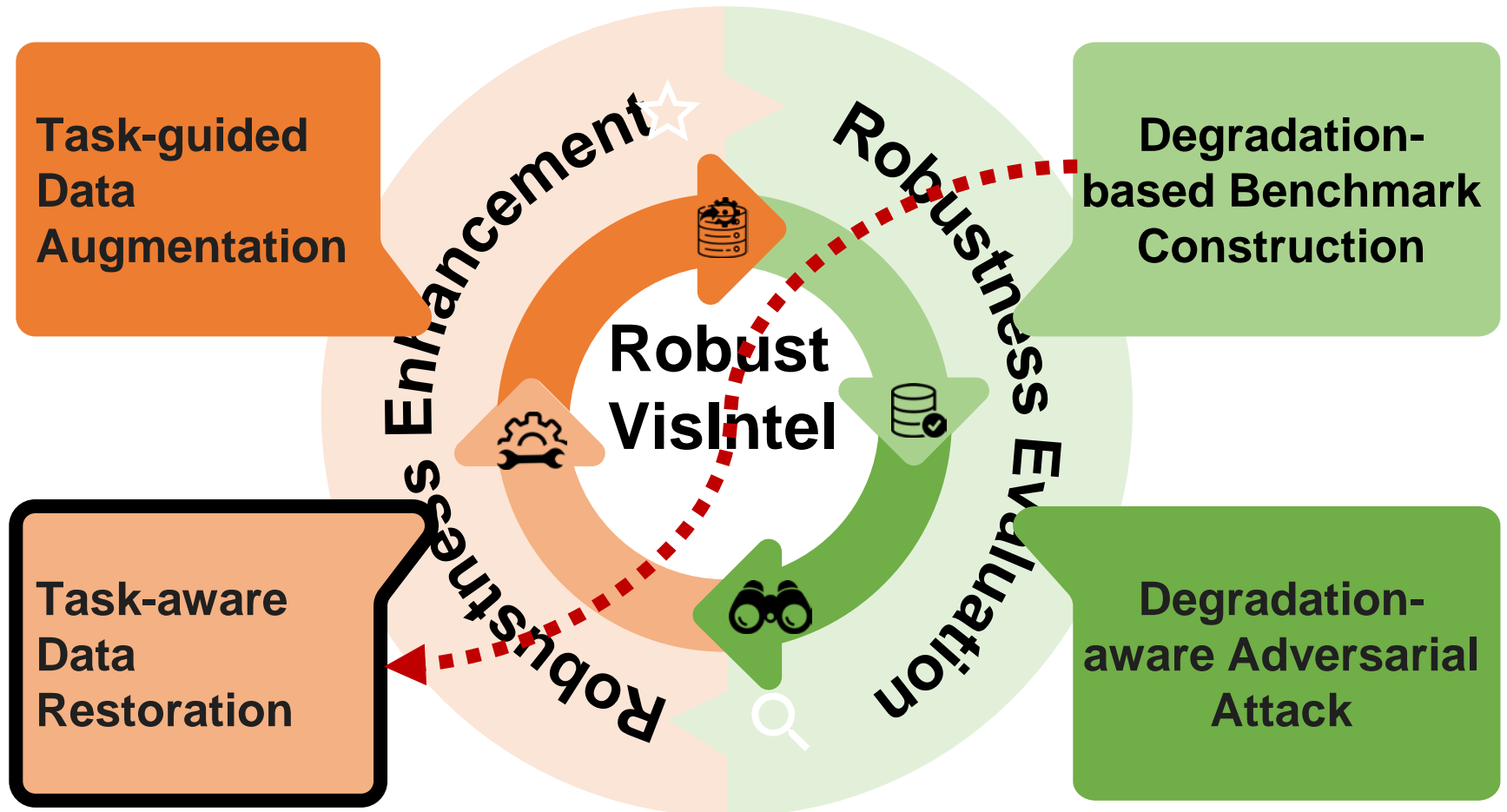
Robustness Evaluation

Goal: Robustness Evaluation and Enhancement of Visual Intelligence to Real-world Degradation:



Robustness Enhancement

Goal: Robustness Evaluation and Enhancement of Visual Intelligence to Real-world Degradation:



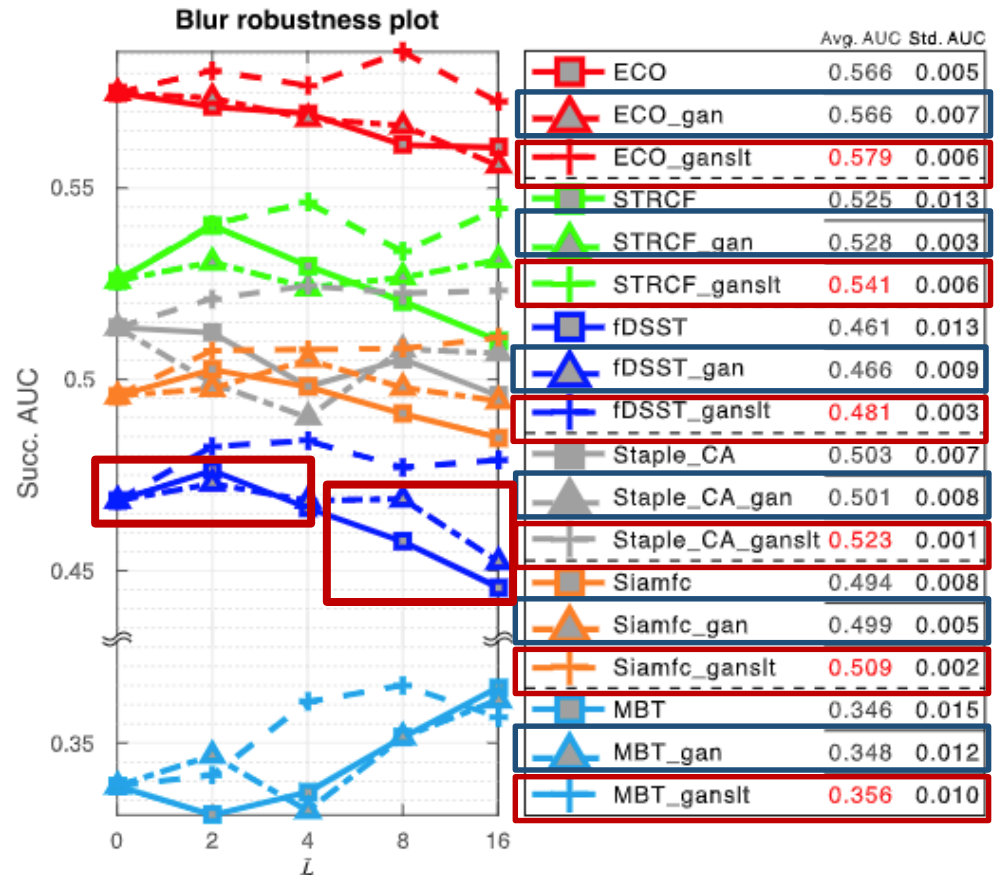
Robustness Enhancement

Selective Deblurring for Blur Robust Tracking (TIP' 21)

➤ Motivation

❖ Blurred Video Benchmark:
Effects of deblurring to
different blur levels are
different.

❖ Blurred Video Benchmark:
Selective deblurring
improves tracking
accuracy significantly

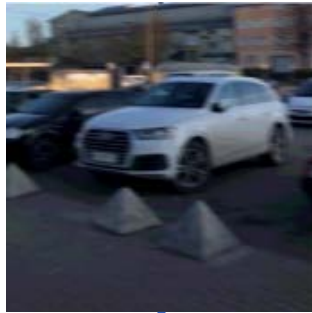


_gan: deblurring all frames _ganslt: selective deblurring w.r.t GT

Robustness Enhancement

Selective Deblurring for Blur Robust Tracking (TIP' 21)

➤ DeblurGAN-D as Blur Assessor



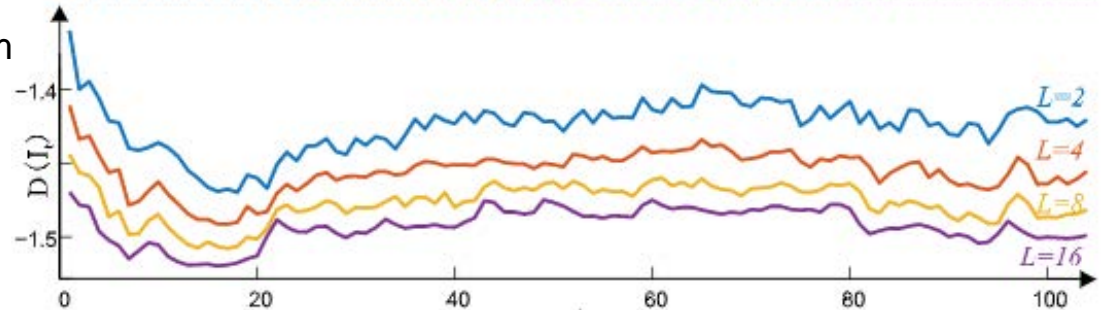
Generator



Blur level from
heavy to
light during
training

Deblurred

Discriminator



Robustness Enhancement

Selective Deblurring for Blur Robust Tracking (TIP' 21)

➤ Pipeline

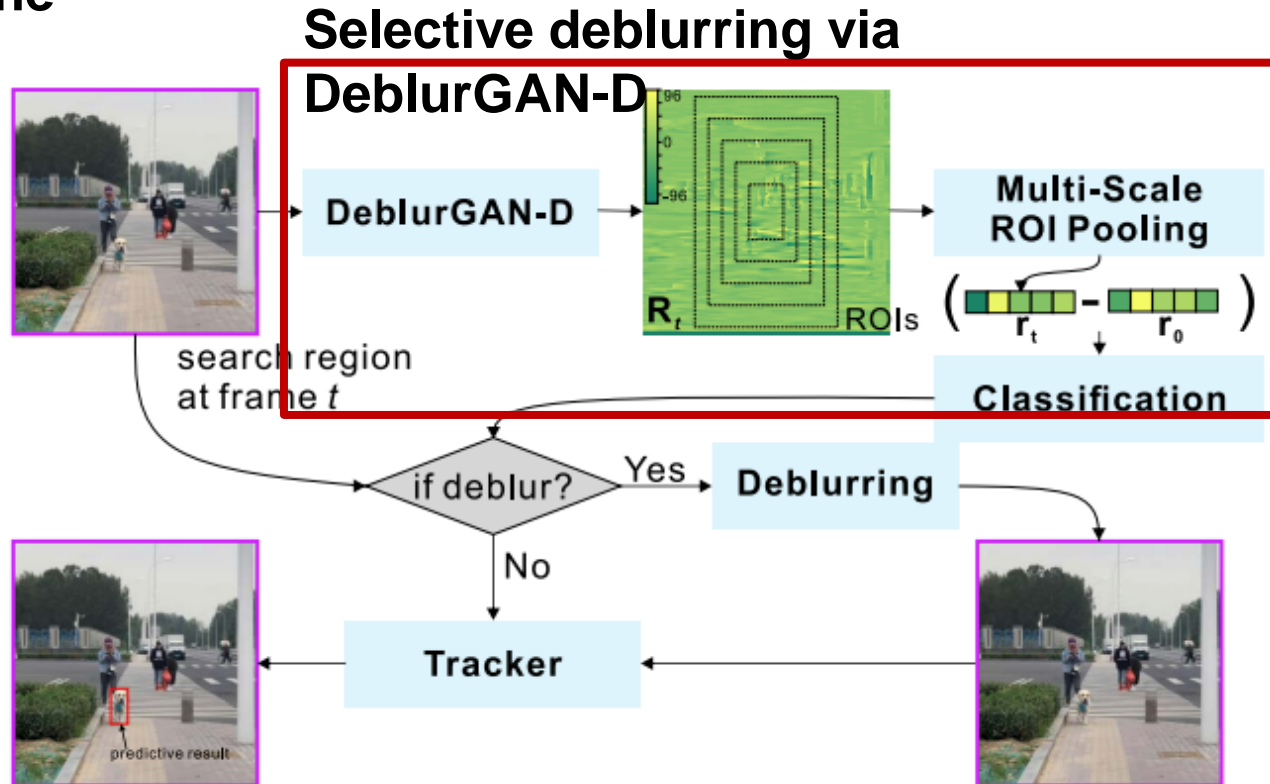


Fig. 10. The pipeline of our selective deblurring-based tracking. We can use existing deblurring methods, *e.g.*, DeblurGAN-G [14] for ‘deblurring’, and the classification is set as an offline trained SVM that indicates when we should deblurring a coming frame t .

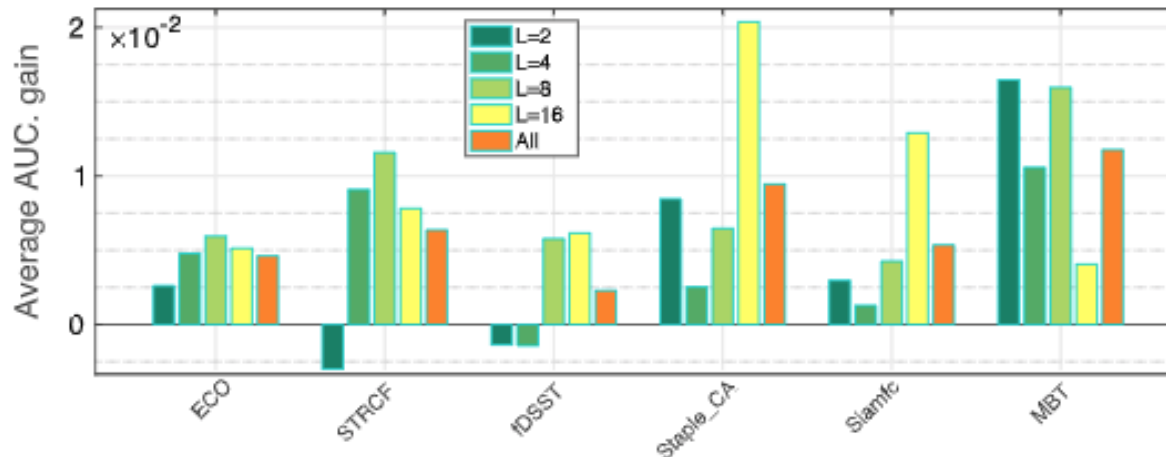
Robustness Enhancement

Selective Deblurring for Blur Robust Tracking (TIP' 21)

➤ Results

TABLE I
COMPARISON RESULTS ON THE MOTION BLUR SUBSET OF OTB.

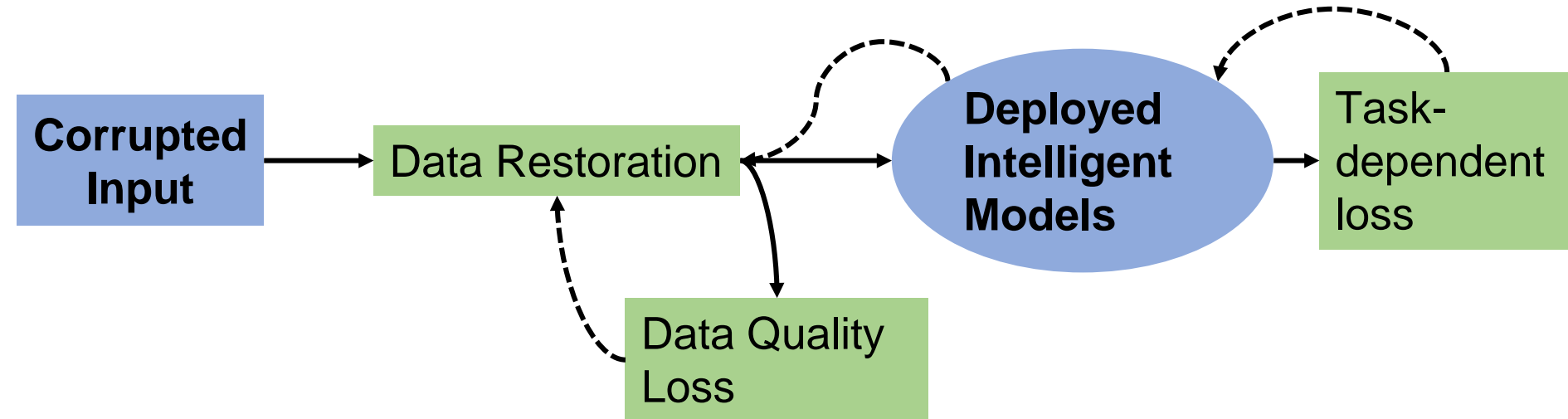
Trackers	raw (AUC)	blur-robust tracking (AUC)
fDSST	0.512	0.530
Staple_CA	0.551	0.561
Siamfc	0.343	0.353
MBT	0.233	0.242
ECO	0.677	0.679
STRCF	0.633	0.637



Robustness Enhancement

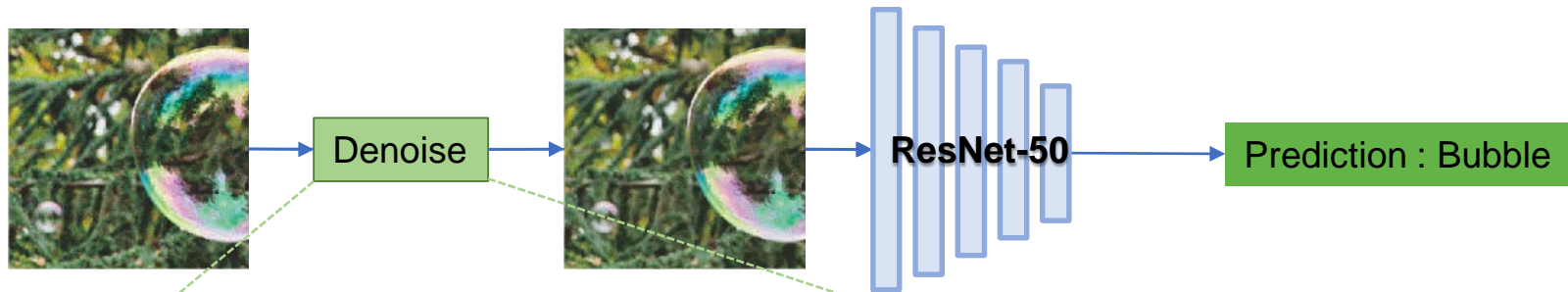
Task-aware Data Restoration

- Generalizing deblurring to other degradation restorations

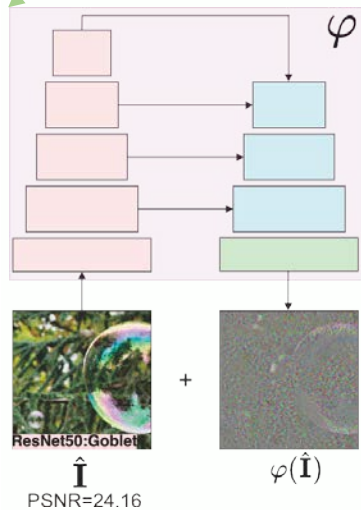


Robustness Enhancement

Task-aware Data Restoration – Denoising (MM'21)



Adv. Example
GT label: Bubble



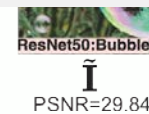
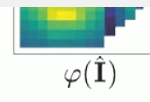
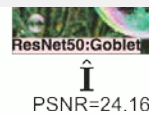
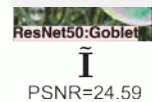
(a) Additive-based denoising method



(b) Filtering-based denoising method

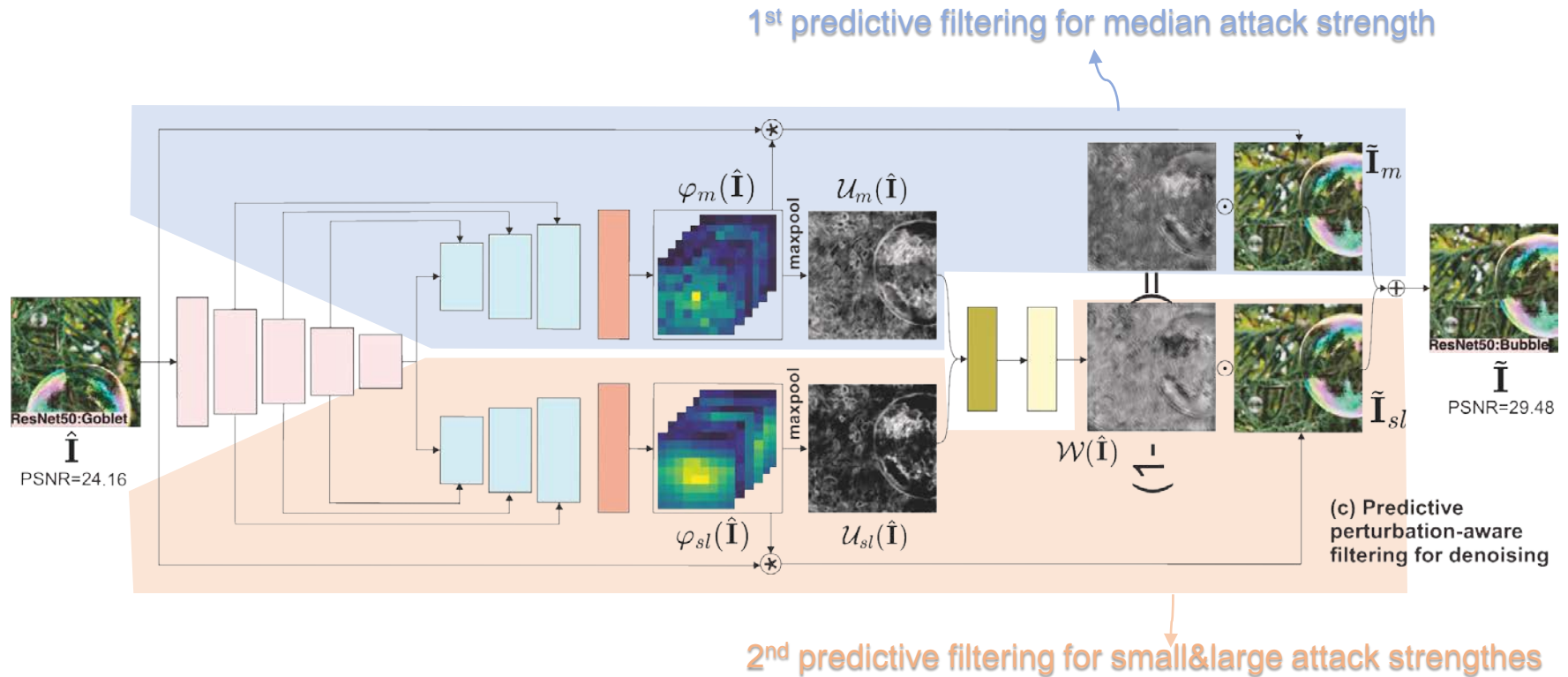
Observations:

- ❖ Solution (b) is more effective than solution (a) for adversarial robustness enhancement.
- ❖ Solution (b) can achieve higher accuracy on both small and large attack strengths but is less effective on the median attack strengths.



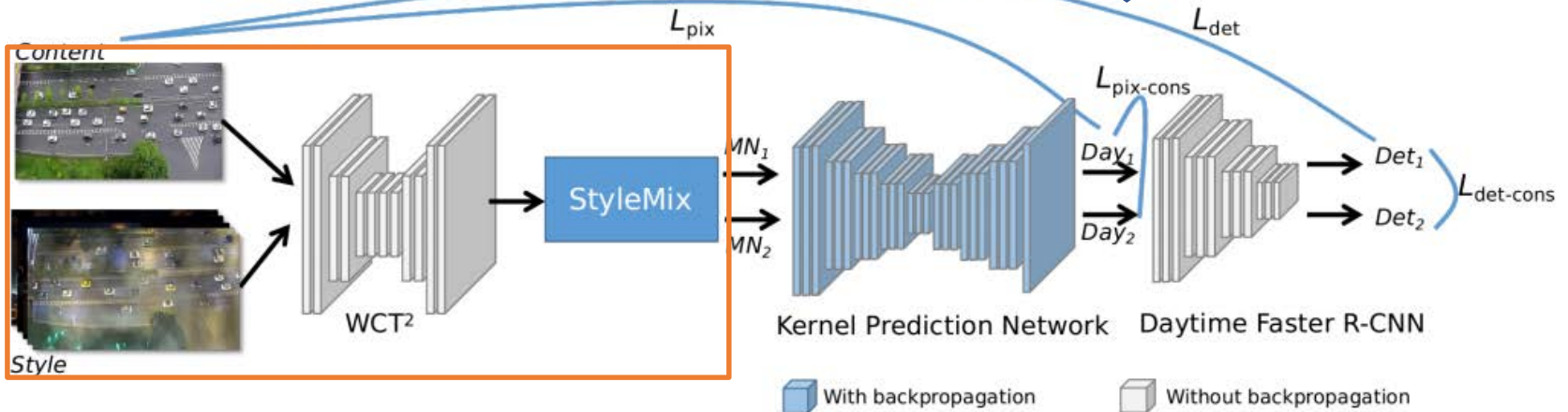
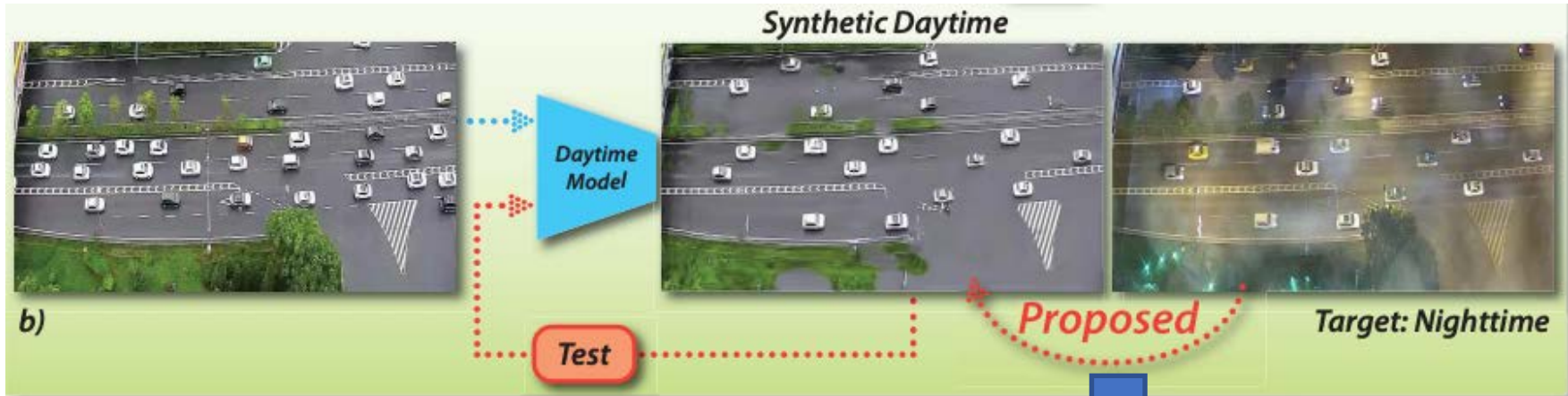
Robustness Enhancement

Task-aware Data Restoration – Denoising (MM'21)



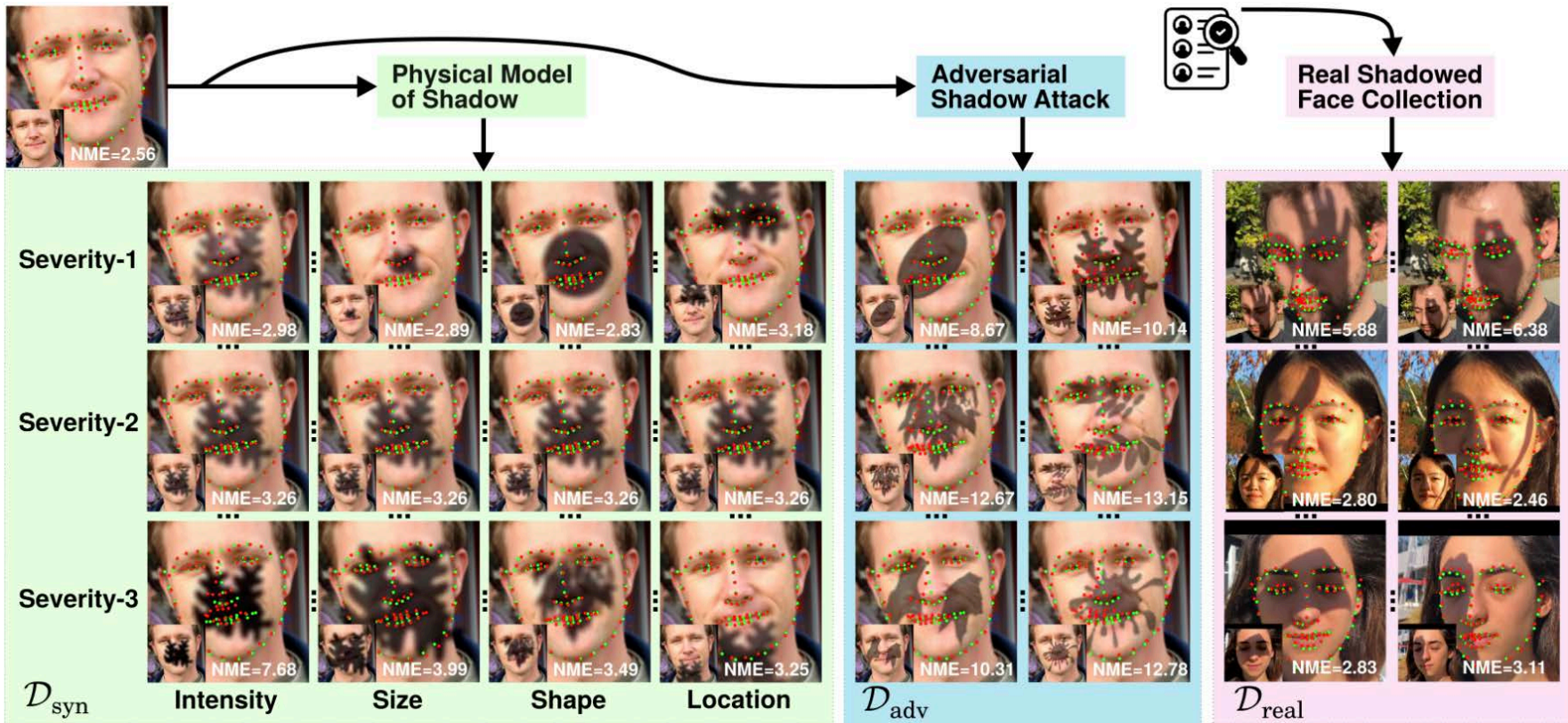
Robustness Enhancement

Task-aware Data Restoration – Night2Day



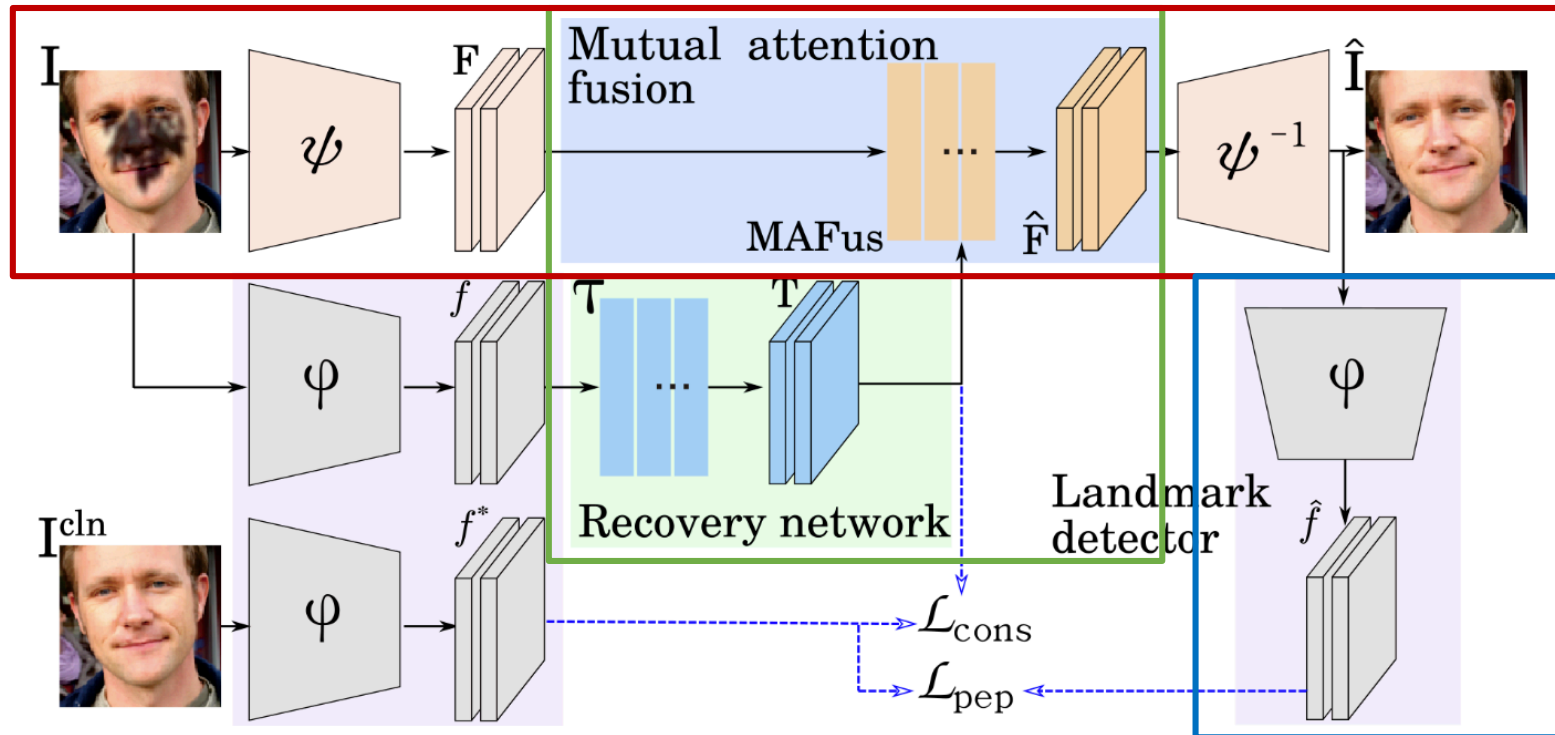
Robustness Enhancement

Task-aware Data Restoration – Shadow Removal



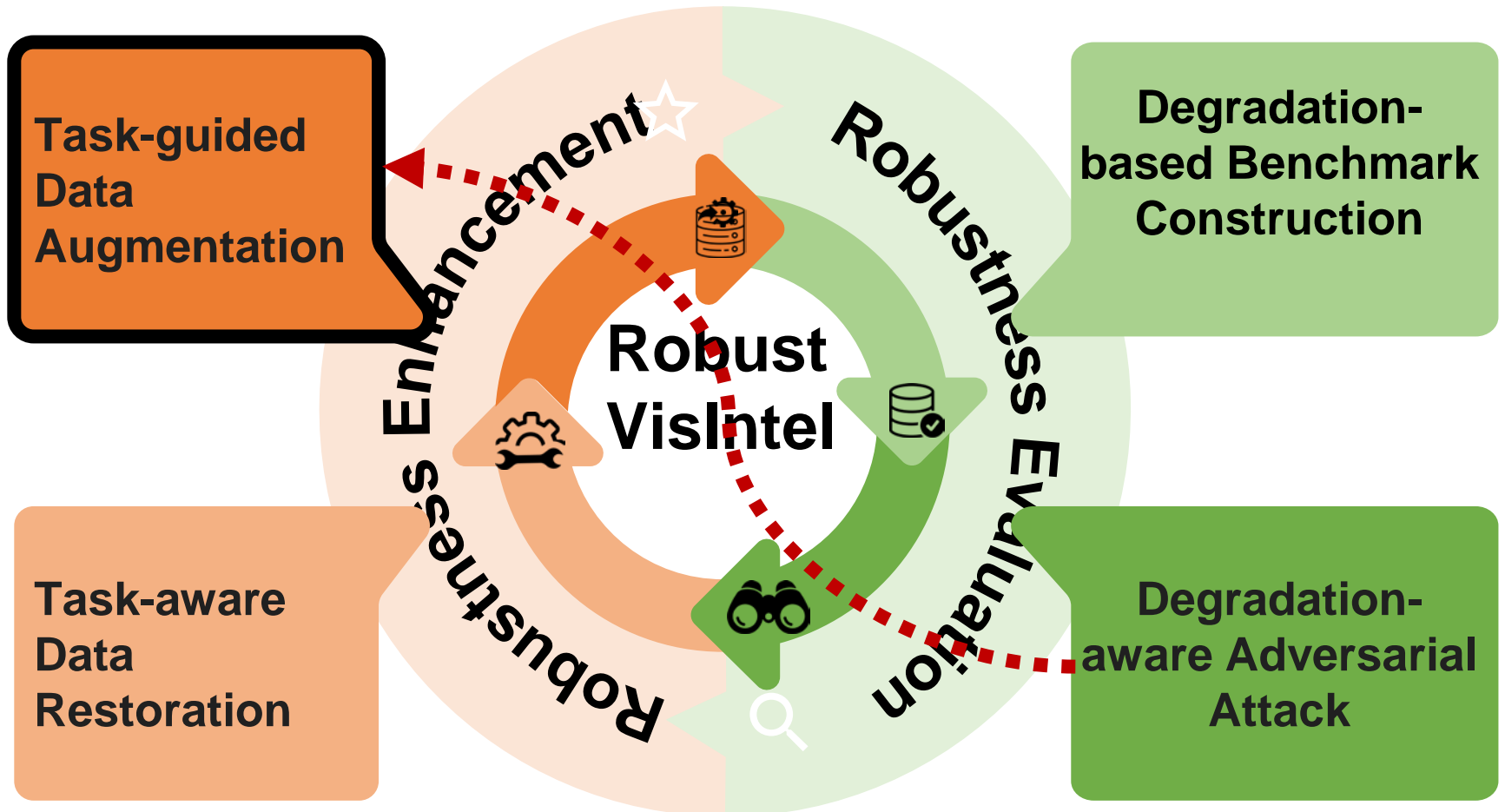
Robustness Enhancement

Task-aware Data Restoration – Shadow Removal



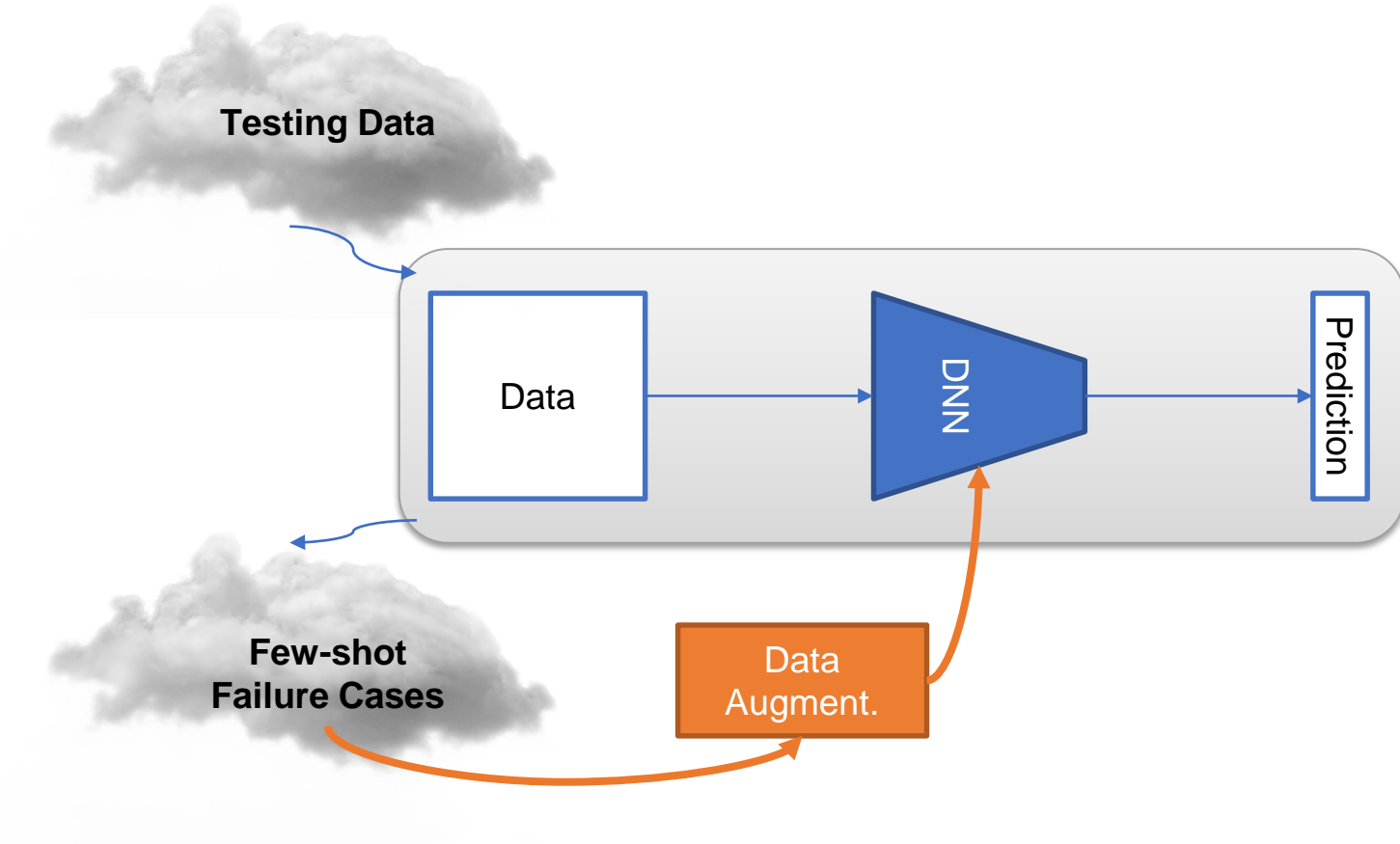
Robustness Enhancement

Goal: Robustness Evaluation and Enhancement of Visual Intelligence to Real-world Degradation:



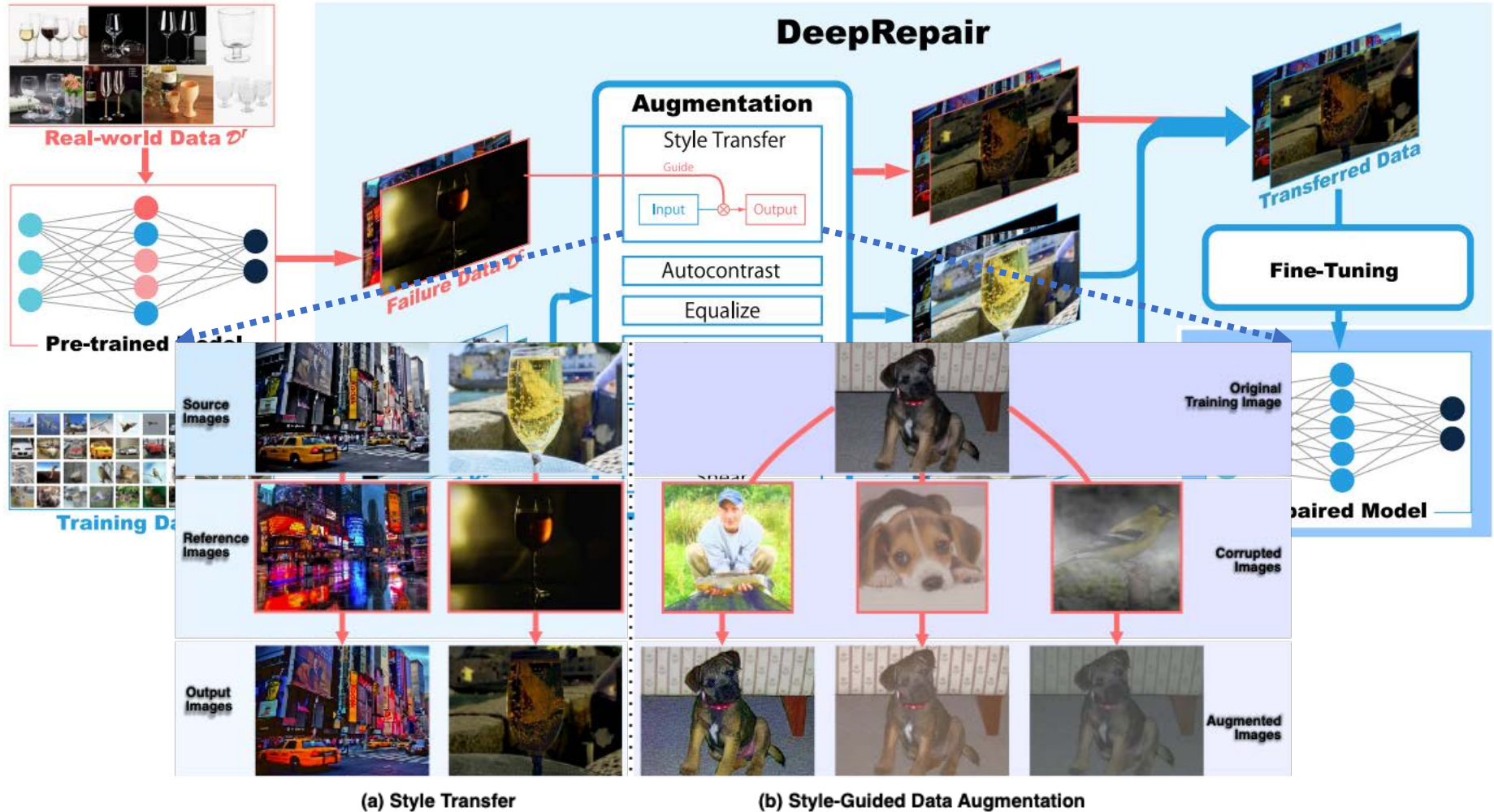
Robustness Enhancement

Failure-set Guided Data augmentation



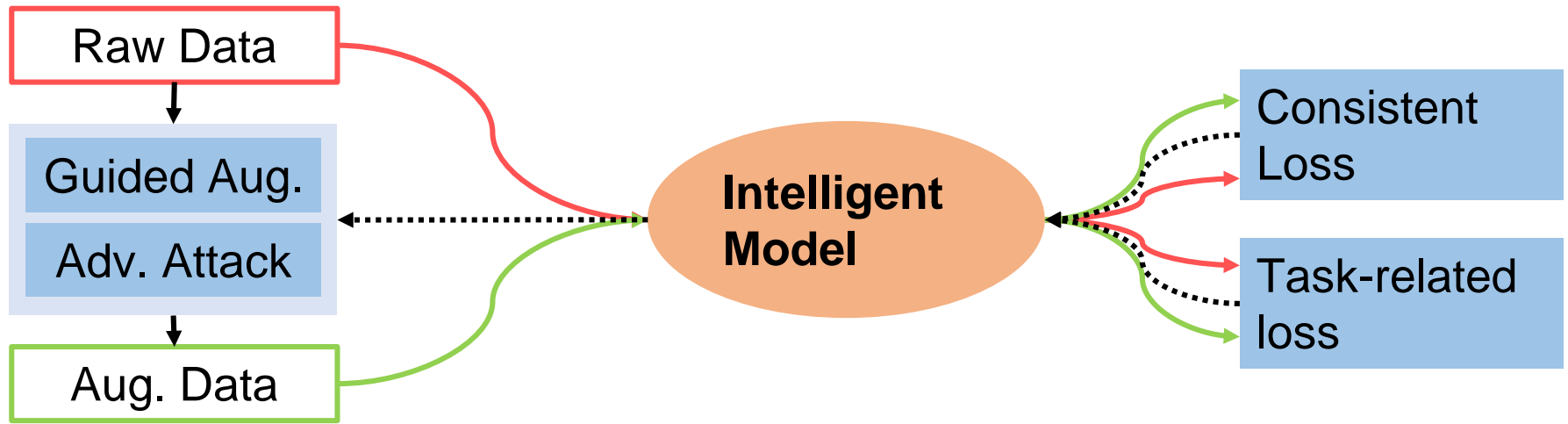
Robustness Enhancement

Failure-set Guided Data augmentation



Robustness Enhancement

Task-guided Data Augmentation



Robustness Enhancement

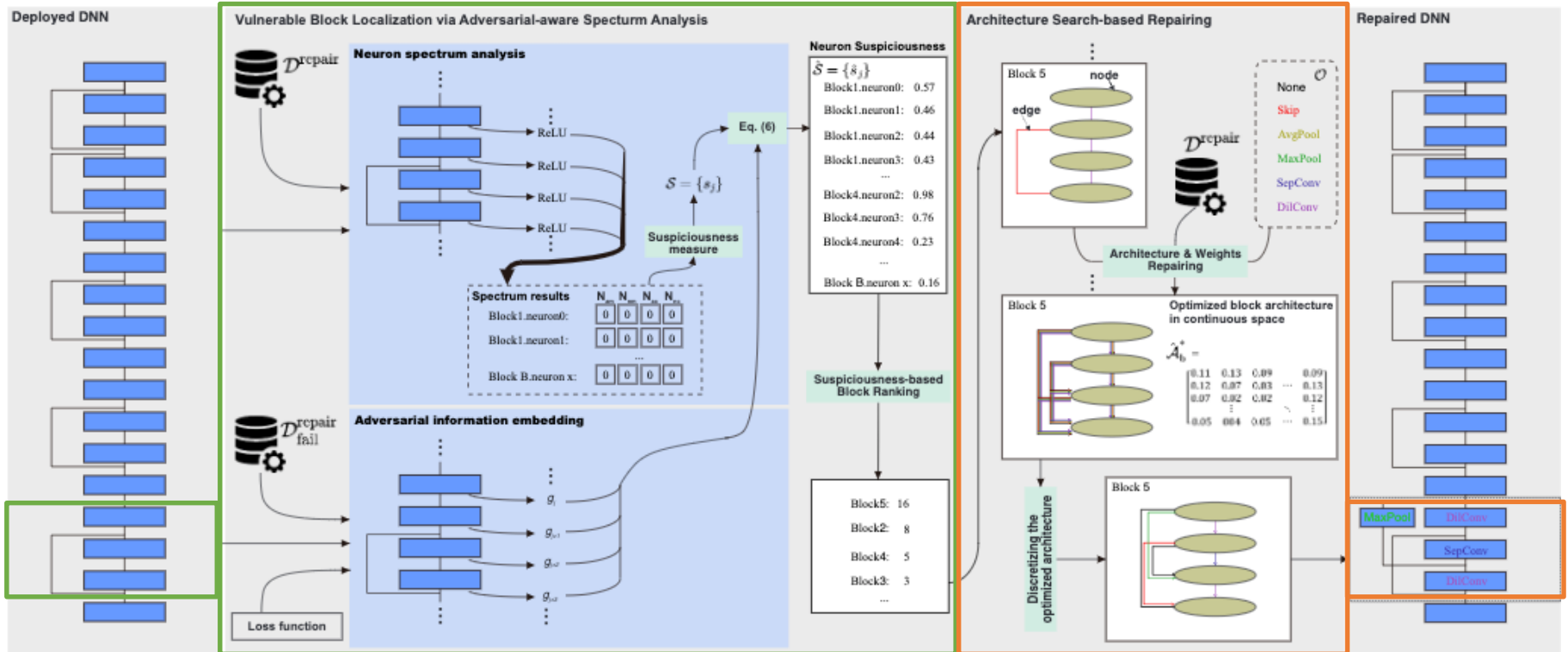
Solution2: Task-guided Data Augmentation

➤ Generalizing Data Repair to Architecture Repair via NAS

ArchRepair for unknown failure patterns

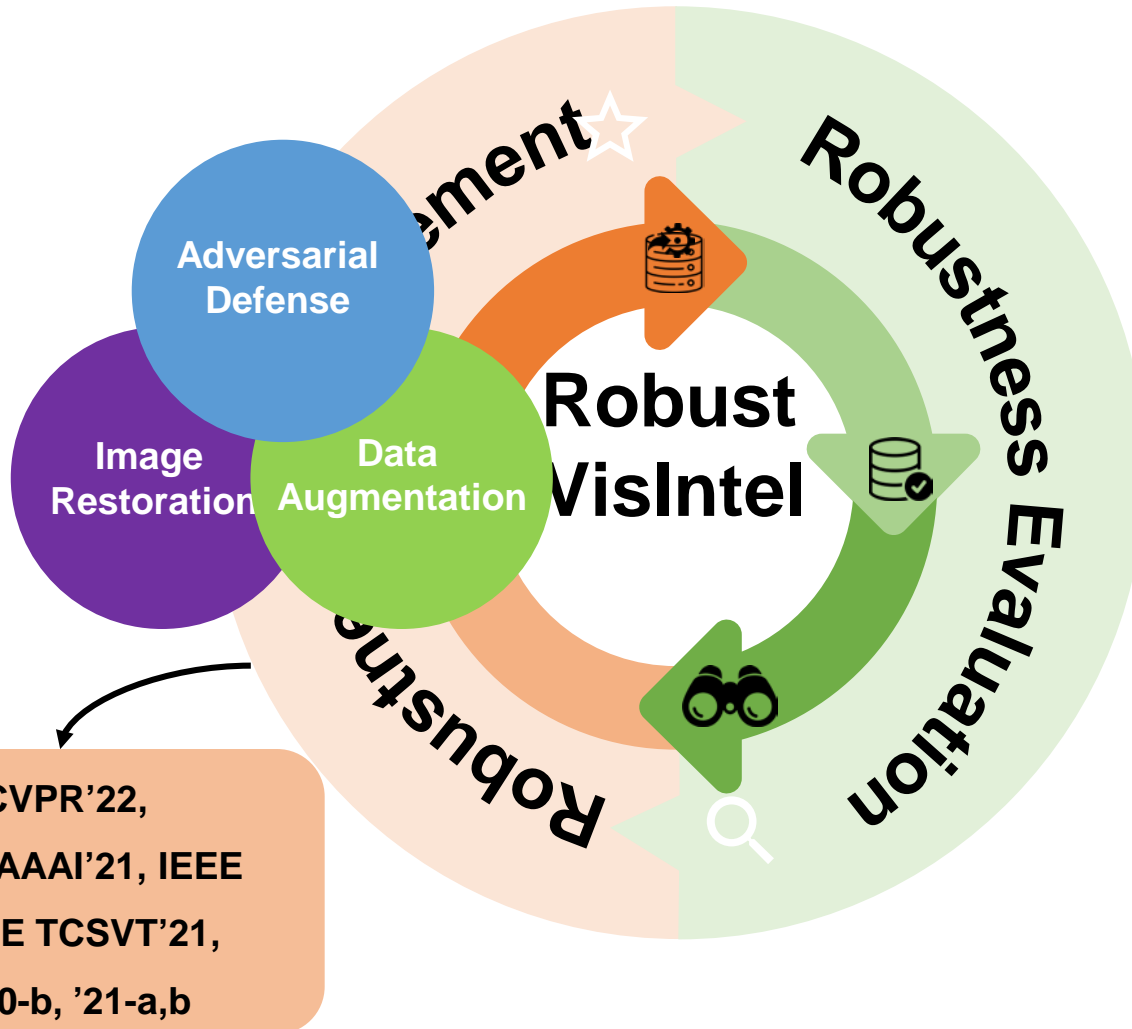
Vulnerable Block Localization

NAS for Repairing

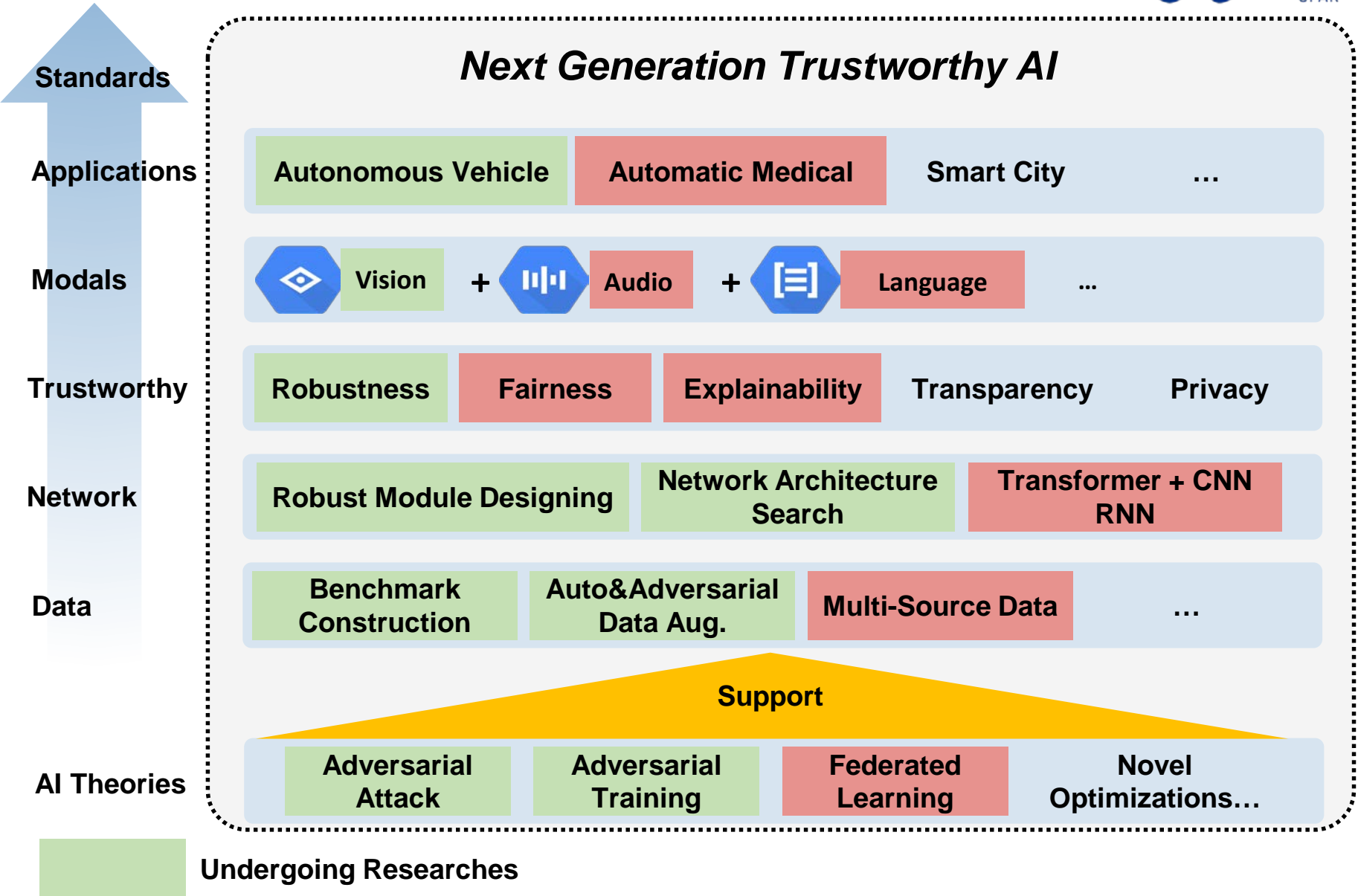


Robustness Enhancement

Goal: Robustness Evaluation and Enhancement of Visual Intelligence to Real-world Degradation:



Next Generation Trustworthy AI



Thank You!

Q & A



GUO Qing, CFAR
tsingqguo@ieee.org

<https://tsingqguo.github.io/>

