Adversarial Attack and Defense of YOLO Detectors in Autonomous Driving Scenarios

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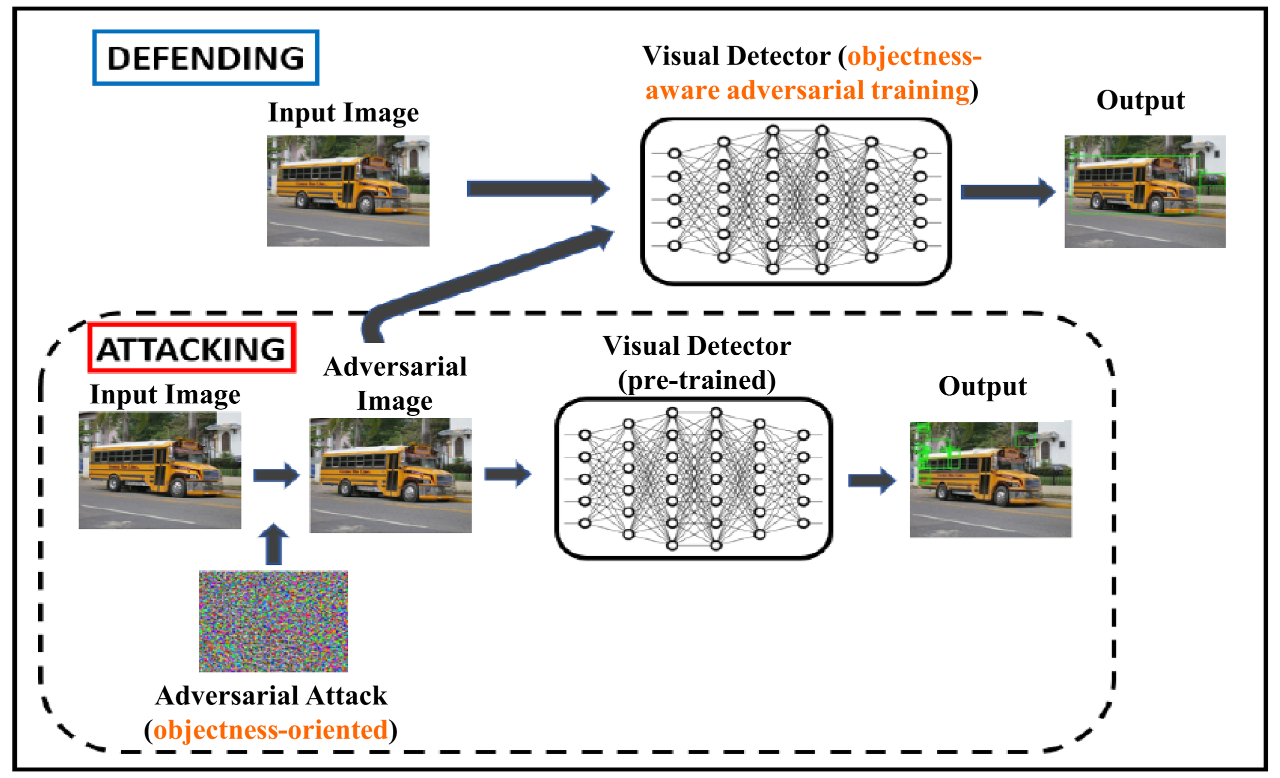
Overview & Research Goals

- Deep visual detectors are **vulnerable to adversarial attacks**. A comprehensive understanding of YOLO detectors' vulnerability is needed before their robustness can be improved. However, only a few adversarial attack/defense works have **focused on visual detection, especially in autonomous driving**.
- **Research Goals:**
  - **Goal 1 (Attacking):** To understand the adversarial vulnerability of deep visual detectors and design **effective adversarial attacks** by utilizing them
  - **Goal 2 (Defending):** To improve detectors' robustness via a new **adversarial training-based approach**



Contributions

- We identified a serious vulnerability in YOLOs which comes from the **objectness aspect** and proposed a more effective objectness-oriented adversarial attack approach.
- We found the direction of the image gradient derived from the objectness loss is more consistent with those from the classification and localization losses.
- We proposed a new defense strategy explicitly paying attention to the objectness aspect.
- Our objectness-aware adversarial training framework can help alleviate the potential conflicts/misalignment of the image gradients sourced from different loss components.

Methods

Decomposition of Adversarial Vulnerability in YOLO

- Overall loss in YOLO consists of three components (i.e., objectness, localization, & classification losses):

$$L(\mathbf{x}, y, \mathbf{b}; \theta) = L_{OBJ}(\mathbf{x}, \mathbf{b}; \theta) + L_{LOC}(\mathbf{x}, \mathbf{b}; \theta) + L_{CLS}(\mathbf{x}, y; \theta)$$

Objectness-Oriented Adversarial Attack

- Unlike prior works, we **explicitly leverage objectness loss** in addition to localization and classification losses to generate adversarial examples for visual detection in self-driving scenarios:

$$\mathbf{x}'_{obj,\,PGD} = \mathcal{P}(\mathbf{x} + \alpha \cdot sign(\nabla_{\mathbf{x}} L_{OBJ}(\mathbf{x}, \mathbf{b}; \theta)))$$
$$\mathbf{x}'_{loc,\,PGD} = \mathcal{P}(\mathbf{x} + \alpha \cdot sign(\nabla_{\mathbf{x}} L_{LOC}(\mathbf{x}, \mathbf{b}; \theta)))$$
$$\mathbf{x}'_{cls,\,PGD} = \mathcal{P}(\mathbf{x} + \alpha \cdot sign(\nabla_{\mathbf{x}} L_{CLS}(\mathbf{x}, y; \theta)))$$

Objectness-Aware (OA) Adversarial Training

Algorithm 1 Objectness-Aware Adversarial Training

Input: Dataset D, Training epochs N, Batch size B, Perturbation bounds ϵ

Output: Learned model parameter θ

for epoch =1 **to** N **do**
  for random batch $\{\mathbf{x}^i, \{yi, \mathbf{b}^i\}\}_{i=1}^{B} \sim D$ **do**
    $(\mathbf{x}'_{obj})^i = P(\mathbf{x}^i + \epsilon \bullet sign(\nabla_{\mathbf{x}} L_{OBJ}(\mathbf{x}^i, \mathbf{b}^i; \theta)))$
    $(\mathbf{x}'_{loc})^i = P(\mathbf{x}^i + \epsilon \bullet sign(\nabla_{\mathbf{x}} L_{LOC}(\mathbf{x}^i, \mathbf{b}^i; \theta)))$
    $(\mathbf{x}'_{cls})^i = P(\mathbf{x}^i + \epsilon \bullet sign(\nabla_{\mathbf{x}} L_{CLS}(\mathbf{x}^i, y^i; \theta)))$
    Choose $\underline{\mathbf{x}}^i$ that leads to the max total loss:
    $\underline{\mathbf{x}}^i = \arg\max_{\tilde{x}^i \in \{(x'_{obj})^i, (x'_{loc})^i, (x'_{cls})^i\}} L(\tilde{x}^i, \{y^i, \mathbf{b}^i\}; \theta)$
    Perform an adversarial training step w.r.t. θ:
    $\arg\min_{\theta} L(x^i, \{y^i, \mathbf{b}^i\}; \theta) + L(\underline{\mathbf{x}}^i, \{y^i, \mathbf{b}^i\}; \theta)$
  end for
end for

Experiments & Results

Datasets

	KITTI	COCO_traffic
Classes #	3	8
Train. Img. #	3,740	71,536
Test Img. #	3,741	3,028

Attack Design:

- Used a range of different attack sizes ϵ = [2, 4, 6, 8]
- Adapted both FGSM and PGD using L_∞ norm

Figure 1. Distribution of adversarial examples derived from the three task losses in YOLO

Qualitative Analysis of Attacks on KITTI and COCO_traffic

Figure 2. Visual comparison of detection results under different task-specific attacks (top: KITTI, bottom: COCO_traffic).

Results – cont.

Quantitative Analysis of Attacks

- The objectness-oriented attacks ($\mathcal{A}_{obj}$) are more effective than $\mathcal{A}_{loc}$ and/or $\mathcal{A}_{cls}$.

Method	Att. Size	$\mathcal{A}_{loc}$	$\mathcal{A}_{cls}$	$\mathcal{A}_{loc+cls+obj}$	$\mathcal{A}_{obj}$
PGD-10 (KITTI)	ϵ = 2	-1.22	-0.87	-42.44	**-42.64**
	ϵ = 4	-4.11	-2.64	-51.47	**-51.67**
	ϵ = 6	-7.00	-5.91	-57.17	**-54.39**
	ϵ = 8	-10.66	-9.59	-55.48	**-55.83**
PGD-10 (COCO)	ϵ = 2	-0.19	-0.15	-36.55	**-37.55**
	ϵ = 4	-0.70	-0.77	-43.84	**-43.93**
	ϵ = 6	-1.88	-2.26	-45.31	**-45.69**
	ϵ = 8	-3.24	-3.58	-46.88	**-47.08**

Table 1. Performance degradation comparison. $\mathcal{A}_{loc}$, $\mathcal{A}_{cls}$, $\mathcal{A}_{obj+loc+cls}$, & $\mathcal{A}_{obj}$: attacks sourced from corresponding task losses.

Adversarial Training Results

- The models adversarially trained with objectness-based attacks ($\mathcal{M}_{OBJ}$ and $\mathcal{M}_{OA}$) leads to more robustness than those utilizing other two task losses.

KITTI

Model	$\mathcal{A}_{obj}$	$\mathcal{A}_{loc+cls+obj}$
$\mathcal{M}_{STD}$	28.43	28.63
$\mathcal{M}_{ALL}$	39.65	40.65
$\mathcal{M}_{MTD}$	36.13	35.94
$\mathcal{M}_{LOC}$	37.86	37.61
$\mathcal{M}_{CLS}$	39.29	39.70
$\mathcal{M}_{OBJ}$	**49.43**	**48.83**
$\mathcal{M}_{OA}$	42.26	41.86

COCO_traffic

Model	$\mathcal{A}_{cls}$	$\mathcal{A}_{loc+cls+obj}$
$\mathcal{M}_{STD}$	22.17	22.29
$\mathcal{M}_{ALL}$	34.58	33.44
$\mathcal{M}_{MTD}$	33.26	33.20
$\mathcal{M}_{LOC}$	33.23	32.10
$\mathcal{M}_{CLS}$	31.71	31.58
$\mathcal{M}_{OBJ}$	33.30	32.69
$\mathcal{M}_{OA}$	**34.77**	**33.61**

Table 2. Performance comparison of **adversarially trained YOLO models.** $\mathcal{M}_{STD}$: trained standardly, $\mathcal{M}_{MTD}$: trained using the multi-task domain algorithm [1], $\mathcal{M}_{OA}$: trained using our OA algorithm.

Conclusion

- We identified a serious vulnerability of YOLO detectors in autonomous driving scenarios.
- We proposed: (1) an effective attack strategy targeting the objectness loss in visual detection, and (2) an objectness-aware adversarial training framework.
- Experiments on both datasets showed the effectiveness of our proposed approaches.

Reference - [1] H. Zhang and J. Wang, "Towards adversarially robust object detection," ICCV'2019