Adversarial Zoom Lens: A Camera-based Physical Attack to DNNs

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Abstract

Although deep neural networks (DNNs) are known to be fragile, there are few studies on the effects of camera-based physical attacks on DNNs’ performance. In this paper, we demonstrate an effective physical-world attack called Adversarial Zoom Lens (AdvZL), which manipulates a zoom lens to zoom in and out of objects to generate adversarial samples, fooling DNNs without modifying the target objects. We use zoom-in images to verify the adversarial effect of AdvZL in the digital environment. Then, we use a zoom lens to generate adversarial samples, verifying the adversarial performance of AdvZL in the physical environment. On the other hand, we discuss some phenomena generated by AdvZL. Finally, we look into the possible threat of the proposed approach to future autonomous driving and variant attack approaches similar to the proposed attack.

Introduction

On the night of March 9, 2018, an unusual car accident occurred when a woman crossing the street was hit and killed by an SUV. What’s unusual about the accident is that the SUV was operating on Autopilot, a system developed by Uber. The accident is believed to be the world’s first fatal driverless crash. It can be seen that advanced DNNs make mistakes even if there is no external interference. If further attackers maliciously interfere with the classification system, it could lead to more accidents.

At present, the attack and defense technologies driven by adversarial attack are hot topics for many researchers. Most researchers focus on adversarial attacks in the digital environment (Chen et al. 2018a, Wiattno and Xu 2018, Su, Vargas, and Sakurai 2019, Moosavi-Dezfooli et al. 2017), which fool advanced DNNs by adding imperceptible perturbations to clean images. However, in physical scenes, images taken by the camera are input into the classifier for classification, attackers cannot directly modify the input images. Many researchers gradually devote themselves to the study of physical attacks (Kurakin, Goodfellow, and Bengio 2017, Chen et al. 2018b, Eykholt et al. 2018). The physical perturbation is designed to be much larger than digital one, so that it could be sensed by camera. Some physical attacks (Eykholt et al. 2018, Duan et al. 2020), use stickers and graffiti as perturbations to perform attacks while maintaining the semantic information of the target objects, which are perceptible to human observers. In addition, some researchers use light (Duan et al. 2021, Gnanasambandam, Sherman, and Chan 2021) to carry out adversarial attacks, which to a certain extent achieves excellent concealment. Different from the existing methods, our proposed method is camera-based and fools the current advanced DNNs without modifying the target objects.

The difficulties of physical attacks include: (1) It’s difficult for camera to capture the printed pixel-level digital perturbations; (2) It is difficult to print perfectly adversarial graffiti (there exists printing loss); (3) Physical attacks are difficult to achieve both robustness and concealment.

Based on the above challenges, we propose a camera-based physical adversarial attack called Adversarial Zoom Lens (AdvZL). Different from the existing methods, we manipulate the zoom lens to zoom in and out on the target objects, realizing effective physical attacks without modifying the target objects. AdvZL fundamentally solves the above difficulties of physical attacks by not adding perturbations...
to target objects. We regard the physical attack shown in Figure 1 as a novel adversarial attack, which is non-negligible but not yet exploited. An automatic zoom lens mounted on a self-driving car camera that zooms in and out on road signs, the self-driving car fails to recognize them correctly.

We perform comprehensive experiments in both digital and physical environments to verify the effectiveness of AdvZL. In a digital environment, we construct datasets of 1000 images from ImageNet (Deng et al. 2009) that can be correctly classified by DNNs for test. Experimental results verify the effectiveness of AdvZL against advanced DNNs. In the physical environment, we use the zoom lens to zoom in and out target objects. Experimental results show that AdvZL achieves a 100% success rate of physical adversarial attack within a certain range of distance and angle. Our main contributions are summarized as follows:

• We propose a camera-based physical attack, AdvZL, which manipulates the zoom lens to carry out physical attacks without modifying the target objects. The proposed method is rather simple to deploy, manipulating the zoom lens to conduct adversarial attacks (See Introduction).

• We summarize the existing physical attacks (See Related work), carry out strict experimental design and comprehensive experimental test. Experimental results verify the effectiveness of AdvZL in the both digital and physical environments (See Approach, Evaluation).

• We explore some AdvZL-based phenomena, which will help scholars research the mechanism of advanced DNNs and study defense strategies against AdvZL (See Discussion). At the same time, we look into some new ideas for camera-based physical attacks (See Conclusion).

Related work

Digital attacks

Adversarial attack was first proposed by Szegedy et al. (Szegedy et al. 2014), after which more and more adversarial attacks were proposed successively (Goodfellow, Shlens, and Szegedy 2015; Moosavi-Dezfooli, Fawzi, and Frossard 2016; Su, Vargas, and Sakurai 2019; Moosavi-Dezfooli et al. 2017).

At present, most digital attacks ensure the perturbations are imperceptible to human observers by limiting them in a norm-ball. In general, $L_2$ and $L_\infty$ are the most commonly used norms (Carlini and Wagner 2017a,b; Dong et al. 2018; Madry et al. 2018; Xie et al. 2019). These methods effectively attack advanced DNNs in the digital environment while ensuring the perturbations are imperceptible to human observers. Some other works have modified other attributes of the clean sample to generate adversarial samples, such as color (Hosseini and Poovendran 2018; Shamsabadi, Sánchez-Matilla, and Cavallaro 2020; Zhao, Liu, and Larson 2020), texture and camouflage (Wiyatno and Xu 2019; Wang et al. 2021; Zhang et al. 2019; Wang et al. 2022), which are usually perceptible to the naked eye. In addition, there are also some works to generate adversarial samples by modifying the physical parameters of the clean images (Zeng et al. 2019; Liu et al. 2019), which retain the key components of images and carry out digital attacks. Different from digital attacks that modify the pixels of clean images in the digital environment, physical attacks cannot directly modify the input images.

Physical attacks

Physical attack was first proposed by Alexey Kurakin et al. (Kurakin, Goodfellow, and Bengio 2017). After this work, many physical attacks were proposed successively (Eykholt et al. 2018; Xu et al. 2020; Brown et al. 2017; Sharif et al. 2016; Athalye et al. 2018).

Traditional street sign attacks. Ivan Evtimov et al. (Eykholt et al. 2018) proposed a general physical adversarial attack, called RP2, that achieved a robust physical attack against road sign classifiers. However, RP2 is susceptible to environmental interference at large distances and angles. Chen et al. (Chen et al. 2018b) proposed ShapeShifter, which successfully fooled classifiers by generating stop signs of reverse interference. Huang et al. (Huang et al. 2021) improved ShapeShifter by adding Gaussian white noise to ShapeShifter’s optimization function. The experiment proved that the improved ShapeShifter could successfully and effectively attack Chinese and English stop signs, and overcome the shortcoming of ShapeShifter’s high requirements for photographic equipment. However, ShapeShifter and the improved ShapeShifter have a defect, disturbance covers almost the whole road sign, failed to achieve concealment. Eykholt et al. (Song et al. 2018) implemented a disappear attack, in which poster and stickers were stickled on the surface of road signs to fool the target detector and realize transferable adversarial perturbations. Similarly, the perturbations cover a large area, which is too conspicuous. Duan et al. (Duan et al. 2020) proposed AdvCam, which camouflages physical perturbations in a natural style and achieves better camouflaging effect while fooling classifiers. AdvCam has better concealment than the above methods, but it needs to manually select the attack area and target. On the whole, traditional road sign attacks have something in common, which is, physical perturbations are printed or pasted onto the road signs. These methods have major drawbacks. Adding physical perturbations is manual work, takes a lot of time, at the same time, there exists printing errors.

Light-based attacks. Light-based physical attack is a crafty solution to above problem. Nguyen et al. (Nguyen et al. 2020) studied the threat of light projection to face recognition system, and implemented white-box and black-box attacks against face recognition system by projecting a well-designed adversarial light projection onto human face. But it’s complex for deployment. Shen et al. (Shen et al. 2019) proposed VLA, which is based on visible light and uses a carefully designed light beam to fool the face recognition system, enabling targeted or untargeted attacks. On the contrary, Zhou et al. (Zhou et al. 2018) generated adversarial samples based on invisible infrared light, and were the first to interpret the threat of infrared adversarial samples to face recognition system. These attacks achieve better concealment, but modify the target objects. Duan et al. (Duan et al. 2021) proposed AdvLB, which achieves efficient and covert physical attacks by manipulating the physical param-
eters of the laser beam. Gnanasambandam et al. (Gnanasambandam, Sherman, and Chan 2021) proposed OPAD, which realized effective optical adversarial attacks against 2D and 3D objects. AdvLB and OPAD, however, can only perform attacks in weak-light conditions. Zhong et al. (Zhong et al. 2022) studied a new type of optical adversarial sample, using a very common natural phenomenon, shadow, generate adversarial sample, to achieve a natural and hidden black box adversarial attack. But it is difficult to work in complex physical scenes. Overall, light-based methods allow for more efficient physical adversarial attacks and better invisibility. However, they require a variety of colors of light as physical perturbations that are perceptible to human observers. In addition, light-based physical attacks tend to paralyze during the daytime.

**Camera-based attacks.** To avoid modifying the target objects, Li et al. (Li, Schmidt, and Kolter 2019) study the physical operation of the camera itself, through an iterative update against perturbations, then elaborate translucent stickers affixed to the camera lens, shooting target objects to generate adversarial samples, this method is to inject perturbations into the optical path between the camera and the object, which has excellent concealment. However, it is difficult to adapt to complex real scenes due to the complicated deployment. Our proposed method (AdvZL) fools the advanced DNNs by manipulating the zoom lens to zoom in and out of the target objects and generate adversarial samples.

**Approach**

**Adversarial sample**

Reviewing the definition of adversarial sample $X_{adv}$, given an input image $X$, ground truth label $Y$, a DNN classifier $f$, $f(X)$ represents the predicted label, the classifier $f$ associates with a confidence score $f_Y(X)$ to class $Y$. Generating adversarial samples satisfies two properties: (1) $f(X_{adv}) \neq f(X) = Y$; (2) $\|X_{adv} - X\| < \epsilon$. The first requires that $X_{adv}$ successfully fool DNN classifier $f$, and the second requires that the adversarial perturbations be small enough to be imperceptible to the human observers.

Different from most of the existing physical attacks, in this paper, we generate adversarial sample by zooming in or out the target objects, which fools the advanced DNNs classifier without adding perturbations to the target objects.

**Zoom lens definition**

**Zoom in.** In the digital environment, as shown in Figure 2, $N$ represents the pixel value to be clipped, the larger $N$ is, the greater zoom is. In the physical environment, in order to keep the physical samples and digital samples consistent, we define an function to convert the pixel value $N$ to the camera zoom factor $T$, which can be expressed as:

$$T = \text{conv}(N; \rho) = \lfloor N/\rho \rfloor$$  \hspace{1cm} (1)

Where, $\lfloor/\rfloor$ indicates that the division takes one decimal place and the second decimal place is rounded. $\rho$ indicates that for every 0.1x zoom of the camera, the number of pixels needed to be cropped in the digital environment is $\rho$ pixel. Through Function 1, we realize the conversion between digital samples and physical samples.

**Zoom out.** In the digital environment, we cannot realize the zoom out attack. Therefore, we perform the zoom out attack experiment in the physical environment. Here, we use camera to take the zoom-out photos, such as the camera’s 0.1x focal length. The image is then used for step-to-step zoom in attacks. The adversarial samples below 1.0x focal length is the adversarial samples of the zoom out attack.

**Zoom lens adversarial attack**

In the digital environment, we perform zoom in attacks on 1000 images selected from ImageNet [45] that could be correctly classified by each advanced DNN, verifying the adversarial effect of the zoom-in image to DNNs. In the physical environment, we manipulate the zoom lens to zoom in and out the target objects, which verifies the feasibility of AdvZL in the physical environment. In the digital environment, generating an adversarial sample is expressed as follows:

$$X_{adv} = \text{ZoomIn}_N(X) \quad s.t. \quad N \in [0, \omega]$$  \hspace{1cm} (2)

Where $N$ represents the magnification degree of the image and $\omega$ represents the threshold of the magnification degree. In the physical environment, zoom lens is used to zoom

![Figure 2: Generating an adversarial sample.](image-url)
in and out the target objects to generate adversarial sample, generating an adversarial sample can be written as follows:

\[ X_{adv} = \text{Zoom}_T(X) \quad \text{s.t.} \quad T \in [\Gamma_{\min}, \Gamma_{\max}] \]  

(3)

Here, \( T \) is a multiple of zooming in or out (e.g., \( \text{Zoom}_{0.8} (X) \)) indicates that the image \( X \) is zoomed out to 0.8 times, and \( \text{Zoom}_{1.2} (X) \) indicates that the image is zoomed in to 1.2 times), \( \Gamma_{\min} \) and \( \Gamma_{\max} \) indicate the threshold of \( T \).

Physical Adaptation. To solve the experimental loss from digital sample to physical adversarial sample, we define an \( \text{Adjust} \) function, the operations include increase and decrease the pixel value of \( N \), which is expressed as:

\[ \text{Adjust}(X_{adv}; N) \]  

(4)

In this experiment, we consider a practical situation: the attacker cannot obtain the knowledge of the model, but only the confidence score \( f_Y(X) \) with given input image \( X \) on ground truth label \( Y \). In our proposed method, we use confidence score as the adversarial loss. Thus, the objective is formalized as minimizing the confidence score on the ground truth label \( Y \), which can be formulated as follows:

\[ \arg \min_N f_Y(\text{ZoomIn}_N(X)) \quad \text{s.t.} \quad N \in [0, \omega] \]  

(5)

Algorithm. As shown in Algorithm 1. The proposed AdvZL takes clean sample \( X \), ground truth label \( Y \), threshold \( \Gamma_{\min} \) and \( \Gamma_{\max} \), classifier \( f \) as input. Then, zooming in and out the clean sample \( X \) to different degrees, the adversarial sample with the smallest confidence score of classifier \( f \) on ground truth label \( Y \) is taken as the most adversarial one. The algorithm finally returns an adversarial sample fooled advanced DNNs, which is used to perform subsequent physical attacks. Here, the value range of \( T \) is generally from 0.5 to 5.4, with an interval of 0.1. Therefore, \( \Gamma_{\min} \) and \( \Gamma_{\max} \) should satisfy: \( \Gamma_{\min} \geq 0.5, \Gamma_{\max} \leq 5.4 \).

Algorithm 1: Pseudocode of AdvZL

**Input:** Input \( X \), Label \( Y \), \( \Gamma_{\min}, \Gamma_{\max} \), Classifier \( f \);  
**Output:** Adversarial sample \( X_{adv}^* \);  
1: Initialization \( X_{adv}^* = X, \text{Score}^* = f_Y(X) \);  
2: for \( T \) in range \( (\Gamma_{\min}, \Gamma_{\max}) \) do  
3: \( X_{adv} = \text{Zoom}_T(X) \);  
4: \( \text{Score} = f_Y(X_{adv}) \);  
5: if \( \text{Score}^* < \text{Score} \) then  
6: \( \text{Score}^* = \text{Score} \);  
7: \( X_{adv}^* = X_{adv} \);  
8: end if  
9: end for  
10: if \( \arg \max f(X_{adv}^*) \neq \arg \max f(X) \) then  
11: if \( \text{Adjust}(X_{adv}^*; N) \) then  
12: return \( X_{adv}^* \);  
13: end if  
14: end if  

Evaluation

Experimental setting

We conduct comprehensive experiment to verify the effectiveness of AdvZL in both digital and physical environments. In the digital environment, we use the advanced DNNs classifiers for experiments. As with the approach in AdvLB (Duan et al. 2021), we use 1000 images from ImageNet (Deng et al. 2009) that could be correctly classified by advanced DNNs as the dataset, although we cannot zoom out the image in the digital environment, we verify the adversarial effect of zoom-out sample in the physical setting. In the physical environment, we use ResNet50 as a target model to conduct experiments, with common objects and road signs as experimental objects. We use a mobile phone camera (iPhone6s) as a zoom lens for all of our experiments. It has been verified that the effectiveness of AdvZL is not affected by using a normal camera or other mobile phone model for our experiments.
Table 1: Attack success rate (ASR) in the digital environment.

|                | DenseNet | ResNet50 | VGG19 | GoogleNet | MobileNet v2 | AlexNet |
|----------------|----------|----------|-------|-----------|--------------|---------|
| ASR(%)         | 36.0     | 33.7     | 40.5  | 40.6      | 41.7         | 51.0    |

Evaluation of AdvZL

Digital test. We test the effectiveness of AdvZL on 6 subsets that randomly selected from ImageNet (Deng et al. 2009), each subset containing 1000 clean samples that could be correctly classified by the corresponding advanced DNN model. Table 1 shows the attack success rate of advanced DNNs on the corresponding dataset.

As can be seen from the experimental results in Table 1, AdvZL achieves an attack success rate of over 30% against advanced DNNs (Huang et al. 2017; He et al. 2016; Simonyan and Zisserman 2015; Szegedy et al. 2015; Sandler et al. 2018; Krizhevsky, Sutskever, and Hinton 2012) without modifying the semantic information of the clean samples, which reduce the Top-1 classification accuracy from 100% to less than 70%. Figure 3 shows the adversarial samples in the digital environment (ResNet50 is used here). It shows that with the image is enlarged, the advanced DNN model misclassifies the images. For example, Brain coral is misclassified as Flatworm, Sea cucumber, etc. In general, without modifying the semantic information of the image, the larger magnification of the image, the stronger adversarial effect to DNNs. Figure 3 also reveals a common phenomenon, advanced DNNs are trained in a dataset in which the images are taken at a specific range of distance. Changing the distance to take a picture is equivalent to zooming in and out of the picture, which means that when zooming in and out of the picture, the classifier makes a wrong classification judgment.

Physical test. We use ResNet50 to perform all the physical tests. In order to execute untargeted attack in the physical environment, it is necessary to eliminate the influence of experimental noise, we design indoor test and outdoor test respectively. In which, physical attacks are not affected by the environmental noise in the indoor test, well, much of the environmental noise may play the role of an adversarial perturbation in the outdoor test. Through our comprehensive experiments, we verified the effectiveness of AdvZL in the both indoor and outdoor environment. In our experiment, Toilet tissue and Ashcan, which are common in daily life, are selected as the testing object. Figure 4 shows the schematic diagram of the adversarial sample after Zooming in the image in the physical environment.

As can be seen from Figure 4, adversarial samples deceive the advanced DNN model as \( T \) increases to the threshold. For example, when Ashcan is magnified to \( T = 1.4 \times \) and \( T = 1.5 \times \) of the focal length of the mobile phone camera, the advanced DNN model misclassifies them as Laptop and Shopping cart respectively. Here, \( 1.4 \times \) represents the zoom multiple of the camera. To get close to the real scenario, we design a comprehensive attack experiment for the outdoor test, where the attacking target object is the common Stop sign. We carry out physical attacks at different distance and angle. Figure 5 shows the schematic diagram of partial adversarial samples at different distances and angles, among which, we test adversarial samples at distances of 6m, 9m, 12m and angles of \( 0^\circ \), \( 30^\circ \) and \( 45^\circ \) respectively.
As can be seen from Figure 5, at different distances, we manipulate the zoom lens to zoom out the image, adversarial samples from different angles fool the target model. Obviously, even though the images contain environmental noise such as Lakeside and Pole, human observers tend to ignore the environmental noise and more inclined to consider them as Street sign. When the distances are 9 meters and 12 meters, it shows that the background environmental noise increases, which makes the physical samples more adversarial. A slight manipulation of the zoom lens generates an adversarial sample to fool advanced DNN model. In the real scenario, since it is difficult to capture the road signs with a long distance, the lens of the autonomous vehicle is properly adjusted during production. Therefore, the effectiveness of AdvZL is not affected even at a distance of 9 meters and 12 meters.

**Discussion**

Here, we show some phenomena generated by AdvZL in the both digital and physical environment. All of the experiments in this section use ResNet50 as the target model.

**Discontinuous misclassification**

As can be seen from the experimental results in Figure 3, we zoom in the clean samples with equal proportions, discontinuous classification errors will occur instead of continuous ones. In view of this phenomenon, we analyze the experimental data. It can be seen from Figure 6 that (1) Some clean samples could not have been classified correctly by the model, but correctly classified after zooming in. (2) Classification errors may occur in some images at a specific magnification. As for the Bee in Figure 6, when $N = 48$ and $N = 54$, it occurs classification errors. (3) Discontinuous misclassification. As shown in Figure 6, Snail is classified as Isopod when $N = 30$, Snail when $N = 36$, Isopod when $N = 42$, Snail when $N = 48$, Leaf beetle when $N = 54$.

![Figure 6: Discontinuous misclassification in the digital environment.](image)

In general, the phenomenon in Figure 6 reflects, to some extent, that the decision boundary between various categories of classifiers is relatively dense, which leads to the advanced DNN model is prone to errors under slight confrontation. Therefore, the security implications of advanced DNNs should be of great concern.

**Defense of AdvZL**

In addition to describing the threat of the proposed AdvZL poses to advanced DNNs, we also try to propose a defense against AdvZL. Consistent with the idea of adversarial training, we construct a dataset for adversarial defense.

![Figure 8: Zooming in image in the digital-setting.](image)

According to the above analysis, adversarial samples generated by AdvZL lead to discontinuous misclassification of models. Therefore, we build a scaled-up dataset derived from ImageNet called ImageNet-ZOOMIN (ImageNet-ZI). In which, 50 images are randomly selected from each category of ImageNet, resulting in 50,000 clean samples. Then, each image is enlarged 10 different times to generate 500,000 adversarial samples. Among them, the approach of generating zoom-in samples is shown in Figure 8. Parameter $N$ ranges from 6 to 60 respectively, and the interval is 6. After the continuous magnification of the image, the semantic information of the zoom-in images is consistent with clean samples even only part of the target object on the images.
Table 2: Discontinuous misclassification in the physical environment.

| 0.5× | 0.6× | 0.7× | 0.8× | 0.9× | 1.0× | 1.1× | 1.2× | 1.3× | 1.4× | 1.5× | 1.6× | 1.7× | 1.8× | 1.9× | 2.0× | 2.5× |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  |
| 970  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  |
| 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  |
| 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  | 975  |
| 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  |
| 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  | 703  |

Note that in the digital environment, we can only zoom in the image. Therefore, we only introduce the defense strategy against zoom in attack.

We use torchvision to train the ResNet50 defense model. The model was optimized on 3 2080Ti GPUs by ADAM with initial learning rate 0.01. Here, we show a comparison of classification performance between the pretrained model of ResNet50 and adversarial trained ResNet50 (Defense-ResNet50). As can be seen from the experimental results in Figure 9, the model’s robustness is improved to some extent through the strategy of adversarial training.

![Figure 9: Performance of ResNet50 vs. Defense-ResNet50.](image)

**Disadvantages of AdvZL**

We admit that in the digital environment, it’s currently unable to zoom out images through data processing techniques, which makes it hard to study zoom out attacks in the digital environment, which is a drawback of the proposed AdvZL. On the other hand, due to the limitation of conditions, we cannot deploy the zoom lens to the inside of the camera of the self-driving vehicle for physical attacks in real scenario, only use the camera of the mobile phone to simulate the attacks.

**Conclusion**

In this paper, we propose a camera-based physical attack, AdvZL, which generates adversarial samples without modifying target objects. Rigorous experimental design and comprehensive experimental results indicate the effective adversarial effect of the proposed AdvZL in both digital and physical environments. Our proposed method demonstrates the security threats to vision-based systems in the real world. If an attacker were to install an automatic zoom lens in the camera of an autonomous vehicle, the self-driving car will fail to recognize target objects, and it would be difficult for technicians to find out the cause of the accident. Our work offers some promising directions for some future physical attacks, manipulating camera to generate adversarial samples rather than manual deployment of physical perturbations. Our proposed AdvZL is very useful for studying the security threats of physical attacks to vision-based applications without modifying the target objects, which is a valuable addition to the current physical-world attacks.

In the future, we will continue to focus on improving the proposed AdvZL, for example, zoom out attacks in digital environments and deploy AdvZL to autonomous vehicles. In addition, we will continue to study physical attacks without adding physical perturbations, such as using lenses to achieve local distortion of images. We will also investigate the application of AdvZL to other areas such as object detection and segmentation. Finally, effective defenses against camera-based attacks will be a promising direction for the future.
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