Catoptric Light can be Dangerous: Effective Physical-World Attack by Natural Phenomenon

Chengyin Hu
University of Electronic Science and Technology of China

Weiwen Shi
University of Electronic Science and Technology of China

Abstract

Deep neural networks (DNNs) have achieved great success in many tasks. Therefore, it is crucial to evaluate the robustness of advanced DNNs. The traditional methods use stickers as physical perturbations to fool the classifiers, which is difficult to achieve stealthiness and there exists printing loss. Some new types of physical attacks use light beam to perform attacks (e.g., laser, projector), whose optical patterns are artificial rather than natural. In this work, we study a new type of physical attack, called adversarial catoptric light (AdvCL), in which adversarial perturbations are generated by common natural phenomena, catoptric light, to achieve stealthy and naturalistic adversarial attacks against advanced DNNs in physical environments. Carefully designed experiments demonstrate the effectiveness of the proposed method in simulated and real-world environments. The attack success rate is 94.90% in a subset of ImageNet and 83.50% in the real-world environment. We also discuss some of AdvCL’s transferability and defense strategy against this attack.

1. Introduction

Nowadays, deep neural networks have made great progress in image classification and object detection. At the same time, many vision-based applications are also becoming popular, such as UAV, autonomous driving and so on. However, recent advances have shown that advanced DNNs are susceptible to slight perturbations, even only one pixel is modified [50]. It is critical to evaluate the reliability of advanced DNNs in safety-sensitive scenarios (medical, autonomous driving, etc.). Up to now, most work has been devoted to attacks in digital environments [18, 19, 20, 21], which attack advanced DNNs by adding imperceptible perturbations to images. Some scholars have gradually devoted to the study of attacks in physical scenes [22, 23, 24]. Different from digital attacks, images are captured by cameras and then fed to the target model. The physical perturbations are designed to be much larger because it’s difficult to capture subtle perturbations with the camera. Thus, physical perturbations are perceptible to human observers. In general, there is a compromise between robustness and stealthiness when an attacker executes physical attacks.

Many natural phenomena play the role of physical perturbations, such as natural light and shadows that can lead to tragic crashes involving self-driving cars. If common catoptric light is used as an attack weapon to deploy physical attacks against advanced DNNs, this poses a potential threat to vision-based systems. At the same time, given the common natural catoptric light, it may reduce the vigilance of defenders, thus achieving temporal stealthiness. As shown in Figure 1, the attacker projects a carefully designed catoptric light onto the road sign so that the autonomous vehicle cannot recognize ‘Street sign’.

![Figure 1: An example. When a self-driving car's camera captures a road sign projected carefully designed catoptric light, it fails to recognize 'Street sign'.](image)
attacks in nighttime by using catoptric light as natural adversarial perturbations. In addition, some scholars have studied camera-based physical attacks [38], in which a tiny translucent patch is sticked on the camera of a mobile phone to perform physical attacks. However, due to the narrow physical operation area, it is difficult to implement in real scenes.

![Figure 2: Visual comparison.](image)

In this work, we introduce a novel light-based physical attack named adversarial catoptric light (AdvCL). Compared to traditional sticker-based physical attacks, our approach uses light as a perturbation, which gives AdvCL flexible maneuverability. Compared with ordinary light-based physical attacks, our approach makes use of a common phenomenon: reflected light, as perturbations, making our approach more natural. In terms of stealthiness, Figure 2 shows a visual comparison of physical samples generated by AdvCL and other methods. Even though the adversarial samples generated by AdvCL have less stealthiness than other methods, such as RP2 [24] and AdvLB [35], it shows temporal stealthiness than RP2 in view of AdvCL’s light-speed attack. On the other hand, compared with AdvLB, the physical samples generated by AdvCL are more natural. Experiments show that our method is more robust in physical scenarios (See Section 4).

Our approach is easy to deploy physical attacks. By formalizing the physical parameters of catoptric light, genetic algorithm [46] is used to find the most aggressive physical parameters, then based on which, the catoptric light is projected to the target object to generate physical samples. We perform comprehensive experiments to verify the effectiveness of AdvCL. In the digital environment, it achieves an attack success rate of 94.90% on a subset of ImageNet. In the physical environment, it achieves an attack success rate of 100% in the indoor test and 83.50% in the outdoor test. Further, we perform transfer attacks using adversarial samples generated by AdvCL to verify its effectiveness in black-box settings. Our main contributions are summarized as follows:

1) We propose a novel light-based attack, named adversarial catoptric light (AdvCL), which exploits the nature of light and performs a transient attack. At the same time, because catoptric light is common natural, it makes AdvCL natural and stealthy (See Section 1).

2) We introduce and analyze existing methods (See Section 2), demonstrate effective optimization strategies, and perform comprehensive experiments to verify the effectiveness of AdvCL (See Section 3, Section 4). Given how well AdvCL has been tested in real-world scenarios, it may prove useful as a tool to explore the threat of light-based attacks in the real world.

3) We analysis AdvCL in depth, including attack transferability, defense strategies, (See Section 5) etc. At the same time, we put forward to some new ideas of light-based physical attacks (See Section 6).

2. Related work

2.1. Digital attacks

Adversarial attack was first proposed by Szegedy et al. [1], showing that advanced DNNs are susceptible to interference by slight perturbations, after which adversarial attacks were successfully proposed [16, 17, 20, 21].

Most digital attacks limit the size of the adversarial perturbations to ensure imperceptible to human observer. Among them, $L_2$ and $L_\infty$ are the most commonly used norms [2,3,4,5,6]. In addition, some scholars modify other attributes of digital images to generate adversarial samples, for example, color [7,8,9], texture and camouflage [10,11,12,13], etc. These methods generate perturbations that are slightly perceptible to the human observers. At the same time, some scholars modify the physical parameters of digital images [14,15] and only retain the key components of images to generate adversarial samples. In general, the assumption of digital attacks is that an attacker can modify the input image, but this is not practical in a real scenario.

2.2. Physical attacks

Physical attack was first proposed by Kurakin et al. [22]. After this work, many physical attacks were proposed successively [24,28,29,30,31].

Traditional street sign attacks. Ivan Evtimov et al. [24] proposed a classic physical attack called RP2, which uses stickers as perturbations to perform attacks at different distances and angles against advanced DNNs. However, RP2 is susceptible to environmental interference at large distances and angles. Eykholt et al. [26] implemented a disappear attack by improving RP2, generating robust and transferable adversarial samples to fool advanced DNNs. However, the perturbations cover a large area, which is too conspicuous. Chen et al. [23] proposed ShapeShifter, by using "Expectation over Transformation" to generate adversarial samples, the experimental results showed that the generated stop sign always fooled the advanced DNNs at different distances and angles. Huang et al. [27] improved ShapeShifter by adding Gaussian white noise to ShapeShifter's optimization function, achieving a more
comprehensive attack. However, ShapeShifter and the improved ShapeShifter have a defect, perturbations cover almost the whole road sign, failed to achieve concealment. Duan et al. [25] proposed AdvCam, which uses style transfer techniques to generate adversarial samples and disguise the perturbations as a style considered reasonable by human observers. This method has better concealment than above methods, but it needs to manually select the attack area and target. All in all, the above methods require manual modification of the target objects. In addition, these works failed to achieve stealthiness.

**Physical attacks against face recognition system.** Nguyen et al. [33] proposed to use projector to attack face recognition system, using light projection as perturbations to generate adversarial samples, verified its antagonism to face recognition system under white-box and black-box settings. However, its deployment mode is complex. Besides, some utilized visible and invisible light to attack face recognition systems [32, 34], project optimized light onto the target to perform covert attacks. These attacks achieve better concealment, which accumulated some experience for our method.

**Laser-based attack.** Duan et al. [35] proposed AdvLB, which uses laser beam as perturbations and manipulates its physical parameters to execute attacks. It is more flexible than traditional street sign attacks. In addition, based on the nature of light, AdvLB achieves better concealment. However, it is prone to displacement errors in physical attack scenarios.

**Projector-based attack.** Gnanasambandam et al. [36] proposed OPAD, which amplifies subtle digital perturbations and projects them onto the target object to generate physical samples. However, its irregular projection patterns make human observers suspicious.

**Shadow-based attack.** Zhong et al. [37] studied shadow-based physical attack, which cast carefully crafted shadows on the target to generate adversarial samples, realizing a natural black-box attack. Since shadows are common, this makes shadow-based attack stealthy. Our proposed AdvCL uses catoptric light as a perturbation to study physical attacks in dim environments. Given that catoptric light is a common phenomenon, our approach is an extension of shadow-based attacks.

**Camera-based attack.** Li et al. [38] studied camera-based attacks by placing well-designed stickers on the camera lens to generate adversarial samples, performing targeted attacks against advanced DNNs, it avoids modifying the target by physically manipulating the camera itself, at the same time, adversarial perturbations are inconspicuous. However, this method is difficult to adjust error due to its complex operation.

### 3. Approach

#### 3.1. Adversarial sample

Given an input picture \( X \), ground truth label \( Y \), the DNN classifier \( f, f(X) \) represents the classifier's prediction label for picture \( X \). The classifier \( f \) associates with a confidence score \( f_r(X) \) to class \( Y \). The adversarial sample \( X_{adv} \) satisfies two properties: (1) \( f(X_{adv}) \neq f(X) = Y \); (2) \( || X_{adv} - X || < \epsilon \). Among them, the first property requires \( X_{adv} \) fools DNN classifier \( f \). The second property requires that the perturbations of \( X_{adv} \) are small enough to be imperceptible to human observers.

In this work, we use genetic algorithm [46] to optimize the physical parameters of catoptric light. Then, in the real scenarios, we project catoptric light onto a target object and generate physical samples. Figure 3 shows our approach.

![Figure 3: The attacker uses genetic algorithm to generate simulated samples, uses EOT to realize the migration between simulated samples and physical samples, and finally obtains the physical samples.](image)

#### 3.2. Catoptric light definition

In this paper, we define catoptric light using three physical parameters: location \( P_t \), color \( C (r, g, b) \), intensity \( I \). Each parameter is described as follows:

**Location \( P_t \):** For the location of catoptric light, we propose to find a polygon \( P_t \) to simulate the catoptric light, which is expressed by a set of vertices \( I = \{(m_1, n_1), (m_2, n_2), \ldots, (m_k, n_k)\} \). Given \( M \) as the mask to locate the target object, the color projection region can be expressed as \( M \cap P_t \). Although \( P_t \) can be any polygon, in our physical attack, through experimental tests, we use a simple triangle, which is sufficient to generate successful adversarial samples and easy to operate. We can use various polygon to achieve a higher attack success rate, however, such a catoptric light would look more unnatural. Therefore, in the both simulated and physical experiments, we use triangle catoptric light to execute attacks.

**Color \( C (r, g, b) \):** \( C (r, g, b) \) represents the color of the catoptric light, where \( r, g, \) and \( b \) represent the red channel,
green channel, and blue channel of the catoptric light respectively.

**Intensity I**: I indicates the intensity of catoptric light.

The parameters \( P_t, \ C \ (r, \ g, \ b) \) and \( I \) form a catoptric light’s physical parameter \( Ph \ (C, \ P_t, \ I) \). We define a simple function \( S(X; \ Ph(C, P_t, I), M) \) that simply synthesizes the input image with catoptric light to generate an adversarial sample:

\[
X_{adv} = S(X, Ph(C, P_t, I), M)
\]  

Formula (1) represents generating an adversarial sample. In Section 3.3, we describe how to use genetic algorithm to optimize the physical parameters of catoptric light.

**Expectation Over Transformation (EOT)** [52] is an effective tool for handling the conversion from digital to physical domains. We define a transformation \( T \) to represent the domain transition. \( T \) is a random combination of digital image processing, including brightness adaptation, position offset, color variation, and so on. Through EOT, the physical sample can be represented as:

\[
X_{phy} = T(X_{adv}, C, P_t, I)
\]  

### 3.3. Genetic algorithm (GA)

GA [46] is a natural heuristic algorithm designed by John Holland according to the laws of biological evolution in nature. It’s a computational model that simulates the biological evolution process of natural selection and genetic mechanism of Darwin's biological evolution, searches the optimal solution by simulating the natural evolution process. In this work, we use no model’s gradient information, require only confidence score and prediction label from the model feedback. The feasibility of using GA to optimize \( AdvCL \) include:

1. GA searches the string set of solutions of the problem, covering a wide area, which is conducive to global optimization. In our method, physical parameters of \( C, \ P_t \) and \( I \) include a total of 256x256x256x512x512x6x4 combinations of problem solutions (in which \( C \) (256x256x256), \( P_t \) (512x512x6), \( I \) (4)), GA is conducive to the global optimization of \( AdvCL \).

2. GA basically need no knowledge of search space or other auxiliary information, uses the fitness value to evaluate individuals, and carries out genetic operation on this basis. The fitness function is not constrained by continuous differentiability, and its definition domain can be set arbitrarily. \( AdvCL \) does not need model’s gradient information, takes the model’s confidence score \( f_Y(X) \) as the individual fitness, \( f(X_{adv}) \neq Y \) as the termination condition.

3. Flexible selection strategy. GA uses evolutionary information to organize search. Individuals with high fitness have higher survival probability, and obtain a more adaptable gene structure. \( AdvCL \) uses the flexibility of genetic algorithm to select specific elimination strategy to further expand the search scope and achieve global optimization.

**Algorithm 1**: Pseudocode of \( AdvCL \)

**Input**: Input \( X \), Classifier \( f \), Ground truth label \( Y \), Population size \( seed \), Iterations \( Step \), Crossover rate \( Pc \), Mutation rate \( Pm \);

**Output**: A vector of parameters \( Ph^* \);

1. Initiation \( Seed \), \( Step \), \( Pc \), \( Pm \);
2. for \( seed \) in range \((0, \ Seed) \) do
3. Encoding individual genotype \( G_{seed} \);
4. end
5. for \( steps \) in range \((0, \ Step) \) do
6. for \( seed \) in range \((0, \ Seed) \) do
7. \( Ph_{seed}(C, I) \leftarrow G_{seed} \);
8. \( X_{adv}(seed) = S(X, Ph_{seed}(C, P_t, I), M) \);
9. \( f_Y(X_{adv}) \leftarrow f(X_{adv}) ; Y \);
10. if \( f(X_{adv}) \neq Y \) then
11. \( Ph^* = Ph_{seed}(C, I) \);
12. Output \( Ph^* \);
13. Exit ()
14. end
15. end
16. Update: \( G_{seed} \leftarrow \) Selection with \( f_Y(X_{adv}) \);
17. Update: \( G_{seed} \leftarrow \) Crossover with \( P_c \);
18. Update: \( G_{seed} \leftarrow \) Mutation with \( P_m \);
19. end

We choose binary encoding to encode the physical parameters. For the physical parameters \( C \ (r, \ g, \ b) \), \( r, \ g \) and \( b \) range from 0 to 255, so \( r, \ g, \ b \) correspond to 8 genes respectively. We set the catoptric light to an irregular triangle, with the position of each corner coded from 0 to 512 (with random cuts for positions beyond the image), so that \( P \) corresponds to 54 genotypes. We set intensity \( I \) to four different intensity values (e.g., 0.3 to 0.6) corresponding to 2 genes. Thus, parameters \( C \ (r, \ g, \ b) \), \( P_t \) and \( I \) contain a total of 80 genes. After randomly encoding the initial population, utilizing binary conversion to convert genotype into phenotype. Then, input phenotype parameters into the model and generate adversarial samples according to Formula (1). For the selection strategy, we select from small to large according to the confidence score, and eliminate the individuals with high confidence scores (for example, 1/10). Note that in this work, the smaller the confidence score, the stronger the individual fitness. Crossover and mutation strategies follow the conventional approach. During population iterations, an individual satisfies \( f(X_{adv}) \neq Y \), saving the adversarial sample and physical parameters. In the physical environment, we project catoptric light according to the physical parameters and take pictures to generate physical adversarial samples.
3.4. Catoptric light adversarial attack

AdvCL focuses on searching $Ph (C, P_l, I)$, the physical parameters of catoptric light, which generates an adversarial sample $X_{adv}$ that fools the classifier $f$. 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 expressed as:

$$
\arg\min_{Ph} E_{c-r}[f_Y(t(X_{adv}, C, P_l, I))] \quad (3)
$$

s.t. $f(X_{adv}) \neq Y$

Algorithm 1 shows the pseudocode of AdvCL. The proposed method takes clean image $X$, target classifier $f$, correct label $Y$, population $Seed$, iteration number $Step$, crossover rate $P_c$, mutation rate $P_m$ as input decided by the attacker. Details of the algorithm are explained in Algorithm 1. Here, our selection strategy is to weed out the top tenth with the largest confidence score (note that the smaller the confidence score, the more antagonistic) and then fill in the randomly encoded genes separately. The benefit of this selection strategy is that it saves a lot of time cost by directly eliminating the most inferior individuals, and further expand the search scope and global optimization. In addition, we set crossover rate $P_c$ and variation rate $P_m$ to 0.7 and 0.1, respectively. The algorithm finally outputs the physical parameters of the catoptric light $Ph^*$, which are used to perform subsequent physical attacks.

4. Evaluation

4.1. Experimental setting

We test the proposed method in both digital and physical environments. Consistent with AdvLB [35], we use ResNet50 as the target model to perform all experiments, and then randomly select 1000 ImageNet [47] images that could be correctly classified by ResNet50 to perform digital tests. For physical tests, our experimental devices are shown in Figure 4. We use color lamps as lighting equipment and iPhone 6S to take photos, experiment verify that different camera devices would not affect the effectiveness of the proposed AdvCL. For all experiments, we use attack success rate (ASR) as a criterion to report the effectiveness of AdvCL.

4.2. Evaluation of AdvCL

Digital test. We test the effectiveness of AdvCL in digital environments on 1000 images that could be correctly classified by ResNet50, achieving an attack success rate of 94.90% (Untargeted ASR of 95.10% in AdvLB [35], targeted ASR of 49.60% in [38]). Figure 5 shows some interesting results. The first column represents the samples we aim to attack, and the catoptric light of red, orange, yellow, green, blue, indigo and purple are added to clean samples respectively. The other columns represent the generated adversarial samples, which can successfully fool the classifier. For example, when adding a blue $(C(I), 0.255)$ catoptric light to the clean sample, seashore is misclassified as volcano. On the other hand, most of the triumphal arch is misclassified as cliff when covering various catoptric light. All in all, AdvCL shows an effective adversarial effect in the digital environment, it leads advanced DNNs to misclassification without changing the semantic information of the target objects.

Physical test. To demonstrate the rigor of AdvCL, we conduct a strict experimental design in the physical test. In the real scenario, the robustness of physical attack is affected by environmental noise, so we design indoor test and outdoor test respectively. In which, the indoor test avoids the influence of outdoor noise, and the outdoor test reflects the performance of AdvCL in real scenarios.

For the indoor test, we use ‘Bonnet’, ‘Plastic bag’, ‘Street sign’, etc. as target objects. and form 30 adversarial samples, achieving an ASR of 100% (ASR of 100% in AdvLB [35]). Figure 6 shows the experimental results of the indoor test. It can be seen that the simulated catoptric light keeps better consistency with the physical catoptric light. In addition, there exists error between the simulated catoptric light and the physical catoptric light, which could be evaded by EOT [52].

In the outdoor test, we select ‘Street sign’ as attack objects, and form 103 adversarial samples, achieving an ASR of 83.5% (ASR of 77.43% in AdvLB [35], ASR of 73.26% in [38]). Figure 7 shows adversarial samples in the outdoor environment. Experimental result shows that by adding the optimized catoptric light to the target objects, it leads the advanced DNNs to misclassifications. On the
other hand, to get close to real scenarios, we conduct outdoor tests on ‘Stop sign’ from different angles, it shows that AdvCL performs effective physical attacks on target objects at various angles.

Figure 5: Adversarial samples generated by AdvCL.

![Image](image_url)

Figure 6: Indoor test.

4.3. Ablation study

Here, we perform a series of experiments to study the adversarial effects of different physical parameters on AdvCL: Intensity $I$, Color $C(r, g, b)$, $P_l$.

Intensity $I$: Here, we conduct experiments on 1000 images that could be correctly classified by ResNet50. The greater $I$, the stronger adversarial effect, and the worse stealthy. We study the adversarial effect of catoptric light with intensity of 0.1 to 0.9. Table 1 shows the attack success rates for each intensity of catoptric light. It shows that AdvCL is aggressive even at a weak intensity.

Color $C(r, g, b)$: Here, we study the ablation of $C(r, g, b)$. We selected 27 colors of catoptric light to execute digital attacks on ResNet50. Figure 8 shows the ASR of each color. It can be seen that $C(255, 0, 255)$ achieves the highest ASR 96.60%, and $C(0, 0, 0)$ gets the lowest ASR 73.90%.

The number of edges $P_l$: Theoretically, $P_l$ can be any polygon, however, the more edges there are, the more unnatural the generated perturbation looks, which violates the stealthiness requirement. Therefore, we perform the attack using triangle, as shown in Table 2, which is sufficient to generate successful adversarial samples even with trilaterals.

| $P_l$ | 3  | 4  | 5  | 6  | 7  | 8  | 9  |
|------|----|----|----|----|----|----|----|
| ASR  | 79.30 | 84.80 | 86.00 | 88.20 | 90.10 | 91.40 | 91.90 |

Table 1: Ablation study of $I$ (%).

| $I$ & 0.1 & 0.2 & 0.3 & 0.4 & 0.5 & 0.6 & 0.7 & 0.8 & 0.9 |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| ASR | 22.60 | 41.90 | 57.60 | 69.80 | 80.40 | 87.90 | 91.10 | 94.90 | 96.80 |

Table 2: Ablation of $P_l$ (%).
5. Discussion

5.1. CAM

We use CAM [48] to show the model’s attention. As shown in Figure 9, by adding the optimized catoptric light even on the corner of clean images, the target model is more biased towards ‘Hotdog’, ‘Angora’, etc. thus given incorrect TOP-1 predictions.

5.2. Transferability of AdvCL

Here, we demonstrate the attack transferability of AdvCL against advanced DNNs [39, 40, 41, 42, 43, 44, 45] in both digital and physical environments. We take the adversarial samples generated by AdvCL that successfully attacked ResNet50 as the dataset. The experimental results are shown in Table 3. It can be seen that AdvCL shows effective attack transferability in the digital environment, and the attack success rate against AlexNet is 77.24%. In the physical environments, AdvCL demonstrates excellent attack transferability, whose black-box attack has paralyzed almost all of the advanced DNNs. Our experimental results imply that AdvCL allows attackers to exploit the transferability to carry out efficient physical attacks against advanced DNNs without any knowledge of the model.

The experimental results in physical test show that AdvCL conducts effective physical attacks in a white-box setting. The data in Table 3 show that AdvCL has excellent...
physical adversarial performance in a black-box setting. AdvCL empowers attacker flexible operations, even without any knowledge of the model, to perform robust physical attacks. Therefore, in view of the excellent adversarial effect of AdvCL on the vision-based system in real scenes, we call for the attention of the proposed AdvCL.

Table 3: Transferability of AdvCL (ASR (\%)).

| $f$ | Inception v3 | VGG19 ResNet101 | GoogleNet | AlexNet | MobileNet | DenseNet |
|-----|--------------|-----------------|-----------|---------|-----------|-----------|
| Digital | 71.34 | 55.85 | 47.21 | 67.02 | 77.24 | 63.01 | 54.58 |
| Physical | 97.67 | 100 | 97.67 | 100 | 100 | 97.67 | 96.51 |

Figure 10: ResNet50 vs. Rob-ResNet50.

5.3. Defense of AdvCL

In addition to demonstrating the potential threats of AdvCL, we attempt to defense against AdvCL with adversarial training. Here, in order to rigorously study the defense strategy against the proposed attack, we construct a larger dataset. First of all, we randomly select 50 clean samples from each of the 1000 categories in ImageNet [47] and get 50,000 clean samples. Secondly, adding 27 color catoptric light to each clean sample with $f=0.5$ to obtain the final data set containing 1.35 million adversarial samples, which is called ImageNet-CatoptricLight (ImageNet-CL).

We use the proposed ImageNet-CL as the dataset for adversarial training. We use torchvision to train the ResNet50 robust model (Rob-ResNet50). The model was optimized on 3 2080Ti GPUs by ADAM with initial learning rate 0.01. The experimental results are shown in Figure 10. It can be seen that Rob-ResNet50 achieves a classification accuracy more than 90% for adversarial samples, which will help scholars to expand adversarial defense strategies against light-based attacks.

6. Conclusion

In this paper, we introduce a light-based physical attack named AdvCL, which takes advantage of the instantaneous nature of the light-speed attack to conduct effective physical attacks. Rigorous experimental design and comprehensive experimental results demonstrate the effectiveness of AdvCL in both digital and physical environments. The proposed method reveals the security threat caused by light-based physical attacks to the physical world. Our work also sheds new light on future physical attacks, for example, using light as physical perturbations instead of stickers, which would improve the flexibility of physical attacks. The proposed AdvCL as an effective light-based physical attack is a useful complementary to recent physical attacks.

In the future, we will improve the proposed AdvCL to adapt to different tasks, such as object detection, domain segmentation, etc. We will also devote ourselves to the studies on light-based physical attacks, e.g., adversarial laser spot, adversarial spot light, etc. Moreover, effective defense strategies against light-based attacks will also become a promising research direction.

References

[1] Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. In ICLR, 2013.
[2] Nicholas Carlini and David Wagner. Adversarial examples are not easily detected: Bypassing ten detection methods. In ACM Workshop on Artificial Intelligence and Security, pages 3–14. ACM, 2017.
[3] Nicholas Carlini and David Wagner. Towards evaluating the robustness of neural networks. In IEEE S&P. IEEE, 2017.
[4] Yinpeng Dong, Fangzhou Liao, Tianyu Pang, Hang Su, Jun Zhu, Xiaolin Hu, and Jianguo Li. Boosting adversarial attacks with momentum. In CVPR, 2018.
[5] Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. ICLR, 2018.
[6] Cihang Xie, Zhishuai Zhang, Yuyin Zhou, Song Bai, Jianyu Wang, Zhou Ren, and Alan L Yuille. Improving transferability of adversarial examples with input diversity. In CVPR, 2019.
[7] Hossein Hosseini and Radha Poovendran. Semantic adversarial examples. In CVPR Workshop, 2018.
[8] Ali Shahin Shamsabadi, Ricardo Sanchez-Matilla, and
Andrea Cavallaro. Colorfool: Semantic adversarial colorization. In CVPR, 2020.
[9] Zhengyu Zhao, Zhuoran Liu, and Martha Larson. Towards large yet imperceptible adversarial image perturbations with perceptual color distance. In CVPR, 2020.
[10] Rey Reza Wiyatno and Anqi Xu. Physical adversarial textures that fool visual object tracking. In ICCV, 2019.
[11] Wang J, Liu A, Yin Z, et al. Dual attention suppression attack: Generate adversarial camouflage in physical world[C]//Proceedings of the IEEE/ACM Conference on Computer Vision and Pattern Recognition. 2021: 8565-8574.
[12] Zhang Y, Foroosh H, David P, et al. CAMOU: Learning physical vehicle camouflages to adversarially attack detectors in the wild[C]//International Conference on Learning Representations. 2018.
[13] Jiang T, Sun J, Zhou W, et al. FCA: Learning a 3D Full-coverage Vehicle Camouflage for Multi-view Physical Adversarial Attack[J]. arXiv preprint arXiv:2109.07193, 2021.
[14] Xiaohui Zeng, Chenxi Liu, Yu-Siang Wang, Weichao Qiu, Lingxi Xie, Yu-Wing Tai, Chi-Keung Tang, and Alan L Yuille. Adversarial attacks beyond the image space. In CVPR, 2019.
[15] Hsueh-Ti Derek Liu, Michael Tao, Chun-Liang Li, Derek Nowrouzezahrai, and Alec Jacobson. Beyond pixel norm-balls: Parametric adversaries using an analytically differentiable renderer. In ICLR, 2018.
[16] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. ICLR, 2015.
[17] Moosavi-Dezfooli S M, Fawzi A, Frossard P. Deepfool: a simple and accurate method to fool deep neural networks[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 2574-2582.
[18] Pin-Yu Chen, Yash Sharma, Huan Zhang, Jinfeng Yi, and Cho-Jui Hsieh. Ead: elastic-net attacks to deep neural networks via adversarial examples. In AAAI, 2018.
[19] Rey Reza Wiyatno, R, Xu A. Maximal jacobian-based saliency map attack[J]. arXiv preprint arXiv:1808.07945, 2018.
[20] Su J, Vargas D V, Sakurai K. One pixel attack for fooling deep neural networks[J]. IEEE Transactions on Evolutionary Computation, 2019, 23(5): 828-841.
[21] Moosavi-Dezfooli S M, Fawzi A, Fawzi O, et al. Universal adversarial perturbations[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 1765-1773.
[22] Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Adversarial examples in the physical world. ICLR, 2016.
[23] Chen S T, Cornelius C, Martin J, et al. Shapeshifter: Robust physical adversarial attack on faster r-cnn object detector[C]//Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer, Cham, 2018: 52-68.
systems[C]//International Conference on Machine Learning. PMLR, 2019: 3896-3904.
[39] Huang G, Liu Z, Van Der Maaten L, et al. Densely connected convolutional networks[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 4700-4708.
[40] He K, Zhang X, Ren S, et al. Deep residual learning for image recognition[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 770-778.
[41] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition[J]. arXiv preprint arXiv:1409.1556, 2014.
[42] Szegedy C, Liu W, Jia Y, et al. Going deeper with convolutions[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2015: 1-9.
[43] Sandler M, Howard A, Zhu M, et al. Mobilenetv2: Inverted residuals and linear bottlenecks[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2018: 4510-4520.
[44] Krizhevsky A, Sutskever I, Hinton G E. Imagenet classification with deep convolutional neural networks[J]. Advances in neural information processing systems, 2012, 25.
[45] Szegedy C, Vanhoucke V, Ioffe S, et al. Rethinking the inception architecture for computer vision[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 2818-2826.
[46] Holland J H. Genetic algorithms[J]. Scientific american, 1992, 267(1): 66-73.
[47] Deng J. A large-scale hierarchical image database[J]. Proc. of IEEE Computer Vision and Pattern Recognition, 2009, 2009.
[48] Zhou B, Khosla A, Lapedriza A, et al. Learning deep features for discriminative localization[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 2921-2929.
[49] De K, Pedersen M. Impact of colour on robustness of deep neural networks[C]//Proceedings of the IEEE/CVF International Conference on Computer Vision. 2021: 21-30.
[50] Kennedy J, Eberhart R. Particle swarm optimization[C]//Proceedings of ICNN'95-international conference on neural networks. IEEE, 1995, 4: 1942-1948.
[51] Sayles A, Hooda A, Gupta M, et al. Invisible perturbations: Physical adversarial examples exploiting the rolling shutter effect[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021: 14666-14675.
[52] Athalye A, Engstrom L, Ilyas A, et al. Synthesizing robust adversarial examples[C]//International conference on machine learning. PMLR, 2018: 284-293.