Adversarial Laser Spot: Robust and Covert Physical Adversarial Attack to DNNs

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Abstract
Most existing deep neural networks (DNNs) are easily disturbed by slight noise. As far as we know, there are few researches on physical adversarial attack technology by deploying lighting equipment. The light-based physical adversarial attack technology has excellent covertness, which brings great security risks to many applications based on deep neural networks (such as automatic driving technology). Therefore, we propose a robust physical adversarial attack technology with excellent covertness, called adversarial laser point (AdvLS), which optimizes the physical parameters of laser point through genetic algorithm to perform physical adversarial attack. It realizes robust and covert physical adversarial attack by using low-cost laser equipment. As far as we know, AdvLS is the first light-based adversarial attack technology that can perform physical adversarial attacks in the daytime. A large number of experiments in the digital and physical environments show that AdvLS has excellent robustness and concealment. In addition, through in-depth analysis of the experimental data, we find that the adversarial perturbations generated by AdvLS have superior adversarial attack migration. The experimental results show that AdvLS impose serious interference to the advanced deep neural networks, we call for the attention of the proposed physical adversarial attack technology.

1. Introduction
The applications based on computer vision are gradually popularized in daily life, such as autonomous vehicle, face recognition system and so on. At the same time, adversarial attack technology has become the focus of many scholars. In the digital environment, adversarial attacks are performed by manipulating pixel-level perturbations [3,4], perturbations generated in this setting are invisible to the naked eye. In the physical environment, stickers are attached to the target object as the perturbations to perform adversarial attacks [16,17,18], which are visible to the naked eye. For example, attaching small pieces of paper to road signs can cause deep neural networks to misclassify, with disastrous results.

In the physical world, there are many natural factors that play the role of imperceptible adversarial perturbations. Such as lighting, shadows, background environments, etc. If an attacker deliberately mimics the physical adversarial perturbations similar to the natural factor, this physical attack method will inadvertently execute adversarial attacks, resulting in unimaginable consequences. For example, literature [1] introduced a physical adversarial attack technology based on shadow, which not only ensures the success of physical attack, but also makes people ignore the existence of the perturbations. Most physical adversarial attack techniques use stickers as physical adversarial perturbations, road signs with stickers, for example, trick deep neural networks. However, this kind of method has a disadvantage, that is, physical adversarial perturbations are always retained on the target object, so this kind of method has a poor covertness. Some researchers have proposed some light-based physical adversarial attack technologies, which make use of the nature of instantaneous attack to ensure the covertness and achieve effective attack. However, these methods usually perform adversarial attacks in dim nighttime environments, and in well-lit daytime, these methods will be completely disabled.

Figure 1: Vision comparison
(a) RP2 (b) AdvLB (c) AdvLS(Our)

In this paper, we demonstrate a novel light-based physical adversarial attack technique (AdvLS), which uses laser spots as physical adversarial perturbations to perform instantaneous attacks on target objects. The advantages of using laser spots to perform physical adversarial attack include: (1) The laser spot projection area is puny, with good concealment; (2) Laser performs instantaneous attacks, adversarial perturbations will not be permanently retained on the target object; (3) Laser spot adversarial attack is currently the first light-based physical adversarial
attack technology that can perform adversarial attacks in the daytime, making AdvLS more aggressive. Figure 1 shows a comparison of our method with RP2 [18] and AdvLB [27], showing that our approach is much better at covertness.

Our method is simple to execute physical adversarial attacks. Firstly, we formalize the physical parameters of laser spots, use genetic algorithm to find the physical parameters of the most aggressive laser spots. Finally, based on the physical parameters of laser spots, we use laser pointers to project laser spots to the target object and generate physical adversarial samples. We verify the robustness and covertness of AdvLS through numerous experiments in both digital and physical environments, at the same time, some ablation experiments were also presented. Furthermore, by analyzing the misclassification of adversarial samples, we find that the laser spots have some semantic features of clean samples, such as Envelope and Petri dish.

The difficulties of physical adversarial attack technology mainly include: print perturbation loss, physical adversarial perturbations covertness, robustness, etc. AdvLS uses the nature of light-speed attack to overcome the difficulty of covertness, but also avoids print perturbations. Our main contributions are as follows:

1. We propose a novel physical adversarial attack method: AdvLS, which is the first light-based method capable of executing physical adversarial attacks in daytime. Our attack equipment is cheap, requires only a set of laser pointers to perform powerful physical adversarial attacks;
2. Extensive experiments were conducted to verify the robustness and covertness of AdvLS. In particular, the light-speed attack nature of laser makes AdvLS very covertness.
3. Through the analysis of adversarial samples generated by AdvLS, we found that adversarial samples have strong adversarial attack migration, which makes AdvLS has strong adversarial attack performance in black-box setting.

2. Related work

Our work is carried out in white-box and black-box settings. This section summarizes the related work of adversarial attacks, previous works are mainly divided into two categories: digital adversarial attacks and physical adversarial attacks.

2.1. Digital adversarial attacks

Szegedy et al. [2] firstly proposed adversarial attack. After this work, many adversarial attack technologies were proposed successively [13,14,15]. Goodfellow et al. [3] proposed an efficient and simple method called fast gradient sign method (FGSM), which utilizes the gradient information of the model to perform efficient adversarial attacks. Moosavi-dezfooli et al. [4] proposed Deepfool, their work effectively calculated the perturbations that fooled deep neural networks, thereby reliably quantizing the robustness of many advanced classifiers. Carlini and Wagner [5] designed a new loss function, which verified that their adversarial perturbations were more difficult to detect, and pointed out that the inherent characteristics considered as adversarial samples were not in fact. Pin-yu Chen et al. [6] proposed an adversarial attack called EAD, their experiments showed that EAD could produce adversarial samples with slight distortion and obtain attack effects similar to those of the most advanced methods in different scenes. Carlini and Wagner [7] proposed C&W attack technology, and proved that defensive distillation attack technology, and proved that defensive distillation network did not significantly improve the robustness of deep neural networks through three attack algorithms. Yinpeng Dong et al. [8] proposed an iterative algorithm based on momentum to enhance the adversarial attack, which can stabilize the update direction and avoid the local maximum value in the iteration process, generating more transferable adversarial samples. Cihang Xie et al. [9] improved the migration of adversarial examples by creating different input modes and applying random transformation to input images in each iteration, experiments have shown that the proposed method is more aggressive. Hossein Hosseini et al. [10] introduced a new adversarial sample: "Semantic adversarial sample", which first converts RGB images into HSV color space and then randomly moves hue and saturation components while keeping value components constant to generate adversarial samples. Ali Shahin Shamsabadi et al. [11] proposed a black-box adversarial attack based on content, which uses image semantics to selectively modify colors within the selected range of human natural perception, generating unlimited perturbations. Zhengyu Zhao et al. [12] used human color perception to minimize the disturbance size of perceived color distance and generate adversarial samples.

Different from the above methods, which is executed in the digital environment, our method is conducted in the physical environment.

2.2. Physical adversarial attacks

Alexey Kurakin et al. [16] discovered the adversarial samples in the physical world, input the adversarial images obtained by mobile phone camera into the classifier and measured the classification accuracy. Experimental results showed that, even perceived by the camera, a large proportion of adversarial samples were misclassified. Ranjie Duan et al. [17] disguise adversarial examples in the physical world as reasonable natural styles, which could both fool classifiers and achieve covertness. Ivan Evtimov et al. [18] proposed a general attack in the physical world, called RP2, which achieves a high rate of misclassification for road sign classifiers in the physical world. Kaidi Xu et
al. [19] proposed an adversarial T-shirt, which could avoid the pedestrian detector even if the T-shirt would be deformed with pedestrians. Brown et al. [20] proposed a method to create generic, robust and targeted adversarial patches, even if the patches were puny, they would make the classifier to ignore other items in the scene and fool the classifier. Mahmood Sharif et al. [21] designed an adversarial eyeglass frame for attacking face recognition system, and successfully implemented white-box and black-box attacks under different conditions. Anish Athalye et al. [22] designed adversarial sample with robustness to synthetic noise, distortion and affine transformation, printed the first 3D adversarial sample, proving the existence of robust 3D adversarial samples. Chen et al. [23] proposed ShapeShifter, which generate Stop signs of reverse interference, and these signals are always mistaken by classifier as other objects.

Different from the above physical adversarial attacks, the light-based adversarial attacks have better covertness. Meng Shen et al. [24] proposed VLA, which is based on visible light, projecting a carefully designed adversarial beam onto the human face to attack the face recognition system. Dinh-Luan Nguyen et al. [25] studied the real-time physical adversarial attack effect of adversarial light projection on face recognition system, proved the vulnerability of face recognition model to light projection attack. Zhe Zhou et al. [26] used infrared ray as adversarial perturbations to generate adversarial samples, and interpreted the threat of infrared adversarial sample to face recognition system. Duan et al. [27] proposed adversarial laser beam (AdvLB), which implements efficient physical adversarial attacks by manipulating the physical parameters of the laser beam. Gnanasambandam et al. [28] introduced an attack system consisting of low-cost projectors, cameras and computers, the proposed attack method can implement effective optical adversarial attack to real 3D objects.

3. Approach

3.1. Problem description

Generating adversarial samples can be regarded as an optimization problem. The input image can be regarded as a high-dimensional vector, in which each element represents a pixel value of the image. Supposing $X$ represents a clean sample, ground truth label $Y, f$ represents the classifier, $f (X)$ represents the classification result of picture $X$ by classifier $f$. $X_{\text{adv}}$ represents the adversarial sample. The optimization problem can be expressed as:

$$\text{Finding } X_{\text{adv}} \text{ satisfying } f(X_{\text{adv}}) \neq f(X) = Y \quad (1)$$

s.t. $\|X_{\text{adv}} - X\| < \epsilon$

In Formula (1), $\|\|$ represents $l_p$ norm, $\epsilon$ represents the threshold of perturbation size. Firstly, the adversarial samples fool the classifier. Secondly, the size of the adversarial perturbation is limited to a certain threshold.

Figure 2 shows our method. Firstly, generating simulation laser points, the genetic algorithm is used to optimize the physical parameters of laser spots and generate the adversarial samples in the digital environment. Secondly, manipulating the laser pointers to generate adversarial samples in the physical environment by referring to adversarial samples in the digital environment.

3.2. Genetic algorithm (GA)

GA [29] is a natural heuristic algorithm proposed by John Holland. As the name implies, GA is an algorithm inspired by the genetic and evolution of nature, simulated and implemented on the computer to solve the optimization problems in real life. The algorithm is an algorithm that can avoid local optimal solutions.

![Flow chart of GA](image)

Figure 3: Flow chart of GA

GA is a simple and efficient optimization method based on Darwin’s theory of evolution. GA has the advantages of learning, adaptation and optimization. The principle is: the scheme of the problem is encoded as chromosomes, and an evaluation standard is used to evaluate each chromosome. The individuals are sorted according to their adaptive values. The individuals with high adaptive values have a greater probability of being selected, the selected individuals get the next generation of individuals through
crossover and mutation. Repeating the process until the individual fitness meets the requirements of the algorithm, The flow chart of genetic algorithm is shown in Figure 3.

In this work, we do not use the gradient information of the model, only need the confidence score and prediction label of the model. The advantages of using GA to optimize adversarial samples include:

1) Simplicity and efficiency: GA is a random optimization algorithm, which does not require excessive mathematical requirements for optimization problems. This algorithm avoids local optimal solutions and find the optimal solution of AdvLS quickly and quickly.

2) Nonlinear problem solving: GA solves the optimization solution of linear problems as well as nonlinear problems. The optimization objective of AdvLS is a nonlinear optimization problem, which can be solved by GA effectively.

3) Requires little information about the target system: GA does not require the optimization problem to be differentiable like the classical optimization problem (e.g. Gradient descent method), which is important in our work. For example, 1) some networks are not differentiable, and 2) computing gradients requires additional information, which in many cases increases the time cost.

3.3. Laser spot definition

In this work, we define a laser spot with two parameters: Center position \( L (m, n) \) and color \( C (r, g, b) \). Each parameter is defined as follows:

Center position \( L (m, n) \): \( L (m, n) \) represents the center position of the laser spot. We assume that the laser spot is round, and use a double tuple \((m, n)\) to represent the center position of the laser spot, where \( m \) represents the horizontal coordinate of the center, \( n \) represents the vertical coordinate.

Color \( C (r, g, b) \): \( C (r, g, b) \) represents the color of the laser spot. \( r \) represents the red channel of the laser color, \( g \) represents the green channel, and \( b \) represents the blue channel. In the digital environment, laser points of any color can be generated to carry out adversarial attacks. In the physical environment, due to the limitation of color can be generated to carry out adversarial attacks. In this work, we design the \( l \) function to limit the position area of the laser spot group. Therefore, the adversarial sample generation formula in the physical environment is shown in Formula (3):

\[
X_{adv} = Syn(X, l(G_\theta)) \quad (3)
\]

By using the \( l \) function, we ensure that the laser spot group position is limited to the region of the target object.

3.4. Adversarial laser spot

Our method consists of two parts: (1) Generating adversarial samples by randomly generating laser spots in the digital environment; (2) In the physical environment, optimizing the physical parameters of laser spots with GA, so as to generate digital adversarial samples, then using laser pointers to generate physical adversarial samples. Our task is to find the adversarial laser spot group \( G_\theta \) that can fool the classifier by GA, the projection area of laser point on the target area is puny, which makes AdvLS well coverness. Our optimization objective function is defined as formula (4):

\[
\text{argmin}_{G_\theta} \text{feedback}(f(X_{adv}); Y) \quad (4)
\]

\( \text{feedback}(f(X_{adv}); Y) \) represents the confidence score of the adversarial sample on the correct label. The smaller the confidence is, the more adversarial the adversarial sample is. The physical parameters of adversarial laser spot group are optimized and searched by GA, the physical parameter \( G_\theta \) is output when adversarial sample fool the classifier.

In the digital environment, we verify the effectiveness of AdvLS by randomly generating adversarial laser spot group to generate adversarial samples. Then, based on GA, design the adversarial attack algorithm in the physical environment.

As shown in Algorithm 1, the algorithm process includes: (1) Taking clean sample \( X \), target classifier \( f \), ground truth label \( Y \), population size \( Seed \), iterations \( Step \), crossover rate \( Pc \), mutation rate \( Pm \) as input, output the physical parameter \( G_\theta \) of the adversarial laser spot group. (2) Initializing \( Seed \), \( Step \), \( Pc \) and \( Pm \), and randomly encoding the initial population of laser spot group; (3) Within the iterations \( Step \), calculate the fitness value of each individual in the population. If an individual attacks the target classifier successfully, the physical parameter \( G_\theta \) of the individual is output and end the algorithm. If the attack fails, the selection operation is carried out according to the size of the adaptive value, and then the crossover and mutation operation is carried out with \( Pc \) and \( Pm \) as the probability value. In this work, our selection strategy is to replace the
top tenth of individuals with the highest fitness value with the lowest top tenth of individuals (note that the smaller the fitness value is, the more confrontational the individual is). The advantage of using this selection strategy is to weed out the least aggressive individuals and reduce the time cost. In addition, we set crossover rate $Pc$ and mutation rate $Pm$ to 0.7 and 0.1, respectively. Experimental results show that our selection strategy, crossover rate and variation rate achieve efficient optimization solution to the target problem. The optimum physical parameter $G_0$ of laser beam group is obtained by GA, the laser pointer is used to project laser spot onto the target object to generate the physical adversarial samples.

**Algorithm 1**: Pseudocode of AdvLS

**Input**: Input $X$, Classifier $f$, Label $Y$, Population size $Seed$, Iterations $Step$, Crossover probability $Pc$, Mutation probability $Pm$;

**Output**: A vector of parameters $G_0$;

1. **Initiation** $Seed$, $Step$, $Pc$, $Pm$;
2. Encoding laser spot group $G_0(i)$ randomly;
3. for steps in range $(0, Step)$ do
4. for seeds in range $(0, Seed)$ do
5. $X_{adv}(seeds) = Syn(X, I(G_0(seeds)))$;
6. $fitness(seeds) = feedback(f(X_{adv}); Y)$;
7. if $f(X_{adv}) \neq Y$ then
8. $G_0^* = G_0(seeds)$;
9. Output $G_0^*$;
10. Exit ()
end
end

Selection with $fitness(seeds)$;

Crossover with $Pc$;

Mutation with $Pm$;

end

4. Experiment

4.1. Experimental setting

As with the method in AdvLB [27], we use ResNet50[31] as a target classifier to carry out the adversarial attack experiment in both digital and physical environments. In the digital environment, we randomly selected 1000 correctly classified images selected from ImageNet [32] for testing. In the physical environment, pictures of common objects are used for testing. Our experimental equipment is shown in Figure 4.

In the physical environment, we perform adversarial attacks with laser pointers. We set the number of physical adversarial laser spots to 10, so we need to use 10 laser pointers and 10 tripods, use an iPhone6s as a camera device.

4.2. Evaluation of AdvLS

To ensure the feasibility of AdvLS, we execute experimental tests in the digital environment. Then, the robustness and covertsness of AdvLS are verified by physical experiments.

Digital test: We conduct digital attack experiments on 1000 correctly classified images selected from ImageNet [32]. We conduct digital attack experiments on random color, red, green and blue laser spots respectively. The experimental results are shown in Table 1:

| Color   | Random | Red  | Green | Blue  |
|---------|--------|------|-------|-------|
| ASR (%) | 75.8   | 82.6 | 87.7  | 78.7  |
| Query   | 237.59 | 204.86 | 143.00 | 241.27 |

Table 1 shows the attack success rate and average query times of laser spots with different colors in the digital environment. The number of laser spots ranges from 10 to 50. It can be seen that the adversarial laser spot has a strong antagonism and achieves a robust attack success rate in the digital environment. In addition, Figure 5 shows the digital adversarial samples generated by AdvLS, which lead to classifier classification errors by adding a small number of adversarial laser spots that are imperceptible to the naked eye without changing the semantic information of the original image. For example, by adding a few adversarial laser spots to a clean sample, the classifier misclassifies Quail as Peacock, Mosquito net, etc.

![Figure 4: Experimental devices](image)

![Figure 5: Adversarial samples in the digital environment](image)
On the other hand, we make statistics on the misclassification results. As shown in Figure 6, most of the adversarial samples were misclassified as Hair Slide, Joystick, etc. By looking at the original clean sample of Hair Slide in ImageNet's training set [32], we found that the Hair slide image had many shiny plastic crystals, and these elements were very similar to the effect against laser points. Some of the same phenomena will be shown in Section 5.

![Figure 6: Statistics of misclassification in the digital environment](image)

As can be seen from the experimental results in Table 2, AdvLS achieves robust attack performance in outdoor physical environment. As can be seen from Figure 7, the adversarial samples generated by AdvLS have excellent covertness and execute adversarial attacks even in the daytime with strong light. Note that this is the only light-based physical adversarial attack technology we know of that can be deployed during the daytime. The experimental results in Table 2 and the demonstration of adversarial samples in Figure 7 verify the robustness and covertness of the proposed AdvLS.

![Figure 7: Demonstration of adversarial samples from different angles](image)

4.3. Ablation study

In this section, we perform a series of experiments on ImageNet [32] to study the adversarial effect of AdvLS with different parameters. The main parameters we study include the number of laser points and the color of laser points.

In order to study the influence of the number of laser spots on the adversarial effect of AdvLS, we set the value range from 5 to 100 with an interval of 5 for the number of laser spots. As for the color of laser spots, we study the influence of random color, red, green and blue laser spots on AdvLS respectively. The experimental results are shown in Figure 9.

![Figure 8: Comparison of digital and physical samples in indoor and outdoor environments](image)

The experimental results in Figure 9 show that: (1) AdvLS achieves a high ASR even with fewer laser spots. When the number of laser spots is 35, it can be seen that AdvLS achieves an ASR about 70%. Even at a laser point
count of 15, AdvLS achieves an ASR about 50%. According to the digital adversarial sample in Figure 5, when the number of laser spots is 15, the adversarial perturbations can hardly be detected by naked eyes. (2) Blue laser point compared with other colors, more antagonistic effect. This phenomenon is consistent with the experimental results in article [30].

In the physical environment, we manipulate 10 laser Points to attack the target object. In the outdoor environment, a total of 96 physical adversarial samples at various angles are obtained. By analyzing the adversarial samples that could be successfully attacked, we found that the adversarial samples were mainly misclassified as Book jacket, Boathouse, Barn, etc. In the indoor environment, a total of 39 adversarial samples are obtained, most of which are misclassified as Switch, and the rest are misclassified as Wall clock.

In addition, we test the adversarial attacks mobility of AdvLS in digital and physical environments. First of all, in the digital environment, the data set is the digital adversarial samples that successfully attack ResNet50 [31], which contains adversarial samples generated by laser points with random colors, red, green and blue. The experimental results are shown in Table 3. Secondly, in the physical environment, the data set is the physical adversarial samples that successfully attack ResNet50 [31], which contains the physical adversarial samples of 0°, 30° and 45°. The experimental results are shown in Table 4.

As can be seen from the experimental results in table 3, in the digital environment :(1) The adversarial samples generated by AdvLS have very strong adversarial attack migration, which means that AdvLS have excellent performance to perform black-box adversarial attack. (2) When AlexNet [35] is attacked by adversarial samples, the classifier was almost completely paralyzed, MobileNet [36] and VGG19 [34] are also almost paralyzed, while Inception_V3 [38] shows excellent classification performance. On the other hand, according to the experimental results in table 4, in the physical environment :(1) The adversarial samples generated by AdvLS also have strong adversarial attack migration. (2) When AlexNet [35] is attacked by physical adversarial samples, the classifier was almost completely paralyzed, while MobileNet [36] and VGG19 [34] are also almost paralyzed, while Inception_V3 [38] shows excellent classification performance. On the other hand, according to the experimental results in table 4, in the physical environment :...
samples generated by AdvLS, it is completely paralyzed, and ResNet101 [31] is also almost completely paralyzed, while Inception_V3 [38] had completely robust robustness to physical adversarial samples generated by AdvLS. In general, AlexNet [35] has almost no robustness to adversarial samples generated by AdvLS, while Inception_V3 [38] has better robustness.

The experimental results in Table 1 and Table 2 show that AdvLS has robust adversarial effect in both digital and physical environments, which means that AdvLS has a non-negligible adversarial effect in white-box conditions. The experimental results in Table 3 and Table 4 show that AdvLS has strong adversarial attack migration in both digital and physical environments, which means that AdvLS is effective to conduct black-box attacks. The experimental results of this work show that AdvLS has robust adversarial attack capability and migration of adversarial attack under different environments, AdvLS conduct robust adversarial attack under white-box and black-box condition. In a nutshell, AdvLS pose a significant security threat to the advanced classification systems, so we call for AdvLS to receive widespread attention.

6. Conclusion

In this paper, we propose an advanced physical adversarial attack technology: AdvLS, which performs adversarial attack by optimizing the physical parameters of laser spots through GA. The advantages of AdvLS include: (1) AdvLS has robust adversarial attack performance in different environments, and shows excellent adversarial attack performance in both white-box and black-box Settings; (2) In the physical environment, AdvLS uses laser spots as adversarial perturbations, which makes AdvLS excellent covertness; (3) AdvLS is the only light-based physical adversarial attack capable of executing attacks in the daytime. In addition, the cost of deploying AdvLS is cheap, it’s easy for an attacker to implement. The attacker performs a quick adversarial attack by remotely controlling the laser device. Our work shows that AdvLS poses a non-negligible security threat to many systems based on computer vision technology. In the future, light-based physical adversarial attack technology will also become a research hotspot.

In the physical world, the quantification of physical adversarial perturbations is not achievable, which is also a defect of physical adversarial attack technology so far. In the future, we will continue to study light-based physical adversarial attack. The security of computer vision based systems and applications can be further improved only when more robust and covert physical adversarial attack technologies are explored.

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