Adversarial Neon Beam: Robust Physical-World Adversarial Attack to DNNs

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Abstract

In the physical world, light affects the performance of deep neural networks. Nowadays, many products based on deep neural network have been put into daily life. There are few researches on the effect of light on the performance of deep neural network models. However, the adversarial perturbations generated by light may have extremely dangerous effects on these systems. In this work, we propose an attack method called adversarial neon beam (AdvNB), which can execute the physical attack by obtaining the physical parameters of adversarial neon beams with very few queries. Experiments show that our algorithm can achieve advanced attack effect in both digital test and physical test. In the digital environment, 99.3% attack success rate was achieved, and in the physical environment, 100% attack success rate was achieved. Compared with the most advanced physical attack methods, our method can achieve better physical perturbation concealment. In addition, by analyzing the experimental data, we reveal some new phenomena brought about by the adversarial neon beam attack.

1. Introduction

Deep learning technology has made breakthroughs in many fields, and even surpassed human level in some fields [6,7,8]. Based on these successful theories and technologies, deep learning technology has been widely applied in autonomous vehicles [1,2], robotics [3], UAV and other fields [4,5]. However, deep neural networks are known to be susceptible to carefully designed adversarial perturbations [9,10,11,12,13,14] that can cause unpredictable abnormal behavior in computer vision-based applications, with disastrous consequences. In the area of autonomous vehicle technology, for example, an attack on deep neural networks can lead to car crashes.

Many natural phenomena can be the main factors to adversarial perturbations, causing many undesirable things to happen. In the physical world, especially in busy cities, there are so many neon beams that they tend to scatter on traffic signs, causing humans to instinctively ignore them. If an attacker deliberately creates an adversarial neon beam that can attack self-driving car systems while lowering human vigilance, it could disrupt traffic and even cause disaster.

Figure 1: Visual comparison: The adversarial perturbations generated by RP2 [25] can be captured by the camera well, achieving good adversarial attack effect, but failed to achieve good concealment. Similarly, the adversarial perturbations generated by AdvLB [29] is difficult to achieve good concealment. In contrast, the adversarial perturbations generated by AdvNB can not only achieve higher attack success rate, but also achieve better concealment.

In this work, we propose the attack shown on the picture (c) of Figure 1, a physical attack method based on neon beams. The influence of light on deep neural network is worth exploring, which has a significant impact on deep learning in the field of adversarial attack and defense. However, there are few studies on the effect of light on deep neural networks. As shown in the picture (a) of Figure 1, most physical attacks currently take the form of stickers, such as RP2[23]. In addition, as shown in the picture (b), AdvLB [27] uses laser beam to carry out physical attacks, which achieve advanced attack effects. As can be seen from the comparison of Figure 1, the attack method proposed by our work has better concealment.

The technical difficulties of adversarial attack in the physical world mainly include: (1) the adversarial perturbations produced in the digital environment is small, and the camera cannot capture them perfectly; (2) It is difficult to perfectly print the adversarial perturbations generated in the digital environment; (3) It is hard for adversarial perturbations to achieve their concealment in the physical world.

Based on the above challenges, we designed the adversarial neon Beam (AdvNB). The adversarial neon beam can be well captured by the camera to attack the target.
object effectively. In addition, there is no need to print the adversarial sample, only need to hit the beams to the designated position on the target object. Although the beams can be seen by the human eyes, people can be confused by the instantaneous attack nature of the neon beams. Even, on the basis of this technology, the size, color and other physical states of the beams can be controlled by remote control, the attacker can carry out instantaneous attack on the target from 100 meters away, and flexibly control the physical state of the adversarial neon beams.

We carried out a lot of experiments to verify the effectiveness of our proposed attack method. In the digital environment, we achieved 99.3% attack success on a subset of Imagenet [29]. In the physical environment, we achieved 100% attack success rate. In addition, we also studied the migration of adversarial samples. Our main contributions are as follows:

(1) We propose a physical attack technology based on neon beams, the beams have the instantaneity of light-speed attack and can carry out instantaneous attack on the attacking target.

(2) We carried out comprehensive experiments to verify the effectiveness of the attack method in the digital environment and physical environment.

(3) Through the adversarial perturbations generated by our physical attack method, the technical problems such as difficulty in capturing physical adversarial perturbations and difficulty in concealing physical adversarial perturbations are effectively solved.

(4) By analyzing the experimental phenomena, we found that AdvNB attack method has the phenomenon of targeted attack in both digital environment and physical environment, which will be helpful for researchers to study physical targeted attack.

(5) Through experimental verification, the adversarial samples generated by our AdvNB attack algorithm have effective attack migration.

2. Related work

Adversarial attack was first proposed by Szegedy et al. [9], which deceives the classification model of deep neural network by adding subtle perturbations to the input image. After this pioneering work, more and more research works have proposed efficient adversarial attack methods [10,15,16,17]. The adversarial methods carried out in these works are all carried out in the digital environment. Through pixel-level modification of the input images, these perturbations can be invisible to human eyes, fool advanced deep neural network models. Even only modifying a single pixel value in an image, the deep neural network model can be tricked [18].

Goodfellow et al. [10] first proposed the fast gradient sign method, which makes use of the gradient information of the deep network classification model to generate adversarial samples in a simple and fast way. Moosavi-dezfooli et al [19], studied the relationship between input image and decision boundary of deep neural network. By finding the shortest path vector between input data and decision boundary, input data can cross the decision boundary of the model and make the model fooled. Carlini & Wagner [20] proposed the C&W attack method claiming the strongest attack, which successfully attacked many defense models proved to be the most successful. In addition, there are some novel attack methods, such as single-pixel attack [18], which only needs to modify one pixel to attack the deep network classification model. Spatial transformation attack [21], which attacks the deep neural network model by translating and rotating local images. These methods focus on adversarial attacks in the digital environment, in contrast to our work on adversarial attacks in the physical environment.

Kurakin et al. [17] first discovered the existence of physical adversarial perturbations in their research work. When the adversarial sample generated in the digital environment was photographed with a mobile phone camera, the printed adversarial sample could realize the purpose of deceiving the classifier. Eykholt et al. [22] indicated in their research that the classification system of autonomous vehicles would be deceived by road signs affixed with strips of paper. Eykholt et al. [23] designed the RP2 physical adversarial attack method, which printed out the calculated perturbations and posted it on the specific position of the road sign. The adversarial road signs could interfere with the classification system in different angles and distances. Athalye et al [30], were the first to design and realize the 3D printed adversarial sample in their work, which ensured that the adversarial sample could attack the target classification model from all angles. Ranjie Duan et al [24], designed AdvCam physical attack algorithm in order to make physical adversarial samples have better camouflage effect. In this work, instead of making modifications on the target object, our method fooled the classifier by directly projecting the neon beams onto the target object.

Dinh-Juan Nguyen et al. [25] studied the feasibility of adversarial light projection attack on face recognition system, and used the projector to project the adversarial image on human face to realize the purpose of attacking face system. Zhe Zhou et al. [26] first revealed the serious consequences of infrared light on face recognition system in their work, and fooled the face recognition system by irradiating infrared light on people's faces. Duan et al. [27] proposed an adversarial laser beam, which successfully fooled DNN by projecting a carefully designed laser beam in front of a road sign. Our work is based on neon beams, which, unlike the adversarial laser beam, are only projected at the target object (such as a road sign) and do not produce a wide range of visual effects. In contrast, the adversarial laser beam not only appears on the target object, but also on the background of the image, and even, in the physical
environment, creates a visually perceptible effect of hundreds of meters.

3. Approach

Generally speaking, given a set of input images $X$ and its corresponding correct label $Y$, target classifier $f$, the attacker's goal is to find an adversarial sample $X'$ with minimal perturbations, so that the human eyes cannot distinguish $X'$ from $X$, but $X'$ can mislead the classifier into the wrong category. The formula is as follows:

\[
\text{find } X' \text{ satisfying } \| X' - X \| < \varepsilon \quad (1) \\
\text{s.t. } f(X') = t \neq Y
\]

$\| \cdot \|$ usually refers to $l_p$ norm. The formula indicates that the attacker limits the perturbations of the adversarial sample and requires the adversarial sample to fool the classifier.

![Figure 2: Schematic diagram of generating an adversarial sample](image)

As shown in Figure 2, our goal is to find groups of neon beams that can fool the classifier. Details of the algorithm are given below.

3.1. Definition of the neon beam

In our work, we define a neon beam by four parameters: center position $L$ ($m, n$), radius $R$, beam intensity $I$, and color $C$ ($r, g, b$). Each parameter is defined as follows:

- **Position $L$ ($m, n$):** $L$ ($m, n$) represents the center position of the neon beam. We assume that the neon beam projected on the target object is a circle, and use a double tuple ($m, n$) to represent the center position of the neon beam, with $m$ representing the horizontal axis of the pixel where the center is located and $n$ representing the vertical axis position.

- **Radius $R$:** the size of $R$ represents the radius of the neon beam. Different shooting distances will lead to different radii of the neon beam. The size of neon beam radius should be determined according to the photo in the actual scene, and the unit is pixel value.

- **Beam intensity $I$:** The size of $I$ represents the intensity of the neon beam on the target object. In the digital environment, we can conditionally set the size of $I$ (values range from 0.1 to 0.9). In the physical environment, due to the limitation of the physical lighting equipment, we set the value range of $I$ to be from 0.2 to 0.6.

Colors $C$ ($r, g, b$): $C$ ($r, g, b$) determines the color of a neon beam. $r$ represents the red channel of digital images, $g$ represents the green channel, and $b$ represents the blue channel. In the physical environment, due to equipment limitations, we chose five common colors, including Red $(225,0,0)$; Green $(0,255,0)$; Blue $(0,0,255)$; Yellow $(255,255,0)$; Purple $(255,0,255)$.

The parameters defined above make up a neon beam $\theta$ $(L, R, I, C)$. Therefore, the definition of the neon beam group can be expressed as $G_\theta$, and each parameter has an adjustable size range. We define a function synthesis $(X_l, X_f)$ that combines two images: $X_l, X_f$. This function is used to simply merge the neon beam group with the clean sample to generate the adversarial sample.

\[
X_{\text{adv}} = \text{Synthesis}(X, G_\theta) \\
\text{s.t.} \quad R \in (y_{\text{min}}, y_{\text{max}}) \\
I \in (I_{\text{min}}, I_{\text{max}})
\]

$X_{\text{adv}}$ represents the generated adversarial sample, which is synthesized from the clean sample $X_l$ and the adversarial neon beam group $G_\theta$. $y_{\text{min}}$ and $y_{\text{max}}$ limit the radius of neon beam, and make the size of neon beam limited within a certain range. Similarly, $I_{\text{min}}$ and $I_{\text{max}}$ limit the range of neon beam intensity. In the digital environment, our adversarial sample is shown by Formula (2). In the physical environment, in order to prevent the neon beams from appearing in the background image, we use the Limited function to represent the range of position of the neon beam group. Therefore, the adversarial sample generation formula in the physical environment is shown as follows.

\[
X_{\text{adv}} = \text{Synthesis}(X, \text{Limited}(G_\theta)) \\
\text{s.t.} \quad R \in (y_{\text{min}}, y_{\text{max}}) \\
I \in (I_{\text{min}}, I_{\text{max}})
\]

Where, the Limited function means that the neon beam is limited to the range of the attack target in the physical environment, so that the neon beam will not appear in the background.

3.2. Adversarial neon beam

Algorithm: The AdvNB attack algorithm consists of two parts: (1) in the digital environment, the adversarial samples are obtained by randomly generating adversarial neon beams; (2) In the physical environment, the model feedback is used to find the optimal physical parameters of the adversarial neon beams, thus generating adversarial samples. Our task is to find the adversarial neon beam group $G_\theta = \{(L_1, R_1, I_1, C_1), (L_2, R_2, I_2, C_2), ...\}$ that can fool the classifiers in a space with a limited number of searches and a certain range of searches. Our goal is to get the minimum confidence of the correct tag that within a certain number of searches. In order to better solve the
difficult of physical perturbations to achieve concealment, we limit the number of beams, the intensity of beams and the radius of beams. Under the condition of misleading classifier, to search neon beam group with the lowest confidence score of the correct label. Our optimization objective function is as follows:

$$\text{arg min}_{\text{conf}} f(X_{\text{adv}}) \neq Y_{\text{true}}$$     \hspace{1cm} (4)
\[\text{s.t.} \ R \in (Y_{\text{min}}, Y_{\text{max}}) \]
\[I \in (I_{\text{min}}, I_{\text{max}}) \]

In the digital environment, the effectiveness of neon beam attack is verified by randomly generating adversarial neon beams and obtaining the adversarial samples. Then, we further design the adversarial algorithm in the physical environment. Obviously, to solve the problem that the camera is difficult to capture perturbations, it is necessary to design relatively large perturbations. Therefore, compared with ordinary digital attack algorithms, the perturbations of AdvNB are significantly larger in the physical environment. The AdvNB attack algorithm is as follows:

Algorithm 1: AdvNB

**Input:** Input $X$; Max step $t_{\text{max}}$; max number of neon beams $N$; classifier $f$;  

**Output:** A vector of parameters $G_{\theta}$;  

1. Initialization $G_{\theta} = \emptyset, \theta_{\text{ran}} = \emptyset, \theta_{\text{opt}} = \emptyset$;  
2. $\text{Score}_{\text{true}} = \text{feedback}_{\text{true}}(X)$;  
3. For $i$ in range (0, $N$) do:  
   4. $G_{\theta} = G_{\theta} + \theta_{\text{opt}}$;  
   5. $X_{\text{adv}} = \text{Syn}(X, G_{\theta})$;  
   6. For step in range (0, $t_{\text{max}}$) do:  
      7. Randomly pick $L, R, I, C$;  
      8. $\theta_{\text{ran}} = \theta(L, R, I, C)$;  
      9. $X_{\text{adv}} = \text{Syn}(X_{\text{adv}}, l(\theta_{\text{ran}}))$;  
      10. $\text{Score}_{\text{true}} = \text{feedback}_{\text{true}}(X_{\text{adv}})$;  
      11. If $\text{Score}_{\text{true}} > \text{Score}_{\text{true}}$ then:  
         12. $\text{Score}_{\text{true}} = \text{Score}_{\text{true}}$;  
         13. $\theta_{\text{opt}} = \theta_{\text{ran}}$;  
      14. End  
   15. If $\text{Adjust}(f(X_{\text{adv}}), Y_{\text{true}})$ then:  
      16. $G_{\theta} = G_{\theta} + \theta_{\text{opt}}$;  
      17. Return $G_{\theta}$;  
      18. Exit ();  
   19. End  
20. End  
21. End

As shown in the Algorithm 1, firstly, we take a test image $X$, max step $t_{\text{max}}$, max number of neon beams $N$, classifier $f$ as the input, a vector of parameters $G_{\theta}$ as the output. Secondly, for each generated neon beam, the parameters with the lowest confidence of the model on the correct label is found within the restricted area. For each addition of a neon beam, within a fixed number of search steps, we obtain the parameters that minimizes the model’s confidence on the correct label. Then, the $\text{Syn}$ function is used to simply merge the clean sample with the adversarial neon beams to obtain the adversarial sample. To solve the experimental error, we design $\text{Adjust}$ function, which indicates that the adversarial sample can still fool the classification model within a certain range of color, position, beam intensity and radius errors. $\text{Adjust}$ function is specified by Equation (5). For the group of neon beams that meet the $\text{Adjust}$ function, the physical parameters of the neon beams are output, and the program is terminated.

$$\text{Adjust}(f(X_{\text{adv}}); Y_{\text{true}})$$     \hspace{1cm} (5)
\[\text{s.t.} \ R \in (\text{Clip}(R - \epsilon_R), \text{Clip}(R + \epsilon_R)) \]
\[I \in (\text{Clip}(I - \epsilon_I), \text{Clip}(I + \epsilon_I)) \]
\[C \in (\text{Clip}(C - \epsilon_C), \text{Clip}(C + \epsilon_C)) \]

$\text{Adjust}(f(X_{\text{adv}}); Y_{\text{true}})$ means that if $f(X_{\text{adv}}) \neq Y_{\text{true}}$, $\text{Adjust}(f(X_{\text{adv}}); Y_{\text{true}}) = 1$. The equation shows that the physical parameters of the neon beam group $G_{\theta}$ can be recorded after the simulated attack is successful. If the physical parameters of the neon beam group (radius, intensity, color and position) are adjusted within a certain range and the neon beam group can attack successfully, the physical parameters are saved. Through Equation (5), we solve the experimental errors in the process of computer simulation and physical implementation. Even if the physical test is slightly different from the computer simulation, the physical neon beams generated according to the physical parameters can carry out effective physical attacks on the target object.

On the other hand, in the physical environment, physical adversarial samples cannot be obtained in the way that digital attack generates adversarial samples. Because the neon beams that appear in the background of the scene cannot be well realized in reality. Therefore, a Limited constraint function is added to the physical test part compared with the digital test part, so that the neon beams generated by the algorithm is limited to the target object region. At the same time, compared with AdvLB [27], the physical perturbations designed by us will not appear in the whole visual field of human eyes, but only appear on the target object, which greatly reduces the visible area of physical adversarial perturbations.

4. Evaluation

4.1. Experimental setting

As with the method in AdvLB [27], we used ResNet50[28] as a target classifier and conducted all experimental tests, including digital and physical tests. Similarly, for the digital test, we randomly selected 1000
correctly classified images from Imagenet [29] for the test. In the physical test part, the equipment used in our experiment is shown in Figure 3.

The neon beam pointer can project red, green, blue, yellow and other colors, with four levels of intensity. In the daytime, outdoor conditions roughly correspond to computer-simulated light intensity values ranging from 0.1 to 0.7. For camera equipment, we used an iPhone6s. Due to limitations, we only used four neon beams for the physical test.

4.2. Evaluation of AdvNB

We firstly tested the effectiveness of the AdvNB attack in the digital environment, and then verified the effectiveness of the attack in the physical environment.

Digital test: In the digital environment, we selected 1000 images from ImageNet [29] that could be correctly classified as the data set. We synthesized the computer-simulated neon beams with clean samples to get the adversarial samples. After the original images was disturbed by AdvNB attack algorithm, we achieved 99.3% attack success rate and the average query times is 2.978 times.

As shown in Figure 4, the experimental settings are as follows: the number of neon beams is 100, the radius is 20 pixels, and the illumination intensity is 0.1. It can be seen that the adversarial neon beams have a strong feature of changing the original data. In addition, it can also be known that the AdvNB attack algorithm proposed by us has a tendency of targeted attack. We make statistics on the classification results of the adversarial samples generated by this data set. As shown in Figure 5, the chart shows that most of the digital adversarial samples were misclassified into a few categories such as Shower curtain, Mosquito net, etc.

Physical test: In order to reproduce our attack method in the physical world, we firstly took the field photos to simulation experiment, and saved the physical parameters and other information of the generated adversarial perturbations. Then, according to the physical parameters, the neon lamps are used to illuminate the target object to obtain the adversarial samples of the physical world. Figure 6 shows a physical adversarial attack on the Guitar, Jersey, and Stop sign.
We verify that the AdvNB attack method can be reproduced in the physical world. The AdvNB-based physical adversarial attack method generates robust adversarial samples. It achieves 100% success rate of physical attack on Acoustic guitar and Jersey, which verifies the strong robustness of AdvNB attack algorithm. For outdoor test, we chose Stop sign that are closely related to daily life. In order to further verify the robustness of AdvNB attack algorithm, we took pictures from different angles, sorted them out and transferred them to the classifier for classification test. The experimental results are shown in Table 1. Experimental settings: the number of beams is 4, the beam size is 40 pixels value, the beam colors are red, green, blue and yellow, and the beam intensity is 0.2 to 0.6.

Table 1: Attack success rates

| Angle | 0’  | 30’ | 45’ |
|-------|-----|-----|-----|
| Rate (%) | 100 | 100 | 25 |

Figure 7 shows the adversarial samples taken from various angles. For further analysis, we have counted the misclassification of each angle. When the angle is 0 degrees, 91% of the adversarial samples are classified as Envelope; when the angle is 30 degrees, 81% of the adversarial samples are classified as Book jacket; when the angle is 45 degrees, all the adversarial samples are classified as Book jacket. Furthermore, we think that the adversarial neon beams have a tendency to form a targeted attack on the target object.

Figure 7: Physical adversarial samples from different angles

4.3. Ablation study

In order to study the influence of various physical parameters of neon beams on the attack effect, a series of experiments were carried out on ImageNet [29] data set. The main parameters we study include: the number of neon beams (N), the radius of neon beams (R), and the intensity of neon beams (I).

Number of neon beams (N): Before studying the influence of the number of neon beams on the attack effect, we first analyze the appropriate value range of the number of neon beams. Too many neon beams can produce a strong visual effect. Therefore, we set the number of beams in the range of 5 to 100, with an interval of 5. Other parameters are set as: Maximum number of queries: 100; Neon beam intensity: 0.3; Neon beam radius: 20 pixels value. In this experiment, 1000 images that can be correctly classified randomly selected from ImageNet [29] were similarly used for the experiment on ResNet50[28]. The experimental results are shown in Table 2.

Neon beam radius (R): To evaluate the influence of neon beam radius on the attack effect, according to the characteristics of uneven image size in ImageNet [29] data set, we selected the value range of the beam radius from 2 pixels to 40 pixels with an interval of 2. Set other physical parameters as follows: Maximum query times: 100; Neon beam intensity: 0.3; Number of neon beams: 40. The experimental results of the influence of neon beam radius on the attack effect are shown in Table 3.

Neon beam intensity (I): the intensity of the neon beam directly affects the visual perceptible effect of adversarial perturbations. Without considering the visual effect, we selected the range of neon beam intensity from 0.1 to 0.9, and carried out the experiment on the influence of intensity on the attack effect. Set other physical parameters as follows: Maximum query times: 100; Neon beam radius: 20 pixels; Number of neon beams: 40. Experimental results of neon beam intensity on attack effect are shown in Table 4.

Table 2. Ablation of N

| N   | 5  | 10 | 15 | 20 | 25 | 30 |
|-----|----|----|----|----|----|----|
| Rate (%) | 42.9 | 54.6 | 63.3 | 69.9 | 74.5 | 77.5 |

Table 3. Ablation of R

| R   | 2   | 4   | 6   | 8   | 10  | 12  |
|-----|-----|-----|-----|-----|-----|-----|
| Rate (%) | 21.8 | 28.4 | 39.8 | 48.6 | 55.5 | 62.3 |

Table 4. Ablation of I

| I   | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 |
|-----|-----|-----|-----|-----|-----|-----|
| Rate (%) | 31.6 | 59.7 | 81.8 | 93.5 | 97.9 | 99.2 |

As shown in Table 2, when the number of neon beams reaches 35, the AdvNB attack algorithm can achieve an attack success rate of more than 80%. Secondly, the analysis of the data in Table 3 shows that when the neon beam radius is 20 pixels, the adversarial sample generated by AdvNB attack algorithm can achieve an attack success rate of more than 80%. Finally, the experimental results in Table 4 show that when the intensity of neon beam reaches 0.3, the adversarial sample can achieve a good attack effect. In addition, when the light intensity is 0.1 and 0.2, and the neon beam radius is 20 and the number of neon beams is 40, the generated adversarial samples can achieve a good
hiding effect and ensure a good success rate of attack.

5. Discussion

This section discusses the adversarial samples generated by AdvNB that show some interesting phenomena in both digital and physical environments.

In the digital environment, most of the adversarial samples generated by the AdvNB were misclassified as Shower curtain, Envelope and so on. As shown in Figure 8, the adversarial perturbations generated by the AdvNB algorithm contains many of the Shower curtain’s characteristic elements. In addition, through our careful analysis of adversarial samples, we find that there are also some characteristic elements in Envelope, which are very similar to the adversarial perturbations generated by AdvNB method. Finally, the adversarial perturbations generated by single-color adversarial attacks on the clear sample also show a great deal of similarity to the Jellyfish. Therefore, we believe that the adversarial neon beams have a strong characteristic of changing the original image. According to Figure 4, in the case of very weak beam intensity, the naked eye can hardly distinguish the difference between the adversarial sample and the clean sample, and the adversarial sample can still fool the classifier.

In the physical environment, the stop sign is projected with an adversarial neon beam of 0.2 to 0.6 intensity. When the Angle is 0 degrees, 91% of the generated adversarial samples are misclassified as Envelope and 9% are misclassified as Book jacket. When the Angle is 30 degrees, 81% of adversarial samples are misclassified as Book jacket, and the rest are misclassified as Carton. When the Angle is 45 degrees, all of the adversarial samples are wrongly classified as Envelope. In addition, in the physical attack experiment on Acoustic guitar and Jersey, the adversarial samples were all misclassified as Book jacket.

In conclusion, we believe that under the disturbance of the adversarial neon beams, the adversarial samples have a certain trend of targeted attack. In addition, we did a lot of physical attack testing, and we found that there are some backgrounds where our adversarial neon beams would not succeed. Therefore, we believe that the environmental background can be used as one of the defense strategies for adversarial neon beams.

We also explore the attack mobility of the adversarial samples in the digital and physical environments. In the digital environment, the data set is the adversarial samples set generated by using AdvNB attack method and able to fool ResNet50 [28]. The experimental comparison results in the digital environment are shown in Table 5. In the physical environment, the data set we used was the adversarial samples of the physical test in the previous section. The experimental comparison results are shown in Table 6. The experimental results show that the physical adversarial samples generated by AdvNB have a good attack migration effect. Therefore, we call for some attention to AdvNB algorithm.

| Angle | 0° | 30° | 45° |
|-------|----|-----|-----|
| Inception v3 | 77.8% | 39.5% | 4.5% |
| Vgg16 | 88.9% | 27.9% | 0 |
| ResNet101 | 100% | 100% | 4.5% |
| ResNet50 | 100% | 100% | 25% |

Finally, we once again explore the concealment of AdvNB attack method. On the one hand, AdvNB attack takes advantage of the instantaneity of illumination attack, which can carry out instantaneous attack on the target object, projecting the adversarial beams to the target object in the blink of an eye, and then turn off the illumination equipment, so as to achieve the concealment of the
adversarial neon beams. On the other hand, by analyzing the difference between physical adversarial attack technology and digital adversarial attack technology, we believe that in physical attack, adding adversarial disturbance to the area outside the target object is a zero-disturbance physical attack technology in a sense. So, we designed a comparative experiment. In the digital environment and the physical environment, we added the adversarial perturbations to the area of non-target object. The experimental comparison results are shown in Figure 9 and Figure 10 respectively.

By observing the experimental results in Figure 9 and Figure 10, it can be seen that we can carry out physical attack on the target object by adding adversarial perturbations to the area of non-target object, so as to further realize the concealment of physical adversarial attack.

6. Conclusion

In this paper, we introduce an advanced physical adversarial attack method (AdvNB), which takes advantage of the instantaneous nature of the light speed attack of neon beams to generate robust and concealed physical adversarial perturbations to the target objects quickly. Our adversarial attack method solves three difficulties of physical adversarial attack: (1) Digital adversarial perturbations are difficult to print perfectly in the physical environment; (2) The adversarial perturbations generated in the digital environment are difficult to be captured by the camera in the physical environment; (3) In the physical environment, the perturbations are difficult to achieve concealment. Meanwhile, it has a high degree of attack flexibility when using adversarial neon beams to carry out attacks. Attackers can attack in real time from hundreds of meters away from the target object by remote control. Our work shows that adversarial neon beams pose a non-negligible security threat to many vision-based computer systems. At the same time, the physical attack based on beam of light will probably become one of the research focuses of physical adversarial attacks and defenses in the future.

In the future, we will continue to devote ourselves to the research of physical adversarial attack based on light beam, and continue to improve the adversarial attack system of neon beam attack. We will continue to explore how to design better algorithms to achieve better concealment of the adversarial perturbations.

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