Meaningful Adversarial Stickers for Face Recognition in Physical World

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Abstract

Face recognition (FR) systems have been widely applied in safety-critical fields with the introduction of deep learning. However, the existence of adversarial examples brings potential security risks to FR systems. To identify their vulnerability and help improve their robustness, in this paper, we propose Meaningful Adversarial Stickers, a physically feasible and easily implemented attack method by using meaningful real stickers existing in our life, where the attackers manipulate the pasting parameters of stickers on the face, instead of designing perturbation patterns and then printing them like most existing works. We conduct attacks in the black-box setting with limited information which is more challenging and practical. To effectively solve the pasting position, rotation angle, and other parameters of the stickers, we design Region based Heuristic Differential Algorithm, which utilizes the inbreeding strategy based on regional aggregation of effective solutions and the adaptive adjustment strategy of evaluation criteria. Extensive experiments are conducted on two public datasets including LFW and CelebA with respective to three representative FR models like FaceNet, SphereFace, and CosFace, achieving attack success rates of 81.78%, 72.93%, and 79.26% respectively with only hundreds of queries. The results in the physical world confirm the effectiveness of our method in complex physical conditions. When continuously changing the face posture of testers, the method can still perform successful attacks up to 98.46%, 91.30% and 86.96% in the time series.

1. Introduction

With the development of Deep Neural Networks (DNNs), face recognition (FR) systems based on DNNs have shown excellent performance [24, 17, 31] and been applied to financial payment, device login, and other safety-critical fields. However, DNNs are vulnerable to attacks of adversarial examples, even in FR tasks [9, 15, 23, 25]. By adding a small malicious perturbation to the face, the system can make a wrong identity judgement, resulting in serious consequences.

Up to now, researchers have achieved successful attacks on FR systems [9, 25] in the digital world by modifying pixels. In real scenarios, however, FR systems work by directly scanning faces. So attackers can only change faces in the physical world to provide malicious inputs to the camera, which is more challenging and needs to tackle complex physical conditions such as lighting, distance, and posture changes. Adv-Hat [15] creates an attack by putting a perturbation image to a hat. Adversarial glasses [26] confuse FR systems by using a pair of eyeglass frames printed with perturbations generated by Generative Adversarial Networks.

Despite the success of the above physical attack methods, they have two limitations. The first one is that the generated perturbation will face a complex transfer process from the digital domain to the physical world. Specifically, Expectation Over Transformation (EOT) [2], Total Variation (TV) loss, and non-printability score (NPS) loss [15, 26] are usually used to ensure the attacking performance of real-world adversarial examples. EOT considers a set of transformations of objects (like postures, distance changes, etc.) when generating adversarial perturbations. TV loss is designed to make the perturbations more smooth, and NPS loss is to deal with the difference between digital pixel values and the actual printed appearance. On the one hand, these operations lead to high computation costs, for example, EOT needs to exhaust different transformations. On the other hand, the perturbations’ values will inevitably become distorted due
to the limitation of printing devices despite the usage of TV and NPS losses. Last but not least, the current physical perturbations are meaningless and irregular, which are not natural enough in appearance, and thus are easy to be suspected by humans. These disadvantages motivate us to explore new forms of physical attacks to solve the above issues. The second one is that previous physical attacks are based on the white-box attack setting. It means that they require detailed structures and parameters of the targeted models. However, these information usually cannot be easily obtained especially in the actual applications. For example, some commercial online face recognition APIs (e.g. Face++ and Microsoft cloud services) can only return the predicted identities and scores for the uploaded face images and the used models are not given. Although these attacks like [15, 26] can adapt to black-box attack setting via the transfer-based property, the attacking ability is relatively weak [23, 25]. Therefore, how to perform black-box physical attacks under limited information is still a problem.

In this paper, we focus on physically feasible attacks under the black-box setting, and propose a novel form called Meaningful Adversarial Stickers to attack FR systems. Instead of generating adversarial perturbations, we use the real meaningful stickers existing in our life and manipulate the stickers’ pasting positions and rotation angles on the face to perform the physical attacks. Compared with the performance due to perturbations, the attack performance caused by stickers’ positions and rotation angles is easier to maintain when attacks are transferred from digital domain to the physical world (see Section 3.1), and the loss functions mentioned before are not necessary. Furthermore, sticking colorful stickers on the face can be seen in some events in our life (shown in Figure 2), so this form of attack looks natural and is not easy to arouse people’s suspicion. In addition, considering the real scenario where only limited information can be obtained, we design a query-based method to efficiently search the available parameters. Thus the black-box attacks in the physical world are achieved.

Technically, to search for the appropriate attack parameters, we formalize the process into an optimization problem and solve it using an evolution method which follows the principle of “survival of the fittest” in the iterative evolution process. Considering the query limit in the actual scenario, we design a new Region based Heuristic Differential Algorithm (RHDE) to improve the solving efficiency. We find that the stickers’ locations of successful attacks show the regional aggregation. Based on this phenomenon, RHDE combines inbreeding and random crossover to generate offspring, and adjusts the evaluation criteria adaptively to better guide the search direction. We also design a sticker deformation calculation method to make the sticker shape fit the curvature changes of different positions on the human face realistically. In summary, this paper has the following contributions:

- We propose Meaningful Adversarial Stickers, a novel physical attack method with good practical applicability. We manipulate the fusing operation and parameters of real stickers on the face instead of designing perturbation patterns like most of the existing works. Experiments show this manner has good transferability from digital domain to the physical world.
- We specialize in black-box physical attacks on face recognition systems with limited information, and further design a Region based Heuristic Differential Algorithm (RHDE) to improve query efficiency. We find that the stickers’ locations of successful attacks show the regional aggregation. RHDE makes full use of this phenomenon and can adjust the direction of evolution adaptively according to the state of the population.
- We conduct a series of experiments in dodging and impersonation tasks, and achieve the highest attack success rate of 81.78% in the digital environment with 483 queries on average. And the results in the physical environment show that it can naturally maintain attack effect under different physical conditions and at most 98.46% of the video frames can be successfully attacked while continuously changing the face postures.

2. Related Work
2.1. Digital Attacks

Box-constrained L-BFGS [29], C&W [5], Deepfool [22], etc. carry out attacks via optimization mechanisms. The classical attack method FGSM [12] is a one-step approach based on the gradient information of DNNs. PGD [19] uses a multi-step iterative method in the projection space to generate adversarial examples. The above methods are attacked in the white-box setting, where the attackers have access to the structures and weights of the threat models.

Black-box attacks do not require detailed parameters of models. For transfer-based methods, the adversarial examples generated for one model can be transferred to another model to achieve successful attacks [8, 18, 32]. For score-based methods, the probabilities predicted by target models are known and methods such as gradient estimation [9] and random search [11, 13] are often used in this setting. Besides, decision-based methods are suitable for more restrictive scenarios where only the final model decisions are known [4, 7]. Dong et al. [9] conduct digital attacks on FR systems in this setting and model the local geometry of solving directions to improve efficiency. Attacks aiming to get a different class
from the true label are called un-targeted attacks (or dodging in face recognition), while those targeting a specific class are called targeted attacks (or impersonation in face recognition). In our case, we conduct black-box attacks and focus on more practical physical attacks.

2.2. Physical Attacks

Physical attacks play an increasingly important role due to their great application value. Kurakin et al. [16] verify the feasibility of physical attacks by the fact that the perturbed images being captured by the camera still have attack effects. In [2], the EOT algorithm makes adversarial examples robust to multiple physical transformations. In traffic sign recognition cases, Eykholt et al. [10] use Robust Physical Perturbations to generate adversarial graffiti which is robust under physical conditions. Several relevant studies considering the safety of autonomous driving can also be found in [11, 27, 28]. Besides, the work in [30] uses the adversarial patch to hide a person from a person detector.

For face recognition cases, the initial attack is in the form of 2D-printed face photos or 3D facial masks [14]. Later, some researchers generate the eyeglass frames with perturbations attached to fool the FR systems [25, 26]. Adv-Hat [15] achieves attacks by sticking rectangular stickers with adversarial perturbations to the hat. Adversarial light projection attacks [24] project transformation-invariant adversarial patterns onto people’s faces.

The previous methods are under the white-box setting and rely on the generated perturbations which are difficult to reproduce faithfully in the physical world [25]. In our method, we use the real stickers which do not need to be generated or printed and conduct black-box attacks by changing the real stickers’ pasting parameters instead of the content.

2.3. Deep Face Recognition

At present, there are many methods to realize face recognition, including three representative models: FaceNet [24], SphereFace [17], and CosFace [31]. FaceNet [24] learns a mapping from face images to a compact Euclidean space where distances directly correspond to a measure of face similarity. SphereFace [17] uses the angular softmax loss that enables DNNs to learn angularly discriminative features. Recently, large margin cosine loss is proposed in CosFace [31] to learn highly discriminative deep features.

3. Methodology

3.1. The regional aggregation

We first explore the influence of pasting positions on face recognition. In such scenes, liveness detection, which mainly relies on motions (e.g. blinking, mouth opening), depth or texture features of the face [21], is often used to confirm the real physiological characteristics of the object and resists attacks such as photos, masks, and screen re-shoots. To ensure the natural look and not interfere with the liveness detection, pasting positions of stickers cannot cover the facial features. Thus, a face mask matrix $M^F \in \mathbb{R}^{n \times m}$ which contains ones in valid regions (e.g. cheek and forehead), and zeros in invalid regions (e.g. eyes and mouth) is used to constrain the candidate pasting areas of stickers.

We randomly select some face images, fix the remaining parameters of stickers, and traverse every valid pasting position by exhaustive method. The distribution of stickers’ pasting positions leading to successful attacks is analyzed, and the corresponding probability variations of ground-truth labels $t$ and predicted wrong labels $t'$ after attacks are studied when we take the point with the highest predicted probability of $t$ as the center $o^*$ and randomly choose one direction to spread outward. Figure 3 shows several relevant examples.

It is found that the positions that can lead to successful attacks are not discretely distributed, but clustered in a certain region. In the small area around $o^*$, the probability of $t$ decreases with the increase of distance to $o^*$, while the probability of $t'$ is opposite. Based on this, we design a region-based differential evolution algorithm to improve the efficiency of searching attack parameters.

3.2. Region based Differential Evolution Algorithm

Let $f(\cdot)$ denote the face recognition model and $f(x, t)$ denote the probability that the model predicts a face image $x$ as label $t$. $\theta = (\theta_1, \ldots, \theta_i, \ldots, \theta_d)$ is the set of attack parameters (including pasting position, rotation angle, etc.). Given the ground-truth label $t$ for $x$ and a real sticker image $s$, the goal of a dodging (un-targeted) attack is to find the optimal attack parameters $\theta^*$ to make the probability corresponding to $t$ as small as possible, so that a person different from $\hat{t}$ is regarded as top-1 identity. So the objective function of dodging attack can be formalized as:

$$\min_{\theta} L_{\text{dodging}}(\theta) = f(g(x; s, \theta), \hat{t})$$

Figure 3. Examples reflecting the regional aggregation of locations for successful attacks. The top row shows the distribution of pasting positions leading to successful attacks, and the bottom row shows the probabilities of $\hat{t}$ and $t$ versus the distance to the center.
For impersonation (targeted) attack, given a target identity \( t^* \), the objective function is defined as follows:

\[
\min_{\theta} \mathcal{L}_{\text{impersonation}}(\theta) = 1 - f\left(g(x; s, \theta), t^* \right)
\]  

(2)

Since we have no access to the specific parameters of \( f(\cdot) \), we carry out score-based black-box attacks by querying the model to obtain predicted labels and probabilities. Although gradient estimation \( \theta \) can solve the optimization problem along the gradient descent direction, in our case, the ranges of position parameters are discontinuous due to the invalid positions. Accordingly, the objective functions are discontinuous and their smoothness versus the parameters is also unknown, so it is not suitable to use gradient-based method to optimize Eq. (1) and Eq. (2). Therefore, we use an evolutionary method, starting from a group of randomly generated solutions in the search space and using crossover and mutation to generate offspring, making the fittest survive according to the evaluation criteria, and finally find the appropriate solution in the iterative evolution process.

However, using traditional evolutionary algorithms directly is not efficient enough because the characteristics of face recognition scenes are not fully considered. In this paper, we propose a novel Region based Heuristic Differential Algorithm (RHDE) to accelerate the search for solutions. We design a new strategy for the generation of offspring, which utilizes the regional aggregation of positions with attacking effectiveness. To better guide the search direction, we also use an adaptive evaluation criteria adjustment method to adjust the attack target in time according to the current state of the solutions. Taking dodging attack for example, the overall RHDE algorithm is outlined in Algorithm 1. Details are shown in the following.

### 3.2.1 Attack setting

In the evolutionary approach, a population represents a set of multiple solution vectors and each individual in the population represents a solution vector. Given the population size \( P \) and the number of attack parameters to be solved \( d \), the \( k \)-th generation population \( X(k) \) is represented as:

\[
X(k) := \{X_i(k) | \theta_{i}^{t} \leq X_i(k) \leq \theta_{i}^{d}, 1 \leq i \leq P, 1 \leq j \leq d\}
\]  

(3)

where \( X_{i,j}(k) \) is the \( j \)-th parameter value of the \( i \)-th individual in the \( k \)-th generation population. \( (\theta_{i}^{t}, \theta_{i}^{d}) \) is the range of the \( j \)-th parameter. Specifically, each individual in the population represents a tuple containing the pasting position, rotation angle, etc.

In Algorithm 1, we first randomly initialize the population \( X(0) \) on the premise of ensuring that the parameters of each individual are within the corresponding value range (Step 1). Then we generate candidate populations \( C(k) \) in iterative evolution process (Step 7). Based on the evaluation criterion \( J(\theta) \), better individuals between \( C(k) \) and \( X(k) \) are chosen to form the next generation \( X(k+1) \). The process stops when the attack using the optimal individual in the current population as the attack parameters is successful (Step 4) or when the maximum number of iterations \( T \) is reached. The generation strategy of \( C(k) \) and the establishment of \( J(\theta) \) are detailed in Sec. 3.2.2 and Sec. 3.2.3.

### 3.2.2 Strategies for the generation of offspring

In our proposed algorithm, we use crossover between random individuals and inbreeding of superior individuals to generate candidate populations \( C(k) \). The first method follows the traditional evolutionary algorithm, and can be formalized as follows:

\[
C_i(k) = \text{clip}(X_{i-1}(k) + \alpha (X_{i-1}(k) - X_{i-2}(k)))
\]  

(4)

where \( C_i(k) \) is the \( i \)-th individual in the \( k \)-th candidate population. \( \gamma_1, \gamma_2 \) are random numbers. \( \gamma^* \) denotes the index number of the best individual in \( X(k) \) and \( \gamma^* \neq \gamma_1 \neq \gamma_2 \). \( \alpha \) is the scale factor and \( \text{clip}(\cdot) \) is a clipping operation to keep individuals within the range described in Eq. (3).

Because the solutions with adversarial effects tend to cluster in a certain region in the parameter space, we propose an inbreeding method, which finds solutions in the regions near the superior solutions of each generation to speed up the solving process. Specifically, the superior individuals in the current population are selected first (by a ratio of \( \mu \)), \( \phi(X_i(k), j, l) \) is defined as an operation, which takes the position in individual \( X_i(k) \) as the center, takes out the position parameter at the step size \( l \) in the \( j \)-th direction around
3.3. The generation of adversarial sticker

After specifying the attack parameters, we deform the sticker accordingly to simulate the effect of the sticker on the face more realistically so that its shape fits the curvature of the face at the current position. We first use the 3DMM method to generate a 3D model of a given 2D face image, and the 3D coordinates corresponding to the face position are obtained. Then we use the information of x-z plane where the highest point \((x_0, y_0, z_0)\) of the pasting area is located to carry out bending transformation, and then use the information of y-z plane where \((x_0, y_0, z_0)\) is located to rotate the sticker in 3D space. The complete process of shape transformation is shown in Figure 4.

For the bending transformation, the projection of points on the x-z plane can be approximated as a parabola \(z = a(x - c)^2 + b\), where \(c = x_0\), \(a = -\Delta h / (\Delta s)^2\), \(b = -a(w_n - c)^2\). \(\Delta s\) is an arbitrary length and \(\Delta h\) is the length on the Z-axis corresponding to \(\Delta z\). The arc length of the bent sticker \(A\) (size: \(h \times w_n\)) is equal to the width of the original sticker \(T\). Let \(v_p(i, j)\) denote the pixel value at position \((i, j)\) in image \(p\), then the pixel value on sticker \(A\) is calculated as:

\[
v_A(i, j) = g_T \left( \int_0^\rho \sqrt{1 + 4a^2(x - c)^2} dx \right)
\]

where \(g_T(i, j)\) is the bilinear interpolation function to calculate the pixel value of position \((i, j)\) on the image \(p\).

For rotation transformation, the information on the y-z plane reflects the rotation angle \(\theta\) of the sticker. \(\Delta y\) denotes an arbitrary length and \(\Delta z\) is the corresponding length on the Z-axis, then \(\theta\) is calculated as follows:

\[
\theta = \text{sign}(h - 2y_0) \cdot \text{arctan}(\Delta z / \Delta y)
\]

According to \(\theta\), we rotate the bent sticker in 3D space to get the information of the final sticker. The sticker patterns of 2D plane corresponding to 3D coordinates are calculated using bilinear interpolation and backward mapping.

3.4. Implementation in the physical world

Based on the above method, the attack parameters corresponding to the subjects’ faces are solved in the digital environment. When conducting the physical attacks, we only need to paste the real stickers on the subjects’ faces according to the calculated parameters. In this process, there are several points worth noting. (1) Our method does not involve the printing and making process, so there is no need to use

Figure 4. The process of bending and rotating the sticker (yellow dot indicates the highest point of the pasting area).
Table 1. The results of dodging attack and impersonation attack. We report the fooling rate (FR) and the number of queries (NQ) of the adversarial examples generated by different stickers on the LFW and CelebA datasets against FaceNet, SphereFace and CosFace.

| Datasets  | LFW | CelebA |
|-----------|-----|--------|
|           | FaceNet | SphereFace | CosFace | FaceNet | SphereFace | CosFace |
|           | FR NQ | FR NQ | FR NQ | FR NQ | FR NQ | FR NQ |
| Dodging   |       |       |       |       |       |       |
| sticker 1 | 63.22% 489 | 42.74% 691 | 54.28% 527 | 73.51% 518 | 57.18% 596 | 69.47% 530 |
| sticker 2 | 76.26% 478 | 64.08% 629 | 69.82% 484 | 81.78% 483 | 72.93% 576 | 79.26% 487 |
| sticker 3 | 73.64% 442 | 44.50% 604 | 66.39% 455 | 80.33% 511 | 59.92% 548 | 72.80% 496 |
| Impersonation | | | | | | |
| sticker 1 | 51.11% 636 | 30.70% 718 | 48.06% 563 | 48.18% 610 | 37.32% 644 | 42.90% 635 |
| sticker 2 | 50.00% 715 | 31.00% 870 | 45.93% 658 | 48.96% 652 | 41.67% 747 | 47.73% 637 |
| sticker 3 | 46.28% 691 | 29.50% 716 | 45.54% 662 | 47.84% 625 | 39.18% 700 | 45.83% 638 |

NPS and TV losses with high calculation costs. (2) We do not use EOT in the solving process to guarantee the performance under different physical conditions but experiments in Section 4.2.2 demonstrate that our method is robust under different physical conditions, such as changing face postures, which shows good adaptability of our method. (3) Even if there is a slight deviation between the calculated solution and the actual pasting position and angle, the follow-up experiments show that owing to the regional aggregation, it can still achieve good attacking results, verifying that the attack effectiveness caused by positions and rotation angles tends to keep consistent when the attacks are transferred to the physical environment.

4. Experiments and Results

4.1. Experimental Settings

Target models: We choose three representative face recognition models as our target models, including CosFace, SphereFace and FaceNet. The open-source models are used to extract feature representations of faces, and then we finetune the models on the corresponding datasets for classification. Dodging attack and impersonation attack are conducted on all the above models. For impersonation attack, we randomly specify the class in the corresponding datasets as the target class.

Datasets: We perform experiments on two public datasets: Labeled Faces in the Wild (LFW) and CelebFaces Attribute (CelebA). All 5749 identities of LFW and 8192 identities of CelebA are used to construct their own face databases. We select 1000 images randomly from each of the two datasets to carry out attacks. All the selected images can be recognized correctly by the face recognition models.

Metrics: Two metrics, fooling rate and the number of queries, are used to evaluate the attack performance. The former refers to the percentage of all testing images that can be successfully attacked, while the latter refers to the number of model queries required for successful attacks. To study the effectiveness against face recognition modules, it is considered as a successful attack if the face can successfully pass face detection and liveness detection but are identified as the wrong identity.

Implementation: We use the library to extract 81 feature points of the face and fill the effective region to generate mask $M_F$. $d$ is equal to 2 in our case. $\theta_1$ refers to the index of the pasting position in the indexed set of valid points $V = \{(i, j) | M_F \neq 0\}$ and $\theta_2$ is the rotation angle. We set $r$ equal to 8. The default $l$ is equal to 1, and $l$ is increased if the corresponding point in the parameter space has already been accessed. Other parameters are set as $P = 120$, $T = 30$, $\alpha = 0.5$, $\rho = 20$ and $\delta = 10$.

4.2. Experimental Results

4.2.1 Performance comparisons in the digital world

Firstly, we report the performance of our method on LFW and CelebA against FaceNet, SphereFace, and CosFace respectively. We use three different stickers to conduct dodging and impersonation attacks and evaluate the fooling rate and the number of queries. The results are shown in Table 1 and three groups of visual examples are given in Figure 5.
Table 2. Comparison results of the fooling rate and average time with the two state-of-the-art physical attack methods for face recognition systems in the black-box setting.

|         | FaceNet | SphereFace | CosFace | average time |
|---------|---------|------------|---------|--------------|
| adv-hat | 28.85%  | 10.36%     | 26.66%  | 325.37s      |
| adv-glasses | 21.21%  | 10.63%     | 9.83%   | 356.25s      |
| ours    | 76.26%  | 64.08%     | 49.82%  | 69.97%       |

From above results, we can see: (1) the proposed Meaningful Adversarial Stickers method has shown good attack effectiveness in both dodging and impersonation attacks, achieving fooling rates of up to 81.78% and 51.11% respectively. (2) Different stickers are all likely to achieve successful attacks, but show differences in attack effects. Stickers with more colorful patterns (e.g. sticker 2 and sticker 3) show stronger attack effectiveness, especially in the case of dodging attack. (3) We can implement an attack at the magnitude of hundreds of queries, and it is understandable that impersonation attack requires more queries than dodging attack, since the former requires perturbing the image to a specific class. (4) Under our attack method, SphereFace shows stronger robustness in both dodging and impersonation attacks, while FaceNet is relatively vulnerable.

4.2.2 Comparisons with SOTA methods

Comparisons between our method and other physically realizable attacks for face recognition on the same face images in LFW are shown in Table 2. Since there are no existing physical attacks on face recognition in the black-box setting, we can only use the adversarial examples generated in white-box setting to carry out transfer-based black-box attacks when calculating the performance of the previous methods. Although score-based black-box attacks can also be carried out through gradient estimation, it is not realistic because the estimation of large areas of pixel gradients requires a large number of model queries. Here we choose adv-hat [15] and adv-glasses [25] which have great performance on the white-box setting. For our method, we use the results of dodging attack by pasting sticker 2 to compare with other methods. The results in Table 2 show that our method can achieve better attack effectiveness in a shorter time when attacking different networks. It outperforms adv-hat with at most more than 83% improvement and adv-glasses with at most 85% improvement, while the average time to attack each image is reduced by 78% and 86% respectively.

4.2.3 Ablation study

To demonstrate the effectiveness of each component in the proposed method, we report the performance when each component of the Region-based Heuristic Differential Evolution algorithm is added separately. We conduct experiments on LFW dataset to carry out dodging attacks using sticker 2. In all experiments, the population size $P$ and iteration number $T$ are consistent. Starting from the traditional differential evolution algorithm (DE), we add adaptive adjustment strategy (adaptive-DE) and region-based offspring generation strategy (region-DE) respectively, and the comparison results are shown in Table 3.

We can see that under the same maximum number of iterations, the success rates of directly using DE to find the attack parameters are very low and relatively more queries are required. When the adaptive adjustment strategy and the offspring generation strategy are added respectively, the success rates of both are improved. When the two strategies are used together, the success rates are greatly improved, and queries required are significantly reduced.

4.2.4 Attacks in the physical world

In this section, we report the performance of our meaningful adversarial stickers in the physical environment. Figure 6 presents the predicted probabilities of some subjects corresponding to the ground-truth identity before and after being attacked in the physical environment. The results show that the probabilities in different models are significantly reduced, and the maximum reduction in FaceNet, SphereFace, and CosFace after attacks are 0.64, 0.65, and 0.76, respectively. This proves that the generated attack parameters in the digital environment can still maintain good attack performance when applied to the physical world.

We also report the results of success rates in complex physical conditions. We use the parameters calculated in the digital world, change face postures (counterclockwise rotation of the head) in the physical world, and count the percentage of successful attacks in consecutive frames. To prove the necessity of 3d deformation (described in Sec. 3.3), we also calculate the relevant physical results of the parame-
Subject A
(n in database)
Original face
Subject A
(0.70)
Michelle_Kwan
(0.69)
Subject B
(n in database)
Perturbed face
Subject B
(0.72)
Clare_Short
Target face
Clare_Short
(0.70)
Figure 7. Examples showing the attack effectiveness at different face postures in the physical environment (un-targeted attacks). The black text on the right side denotes the predicted wrong name after attacks.

Figure 8. Examples of attacks under face identification task. The black text at the bottom of the image denotes the identified person name and the corresponding cosine similarity (shown in brackets).

Table 4. The percentage of video frames successfully attacked when different subjects continuously change their face postures in the physical world.

| model     | subject | with-def | no-def | difference |
|-----------|---------|----------|--------|------------|
| FaceNet   | A       | 98.46%   | 39.78% | 38.68%     |
|           | B       | 98.30%   | 48.74% | 49.56%     |
|           | C       | 92.94%   | 48.39% | 44.55%     |
|           |         | 91.30%   | 55.17% | 36.13%     |
| SphereFace| B       | 83.45%   | 33.33% | 50.12%     |
|           | C       | 85.92%   | 40.76% | 45.16%     |
| CosFace   | A       | 85.37%   | 48.09% | 37.28%     |
|           | B       | 86.96%   | 46.67% | 40.29%     |
|           | C       | 82.61%   | 45.45% | 37.16%     |

| with-def: using 3D deformation in parameters’ solving process. |
| no-def: pasting the sticker directly without considering deformation. |
| difference: the difference between with-def and no-def. |

Table 5. The results of fooling rate (FR) and the number of queries (NQ) after adversarial training, and the change compared to the undefended situation (shown in brackets).

| dataset | FR            | NQ             |
|---------|---------------|----------------|
| LFW     | 72.31% (--3.95%) | 60.66% (--3.42%) |
|         | 68.3% (↑ 6)   | 501 (↑ 17)     |
| CelebA  | 78.54% (--3.24%) | 70.22% (--2.71%) |
|         | 77.33% (↑ 1.93%) | 509 (↑ 22)     |

We also test the robustness of our method in response to defense measures. We here choose adversarial training [20] as the defense method and test the performance of our attack method with sticker 2 on two datasets against three models after adversarial training. Table 5 lists the results of fooling rate and the number of queries after the defense, as well as the changes compared to the results without defense. It can be seen that the variation range of fooling rate and queries is relatively small, with the maximum variation range of 3.95% and 54 respectively. Therefore, our attack method still maintains good attack effectiveness under adversarial training, and has good robustness against the defense method.

5. Conclusion

In this paper, we proposed Meaningful Adversarial Stickers, a physically feasible attack method for face recognition systems in the black-box setting. We conducted attacks based on the real stickers in our life by changing their pasting position, rotation angle, and other parameters and designed RHDE algorithm to improve the solving efficiency. Extensive experiments in the digital and the physical world demonstrate the effectiveness of our method. In the case that the model information is unknown, face recognition can also be successfully misled in a concealed way, which reveals the potential safety hazard.
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