Towards Transferable Adversarial Attack against Deep Face Recognition
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Abstract—Face recognition has achieved great success in the last five years due to the development of deep learning methods. However, deep convolutional neural networks (DCNNs) have been found to be vulnerable to adversarial examples. In particular, the existence of transferable adversarial examples could severely hinder the robustness of DCNNs since this type of attacks could be applied in a fully black-box manner without queries on the target system. In this work, we first investigate the characteristics of transferable adversarial attacks in face recognition by showing the superiority of feature-level methods over label-level methods. Then, to further improve transferability of feature-level adversarial examples, we propose DFANet, a dropout-based method used in convolutional layers, which could increase the diversity of surrogate models and obtain ensemble-like effects. Extensive experiments on state-of-the-art face models with various training databases, loss functions and network architectures show that the proposed method can significantly enhance the transferability of existing attack methods. Finally, by applying DFANet to the LFW database, we generate a new set of adversarial face pairs that can successfully attack four commercial APIs without any queries. This TALFW database is available to facilitate research on the robustness and defense of deep face recognition.

I. INTRODUCTION

Deep convolutional neural networks (DCNNs) have achieved great success in face recognition [1], [2], [3], [4], [5], [6], [7]. In unconstrained environments, the face recognition performance is reaching saturation levels on several benchmarks, e.g., LFW [8], MegaFace [9] and IJB-A [10]. Even in the real security certificate environment, which requires a very low false positive rate [11], state-of-art performance has been achieved [7]. Although deep face models have already surpassed human performance [12], [13] on some benchmarks, we must keep in mind that benchmarks may not be able to capture realistic performance [14]. Due to the remarkable performance, face recognition applications could be numerous as well as diverse in our daily lives and could be used in security agencies, law enforcement agencies, the airline industry, the banking and securities industries and so on, which further increases the demand for security in deep face models.

Researchers found that the basis of deep face models, DCNNs, can be easily fooled by adversarial examples, which are modified from original test images by adding noise not imperceptible to humans [15], [16]. Moreover, adversarial examples are transferable in different models [17], [18], [19], [20], which means that black-box attacks can be launched from the local surrogate models without having information on the remote target systems, including network architectures, network parameters, training databases and defensive methods.

Face recognition systems are not robust as we think when test images are not drawn from the same distribution as the training images. Previous works have already demonstrated the existence of the vulnerability of deep face models [21], [22], [23]. However, previous works in white-box settings [21], [24] assume that the attacker has full access to the target models. Query-based methods in black-box settings [23] require a large number of queries, which could be detected relatively easily by the target system. Both settings are not practical in real-world situations because the remote target system can neither release the network information proactively nor allow a large number of queries on a face pair.

In contrast, transferable adversarial attacks could severely hinder robustness since this type of attack could be applied in a fully black-box manner without any queries on the target system. We demonstrate that, with this type of adversarial attack, state-of-art face models and even commercial APIs could be easily attacked, as shown in Fig. 1. Both the original face pair and the modified face pair are shown. The face images of the original pair belong to different identities while the modified pair are judged as the same identity by four commercial APIs: Amazon [25], Microsoft [26], Baidu [27] and Face++ [28]. Because of the great potential harms of transferable adversarial attacks in deep face recognition, it is valuable to study this issue in a black-box setting without any...
queries.

Although recent works have investigated the transferability of adversarial examples [17], [18], [19], [20] in DCNNs used for close-set object classification tasks [29], [30], [31], some works remained to be done on transferable adversarial attacks in deep face recognition because of the particularity of deep face models. First, face recognition is an open-set task, and deep face models are more like a feature extractor where the test identities are usually different from the training identities [4]. Second, compared with the 1,000 categories of ImageNet [41], the number of identities/categories could be in the millions [32]. Based on these two points of particularity, it is difficult to generate transferable target attacks because of the absence of accurate labels for both the source and target images.

In addition, we have no knowledge of a target black-box deep face model for which there are a wide range of options for its training databases [33], [32], [34], [35], training loss functions [1], [2], [3], [4], [5], [6], [7] and network architectures [66], [67], [68], [69]. Because it has been widely accepted both in academia and industry that these three key pieces of information could improve recognition performance, there are still many works insisting on designing new, effective ones, which will undoubtedly increase the difficulty of attacking a black-box face model.

The objective of this work is to study transferable adversarial attacks towards deep face models, i.e., to generate adversarial face pairs from surrogate models and lead the black-box face models to misjudge these generated face pairs by depending only on the transferability without any queries of the target models. Furthermore, to simulate the potential scenarios, we aim to increase the difference between source and target models by attacking deep face models with different training datasets, training loss functions, and network architectures. To this end, considering the aforementioned characteristics and particularity, we first start by investigating the applicable strategies of transferable adversarial attacks against deep face recognition to select a suitable baseline method. To further improve the transferability of adversarial examples, we propose the dropout face attacking network (DFANet), a dropout-based method used in convolutional layers. DFANet could be combined with existing black-box attack enhancement methods to achieve further improvements over them by increasing the diversity of surrogate models and preventing the overfitting of adversarial examples to them. Finally, based on our study, we contribute an adversarial face database as a benchmark to facilitate research on the robustness and defense of deep face recognition.

The main contributions of our paper are as follows:

- We show that feature-level attack is more effective than commonly used label-level attack towards deep face-recognition models. Furthermore, we empirically demonstrate that momentum boosting method [19], diverse input method [20], and model ensemble method [17] are useful to improve the transferability of the feature-level attacks. They can be combined to provide a strongest attacking method.

- We propose a dropout face attacking networks (DFANet), which applies a dropout-based strategy to a variety of deep CNNs to enhance the transferability of adversarial attacks. Extensive experiments show that the proposed method can be combined with previous transferability enhancement methods [17], [19], [20], which obtain more effective black-box adversarial attacks towards the state-of-the-art face models with different training databases, loss functions and network architectures.

- Based on the proposed DFANet, we generate the adversarial images from the well-known LFW database with visually imperceptible noise, which provides a new database, TALFW, to serve as a benchmark to evaluate the robustness of deep face models. With the same protocol as the LFW database, four state-of-the-art algorithms and four commercial APIs yield unpleasant performance on the TALFW database. The severe degradation clearly shows the vulnerability of deep face-recognition models even with massive training data.

The remainder of the paper is organized as follows. Section II briefly reviews the literature related to adversarial attacks, deep face recognition, and adversarial attacks towards deep face models. In Section III, we first introduce the applicable strategies of transferable adversarial attacks towards deep face recognition. Then, we present the proposed method and incorporate it into existing transferability enhancement methods to further improve adversarial transferability. In Section IV, we first demonstrate the superiority of the feature-level attack method and select it as the baseline method. Next, we evaluate the proposed method on deep face models with different training databases, loss functions and network architectures. Then, we provide an ablation study on hyperparameters and provide some interpretation of the intermediate generation process of adversarial examples for better comprehension of DFANet. Finally, we adopt the proposed method to the LFW database and build the TALFW database. Section V summarizes the conclusions.

II. RELATED WORKS

In this section, we briefly review the literature related to adversarial attacks, deep face recognition, and adversarial attacks against deep face models.

A. Adversarial Attacks

Previous works have discovered that, with elaborate strategies, DCNNs can be easily fooled by test images with imperceptible noise [15]. This type of image is called adversarial examples. The existence of adversarial examples has led to a variety of studies on adversarial defenses [15], [40], [41]. The robustness of DCNNs is crucial; therefore, adversarial attacks and defenses draw great attention. A comprehensive survey in the field of computer vision tasks can be found in [42].

Adversarial examples can be classified as white-box attacks [15], [16], [43], [44], [45] and black-box attacks [18], [19], [46], [47]. White-box attacks assume that the attacker knows everything about the target models, including the network architectures, network parameters, training databases
and even defensive methods. Black-box attacks assume that the attacker has no access to the target model. Some works broaden this restriction and assume that the attacker can obtain the output of the model (label or confidence score). Therefore, these works have developed a serious of query-based attack methods. In this paper, we assume that the attacker only has one chance to attack a face pair; therefore, they can only leverage the transferability of adversarial examples without any queries.

First, we introduce mainstream white-box attacks [15], [16], [33], [44], [45]. Szegedy et al. [15] first found that they can cause DCNNs to misclassify images by a certain hardly perceptible perturbation generated using a box-constrained L-BFGS method. Compared with L-BFGS attacks [15], Goodfellow et al. [16] proposed a more time-saving and practical method, referred to as the fast gradient sign method (FGSM), which generates the adversarial perturbation $\Delta x$ from the source image $x^{(s)}$ to build an adversarial example $x_{adv} = x^{(s)} + \Delta x$, by performing one-step gradient updating along the direction of the sign of the gradient at each pixel:

$$x_{adv} = x^{(s)} + \Delta x = x^{(s)} + \varepsilon \text{sign}(\nabla_{x^{(s)}} J(x^{(s)}, y^{(s)})),$$

where $J$ represents the cross-entropy loss, $\varepsilon$ limits the maximum deviation of the perturbation. To generate adversarial examples of a specific desired target class, the fast target gradient sign method (FTGSM) [44] leads the model to misclassify a source image $x^{(s)}$ with label $y^{(t)}$ as another target category $y^{(n)}$, which satisfies $y^{(t)} \neq y^{(n)}$, which is formulated as:

$$x_{adv} = x^{(s)} + \Delta x = x^{(s)} - \varepsilon \text{sign}(\nabla_{x^{(s)}} J(x^{(s)}, y^{(n)})),$$

Moreover, a straightforward method called the basic iterative method (BIM) [44] extends the FGSM by applying it multiple times with a small step size and clip pixel values after each step to ensure the $L_\infty$ constraint:

$$x_{adv,0} = x^{(s)}$$

$$x_{adv,N+1} = C_{x^{(s)},r}(x_{adv,N} + \varepsilon \text{sign}(\nabla_{x_{adv,N}} J(x_{adv,N}, y^{(n)}))),$$

where the iteration can be chosen to be $\min(\varepsilon + 4, 1.25\varepsilon)$ and $C_{x^{(s)},r}(x^{(s)}) = \min(255, x + \varepsilon \max(0, x - \varepsilon, x^{(s)}))$. Compared with BIM [44], the iterative target gradient sign method (ITGSM) [44] leads the model to misclassify a source image $x^{(s)}$ with label $y^{(s)}$ as another target category $y^{(n)}$, which satisfies $y^{(t)} \neq y^{(n)}$, which is formulated as:

$$x_{adv,0} = x^{(s)}$$

$$x_{adv,N+1} = C_{x^{(s)},r}(x_{adv,N} - \varepsilon \text{sign}(\nabla_{x_{adv,N}} J(x_{adv,N}, y^{(n)}))).$$

According to [44], iterative methods can attack white-box DCNNs at a higher rate than the fast method at the same constraint level.

Finally, we introduce transferable black-box attacks [17], [18], [19], [38], [20], [49], which are more practical in real-world situations than white-box attacks and could severely hinder robustness. Researchers have discovered that attacking an ensemble of multiple models simultaneously [17], [19] could improve the transferability of adversarial images. Usually, iterative attacks achieve a higher attack success rate than the fast attack method in a white-box setting, but performs worse when transferred to other models [44]. While Dong et al. [19] proposed to integrate the momentum term into the attack process to stabilize the update directions and escape from poor local maxima, improving the transferability of iterative attacks. Furthermore, Dong et al. [19] proposed a translation-invariant attack method that optimizes a perturbation over an ensemble of translated images. At the same time, Xie et al. [20] proposed to improve the transferability of adversarial examples by creating diverse input patterns, e.g., through resizing, cropping and rotating. Wu et al. [49] proposed to improve the transferability by using more gradients from the skip connections rather than the residual modules according to a decay factor.

B. Deep Face Recognition

Deep learning has brought great success to face recognition. A comprehensive survey can be referred to [50]. The success could be mainly attributed to the large-scale training databases [23], [32], [34], [35]. effective training loss functions [1, 2, 3], [4], [5], [6], [7] and advanced network architectures [51], [52]. [33]. [36], [34]. Large scale training databases play an important role in deep face recognition, and we introduce four mainstream large scale databases here. CAIIS-A-WebFace [33] is the first widely used large-scale training database in deep face recognition and contains 0.49M images of 10,575 celebrities. At that time, the scale of CASIA-WebFace ranked second, only smaller than the private database of Facebook [51], which significantly boosted the performance of face recognition performance on the mainstream benchmark LFW [8]. MS-Celeb-1M [32] is the first publicly available million-scale training database, which originally contains 10M images of 100K celebrities. Considering the existence of label noise [35], the cleaned versions of MS-Celeb-1M are widely in academia today. VGGFace2 [34] database has 3.31 million images of 9,131 identities and have large variations in pose, age, illumination, ethnicity and profession. IMDB-Face [33] is a million-scale noise-controlled training database, containing 1.7M images of 59K identities, which is competitive as a training source despite its relatively smaller size.

It has been widely accepted that learning discriminative features is the key for open-set face recognition and the major focus in deep face recognition has become to learn a discriminative feature space by supervising networks using effective loss function. Some loss functions are based on Euclidean metric learning methods [1, 2], some of which either minimize the distance between features in the positive pair or maximize that in the negative pairs, or both. Some loss functions modify softmax loss by incorporating weight or feature normalization [54], [55], [56]. Another powerful type of loss function is the large-margin softmax loss, mainly containing SphereFace [4], CosFace [6] and ArcFace [7]. CosFace [6] and ArcFace [7] introduce additive margins to guarantee convergence, which are easier to implement than multiplicative margins, which are used by SphereFace [4].
Large-margin softmax loss functions significantly boost the performance, which seem to be the most effective loss functions in deep face recognition.

Network architectures have also shown significant gains in the deep face recognition literature. DeepFace [51] first uses a 9-layer CNN with locally connected layers in face recognition, and achieves a 97.35% accuracy on the LFW database. SphereNet [4] adopts a 64-layer ResNet [36] network, supervised by an advanced large-margin loss function, achieving a 99.42% accuracy on the LFW database. Adacos [57] adopts an Inception-ResNet architecture [38] in face recognition and reports comparable results. ArcFace [7] develops ResNet [36] and squeeze-and-excitation network (SENet) [59] with an IR block and achieves new state-of-art performance on several benchmarks. In addition, lightweight deep face models aiming at model compactness and computational efficiency have also attracted attention [58], where MobileNet [37] has been proven to be a successful attempt.

C. Attacks against Deep Face Models

Face recognition systems can be applied to domains in which safety is crucial. Therefore, it is important to understand the extent to which deep face models are subject to attacks. Previous works have already investigated several attacks [21], [59], [22], [23] and demonstrated the vulnerability of deep face models.

A gradient-based attack method was first proposed in [21], which restricts the perturbation to eyeglasses and physically realizes impersonation and dodging attacks in deep face recognition. Then the eyeglass attack was developed in [60] by using generative methods. The LOTS attack was proposed in [24] to form adversarial examples that mimic the deep features of the target. LOTS was the first work to launch feature-level attacks against deep face models, which shows similarities to the technique of Sabour et al. [61] in terms of directly adjusting internal feature representations. To date, adversarial attacks against face models have mainly focused on the white-box setting. Considering the impracticality of the white-box setting, [23] proposed an evolutionary attack method for query-based adversarial attacks in the decision-based black-box settings.

Previous works explore attacks lie in two aspects: attacks in white-box settings and attacks in black-box settings. Although the attack success rate in the white-box settings [21], [24] reaches almost 100%, this setting is not practical in real-world situations because it assumes that the attacker has full access to the target models. Query-based methods in the black-box setting [23] are also effective in terms of the attack success rate; however, these methods require a large number of queries, that can be relatively easy detected by the target system. [62], [63] proposed to attack deep face models by generating adversarial examples with GANs, which can be transferred to unseen models to some degree, but this type of method is difficult to achieve.

Therefore, in this work, we aim to study the transferable adversarial attacks against deep face models, which could severely hinder the robustness since this type of attack is launched in a fully black-box manner without any query feedback. We investigate transferable gradient-based adversarial attack methods and the corresponding new transferability enhancement method. We generate adversarial examples using surrogate models and propose a new transferability enhancement method to increase the possibility of surrogate gradients covering the target gradients. The proposed method achieves a consistently high success attack rate. In addition, it is easy and stable for implementation.

III. TRANSFERABLE ADVERSARIAL ATTACKS AGAINST DEEP FACE MODELS

In this section, we first introduce the applicable feature-level adversarial attacks towards deep face models. Then we propose the dropout face attacking networks (DFANet) to further increase the transferability of adversarial attacks, which could be combined with existing black-box attack enhancement methods, and achieve improvements over them.

A. Adversarial Attacks against Deep Face Models

We start with some notations for the background of deep face models and the corresponding adversarial attacks.

**Deep Face Models.** Let $D = \{x(i), y(i)\}$ denote a labeled database, where $x(i)$ and $y(i) \in \{1, 2, ..., C\}$ ($C$ is the number of identities) denote an input image and the corresponding label, respectively. In the training process, a network with parameters $\theta_N$ is originally trained on a database $D$ by minimizing the cross-entropy loss

$$J(x(i), y(i)) = -\frac{1}{N} \sum_{i=1}^{N} \log p(y(i)|x(i), \theta_N),$$

where $N$ is the mini-batch size. In the entropy loss function,

$$p(y(i)|x(i), \theta_N) = \frac{e^{W_i^T x(i) + b_i}}{\sum_{j=1}^{C} e^{W_j^T x(i) + b_j}},$$

where $x(i) \in \mathbb{R}^d$ denotes the embedding feature of the $i$-th training image $x(i)$, $y(i)$ is the label of $x(i)$, $W_j \in \mathbb{R}^d$ is the $j$-th column of the weight of the last fully connected layer, and $b_j \in \mathbb{R}^C$ is the bias.

For a deep face model, in the training process, the network obtains an input face image $x(i)$, and then outputs the probability $p(y(i)|x(i), \theta_N)$ and the output label $l(x(i))$. In the testing process, we use the face model as a feature extractor, which means that we do not care about the softmax layer. We only extract the normalized embedding feature of images in the testing databases and make comparisons using distance metrics such as the cosine similarity. Some softmax-based loss functions [55], [4], [6], [7] remove the bias term, normalize the embedding features, and incorporate the large margin, which improves the recognition performance but does not change the pipeline of deep face models.

**Feature-level Attacks.** Given a deep face model and a face pair, denoted by $\{x(i), x(i)\}$, we compare this face pair by calculating the distance between normalized deep representations $F(x(i))$ and $F(x(i))$. Note that in equation [6], $x(i) \in \mathbb{R}^d$ denotes the embedding feature of the $i$-th training image $x(i)$,
while here, $F(x^{(i)})$ is the deep feature after normalization, which is primarily used for distance comparison in deep face recognition. Ideally, the distance between features in a negative pair is larger than that in a positive pair. However, to explore the vulnerability of deep face models, we try to add imperceptible perturbation $\Delta x$ on one of the face images $x^{(s)}$ to generate an adversarial example $x_{adv}\approx x^{(s)}+\Delta x$ and deceive the face model. Therefore, for a positive face pair $(x^{(s)}, x^{(t)})$, where $y^{(s)} = y^{(t)}$, the optimized objective can be formulated as:

$$\Delta x = \arg \max_{\Delta x} \left\| F(x^{(s)} + \Delta x) - F(x^{(t)}) \right\|_2, \left\| \Delta x \right\|_\infty < \epsilon, \quad (7)$$

while for a negative face pair $(x^{(s)}, x^{(t)})$, where $y^{(s)} \neq y^{(t)}$, the optimized objective is:

$$\Delta x = \arg \min_{\Delta x} \left\| F(x^{(s)} + \Delta x) - F(x^{(t)}) \right\|_2, \left\| \Delta x \right\|_\infty < \epsilon, \quad (8)$$

where $\epsilon$ limits the maximum deviation of the perturbation. For computational efficiency, we adopt the optimized loss function

$$J \left( x^{(s)} + \Delta x, x^{(t)} \right) = \left\| F \left( x^{(s)} + \Delta x \right) - F \left( x^{(t)} \right) \right\|_2$$

for negative pairs, and

$$J \left( x^{(s)} + \Delta x, x^{(t)} \right) = - \left\| F \left( x^{(s)} + \Delta x \right) - F \left( x^{(t)} \right) \right\|_2$$

for positive pairs to form adversarial perturbations in an fast way, referred to as feature fast attack method (FFM)

$$x^{(s)} + \Delta x = C_{x^{(s)}, \epsilon}(x^{(s)}) + \text{sign}(\nabla_{x^{(s)}} J(x^{(s)}, x^{(t)})),$$ \hspace{1cm} (11)

or in an iterative way, referred to as feature iterative attack method (FIM) \cite{64}

$$\Delta x_0 = 0,$$

$$g_{N+1} = \nabla x^{(s)} + \Delta x_N J \left( x^{(s)} + \Delta x_N, x^{(t)} \right),$$

$$x^{(s)} + \Delta x_{N+1} = C_{x^{(s)}, \epsilon}(x^{(s)}) + \Delta x_N + \text{sign}(g_{N+1}),$$

where $C_{x, \epsilon}(x') = \min(255, x + \epsilon, \max(0, x - \epsilon, x'))$; the iteration can be chosen heuristically $\min(\epsilon + 4, 1.25\epsilon)$. Note that in FFM and FIM, the loss functions $J$ are no longer the cross entropy loss as Equation (5), but the feature-level loss functions in Equation (7) and Equation (8).

B. Dropout Face Attacking Networks (DFANet)

To further improve the transferability of adversarial attacks, there are some previous works on transferability enhancement methods \cite{17, 19, 48, 20, 49}, which we reviewed in Section I-A. The existing methods mainly improve the transferability of adversarial attacks by increasing the diversity and variability of the gradient \cite{19, 49}, input images \cite{48, 20}, and surrogate models \cite{17} to prevent adversarial examples overfitting to surrogate models and increase the possibility that the surrogate gradients will cover the target gradients. However, in existing methods, a surrogate deep face model usually appears as a whole part, which can be expressed as $\theta_N$ in Equation (5). The parameters $\theta_N$ always remain fixed in the forward propagation and backpropagation process of the adversarial example generation. In this work, we propose an easy and general method by increasing the diversity and variability in a surrogate model $\theta_N$ itself although surrogate models have already been trained well and could be combined with many existing transferability enhancement methods and applied to a variety of convolutional neural network architectures.

The basis of deep face models is deep convolutional neural networks (DCNNs) in which convolutional layers play an important role. Since the aim is to further improve the transferability by increasing the diversity and variability, we incorporate dropout \cite{65} in the convolutional layers in the iterative steps of the generation process. Although dropout has brought great success to DCNNs, it is primarily used in the fully connected layers \cite{66, 67} by dropping units along with their connections during the training process to improve the performance of the trained model. We use dropout in the testing process when deep face models are used to generate adversarial examples to improve the transferability of adversarial examples. In this way, the dropout increases the possible settings of the subnetworks and combines the possible subnetworks in the iterative steps.

Specifically, for a face model composed of convolutional layers, given the output $o_i \in \mathbb{R}$ from the $i$-th convolutional layer, we first generate a mask $M_i \in \mathbb{R}$ where each element $m_i$ is independently sampled from a Bernoulli distribution with probability $p_d$:

$$m_i \sim \text{Bernoulli} \left( p_d \right), \quad m_i \in M_i.$$ \hspace{1cm} (13)

Then, we use this mask to modify the output as $o_i = M_i \times o_i$, where $\times$ denotes the Hadamard product. We name this modified model as dropout face attack networks (DFANet). To obtain the ensemble effect of the random sampling of the subnetworks, we incorporate the DFANet into the generation process of transferable adversarial examples. In the $N$-th iterative step of the adversarial example generation, we generate the mask $M^N_i$ for the output $o^N_i$ of the $i$-th convolutional layer using Equation (13), then change the output to $o^{N+1}_i = M^N_i \times o^N_i$ in the forward propagation process. Accordingly, in the gradient backpropagation process, the same mask is used. In the $N$-th iterative step, for an input image $x$, the normalized deep representations can be denoted by $F^N(x)$.

In this way, DFANet can be applied to the generation of FIM (by Equation (12)) and combined with transferability enhancement methods like momentum boosting method \cite{19}, diverse input method \cite{20}, and model ensemble method \cite{17}. To explain the generation process more clearly, we detail these combinations of methods in turn. For convenience, we do not detail the combination of DFANet and FIM here. We start with DFANet-M-FIM, which is the combination of DFANet, momentum boosting method, and FIM. DFANet-M-FIM is shown in Algorithm 1 where the integrated momentum \cite{68} stabilizes the update directions and prevents the optimization from dropping into poor local maxima. Specifically, $g_{N+1}$ gathers the gradients of the first $N+1$ iterations with a decay factor $\mu$. The combination of DFANet, diverse input method, momentum boosting method, and FIM is referred to
Algorithm 1: DFANet-M-FIM

Input: The face pair \( \{x^{(s)}, x^{(t)}\} \), maximum deviation of perturbations \( e \), decay factor \( \mu \), maximum iterative steps \( N_{\text{max}} \), deep face model \( F(\cdot) \), dropout probability \( p_d \).

1. Initialize: \( \Delta x_0 = 0, g_0 = 0, N = 0 \);
2. while step \( N < N_{\text{max}} \) do
   3. Generate DFANet \( F^N(x) \) of the \( N \)-th step (with \( p_d \));
   4. \( J^N(x^{(s)} + \Delta x, x^{(t)}) = \frac{1}{2} \left\| F^N(x^{(s)} + \Delta x) - F^N(x^{(t)}) \right\|_2 \);
   5. \( g_{N+1} = \mu \cdot g_N + \nabla_{x^{(s)} + \Delta x} J^N(x^{(s)} + \Delta x, x^{(t)}) \);
   6. \( x^{(s)} + \Delta x_{N+1} = C_{x^{(s)}, x^{(t)}}(x^{(s)} + \Delta x_N + \text{sgn}(g_{N+1})) \);
3. end

Output: Adversarial example \( x_{\text{adv}} = x^{(s)} + \Delta x_{N_{\text{max}}} \).

Algorithm 2: DFANet-DI-M-FIM

Input: The face pair \( \{x^{(s)}, x^{(t)}\} \), maximum deviation of perturbations \( e \), maximum iterative steps \( N_{\text{max}} \), decay factor \( \mu \), stochastic image transform function \( T(x; p) \), dropout probability \( p_d \).

1. Initialize: \( \Delta x_0 = 0, g_0 = 0, N = 0 \);
2. while step \( N < N_{\text{max}} \) do
   3. Generate DFANet \( F^N(x) \) of the \( N \)-th step (with \( p_d \));
   4. \( J^N(x^{(s)} + \Delta x, x^{(t)}) = \frac{1}{2} \left\| F^N(x^{(s)} + \Delta x) - F^N(x^{(t)}) \right\|_2 \);
   5. \( g_{N+1} = \mu \cdot g_N + \nabla_{x^{(s)} + \Delta x} J^N(T(x^{(s)} + \Delta x, x^{(t)}) \cdot x^{(t)}) \);
   6. \( x^{(s)} + \Delta x_{N+1} = C_{x^{(s)}, x^{(t)}}(x^{(s)} + \Delta x_N + \text{sgn}(g_{N+1})) \);
3. end

Output: Adversarial example \( x_{\text{adv}} = x^{(s)} + \Delta x_{N_{\text{max}}} \).

Algorithm 3: DFANet-E-DI-M-FIM

Input: The face pair \( \{x^{(s)}, x^{(t)}\} \), maximum deviation of perturbations \( e \), maximum iterative steps \( N_{\text{max}} \), decay factor \( \mu \), stochastic image transform function \( T(x; p) \), dropout probability \( p_d \), ensemble weight \( w_k \) (\( K \geq 0 \), \( K \) deep face models \( F_k(\cdot) \), \( \sum_{k=1}^{K} w_k = 1 \)).

1. Initialize: \( \Delta x_0 = 0, g_0 = 0, N = 0 \);
2. while step \( N < N_{\text{max}} \) do
   3. while model \( k < K \) do
      4. Generate DFANet \( F^N_k(x) \) of the \( N \)-th step and the \( k \)-th model (with \( p_d \));
   5. end
   6. \( J^N_k(x^{(s)} + \Delta x, x^{(t)}) = \frac{1}{2} \left\| F^N_k(x^{(s)} + \Delta x) - F^N_k(x^{(t)}) \right\|_2 \);
   7. \( g_{N+1} = \mu \cdot g_N + \nabla_{x^{(s)} + \Delta x} J^N_k(T(x^{(s)} + \Delta x, x^{(t)}) \cdot x^{(t)}) \);
   8. \( x^{(s)} + \Delta x_{N+1} = C_{x^{(s)}, x^{(t)}}(x^{(s)} + \Delta x_N + \text{sgn}(g_{N+1})) \);
3. end

Output: Adversarial example \( x_{\text{adv}} = x^{(s)} + \Delta x_{N_{\text{max}}} \).

as DFANet-DI-M-FIM and is shown in Algorithm 2. In Algorithm 2 \( T(x; p) \) is the stochastic image transform function (e.g., resizing, cropping and rotating), creating diverse input patterns to improve the transferability:

\[
T(x; p) = \begin{cases} 
T(x) \text{ with probability } p \\
 x \text{ with probability } 1 - p 
\end{cases}
\]

Finally, we describe the most complex one: the combination of DFANet, model ensemble method, diverse input method, the momentum boosting method, and FIM, referred to as DFANet-E-DI-M-FIM. Algorithm 3 details DFANet-E-DI-M-FIM, where instead of optimizing a single face model \( J \) we apply model ensemble method by attacking \( K \) models. In addition, the feature loss functions in Line 4 of Algorithm 1 Algorithm 2 and Line 6 of Algorithm 3 can be replaced as those for positive pairs, but for convenience, we input negative pairs as examples here.

IV. EXPERIMENTS

In this section, we first explore applicable strategies of adversarial attacks towards deep face models, from label-level attacks to feature-level attacks to select a baseline method for further study. Then we conduct experiments on state-of-the-art face models with various training databases, training loss functions and network architectures to evaluate the proposed DFANet. Finally, we apply the DFANet to the LFW database and generate new face pairs with adversarial perturbations, called the TALFW database. We use the LFW and TALFW databases to evaluate the robustness of mainstream open-sourced deep face models, commercial APIs and defensive methods.

A. Experimental Settings and Evaluation Protocol

We use target adversarial examples to evaluate transferability since target attacks are more difficult to transfer between deep models [17]. (1) First, we selected 100 source images from MS-Celeb-1M [32] and 100 target images from VGGFace2 [34] to generate 10,000 pairs, which are originally judged as negative pairs. Some of the source and target images are shown in Fig. 2 where the first line shows the source images, the second line shows the corresponding adversarial examples generated by DFANet-E-DI-M-FIM, and the third line shows target images. Therefore, the goal of the attack is to generate adversarial examples from the source images to be disguised as target ones. Specifically, the goal is to obtain face embedding representations of source images closer to those of target images than the distance threshold of a face recognition system. (2) Next, we define the threshold \( t_m \) of a face model \( m \). Using 6,000 face pairs from the LFW database [38], we compute the Euclidean distance of normalized deep features to obtain ROC curves. Then we identify distance thresholds for judging whether a pair is positive or negative. Since we would like to compare the adversarial robustness of the trained models with real-world applications, we define the distance threshold for attacking (or distinguishing a positive and a negative pair) to have a low false acceptance rate (FAR = 1e-3). An attack is defined as a success (hit) if the embedding
distance between the source image and target is less than the threshold. We use the average hit rate of the \( N_p = 10,000 \) face pairs to report the transferable attack success (hit) rate:

\[
\text{Hit Rate} \, (\%) = 100 \times \frac{1}{N_p} \sum_{i=1}^{N_p} \mathbb{I}\left[ \| F(x_i^{(s)}) - F(x_i^{(t)}) \|_2 < \tau_m \right]
\]

(15)

The higher the hit rate is, the stronger the transferability of the attack.

To simulate potential scenarios, we aim to increase the difference between the source and target models by attacking deep face models with different training datasets, training loss functions, and network architectures. The first setting is attacks between models with different training databases. Specifically, we use the four mainstream training databases in the deep face recognition literature, namely, CAISA-WebFace [33], MS-Celeb-1M [32], VGGFace2 [34], and IMDb-Face [35], to train a modified version [7] of a ResNet-50 [36] model supervised by softmax loss. The statistics for the four training databases are listed in Table A1. The second setting is attacks between models with different training loss functions. We use the softmax loss, triplet loss [4], CosFace [6] and ArcFace [7] in the experiment. Then the third setting is attacks between models with different architectures. We use the modified version [7] of ResNet [36], the modified version [7] of squeeze-and-excitation Network (SENet) [39], MobileNet [37], and Inception-ResNet [38]. To keep it simple, we refer to the modified version [7] of ResNet and SENet with 50 layers as ResNet-50 and SENet-50; both use IR blocks [7]. The recognition performance of these models is listed in Table A2.

**B. Experiments for the Baseline Method**

To explore adversarial attacks against deep face models and find a baseline method for further study on transferability enhancement methods, we compare the attack performance of applicable adversarial attacks towards deep face models including label-level and feature-level attacks.

We use FTGSM and ITGSM to generate label-level adversarial examples and FFM and FIM to generate feature-level adversarial examples. Since we introduced the feature level in detail earlier, let us clarify something noticeable in the label-level attacks in deep face recognition. In label-level attacks, several gradient-based generative strategies, including FGSM [16], FTGSM [44], BIM [44], and ITGSM [44] have been proposed in the literature. However, in the deep face recognition, test identities are usually different from those in the training databases. We actually cannot always use \( y^{(s)} \) and \( y^{(t)} \) for comparison. Therefore, first, we forward propagate the input images and output the obtain the output labels \( l(x^{(s)}) \) and \( l(x^{(t)}) \). In the following label-level adversarial attacks, we use \( l(x^{(s)}) \) and \( l(x^{(t)}) \) to replace \( y^{(s)} \) and \( y^{(t)} \) in FTGSM (Equation (2)) and ITGSM (Equation (4)). Specifically, the maximum deviation of perturbations \( \epsilon \) is set to 10. Correspondingly, the number of iterations for ITGSM and FIM are chosen to be \( 13 \). We use four aforementioned deep face models trained on different training databases.

The experimental results are shown in Table I. In terms of the transferability of the black-box attacks, feature-level attacks (FFM and FIM) are much more effective than label-level attacks (FTGSM and ITGSM) at the same constraint level. In fact, the lack of accurate labels and the large number of categories not only increase the difficulty of label-level attacks but also reduce the similarity between the source and target models. Instead, the embedding space of deep face models share more similarities, which benefits the transferability of adversarial attacks. These properties may explain why feature-level attacks are more transferable than label-level attacks to some extent. In addition, for both label-level and feature-level attacks, iterative methods (ITGSM, FIM) are much more effective than fast methods (FTGSM, FFM) at the same constraint level. Taken together, we choose FIM as the baseline method in the following experiments.

**C. Strong Baseline and DFANet**

As Table I shows, with the basic iterative label-level and feature-level method, it is still hard to guarantee the consistent success of transferable adversarial attacks against deep face models. Therefore, we intend to incorporate the transferability enhancement method [17], [19], [20] into the baseline method, FIM, to serve as a strong baseline. In addition, we propose a new DFANet method to further improve the transferability.

Apart from deep face models trained on different training databases, we also experiment using deep face models trained with different loss functions and network architectures. We first extend attack methods from FIM to DFANet-FIM, from M-FIM to DFANet-M-FIM, and from Di-M-FIM to DFANet-DI-M-FIM. Specifically, the maximum deviation of perturbations \( \epsilon \) is set to 10. For integrating momentum terms, the decay factor \( \mu \) is set to 1. For the method of incorporating diverse input patterns, we introduce several transformations including translation, rotation and scaling. The transformation probability \( p \) is set to 1 as in the original paper to reach the maximum transferability. In addition, we also try adding Gaussian noise but it has little effect. For the proposed DFANet, the maximum
Iterative step $N_{max}$ is set to 1,500, the drop rate $p_d$ of ResNet-50 and SENet-50 model is set to 0.1. $p_d$ of MobileNet model is set to 0.025 and $p_d$ of Inception-ResNet model is set to 0.05. We will discuss the effects of hyperparameters $p_d$ and $N_{max}$ in the following experiments. The experimental results from FIM to DFANet-FIM, from M-FIM to DFANet-M-FIM, and from DI-M-FIM to DFANet-DI-M-FIM are listed in Table I, Table II and Table V. We can see a constant improvement, from FIM to DFANet-FIM, from M-FIM to DFANet-M-FIM, and from DI-M-FIM to DFANet-DI-M-FIM in terms of the hit rate between deep face models trained with different loss functions and network architectures. Compared with the strong baseline DI-M-FIM, DFANet-DI-M-FIM still achieves significant improvement. In addition, compared with the initial FIM, most of the successful hit rates of adversarial examples generated by DFANet-DI-M-FIM between the four models have been improved to approximately 90%.

Furthermore, to evaluate the ability of DFANet to enhance the model ensemble method, we generate adversarial examples using E-DI-M-FIM and DFANet-E-DI-M-FIM, and apply this attacks towards a commercial API, Face++ [28]. Specifically, we generate three groups of attacks: the first group combines three ResNet-50 models trained on WebFace and supervised by the softmax loss, CosFace, and ArcFace, and the second and third groups use the VGGFace2 and MS1M models respectively, with these three loss functions. The other parameters are set as above. We input the generated face pair to Face++, and the API returns both the similarity of this pair and the output information as aforementioned, we can calculate the success (hit) rate as before. We list the results in Table V from which we can see that with the combination of DFANet, the transferability of adversarial attacks generated from E-DI-M-FIM can be improved further. Above all, the exten-
TABLE IV
EVALUATION TRANSFERABILITY ENHANCEMENT METHODS FROM FIM TO DFANET-FIM, FROM M-FIM TO DFANET-M-FIM, AND FROM DI-M-FIM TO DFANET-DI-M-FIM. THE METHODS ARE EVALUATED BY THE SUCCESS (HIT) RATE OF THE ADVERSARIAL EXAMPLES BETWEEN FOUR DEEP FACE MODELS (TRAINED ON CAISA-WEBFACE) USE THE SOFTMAX LOSS WITH DIFFERENT NETWORK ARCHITECTURES INCLUDING RESNET-50 [36], SENET-50 [39], MOBILENET [37], AND INCEPTION-RESNET [35]).

| Method | Src | Tar | ResNet-50 | SENet-50 | MobileNet | Incep-ResNet |
|--------|-----|-----|-----------|---------|-----------|-------------|
| FIM    |     |     | 39.91%    | 13.46%  | 11.62%    |             |
|        | ResNet-50 | / | 52.17%    |         | 18.49%    | 15.32%      |
|        | SENet-50  | / | 12.92%    |         | 12.76%    | 4.09%       |
|        | MobileNet | / | 18.54%    | 17.84%  | 9.32%     | /           |
|        | Incep-ResNet | / | 90.56%    | 67.51%  | 54.20%    |             |
| DFANet-M-FIM | ResNet-50 | / | 88.62%    | 49.59%  | 36.62%    |             |
|        | SENet-50  | / | 36.28%    |         | 36.38%    | 11.74%      |
|        | MobileNet | / | 41.50%    | 40.66%  | 23.57%    | /           |
|        | Incep-ResNet | / | 99.17%    | 92.41%  | 86.14%    |             |
| M-FIM  | ResNet-50 | / | 77.48%    |         | 37.51%    | 34.46%      |
|        | SENet-50  | / | 32.82%    |         | 33.80%    | 13.52%      |
|        | MobileNet | / | 35.89%    |         | 36.34%    | 20.18%      |
|        | Incep-ResNet | / | 98.24%    | 78.58%  | 67.79%    |             |
| DFANet-M-FIM | ResNet-50 | / | 62.14%    | 64.45%  | 27.78%    |             |
|        | SENet-50  | / | 62.15%    | 62.92%  | 41.59%    | /           |
|        | MobileNet | / | 85.16%    | 83.59%  | 65.03%    | /           |
|        | Incep-ResNet | / | 99.53%    | 94.22%  | 88.41%    |             |
|        | ResNet-50 | / | 99.68%    | 92.77%  | 87.61%    |             |
|        | SENet-50  | / | 83.94%    |         | 87.30%    | 54.24%      |
|        | MobileNet | / | 90.17%    |         | 92.01%    | 64.80%      |
|        | Incep-ResNet | / | 89.89%    | 88.56%  | 73.44%    | /           |
| DLM-FIM | ResNet-50 | / | 98.56%    | 84.16%  | 78.14%    |             |
|        | SENet-50  | / | 99.02%    |         | 85.56%    | 77.95%      |
|        | MobileNet | / | 99.96%    |         | 87.30%    | 54.24%      |
|        | Incep-ResNet | / | 83.61%    | 83.59%  | 65.03%    | /           |
|        | ResNet-50 | / | 99.68%    | 92.77%  | 87.61%    |             |
|        | SENet-50  | / | 90.02%    |         | 94.22%    | 88.41%      |
|        | MobileNet | / | 92.07%    |         | 92.01%    | 64.80%      |
|        | Incep-ResNet | / | 89.89%    | 88.56%  | 73.44%    | /           |

TABLE V
EVALUATION TRANSFERABILITY ENHANCEMENT METHODS FROM E-DI-M-FIM TO DFANET-E-DI-M-FIM. THE METHODS ARE EVALUATED BY THE TRANSFERABLE ADVERSARIAL SUCCESS (HIT) RATE OF ADVERSARIAL EXAMPLES ON FACE++.

| Method | Surrogate Models | Hit Rate@FAR |
|--------|------------------|-------------|
|        |                  | 1e-5 | 1e-4 | 1e-3 |
| E-DI-M-FIM | ResNet-50,WebFace(softmax,CosFace,ArcFace) | 51.90% | 67.20% | 80.50% |
| E-DI-M-FIM | ResNet-50,WebFace(softmax,CosFace,ArcFace) | 56.70% | 69.80% | 83.80% |
| E-DI-M-FIM | ResNet-50,VGGFace2(softmax,CosFace,ArcFace) | 67.19% | 76.99% | 86.49% |
| E-DI-M-FIM | ResNet-50,VGGFace2(softmax,CosFace,ArcFace) | 71.29% | 80.50% | 88.30% |
| E-DI-M-FIM | ResNet-50,MSTIM(softmax,CosFace,ArcFace) | 68.50% | 76.29% | 83.59% |
| E-DI-M-FIM | ResNet-50,MSTIM(softmax,CosFace,ArcFace) | 73.70% | 81.69% | 88.40% |

We then study the influence of the maximum number of iterations $N_{\text{max}}$ on the success (hit) rates. We generate transferable adversarial examples of ResNet-50 model trained

Fig. 3. The success (hit) rates of the transferable adversarial attacks when varying the drop rate $p_d$. The adversarial examples are generated from model by DFANet-DI-M-FIM. Note that DFANet-DI-M-FIM degrades into DI-M-FIM when the drop rate is $p_d = 0$. The source models are trained on different architectures: MobileNet, ResNet-50, SENet-50, and Inception-ResNet.

We first study the influence of the drop rate $p_d$ on the success (hit) rates. We generate transferable adversarial examples of the four models trained on WebFace supervised by the softmax loss, with different architectures, namely, ResNet-50, SENet-50, MobileNet and Inception-ResNet, using DFANet-DI-M-FIM. We set the maximum number of iterations $N_{\text{max}}$ to 1500 and then change the drop rate $p_d$. Note that DFANet-DI-M-FIM degrades into the baseline method, DI-M-FIM, when the drop rate is $p_d = 0$. The results are shown in Fig. 3. We find that the success (hit) rate first increases and then decreases with increasing the drop rate $p_d$. This finding indicates that a certain degree of randomness incorporated into the convolutional layers would help, but applying excessive randomness would have a negative effect. The optimal drop rate $p_d$ may vary across different architectures. In addition, the change curves of similar architectures ResNet-50 and SENet-50 are also similar.

D. Ablation Studies

We conduct ablation experiments to study the impact of hyperparameters including the drop rate $p_d$ and the maximum number of iterations $N_{\text{max}}$, for a better understanding of the proposed DFANet.
on WebFace supervised by the softmax loss, using FIM, M-FIM, DI-M-FIM and DFANet-DI-M-FIM. Since we find that the optimal value of the drop rate $p_d$ for ResNet-50 is approximately 0.1, we maintain it as 0.1 and then change the maximum number of iterations $N_{\text{max}}$ from 13 to 1500. The experimental results are shown in Fig. 4. We see that, the success (hit) rates for both DI-M-FIM and DFANet-DI-M-FIM improve as the maximum number of iterations $N_{\text{max}}$ increases. Although at the beginning, the success (hit) rate of DFANet-DI-M-FIM is lower, it gains more improvements and outperforms DI-M-FIM as $N_{\text{max}}$ increases. In addition, the trends in FIM and M-FIM are different from those in DI-M-FIM and DFANet-DI-M-FIM, where as the maximum number of iterations $N_{\text{max}}$ increases, the success (hit) rate remains almost unchanged. It is not hard to see the reason that, with more iterations, the proposed method could further increase the diversity of the generated DFANet models and obtain better ensemble effects.

### E. Discussion

To achieve more intuitive understanding of the transferable adversarial attacks and the proposed DFANet, we next interpret the intermediate generation process of adversarial example.

Since for deep face recognition, positive and negative pairs are judged according to the distances between their deep features, we observe the Euclidean distance of the normalized deep features in the generation process, which is also the objective loss function of feature-level attacks (referred to Equation (7)) [8]. First, we pick 100 face pairs randomly from the aforementioned 10,000 face pairs. Then, we generate adversarial examples from the ResNet-50 model trained on WebFace supervised by the softmax loss, using FIM, M-FIM, DFANet-FIM, DI-M-FIM and DFANet-DI-M-FIM. At the end of each iteration, we extract the deep features of the source model and three other target models, which are three ResNet-50 models trained on IMDb-Face, VGGFace2, MS1M and supervised by the softmax loss. For both source model and target models, as the number of iterations increases, we record the average normalized Euclidean distances of the 100 face pairs, as shown in Fig. 5.

We can see two phenomena from the figure. (1) We first focus on the average normalized Euclidean distances of the source model. For FIM and M-FIM, the average normalized Euclidean distances of the source models decrease constantly as the number of iterations increases. For DFANet-FIM, DI-M-FIM and DFANet-DI-M-FIM, although in the long term, the average normalized Euclidean distances of the source model decrease overall as the number of iterations increases; there are high fluctuations of these distances in a short term. The fluctuations reflect the ensemble effects of the DFANet and DI method. DFANet obtain diversity of different surrogate models generated by dropout, while the DI method obtains diversity of the input images, which both lead to a variety of gradients and therefore prevent overfitting to the single-source model. (2) In the figure, there exists a gap between the average normalized Euclidean distances for source models and those for target models under any method. We can see that for DFANet-DI-M-FIM, the performance of the source model is almost consistent with that of the target models, which reflects the advantage of the combination of DFANet and the strong baseline method, because the smaller these gaps are, the more transferable the generated adversarial examples are.

**Fig. 5.** The average Euclidean distance of normalized deep features of 100 face pairs as the number of iterations increases. We provide two types of deep features: one type is extracted from the source model, while the other one is extracted from three target models. The adversarial examples are generated by FIM, M-FIM, DFANet-FIM, DI-M-FIM and DFANet-DI-M-FIM.

### F. TALFW Database

We have thoroughly investigated adversarial attack methods against deep face recognition in this paper. With the help of transferability enhancement methods, the success (hit) rate can be as high as almost 90%, which should raise security concerns for deep face models. Therefore, we aim to build a test benchmark to facilitate research on the robustness and generalization of face recognition. The Labeled Faces in the Wild (LFW) [8] database is a well-known test benchmark in the deep face recognition literature. Although the performance on the LFW database has been saturated, due to its ease of use and popularity, there may be a potential possibility for it to become an appropriate baseline for studying the robustness issue. In this section, based on the aforementioned transferable adversarial attack methods, we create the Transferable Adversarial LFW (TALFW) database by adding noise imperceptible to human to the original LFW images. Since the only difference is the imperceptible noise, the evaluation protocol of TALFW is exactly the same as that of LFW, which will make it an easy-to-use and outstanding test database for the community.

Based on the aforementioned methods, we modify the original Labeled Faces in the Wild (LFW) [8] database using our private models. This modified database could be used to evaluate the robustness of mainstream open-sourced deep face models and commercial APIs. The original LFW database contains 13,233 face images of 5,749 identities. In the recent literature, the LFW database has been widely used to evaluate the performance of deep face models by testing on 3,000

[http://www.whdeng.cn/TALFW/index.html](http://www.whdeng.cn/TALFW/index.html)
Fig. 6. Ten positive (left) and ten negative (right) pairs in the TALFW database. The similarity scores of commercial APIs, namely, Amazon [25], Microsoft [26], Baidu [27] and Face++ [28] are also listed. The modification is nearly imperceptible (1.34 ± 0.32, measured by the root mean squared deviation) to humans but can change the face similarity scores significantly in the black-box setting without queries.
positive and 3,000 negative face pairs, which involve 7,701 face images. Therefore, considering the evaluation protocol of the LFW database, the principal is to modify the face image in the pixel space slightly while significantly change the similarity of the corresponding face pairs in the deep feature space of unknown models.

The steps to set up the Transferable Adversarial Labeled Faces in the Wild (TALFW) database are as follows. First, based on the greedy algorithm, we choose the minimum number of candidate face images to cover the maximum number of face pairs. Then we modify the candidate images in an imperceptible way. Apart from the aforementioned transferable attack methods, we also use some techniques to reduce the visual impact of the modification. In total, 4,069 face images are modified and compared with the original LFW database which has 3,000 positive and 3,000 negative face pairs. The average perturbation is only $1.34 \pm 0.32$, measured by the root mean squared deviation. Additionally, we evaluate the robustness of the four commercial APIs and four state-of-the-art (SOTA) open-sourced models on the TALFW database and the original LFW database. Fig. 6 shows ten positive (left) and ten negative (right) face pairs in the TALFW database. We also list the similarity score of the four commercial APIs: Amazon [25], Microsoft [26], Baidu [27] and Face++ [28]. From the figures, the modification is nearly imperceptible to humans but can change the face similarity score significantly in the black-box setting without queries.

We first test open source models of SOTA algorithms, i.e., the center-loss [3], SphereFace [4], VGGFace2 [34] and ArcFace 7. The ArcFace (ResNet-100) model has reported SOTA performance on several benchmarks including YTF, MegaFace challenge, and IJB-C 7. We use MTCNN for face detection and strictly follow the preprocessing steps of the original algorithms. Compared with the original images in the LFW database, the perturbed images in the TALFW database have no influence on the accuracy and reliability of face detection. The accuracy of open-sourced models of the four SOTA algorithms on the LFW and TALFW databases is listed in the first cell of Table VI. From the experimental results, there indeed exists a striking gap between the accuracy on the LFW and TALFW databases, which reflects that even the SOTA algorithms for deep face recognition are extremely vulnerable to transferable attacks.

Then we tested LFW and TALFW on the commercial APIs including Amazon [25], Microsoft [26], Baidu [27] and Face++ [28]. Specifically, since the TALFW database is generated based on transferability, we obtain the similarity score only by once calling without any query feedback. We also have no knowledge about the whole pipelines of the commercial APIs. We only need to give the original images in both the LFW and TALFW database to the commercial APIs directly without any image preprocessing, and then we get the similarity score. The performance of the four commercial APIs on the LFW and TALFW databases is listed in the second cell of Table VI. All the commercial APIs deteriorate seriously when transferring from the LFW database to the TALFW database, which reflects the idea that transferable adversarial attacks seriously threaten commercial face APIs.

Furthermore, we test some defensive methods including JPEG encoding [44], Gaussian blur [44], and adversarial training [40]. The compared no-defense model is a ResNet-50 [36] model trained on MSIM with ResNet-100 supervised by ArcFace, and a defensive method by adversarial training [40].

![ROC Curves on LFW and TALFW](image)

**Fig. 7.** Comparison of the LFW and TALFW databases. We select some algorithms as example here: the fusion of commercial APIs (Amazon [25], Microsoft [26], Baidu [27] and Face++ [28]); the SOTA model trained on MSIM with ResNet-100 supervised by ArcFace; and a defensive method by adversarial training [40].

**Table VI**

| **Evaluation Results of the Commercial APIs, SOTA Algorithms and Defensive Models.** |
|---|---|---|
| **Model** | **LFW** | **TALFW** |
| **SOTA Algorithms** | | |
| Center-loss [3] | 98.78 | 70.65 |
| SphereFace [4] | 99.27 | 62.47 |
| VGGFace2 [34] | 99.43 | 71.47 |
| ArcFace (MobileNet) [7] | 99.35 | 50.77 |
| ArcFace (ResNet-100) [7] | 99.82 | 63.45 |
| **Commercial APIs** | | |
| Amazon [25] | 99.47 | 69.28 |
| Microsoft [26] | 98.12 | 70.93 |
| Baidu [27] | 97.72 | 72.07 |
| Face++ [28] | 96.95 | 73.90 |
| Fusion of four APIs | 99.65 | 72.33 |
| **Defensive Methods** | | |
| No Defense | 99.78 | 54.15 |
| JPEG Encoding [44] | 99.55 | 73.93 |
| Gaussian Blur [44] | 99.57 | 77.95 |
| Adversarial Training [40] | 99.62 | 82.17 |
For JPEG encoding, the JPEG quality is chosen to be level 20 (out of 100); and for the Gaussian blur, the kernel size is set to 5 with standard deviation 2. Adversarial examples incorporated into adversarial training are generated by FIM since they are more effective in face models than label-level methods. From the results, we find that compared with the original model, which only has 54.15% accuracy on the TALFW database, although defensive methods can improve the performance to different degrees, the performance gap between the LFW and TALFW databases still exists, which reflects the idea that transferable adversarial attacks could be alleviated but there is still plenty of scope to push the corresponding techniques further.

We have evaluated the robustness of mainstream open-sourced deep face models, commercial APIs and defensive methods on the LFW and TALFW databases. Some typical comparison ROC curves are selected in Fig. 7. Overall, the severe performance degradation from the LFW to TALFW databases clearly shows the vulnerability of deep face models.

V. CONCLUSION

As the recognition performance of deep face models improves, robustness and generalization have become increasingly essential and crucial. In this paper, we study applicable transferable adversarial attacks against deep face models. We first find a baseline method by exploring the attack methods from the label-level to the feature-level and demonstrate empirically that iterative feature-level attacks are more effective and transferable. We find that it is difficult to guarantee successful attacks on deep face models with basic iterative adversarial attacks. Therefore we study transferability enhancement methods and propose the DFANet method to further improve transferability by increasing the possible settings of the network parameters and combining the possible networks in the iterative steps. The experimental results demonstrate that the proposed method can be combined with various networks and existing transferability enhancement methods, which achieve effective black-box adversarial attacks against deep face models with different training databases, loss functions and network architectures. Based on the aforementioned study, we contribute a test database, TALFW, to help study the robustness and defensibility of deep face models. The hope is that TALFW database could raise much attentions from researchers and industries in a timely manner.

APPENDIX A

OTHER INFORMATION OF MODELS IN THE PAPER

The statistics for the four training databases are listed in Table A1.

We show the recognition performance of the face models in this paper in Table A2, where the recognition performance is evaluated on several popular benchmarks: LFW [8] and YTF [22]. LFW database contains 13233 face images from 5,749 different identities, which is popular and widely used for evaluation. YTF is a database of face videos collected from YouTube, which consists of 3,425 videos of 1,595 different people. We follow the unrestricted with labeled outside data protocol on these test databases.

| Table A1 | STATISTICS FOR TRAINING DATABASES INCLUDING CAISA-WebFace [33], MS-Celeb-1M [32], VGGFace2 [34], AND IMDb-Face [35]. Note that this IMDb-Face is an incomplete version, compared with 1.7M images in the original paper, because some of the image URLs throw a 404 error. MS-Celeb-1M is a refined version compared with the original one with 10M images. |
|---|---|---|---|
| database | Source | #Identities | #Images |
| CAISA-WebFace [33] | IMDb | 10,575 | 0.49M |
| IMDb-Face [35] | IMDb | 51,348 | 1.4M |
| VGGFace2 [34] | Search Engine | 9,131 | 3.3M |
| MS-Celeb-1M [32] | Search Engine | 84,164 | 3.8M |

| Table A2 | RECOGNITION PERFORMANCE ON LFW [8] AND YTF [22] OF DEEP FACE MODELS WITH DIFFERENT TRAINING DATABASES (CAISA-WebFace [33], MS-Celeb-1M [32], VGGFace2 [34], AND IMDb-Face [35]), LOSS FUNCTIONS (THE SOFTMAX LOSS, TRIPLET LOSS [38], COSFACE [8], AND ARFACE [7]) AND NETWORK ARCHITECTURES (THE MODIFIED VERSION [3] OF SQUEEZE-AND-EXCITATION NETWORK (SENET) [39], MOBILENET [37], AND INCEPTION-RESNET [38]). |
|---|---|---|---|
| Database | Face | LFW | YTF |
| ResNet-50, WebFace, Softmax | 99.25 | 94.74 |
| ResNet-50, IMDb-Face, Softmax | 99.53 | 96.66 |
| ResNet-50, VGGFace2, Softmax | 99.55 | 96.92 |
| ResNet-50, MS-1M, Softmax | 99.57 | 96.28 |
| Loss | ResNet-50, WebFace, Softmax | 99.25 | 94.74 |
| ResNet-50, WebFace, Triplet | 99.45 | 95.52 |
| ResNet-50, WebFace, ArcFace | 99.52 | 95.66 |
| ResNet-50, WebFace, CosFace | 99.53 | 95.76 |
| Architecture | MobileNet, WebFace, Softmax | 99.12 | 94.24 |
| ResNet-50, WebFace, Softmax | 99.25 | 94.74 |
| SENet-50, WebFace, Softmax | 99.13 | 95.20 |
| Inception-ResNet, WebFace, Softmax | 99.37 | 95.42 |

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