Threat of Adversarial Attacks on Face Recognition: A Comprehensive Survey

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Abstract

Face recognition (FR) systems have demonstrated outstanding verification performance, suggesting suitability for real-world applications ranging from photo tagging in social media to automated border control (ABC). In an advanced FR system with deep learning-based architecture, however, promoting the recognition efficiency alone is not sufficient and the system should also withstand potential kinds of attacks designed to target its proficiency. Recent studies show that (deep) FR systems exhibit an intriguing vulnerability to imperceptible or perceptible but natural-looking adversarial input images that drive the model to incorrect output predictions. In this article, we present a comprehensive survey on adversarial attacks against FR systems and elaborate on the competence of new countermeasures against them. Further, we propose a taxonomy of existing attack and defense strategies according to different criteria. Finally, we compare the presented approaches according to techniques’ characteristics.

Keywords: Face recognition, adversarial attacks, adversarial perturbation, deep learning.

Contents

1. Introduction .................................................................................................................................2
2. Terms and Definitions ...............................................................................................................5
3. Adversarial Attack Generation ................................................................................................6
   3.1. CNN Models-Oriented .........................................................................................................6
   3.2. Physical Attacks-Oriented ...................................................................................................8
   3.3. Facial Attributes-Oriented ................................................................................................11
   3.4. De-identification-Oriented .................................................................................................14
1. Introduction

Face recognition (FR) systems are becoming a prevalent authentication solution in the majority of access control applications. The goal of a typical FR system is to identify or verify a person from a digital image or a video frame taken from a video source. Researchers describe FR as a biometric artificial intelligence-based application that can exclusively identify a person through analyzing patterns of the person’s facial features. The idea of using the face as a biometric trait inspired in the 1960s and the design of the first successful FR system dates back to the early ‘90s [1]. In recent times, the latest advancements of deep learning, together with the use of mounting hardware and abundant data, have resulted in massive development in FR algorithms with the excellent performance [2–4]. This performance permits the broad deployment of FR technologies in further diverse applications, ranging from photo tagging in social media to dubious identification in automated border control (ABC) systems.

In an advanced FR model, however, promoting the recognition efficiency alone is not sufficient, and the system should also withstand potential kinds of attacks designed to target its proficiency. Recently, researchers found that (deep) FR systems are vulnerable against different types of attacks that create data variations to fool classifiers. These attacks can be accomplished either via (a) physical attacks, which modify the physical appearance of a face before image capturing, or (b) digital attacks, which implement modifications in the captured face image [5]. Presentation attacks also referred to as spoofing attacks [6], are one of the main techniques used for physical attacks. In contrast, adversarial attacks [7], as well as the variations resulting from morphing attacks [8], are some critical techniques utilized for the digital invasion. Note that adversarial attacks are mainly categorized in the class of digital attacks, but some methods of this
type are designed to accomplish physically. Among these, adversarial attacks are fascinating since they generally target deep neural networks (DNNs) and specifically focus on convolutional neural networks (CNNs), based on which the state-of-the-art FR models are established. The massive growth in the number of papers published each year in the field of adversarial example generation demonstrates the attractiveness of this type of attack (see Fig. 1).

An adversarial attack (or an adversarial perturbation), consists of finely modifying/perturbing an original image with the intention of the alterations/perturbations become almost imperceptible to the human eye, to fool a specific classifier. In the realm of digital attacks, this can be implemented as the addition of a minimal vector $n$ to the input image $x$, i.e. $(x + n)$, such that the deep learning model $\mathcal{F}$ predicts an incorrect output for the altered input $x + n$. As represented in Fig. 2, to fool the FR model (VGG16 in this case), the input images are perturbed in such a way that while the human can still forecast the correct class, the network will be confused and misled to the wrong category. Szegedy et al. [10] were the first to demonstrate the vulnerabilities of CNN models to adversarial attacks generated by the introduction of a minute noise in the input image. The accuracies of GoogLeNet [11] and VGG-Face [2] models also demonstrated to be degraded with color balance manipulation. Note that the invisibility of adversarial attacks and the widespread application of deep learning algorithms can cause severe damages in real-world scenarios [12]. For example, in self-directed driving, if the signboard is perturbed, adversarial examples can extremely threaten the car, pedestrians, and other automobiles.
Fig. 2: Visualization of original face image (first column), perturbation vector of VGG-16 (second column), and perturbed image (last column). From top to bottom, the four rows represent the addition of perturbation to the original RGB image and corresponding grayscale representations of R, G, and B color channels, respectively. Perturbation is magnified by a factor of 4 to enhance visibility [13].

Similarly, in the case of FR applications, the failure to verify the perturbed input could lead to the degraded performance that can take benefit in the closed-set verification scenarios.

This research presents a comprehensive survey on different techniques of adversarial attack generation intended to deceive FR systems, along with the potential countermeasures established against them. To the best of our knowledge, this is the first study that attempts to review adversarial attack and defense strategies on FR systems. As stated before, an FR system may refer to each of the two applications of face identification or face verification. In current work, we review both forms. The main contributions of this paper are:

- We review recent studies on adversarial example generation approaches on FR systems, present an illustrative taxonomy of the corresponding techniques, compare these approaches concerning techniques’ characteristics, and demonstrate a timeline of milestone studies that have created the impact.
- We review the new adversarial example detection methods regarding the FR systems, categorize the presented algorithms, and demonstrate a descriptive taxonomy of this classification.
The remainder of this paper is organized as follows: First, we describe the standard terms related to adversarial attacks and defenses in the context of the FR course in Section II. In Section III, we review adversarial attack generation methods intended to deceive the FR mission. We present primary categories of different adversarial example detection approaches along with corresponding studies in Section IV. Finally, we conclude in Section VI.

2. Terms and Definitions

In this section, we give a brief introduction to the standard terms related to adversarial attacks on (deep) FR models. Our definitions of words are essential to understand the technical components of the reviewed studies. The remainder of this article follows the same definitions of the terms.

- **General Terms**

  1) **Adversarial example/image**: An intentionally perturbed (e.g., by adding noise) version of a clean image to fool machine learning (ML) models, such as FR models.

  2) **Adversarial perturbation**: A kind of noise that is added to the clean image to make it an adversarial example.

  3) **Adversarial training**: A model training process that uses adversarial images along with clean images.

  4) **Adversary**: The agent who creates an adversarial example or the example itself, depending on the case study.

  5) **Targeted attacks**: A kind of attack which deceives a model into falsely predicting a specific label for the adversarial image. These attacks are opposite to the non-targeted attacks, which predict labels of the adversarial images irrelevantly, as long as the results are not the correct labels.

  6) **Transferability**: The ability of a perturbed example to continue to make an impact on the models other than the one employed to create it.

  7) **Universal perturbation**: A kind of disruption with the ability to fool a given model on ‘any’ image with high probability. Note that the universality itself refers to the characteristic of a perturbation to have a good transferability and
to be generated without knowing the underlying details of given images, i.e., to be ‘image-agnostic’.

- **Specific Terms**

  1) **Black-box attacks:** A kind of attack that feeds a target model with the adversarial examples (during testing) created without knowing that model (e.g., its training procedure or its architecture or its parameters).

  2) **Dodging attack:** A kind of attack in which the attacker tries to have a face misidentified as any other arbitrary face.

  3) **Evasion attack:** A kind of attack which seeks to evade the system by altering samples during the testing phase yet not influence the training data.

  4) **Impersonation attack:** A kind of attack that seeks to have a face misidentified as a specific another face.

  5) **Poisoning attack:** A kind of attack that takes place during the training time to contaminate the training data. In this attack, the attacker tries to poison data by inserting wisely designed samples to compromise the whole learning process ultimately.

  6) **White-box attacks:** A kind of attack that assumes the complete knowledge of the target model, i.e., its parameter values, architecture, training method, even in some cases, its training data.

3. **Adversarial Attack Generation**

Despite the high classification performance obtained by deep FR systems, they are highly susceptible to changes in the input space. A general taxonomy of existing adversarial attack generation techniques against FR systems is depicted in Fig. 3. These techniques are mainly classified into five categories, namely, (1) CNN models-oriented; (2) physical attacks-oriented; (3) facial attributes-oriented; (4) de-identification-oriented; and (5) geometry-oriented. The remainder of this section is structured according to this classification.

3.1. **CNN Models-Oriented**

As stated earlier, the deep learning paradigm has seen a remarkable propagation in FR mission. Several models, such as DeepFace [3], DeepID [14], and FaceNet [15] are successful
examples of deep-learning application in this regard. These models are deep CNN-based architectures with many hidden layers and millions of parameters designed to achieve very high accuracies when tested on different databases. While astonishing progress in the reported efficiencies of such models improves, they are shown to be susceptible to adversarial attacks. Realizing this, many researchers have started to design approaches to exploit the weaknesses of such algorithms investigating their robustness and revealing their singularities.

Goswami et al. [16] considered the vulnerability of several deep CNN-based FR algorithms in the presence of image processing-based distortions at (1) image-level and (2) face-level. They confirmed that attacks to systems do not need to be sophisticated learning-based. Instead, a random noise or even horizontal and vertical black grid lines drawn in the face image can drastically reduce the face verification accuracies. Dong et al. [17] evaluated the robustness of multiple advanced FR models, including SphereFace [18], CosFace [19], and ArcFace [20], in the decision-based black-box attack setting. They proposed an evolutionary attack algorithm, based on a simple and efficient variant of the covariance matrix adaptation evolution strategy (CMA-ES) [21], which is (1+1)-CMA-ES [22]. To accelerate this algorithm, they proposed to model the local geometry of the search direction and lessen the dimension of the search space. On the Labeled Faces in the Wild (LFW) [23] and MegaFace [24] datasets, the performance of the evolutionary attack method compared with the boundary attack method [25], optimization-based practice [26], and an
extension of NES in the label-only setting (NES-LO) [27]. Experiments showed that across both tasks of face verification and face identification, both attack settings of dodging and impersonation, and against all FR models, the proposed method could converge much faster and achieve smaller distortions compared with other methods consistently.

Zhong and Deng [28] explored the vulnerability of deep CNNs to transferable adversarial examples, spotting that feature-level attack methods are more effective and transferable than label-level ones. To promote the transferability of feature-level adversarial examples, they proposed a dropout-based technique, DFANet. They observed that this approach could significantly enhance the transferability of existing attack methods. Applying their practice on the LFW dataset, they generated a new set of adversarial face pairs that achieve operative black-box adversarial attacks against four commercial APIs. They made this TALFW database available to the public for future investigations. Recently, Goodman et al. [29] proposed a new Python-based toolbox, termed Advbox, to generate adversarial examples. With Advbox, it is possible to fool neural networks (NNs) in PaddlePaddle, PyTorch, Caffe2, MxNet, Keras, and TensorFlow, with the additional capability to benchmark the robustness of ML models. Compared to previous works, this platform supports new features of (1) black-box attacks on ML-as-a-service and (2) actual attack scenarios, such as FR attacks.

3.2. Physical Attacks-Oriented

Intruders to facial biometric systems often encountered with two kinds of challenges: (1) they do not have precise control over the FR systems’ (digital) input; instead, they may be able to control their physical appearance, and (2) by manipulating their appearances to evade recognition, e.g., with an excessive amount of makeup, they might be easily observed by traditional means like the police. In light of such challenges, a new class of adversarial attacks has emerged based on the physical state of the attackers.

Sharif et al. [30] developed a systematic method to generate a physically realizable yet inconspicuous class of attacks via printing a pair of eyeglass frames. Focusing on white-box attacks, they were able to evade recognition or impersonate other subjects by changing the test inputs. In [31], the authors defined generative adversarial nets (GANs) to attack VGG-Face and
OpenFace [32] models, on both digital and physical levels, for evasion purposes. The FR algorithms were targeted on the digital-level by traditional attacks, such as Szegedy’s L-BFGS method [10], and deceived on the physical-level by requesting individuals to wear their 3D printed sunglasses frames. Fig. 4 illustrates an example of an impersonation attack by wearing such an accessory.

Zhou et al. [33] designed a cap, mounting some penny size lit Infrared LEDs on the peak, to implement inconspicuous physical adversarial attacks. In this approach, the Infrared dots are directed on the strategic spots on the face of the carrier to alter the facial features subtly. The loss in this work is optimized by adjusting light spots in line with the model on the attacker’s photo. The attacker could either evade detection or impersonate a different person by adjusting the positions, sizes, and strengths of the dots. Using the LFW dataset, the effectiveness of the proposed technique was examined on the FaceNet FR system, demonstrating that a single attacker could successfully target over 70% of the people.

Motivated by the differences in image-forming principles between cameras and human eyes, Shen et al. [34] proposed a visible light-based attack (VLA) against black-box FR systems, where visible light-based adversarial perturbations are crafted and projected on human faces. According to their work, adversarial perturbation is decomposed into a perturbation frame and a concealing frame to add modifications to human facial images and make modifications inconspicuous to human eyes, respectively. Extensive experiments were conducted on the LFW dataset and against FaceNet, SphereFace, and dlib [35] FR systems to evaluate the success rate of the proposed method. As compared with the fast gradient sign method (FGSM) [36], the proposed approach demonstrated to achieve significantly higher success rates. Further experiments also revealed inconspicuousness and robustness of the adversarial examples crafted by VLA in physical
scenarios. In a similar study, Nguyen et al. [37] studied the feasibility of directing real-time physical attacks on FR systems by adversarial light projections, using a web camera and a projector. In this approach, the authors captured the facial image of the adversary with a camera and used one or more target images (1) to adjust the camera-projector setup according to the attack environment and (2) to create a digital adversarial pattern. The digital pattern is then projected onto the adversary’s face in the physical domain with a projector to either evade recognition or impersonate a target. Although the objectives of this work are identical to the infrared-based adversarial attacks proposed by Zhou et al. [33], this work does not necessitate the creation of a wearable artifact; thus, it offers a more comfortable alternative setup to direct physical attacks on FR systems. Experimental results on FaceNet, SphereFace, and one commercial FR system demonstrated the vulnerability of such models to light projection attacks in both white-box and black-box attack settings.

In another study, Komkov and Petiushko [38] proposed to target the public Face ID model LResNet100E-IR, ArcFace@ms1m-refine-v2 [39], by an easily reproducible adversarial attack generation method called AdvHat. They printed a rectangular paper sticker on a standard color printer and put it on the hat with an algorithm for off-plane transformations. The proposed algorithm split into two steps: (1) off-plane bending of the sticker, which is simulated as a parabolic transformation in the 3D space to map each point of the sticker to the new point on the parabolic cylinder, and (2) pitch rotation of the sticker, which is simulated by the application of a 3D affine transformation to the obtained new points. The authors projected the resulted sticker on the high-quality face image with small perturbations in the projection parameters. They transformed the new face image into the standard template of ArcFace input to pass it to the optimization step. Regarding the optimization step, the sum of two parameters is minimized to achieve the gradient signs used to modify the sticker image. These parameters are (1) total variation loss, or TV loss, of the original rectangular paper sticker, and (2) cosine similarity between two embeddings, one for the resulted face image of the attacker and another for the face image of the desired person calculated by ArcFace. On the CASIA-WebFace dataset, experimental results verified that such an approach can easily confuse LResNet100E-IR and is transferable to other Face ID models.

Similarly, Pautov et al. [40] examined the security of the same recognition system, LResNet100E-IR, and proposed to print, add (as face attributes) and photograph adversarial patches; the snapshot of the individual with such attributes is then delivered to the classifier to alter
the correctly recognized class to the desired one. In this work, patches could be either various parts of the attacker’s face, for instance, nose or forehead, or some wearable accessories like eyeglasses. On CASIA-WebFace dataset and photos of the first and second authors of this work as images of attackers, experiments showed that such a simple attacking technique could deceive the FR system not only in the digital domain but also in the physical world. In other words, the authors demonstrated that it is possible to attack ArcFace in the real world by the application of adversarial stickers on eyeglasses or forehead.

3.3. Facial Attributes-Oriented

Intensive research efforts, together with the use of deep learning models, have resulted in high performance for tasks tangled with face analysis. Though these high accuracies have led to several advantages, they also pose a threat to individuals’ privacy. For instance, numerous facial attributes, including age, gender, and race, can be predicted from social media images or directly from one’s profile. Motivated by the concern to protect individuals’ privacy, unusual attacks have been generated against face attributes. Take into account that the influence of facial attributes-oriented attacks on the FR task is somewhat different from other categories depicted in Fig. 3. This class of attack intends to protect identity. Therefore, the general goal is to accomplish the FR mission while anonymizing the desired attributes selectively.

Rozsa et al. [41] studied the stability of several deep learning methods against their crafted flipped-attribute adversarial images. Using the CelebA dataset [42], they presented that the fast flipping attribute (FFA) method could change the outcomes of facial attribute recognition while creating further adversarial examples than FGSM. A typical result of this effort is depicted in the top row in Fig. 5. With their newer layerwise origin-target synthesis (LOTS) technique [43], authors formed adversarial examples that mimic deep features of the target image. They demonstrated that biometric systems using such features accompanied by some distance metrics are more vulnerable to attacks as compared with end-to-end networks that straightly predict the output label. In another work [44], Rozsa et al. introduced the concept of natural adversarial examples and showed that with their FFA technique, these samples could be flipped to the proper classification. An example of this exertion is depicted in the bottom row in Fig. 5.

Mirjalili and Ross [45] followed this paradigm, proposing a technique that perturbs a face image so that its gender (using a gender classifier) is changed while its biometric efficiency (for a
face matching system) preserved. They used a warping technique to simultaneously modify a group of pixels, which formerly determined via Delaunay triangulation application on facial landmark points. Mirjalili et al. [46] extended this idea by putting forward a convolutional autoencoder, which could modify an input face image to protect the privacy of a subject. They suggested an adversarial training scheme that is expedited by connecting a semi-adversarial module of a supplementary gender classifier and a face matcher to an autoencoder. Authors further tackled the generalizability of the proposed semi-adversarial networks (SANs) through various arbitrary gender classifiers via (1) establishment of an ensemble SAN model, which generates a different set of modified outputs for an input face image [47], and (2) development of the FlowSAN method, which allows SANs to generalize to several unseen gender classifiers [48]. In the latter approach, a different set of SAN models is unified to recompense their overall weaknesses, thereby constructing a robust model.

In their newest effort, Mirjalili et al. [49] proposed a GAN-based SAN model, called PrivacyNet, which is further advanced to impart selective soft biometric privacy to several soft biometric attributes like gender, age, and race. They showed that PrivacyNet provides a condition for users to decide which attributes should be obfuscated and which ones should remain unchanged. To be more precise, authors used CelebA and MORPH [50] datasets for training the PrivacyNet model, and MUCT [51], RaFD [52], and UTK-face [53] datasets for evaluation.
purposes. The authors conducted three separate experiments to evaluate the performance of the proposed model against gender classification, race prediction, and age estimation. Regarding the gender attribute perturbation, the classification performance of a commercial-off-the-shelf gender predictor (G-COTS), IntraFace [54], and AFFACT [55] were measured on the original and perturbed outputs of the proposed model, using the equal error rate (EER). This experiment showed a significant increase in the value of EER of gender classification, when G-COTS software is used to predict gender perturbed outputs, and demonstrated the superior performance of the model compared with the reference works [56,57].

Regarding the race attribute perturbation, authors measured the EER of race classification similarly, using commercial-off-the-shelf race predictor (R-COTS). In this experiment, the EER values were increased considerably for CelebA and UTK-face datasets and enlarged to a lesser extent for MORPH and MUVT datasets. To evaluate the ability of PrivacyNet for confounding age information, the authors implemented a commercial-off-the-shelf age predictor (A-COTS). In this regard, mean absolute error (MAE) values, in units of years, were considered to measure the change in age prediction before and after perturbing the images. Results of age-prediction showed that the outputs’ MAE led to its highest value when the age of the face intended to be modified and remained low otherwise.

In parallel, Chhabra et al. [58] proposed an adversarial perturbation-based algorithm for anonymizing particular attributes, which an individual does not want to share. Experiments on three accessible databases of MUCT, LFW, and CelebA demonstrated that the proposed algorithm not only anonymizes k-attributes, such as ‘Gender,’ ‘Attractive,’ ‘Smiling,’ ‘Heavy Makeup’ and ‘High attractiveness’ but also preserves image quality and identity information. The application of makeup effect to face images can also generate adversarial examples. Zhu et al. [59] proposed a combination model of two GAN-based subnetworks, ‘Makeup Transfer Sub-network’ and ‘Adversarial Attack Sub-network,’ to alter non-makeup face images to makeup faces and hide attack information within makeup effect. Experimental results showed the capability of the proposed method in generating high-quality face makeup images and achieving high fooling rates on various FR models compared.

In contrast to above adversarial attacks that globally control the image pixel space, Joshi et al. [60] proposed to generate adversarial examples by modifying semantic attributes, such as existence/lack of eyeglasses, skin color, and shape of the nose. They called such adversarial examples semantic (natural), as they may be noticeable yet semantically meaningful, thus, hard to
identify. Authors focused on white-box attacks using a binary gender classifier as the target model and CelebA as the dataset. They trained a range of parametric models, such as Fader Networks [61] and Attribute GANs (AttGAN) [62], and demonstrated that with such models, they were able to fulfill their goal. Regarding Fader Networks, authors constructed three approaches to generate semantic adversarial examples: (1) a single attribute Fader Network; (2) a multi-attribute Fader Network; and (3) a cascaded sequence of single attribute Fader Networks. For the latter parametric models, they only considered a multi-attribute AttGAN implementation. Experimental results showed that adversarial Fader Networks successfully generate examples that confound the binary classifier in all cases. Likewise, the evaluations revealed a significant improvement in the multi-attribute AttGAN performance as the number of semantic attributes increased. Authors also compared semantic attacks with the state-of-the-art Carlini-Wagner (CW) $l_{\infty}$-attack [63], as well as several other attack generation methods [12,36,64]. They concluded that even though the CW attack is tremendously effective, semantic attacks are the second-best competitor methods, which could significantly outperform other attack generation methods like FGSM and projected gradient descent (PGD) [65]. In a similar study, Qiu et al. [66] proposed SemanticAdv to generate adversarial examples via attribute-conditioned, or semantically meaningful, image editing, based on feature-space interpolation. The authors demonstrated that their proposed SemanticAdv enables fine-grained DNNs analysis and evaluation with input variations in the attribute space. They noticed the high attack transferability and high query-free black-box attack success rate of this approach on a real-world face verification platform. They also claimed that both per-pixel-based and attribute-based detection methods fail to defend against their proposed SemanticAdv.

3.4. De-identification-Oriented

Since the face as a biometric tool has achieved high acceptance, much effort has been made to develop its security. In return, smart adversaries aim to deny service to authentic users or let impostors evade the FR system. Considering this fact, researchers focused on the security aspect of face authentication systems.

Garofalo et al. [67] deployed a poisoning attack against an authentication system based on the OpenFace recognition framework. They implemented the attack against the underlying support vector machine (SVM) model used to classify face templates extracted by the FaceNet model. Within their evaluation framework, the most successful attacks triggered an authentication error of more than 50%. Chatzikyriakidis et al. [68] proposed to utilize adversarial examples in cases of
face de-identification. They introduced a penalized fast gradient value method (P-FGVM) adversarial attack technique, which runs on the image spatial domain and generates adversarial de-identified facial images similar to the original ones. This technique is inspired by the fast gradient value method (I-FGVM), with a minor exception of combining an adversarial loss and a ‘realism’ loss term in its gradient descent update equations. The proposed P-FGVM method was evaluated on two CNN-based face classifiers: (1) a simple architecture model and (2) a fine-tuned model with transfer learning, based on the pre-trained VGG-Face CNN descriptor, using the VGG-16 architecture [69]. Comparing with the baseline I-FGVM, against the face classifiers described above, and on a subset of the CelebA dataset, the authors demonstrated that the P-FGVM method both protects the privacy and preserves visual facial image quality more efficiently.

Lately, Kwon et al. [70] proposed to generate face friend-safe adversarial examples, aiming to be misrecognized by an enemy FR system, nonetheless, appropriately recognized by friend FR system with least distortion. The proposed method consists of a transformer, a friend classifier $M_{friend}$, and an enemy classifier $M_{enemy}$, to generate adversarial face images. Considering the FaceNet recognition system as a target model, authors trained their method on VGGFace2 [71] and tested it on the LFW dataset. They evaluated the efficiency of the proposed method by measuring the attack success rate of the enemy classifier, the accuracy of the friend classifier, and the average distortion. The reported attack success rate of 92.2% for the enemy classifier, the accuracy of 91.4% for the friend classifier, and minimum distortions of 64.22 demonstrated that the objectives of this work could be accomplished.

3.5. Geometry-Oriented

Prevalent intensity-based adversarial attack methods, which manipulate the intensity of input images directly, are computationally cheap but sensitive to spatial transformations. In these methods, a small rotation, translation, or scale variation in the input image, could result in a drastic change in similarity. Due to this limitation, a new class of attacks initiated to generate geometry-based adversarial examples.

Dabouei et al. [72] proposed a fast landmark manipulation approach to craft adversarial faces almost 200 times quicker than the other geometric attacks which use L-BFGS optimization. They proposed to generate adversarial examples by spatially transforming original images. contrast with the reference work [73], which fulfills this purpose by defining a flow (displacement)
field $f$ for all pixel locations in the input image, in this work, authors defined $f$ only for $k$ landmarks. They computed the corresponding location of landmarks in the adversarial image by the displacement field. The gradients of the classification loss concerning the landmark locations are then employed iteratively to update the displacement field for generating the adversarial face images. The authors referred to this approach as the fast landmark manipulation method (FLM). They also proposed grouped fast landmark manipulation method (GFLM) to semantically group landmarks and manipulate the group properties instead of perturbing each landmark. This idea was formed to resolve severe distortion of the adversarial faces generated by FLM and to preserve the whole structure of the created images. Training FaceNet model on VGGFace2 and CASIA-WebFace [74] datasets and evaluating its performance on CASIA-WebFace dataset, experiments represented that both the FLM and GFLM could generate powerful adversarial face images that fool the classifier for more than 99.86% of the samples. Fig. 6 demonstrates an overview of the fast geometry-based adversarial attack proposed by Dabouei et al. [72].

Song et al. [75] focused on attacks that mislead the FR networks to detect someone as a target person, not misclassify inconspicuously. They introduced an attentional adversarial attack generative network ($A^3$GN) to generate adversarial examples similar to the original images while having the same feature representation as to the target face. To capture semantic information of the target person, they appended a conditional variational autoencoder and attention modules to
learn the instance-level correspondences between faces. The proposed network was trained on CASIA-WebFace and evaluated on LFW. Comparing with the previous works, stAdv [73] and GFLM [72], this approach achieved a satisfactory attack success rate. Overall, the authors demonstrated the excellent performance of A^3GN by a set of evaluation criteria in physical likeness, similarity score, and accuracy of recognition on different target faces.

Utilizing GANs, Deb et al. [76] crafted natural face images with a barely distinguishable difference from target face images. They proposed AdvFaces adversarial face synthesis method to craft minimal perturbations in the prominent facial regions. This method comprises a generator, a discriminator, and a face matcher to automatically generate an adversarial mask, which is added to the image to obtain an adversarial face image. Training AdvFaces on CASIA-WebFace and testing it on LFW, it was shown that adversarial faces generated by this approach are model-agnostic and transferable, can evade several contemporary face matching techniques, and capable
of achieving remarkable attack success rates. Table 1 presents an overall overview of different adversarial example generation approaches, along with their essential characteristics. Also, the milestones of adversarial attacks against FR systems over the past years are presented in Fig. 7, in which the potentials of the proposed approaches are highlighted.
| Authors (Articles) | Black/White Box | Image-specific/Universal | Targeted/Non-targeted | Description |
|-------------------|----------------|--------------------------|-----------------------|-------------|
| Goswami et al. [16] | None | Image-specific | None | Adversarial image creation with distortions at image-level and face-level |
| Dong et al. [17] | Black-box | Image-specific | Both | Decision-based attack generation with a (1+1)-CMA-ES-based evolutionary algorithm |
| Zhong & Deng [28] | Black-box | Image-specific | Targeted | Feature-level transferability enhancement by dropout-based DFANet method |
| Goodman et al. [29] | Both | Image-specific | Both | Advbox toolbox |
| Sharif et al. [30,31] | White-box | Image-specific | Both | Evasion attacks on digital-level with traditional L-BFGS method and physical-level with 3D printed sunglasses frames |
| Zhou et al. [33] | White-box | Image-specific | Both | Physical adversarial examples creation with infrared LEDs attached to a cap |
| Shen et al. [34] | Black-box | Image-specific | Both | VLA in the physical world |
| Nguyen et al. [37] | Both | Image-specific | Both | Real-time light projection-based physical adversarial attacks |
| Komkov & Petiushko [38] | White-box | Image-specific | Non-targeted | Reproducible transferable attack on LResNet100E-IR Face ID system through projecting a paper sticker on the hat |
| Pautov et al. [40] | White-box | Image-specific | Both | Adversarial attack on LResNet100E-IR Face ID system by printing, adding and photographing adversarial patches of nose, forehead, and eyeglasses of the attacker |
| Rozsa et al. [41] | White-box | Image-specific | None | Adversarial attacks on biometric attribute predicting deep CNNs with FFA technique, based on inverting classifier score |
| Rozsa et al. [43] | White-box | Image-specific | Targeted | LOTS: Layerwise target-origin synthesis method to attack deep feature-based systems |
| Authors                  | Attack Method                  | Specificity          | Targeting | Summary                                                                 |
|-------------------------|--------------------------------|----------------------|-----------|-------------------------------------------------------------------------|
| Mirjalili & Ross [45]   | White-box                      | Image-specific       | None      | Attribute (gender) alteration yet biometric utility (face) preservation by a warping-based attribute perturbation algorithm using Delaunay triangulation |
| Mirjalili et al. [46]   | White-box                      | Image-specific       | None      | Connection of SAN of a supplementary gender classifier and a face matcher to a convolutional autoencoder |
| Mirjalili et al. [47,48]| White-box                      | Image-specific       | None      | SAN generalization by ensemble SAN model & FlowSAN method              |
| Mirjalili et al. [49]   | White-box                      | Image-specific       | None      | PrivacyNet model for multi-attribute privacy that generalizes to unseen attribute classifiers while preserving the recognition utility of face images |
| Chhabra et al. [58]    | White-box                      | Image-specific       | None      | Facial attribute anonymization using adversarial noise                 |
| Zhu et al. [59]         | White-box                      | Image-specific       | Both      | Non-make up to makeup face images alteration with GAN-based ‘Makeup Transfer Sub-network’ and ‘Adversarial Attack Sub-network’ |
| Joshi et al. [60]       | White-box                      | Image-specific       | None      | Semantic adversarial examples generation by optimizing adversarial loss over Fader Network and AttGAN through single and multi attributes modifications |
| Qiu et al. [66]         | Both                           | Image-specific       | Targeted  | High attack transferability and query-free black-box attack success rate by SemanticAdv, implementing attribute-conditioned image editing |
| Garofalo et al. [67]    | White-box                      | Image-specific       | Non-targeted | Poisoning attack on an authenticator, based on OpenFace framework extended with an SVM classifier |
| Chatzikyriakidis et al. [68] | White-box                     | Image-specific       | Targeted  | De-identified facial images generation with P-FGVM adversarial attack technique |
| Kwon et al. [70]        | White-box                      | Image-specific       | Targeted  | Face friend-safe adversarial examples generation                        |
| Dabouei et al. [72]     | White-box                      | Image-specific       | Non-targeted | Geometrically face transformation via fast landmark manipulation |
| Song et al. [75]        | White-box                      | Image-specific       | Targeted  | Attentional adversarial attack generative network, A³GN, to generate adversarial examples not misclassify inconspicuously |
| Deb et al. [76]         | Black-box                      | Image-specific       | Both      | Model-agnostic and transferable adversarial face generation via adversarial face synthesis method, AdvFaces, through minimal perturbations in salient facial regions |
In conclusion, findings demonstrate CNN-based FR systems as the most attacked target models, which shown to be vulnerable to not necessarily the sophisticated learning-based approaches but even very simple random noises. Considering the transferability aspect of the adversarial images, it is apparent that feature-level attacks are more operative and more transferable than label-level methods. Thus, biometric systems using such (deep) features will become weaker as compared with end-to-end networks. It is also evident that the majority of the attacks against FR models devoted to altering face attributes, ranging from skin color, nose shape, and hairstyle to gender, age, attractiveness, and makeup. Fortunately, this line of research provides a condition for users to anonymize particular attributes, i.e., to choose to obfuscated desired attributes while preserving others. In recent times, deceiving approaches have been directed toward semantic attributes that are not imperceptible due to the underlying natural appearance of adversaries. Therefore, a particular unexplored vulnerable landscape of DNNs has emerged and may draw the attention of more researchers toward itself in the future.

4. Adversarial Example Detection

As novel approaches for crafting adversarial examples proposed, research also directed to confront attacks based on these examples, aiming to moderate their consequence on the performance of a target deep network. Generally, the defense strategies against the adversarial attacks can be divided into three categories: (1) altering the training during learning, e.g., by injecting adversarial examples into training data, or incorporating altered input throughout testing, (2) changing networks, e.g., by changing the number of layers, subnetworks, loss, and activation functions, and (3) supplementing the primary model by external networks to associate in classifying unseen samples. The methodologies in the first category are not concerned with the learning models. However, the other two categories directly deal with the NNs themselves. The difference between ‘changing’ a network and ‘supplementing’ a network by external networks is that the former changes the original deep network architecture/parameters during training. At the same time, the latter keeps the original model intact and attaches external model(s) to it in the course of testing. The taxonomy of the described categories is also displayed in Fig. 8. The remainder of this section organized consistent with this taxonomy.

4.1. Altering Training/Test Input

Agarwal et al. [13] presented an efficient adversarial detection method to identify an image
agnostic universal perturbations. This method operates on (1) the pixel values and (2) the projections obtained from principal component analysis (PCA) features, as test inputs which are coupled with SVM classifier to detect perturbations. Due to flattening, hence, altering the images in the training database to form a row vector to be used either as the pixel values or dimensionally reduced vectors, the proposed solution is considered in the first category. The authors evaluated the effectiveness of this approach by two perturbation algorithms, universal perturbation [77] and a variant of it, called fast feature fool [78]. Doing experiments with three different databases, MEDS [79], PaSC [80], and Multi-PIE [81], and four different DNN architectures, VGG-16, GoogLeNet, ResNet-152 [82], and CaffeNet [83], they showed that more straightforward approaches, such as the one proposed, can yield higher detection rates for image-agnostic adversarial perturbation. In another research, Kurnianggoro et al. [84] proposed a defense strategy, based on an ensemble of classification from domain transformed input data. According to this approach, input images are transformed into a grayscale format, cropped and rotated to pass the classifier, the predictions of which assembled to create the ensemble decision. The goal of this research was to discover a method that does not necessitate any retraining. On the VGGFace2 dataset, experiments showed that domain transformation is useful to suppress the impact of adversarial attacks on face verification tasks.

### 4.2. Changing the Network

Goswami et al. [85], proposed two defense algorithms: (1) an adversarial perturbation detection algorithm, which utilizes the intermediate filter responses of a CNN, and (2) a mitigation algorithm, which incorporates a specific dropout technique. In the former, authors compared the patterns of the in-between representations for original images with corresponding distorted images at each layer. They applied the differences of the two patterns to train a classifier that can categorize
an unseen input as an original/distorted image. In the latter, they selectively dropped out the most affected filter responses of a CNN model, i.e., filter responses for in-between layers that reflect the most sensitivity towards noisy data, to lessen the impact of adversarial noise. Subsequently, they made a comparison with unaffected filter maps. Using the VGG-Face and LightCNN [86] networks, authors assessed the detection and mitigation algorithms according to a cross-database protocol; they performed training only with the Multi-PIE database and accomplished testing on the MEDS, PaSC, and MBGC [87] databases. Across all distortions on the three databases, it was shown that the proposed detection algorithm maintains high true positive rates even at meager false positive rates, which are desirable for the system. Also, it was observed that by discarding a certain fraction of the most affected in-between representations with the proposed mitigation algorithm, better recognition outputs could be achieved.

In another study, Goel et al. [88] presented a blockchain security mechanism to protect against attacks on FR models. Traditional blocks of any deep learning models, such as CNNs, are converted into blocks similar to the blocks in the blockchain to offer fault-tolerant access in a distributed setting. In this way, tampering in one specific component alerts the entire system and helps in easy detection of ‘any’ probable alteration. Experiments revealed the resilience of the proposed network to both the deep learning model and the biometric template, using Multi-PIE and MEDS databases.

Su et al. [89] proposed a deep residual generative network (ResGN) to clean adversarial perturbations for face verification. They suggested an innovative training framework composed of ResGN, VGG-Face, and FaceNet; they presented a joint of three losses: a pixel loss, a texture loss, and a verification loss, to optimize ResGN parameters. The VGG-Face and FaceNet networks contribute to the learning procedure by providing texture and verification losses, respectively, hence, improve the verification performance of cleaned images, fundamentally. The empirical results validated the effectiveness of the proposed method on the LFW benchmark dataset. Zhong and Deng [90] offered to recover the local smoothness of the representation space by integrating a margin-based triplet embedding regularization (MTER) term into the classification objective so that the acquired model learns to resist adversarial examples. The regularization term consists of a two-phase optimization that detects probable perturbations and punishes those using a large margin in an iterative approach. Experimental outcomes on CASIA-WebFace, VGGFace2 and SCeleb-
1M [91] demonstrated that the proposed method elevates the robustness of network against both feature-level and label-level adversarial attacks in deep FR models.

According to the concept of feature distance spaces explored in [92], Massoli et al. [93] proposed a detection approach, based on the trajectory of internal representations, i.e., hidden layers neurons activation, also known as deep features. They argued that the representations of adversarial inputs follow a different evolution for genuine inputs. Specifically, they collected deep features during the forward step of the target model, applied average pooling over deep features to achieve a single features vector at each selected layer, and computed the distance between each vector and the class centroid of each class at each layer, to acquire an embedding that represents the trajectory of the input image in the features space. Such a trajectory was finally fed to a binary classifier or adversarial detector. As the adversarial detector, two different architectures of a multi-layer perceptron (MLP) and a long-short term memory (LSTM) network were considered in this work. Authors conducted the experiments on the VGGFace2 dataset and the state-of-the-art Se-ResNet-50 from [71]. To assess the efficiency of the proposed approach, they showed the Receiving Operating Characteristics (ROC) curves from the adversarial detection considering targeted and non-targeted attacks for each architecture. They reported the Area Under the Curve (AUC) values relative to each attack. Accordingly, the AUC values found to be very close for the targeted attacks, while in the case of non-targeted attacks, the LSTM performance shown to be considerably better than the MLP.

Recently, Kim et al. [94] proposed a low-power highly-secure always-on FR processor for verification applications on mobile devices. This processor operates based on three key features of (1) a branch net-based early stopping FR (BESF) method to prevent adversarial attacks and consume low power, (2) a unified processing element (PE) for point- and depth-wise convolutions with layer fusion to reduce external memory access and (3) a noise injection layer (NIL) incorporated between bottleneck layers to make the network more robust against adversarial attacks with lower external memory access. They demonstrated that under the FGSM and PGD, BESF could result in high recognition accuracies, while reducing the average power consumption significantly. They also showed that the PE reduces the external memory access, and the NIL could further lessen the FGSM and PGD attack success rates. Overall, this processor resulted in 95.5% FR accuracy in the Labeled Faces in the LFW dataset.
4.3. Supplementing External Network(s)

Xu et al. [95] proposed a feature squeezing strategy that moderates the search space available to an adversary by coalescing samples correspond to different feature vectors in the original space into a single sample. Adding two external models to the classifier network, they explored two feature squeezing approaches by (1) decreasing the color bit depth of each pixel and (2) spatial smoothing. Goswami et al.[85], stated that although this approach is simple and operative for high-resolution images with detailed data, it may not be operational for low resolution cropped faces that are frequently used in FR settings. In [96], an open-source Python-based toolbox, termed as SmartBox, is proposed to benchmark the function of adversarial attack detection and mitigation algorithms against FR models. The detection approaches included in this toolbox are: ‘Detection via Convolution Filter Statistics,’ ‘PCA-based detection,’ ‘Artifacts Learning’ and ‘Adaptive’ Noise Reduction,’ which are respectively considered in ‘Changing the Network,’ ‘Alterning Training/Test Input,’ and ‘Supplementing External Networks’ defense categories. We put this study under the ‘Supplementing External Networks’ category since it covers the last two and hence, the majority of SmartBox detection methods.

While most of the current defense methods either assume prior knowledge of specific attacks or may not operate well on complex models due to their underlying assumptions, a new window was opened to adversarial detection techniques by leveraging the interpretability of DNNs [97]. Tao et al. [97] proposed a detection technique, called Attacks meet Interpretability (AmI), in the context of FR practice. This technique features an innovative bi-directional correspondence inference amongst face attributes and internal neurons, using attribute-level mutation and neuron strengthening/weakening. More precisely, those neurons that are critical for individual attributes are identified, and the activation values of them are enhanced to amplify the reasoning part of the computation. In contrast, other neurons’ activation values are weakened to suppress the uninterpretable part. Employing three different datasets, VGG Face (VF) [95], LFW, and CelebA, AmI applied to VGG-Face, with seven different kinds of attack. Extensive experiments represented that the proposed technique could successfully detect adversarial samples with a true positive rate of 94% on average, which is significantly higher than what achieved with the state-of-the-art reference technique called feature squeezing [95]. Similarly, the false positive rate, i.e., misclassification rate of benign inputs as malicious, of the AmI technique, is lower than the reference work, demonstrating its high effectiveness in this endeavor.
Mentioned adversarial example detection techniques considered in the ‘supplementing external network(s)’ category, are the most suitable for defending black-box classifiers. However, they do not quantify the amount of adversarial component left in the resulting purified image and perform well only under feebly bounded adversarial perturbations. For online biometrics verification systems, this becomes crucial since an adversary can always use an attack with a relatively higher perturbation that is just enough to deceive the system. As a solution, Theagarajan and Bhanu [98] proposed a framework not subdivided into the mentioned adversarial example detection categories. They proposed an approach to defending black-box face biometrics classifiers from adversarial attacks using an ensemble of defenses, i.e., iterative adversarial image purifiers, whose performance continuously validated in a loop by quantifying the remaining amount of adversarial component after each iteration of purification, using Bayesian uncertainties. This approach, which fulfilled without the need for any ground-truth/human observer, is (1) model-agnostic, (2) able alter single step black-box defenses into an iterative defense, and (3) capable of rejecting adversarial examples. Experimental results on the MS-Celeb dataset demonstrated that with the proposed approach, it is possible to detect adversarial examples, consistently, and purify/reject them against a diversity of adversarial attacks with perturbations of different ranges. A general overview of different adversarial example detection approaches, along with their category, is provided in Table 2.

In summary, reviewed articles exhibit that ‘changing the network’ category attracts more attention in designing different adversarial example detection approaches compared to the other two categories. However, it is not yet entirely specified which group withstands more attacks and results in more generalizability. As actively followed by researchers [99], focusing more on identifying the causes of adversaries and trying to provide empirical and theoretical evidence of the underlying phenomenon could be another perspective to consider in the future, hoping to achieve more desirable findings.
Table 2
Adversarial example detection approaches.

| Authors (Articles) | Defense Categories | Description |
|--------------------|--------------------|-------------|
|                     | Altering Training/Test Input | Changing the Network | Supplementing External Network(s) |
| Agarwal et al. [13] | ×                   |             | Image Pixels + PCA + SVM |
| Kurnianggoro et al. [84] | ×                   |             | An ensemble of classification results from domain transformed (grayscale, cropped and rotated) input data |
| Goswami et al. [85] |             | ×           | Filter responses of CNN, Dropout of filter responses |
| Goel et al. [88]    | ×                   |             | Conversion of traditional blocks of deep learning models into blocks similar to the blocks in the blockchain |
| Su et al. [89]      | ×                   |             | Design of ResGN model + employment of a pixel loss, a texture loss and a verification loss for parameter optimization |
| Zhong & Deng [90]   | ×                   |             | Integration of MTER term into the classification objective for detection and punishment of perturbations |
| Massoli et al. [93] | ×                   |             | Exploration of the adversary’s evolution by tracking the trajectory of deep features representations |
| Kim et al. [94]     | ×                   |             | Design of a low-power and highly-secure always-on FR processor |
| Xu et al. [95]      | ×                   |             | Feature squeezing strategies of (1) pixel’s color bit depth decreasing and (2) spatial smoothing via the addition of two external models to the classifier |
| Goel [96]           | ×                   |             | SmartBox toolbox |
| Tao [97]            | ×                   |             | Bi-directional correspondence inference amongst face attributes and internal neurons via AmI technique |
| Theagarajan & Bhanu [98] | ×            |             | Defending black-box FR classifiers via iterative adversarial image purifiers |
5. Conclusion

This article presented a comprehensive survey in the course of adversarial attacks against competent deep FR systems. Despite the outstanding performance of advanced FR models, they have been found vulnerable to imperceptible or perceptible but natural-looking adversarial input images that lead them to modify their outputs entirely. This fact has opened a new window to numerous recent contributions to devise adversarial attacks and countermeasures in FR mission. This article reviewed these contributions, mainly concentrating on the most effective and inspiring works in the literature. Regarding the reviewed adversarial attacks and defenses, it turns out that CNNs, as the target models, and facial attributes, as the target zones, have attracted the most attention, while much efforts made in the network modification defense strategy. We hope this work can shed some light on the key concepts in this regard to encourage progress in the future.

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