Robustness of Facial Recognition to GAN-based Face-morphing Attacks

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Abstract

Face-morphing attacks have been a cause for concern for a number of years. Striving to remain one step ahead of attackers, researchers have proposed many methods of both creating and detecting morphed images. These detection methods, however, have generally proven to be inadequate. In this work we identify two new, GAN-based methods that an attacker may already have in his arsenal. Each method is evaluated against state-of-the-art facial recognition (FR) algorithms and we demonstrate that improvements to the fidelity of FR algorithms do lead to a reduction in the success rate of attacks provided morphed images are considered when setting operational acceptance thresholds.

1. Introduction

The potential threat of morphing attacks to systems secured by facial recognition (FR) was first identified in the 2014 paper “The Magic Passport” \cite{10}. The paper demonstrated the relative ease with which images can be manipulated to simultaneously resemble multiple identities using commercially available tools, and the vulnerability of FR systems to those images. The extent to which face-morphing as a method of attack has been adopted by criminals is not known since, by definition, successful attacks remain undetected. Nevertheless, a pre-emptive arms race was spawned in the literature, with evermore sophisticated morphing methods being proposed in conjunction with tools for their detection \cite{4, 5, 11, 23, 27}. Various datasets of morphed examples have been made publicly available \cite{18, 22} and an ongoing morphing detection benchmark has been included as part of NIST’s Face Recognition Vendor Test (FRVT) \cite{21}.

In this paper we evaluate the robustness of FR algorithms to two morphing methods that make use of style-based, generative networks; specifically we produce morphed images using StyleGAN pre-trained on the Flickr-Faces-HQ (FFHQ) dataset \cite{16}. The work of \cite{29} evaluates a method similar to the “midpoint method” presented here. Whereas \cite{29} focusses on assessment of the extent to which FR systems are vulnerable to GAN-based face-morphing attacks in comparison to landmark-based attacks, and also on detection of such attacks, here we focus on the changing response of FR systems to morphed images as fidelity improves. We observe that improvements to FR systems do not necessarily translate to improved robustness to morphing attacks and that morphed images should therefore be taken into account when setting operational acceptance thresholds. We also introduce and evaluate a second, style-based morphing method: the “dual biometric method”.

The rest of the paper is organised as follows: in Section 2 we provide a recap of how morphing attacks proceed and identify potential approaches that might be used to prevent them; in Section 3 we discuss work in the literature proposing to complement FR systems with algorithms for detection of morphed images, and also work leading to the development of the style-based morphing methods proposed here; in Section 4 we describe the style-based morphing methods being evaluated, providing results in Section 5; and in Section 6 we draw conclusions.
2. Morphing attacks

2.1. How does a face-morphing attack work?

For the benefit of the uninitiated reader, we recap on how a morphing attack might proceed:

1. An accomplice is identified who is willing to share their passport with an imposter. Ideally the accomplice will resemble the imposter.
2. A morphed image is produced that resembles both the accomplice and the imposter.
3. The accomplice presents the morphed image at the time of application for the identity document. (The image is found to be plausible and so is accepted.)
4. The resulting identity document is shared with and used by the imposter.

2.2. Prevention of morphing attacks

There are three broad approaches that might be taken to prevent such an attack:

1. **Trusted capture.** In the prelude to a morphing attack, the accomplice exploits his freedom to provide an image to the issuing authority. Removing this freedom by enforcing live image-capture at the time of application would make attacks significantly more challenging to perpetrate.

2. **Morph-detection.** Although currently known morphing methods produce images of high quality, none of them is perfect. Morphed images may contain certain features that betray their dubious provenance. Deploying automated detection of these features, either prior to creation of the identity document or at the time of use, could potentially prevent attacks.

3. **Robustness of recognition.** A morphed image contains an identity that is neither that of the accomplice nor of the imposter. A facial recognition system that is effective enough to recognise the identity as such would not be vulnerable to the attack.

In this work we show that the third approach, i.e. working to improve the robustness of facial recognition algorithms to similar but subtly different identities, is an important and effective way of ensuring the integrity of FR-secured systems.

3. Related Work

3.1. Securing systems against morphing attacks

The largest part of the face-morphing attack literature consists of the development of methods for the detection of morphs, for example, by using deep learning techniques [4], analysis of sensor noise in images [5], detection of landmark shifts [23], verification of the consistency of lighting conditions [27], or by de-morphing images to reveal the original subject [11]. Most current detection methods, however, are ineffective and suffer from high error rates that worsen when morphed images are printed and scanned [19, 25]. In [19] it is therefore recommended that identity document-issuing authorities enforce the submission of high-resolution digital images. However, they also point out that attackers could still manipulate digital noise signatures to obfuscate traces of image editing. In a recent survey of morphing attacks and detection methods [26] it was concluded that morphing attack detection methods do not generalise well to datasets incorporating real-world capture conditions. Indeed, in the most recent FRVT morph detection report [21], the best value of APCER@BPCER=0.01 (Attack Presentation Classification Error Rate at a Bona fide Presentation Classification Error Rate of 0.01) for detection of morphs of the types shown in Figure 2 (i.e. the “Local Morph Colorized Match”, “Splicing”, “Combined” and “DST” methods) was 88% for the “Splicing” method.

An assessment of the vulnerability of FR to the average of images of two identities [22] showed it to be a more effective method than morphing. They also showed, however, that the averaged images were much easier to detect. It is unlikely, therefore, that an attacker would choose this type of method. In this work we propose two StyleGAN-based morphing methods and, in light of the evident difficulty of detecting morphs, we instead focus on demonstrating the effect on morphing attacks of improvements to the robustness of FR algorithms.
3.2. The development of style-based face-morphing

Generative Adversarial Networks (GANs) [12] learn to map latent vectors of random values to points on a manifold in data-space, usually image-space, representing realistic data-samples that can fool a concurrently trained discriminator into classifying them as real samples. Typically, generator architectures take a similar form to other deep neural networks, starting with the input - in this case a random vector - and applying a series of convolutions. In [16], however, the vector of random values is projected to each convolutional layer of the network and used to directly influence the scale of variation in each feature map of each convolutional layer. This is achieved via conditional instance normalisation [9], which was originally introduced as a method to manipulate the styles of images via the use of image-to-image translation networks [15]. Since the generators of GANs do not translate images but grow them, each convolutional layer naturally learns to control image features at different scales. For example, pose is controlled by early, large-scale features at low resolutions, whereas high-frequency, small-scale details such as wrinkles are controlled later on, at higher resolutions [16]. This natural, scale-wise disentanglement (in conjunction with the “style mixing” used in [16]) causes the projections of the latent vector - the so-called “w+” vectors - to be largely independent of one another. It is this independence, and therefore flexibility, that makes style-based GANs particularly suitable for image-reconstruction and then morphing.

In order to use GANs to perform morphing attacks, one needs to be able to invert the generator, i.e. to find the latent vector that best describes some input image. There are various one-shot ways to do this, for example, one could train an encoder to regress the latents from synthetic images or, alternatively, train an encoder via Adversarially Learned Inference (ALI) [8, 7] as was done in [4]. However, it is more effective, albeit slower, to find the latents using some iterative gradient descent method. Typically, it is difficult to fit GANs to non-synthetic images; so much so that the failure to reproduce images precisely has been used as a evidence that memorisation of images is not taking place in GANs [31]. However, in [1] it was noticed that precise reconstructions could be achieved by treating the projected latents of StyleGAN independently during fitting, thereby taking advantage of the aforementioned scale-wise disentanglement. (This increase in precision can be seen by comparing the reconstructed images in the top and bottom rows of Figure 3.) It is then straightforward to generate realistic face-morphs by linearly interpolating between two sets of recovered w+ vectors. In this work, we also manipulate images in the w+ latent space. Further details of our methods are given in the following section.
4. Face-morphing with StyleGAN

We will evaluate robustness of FR algorithms to two different methods of face-morphing based on StyleGAN: the “midpoint method”, which is similar to that demonstrated in [1] and [29], and the “dual biometric method”, which was developed for this study. In both methods we optimise the loss functions using Adam [17]. To speed up convergence and improve reconstruction quality, initialisations of the latent vectors are provided by a one-shot encoder trained on pairs of random vectors and associated synthetic images.

4.1. The midpoint method

Face-morphing using the midpoint method consists of two steps: recovering the two latent vectors that best describe two input images, and generating a synthetic image from the midpoint interpolation of those two vectors. To recover \( w^+ \) for an input image \( x \), the following loss function is minimised:

\[
\mathcal{L}_{w^+} = \mathcal{P}(G(w^+), x) + \lambda_w \frac{1}{N_x} ||G(w^+) - x||_2^2 + \lambda_w ||w^+ - \bar{w}||_1
\]

(1)

where \( G \) is the generator (with StyleGAN’s mapping network removed), \( N_x \) is the number of image pixels, \( \bar{w} \) is the average of the \( w^+ \) seen during training of \( G \), and \( \mathcal{P} \) is a perceptual loss given by

\[
\mathcal{P}(G(w^+), x) = \frac{\lambda_v}{N_v} ||VGG_9(G(w^+)) - VGG_9(x)||_2^2 + \lambda_m (1 - MSSSIM(G(w^+), x))
\]

(2)

where \( VGG_9 \) is the output of the ninth layer of the VGG classification network [28] used to extract discriminative features, \( N_v \) is the number of VGG features, and MSSSIM is the Tensorflow implementation of the MS-SSIM metric described in [30]. The generator, \( G \), is the official version of the StyleGAN generator trained on the Flickr-Faces-HQ dataset. The code implementing the inversion of StyleGAN’s generator was taken from [2] and the coefficients weighting each term of equations (1) and (2) are left at their default values of \( \lambda_r = 1.5, \lambda_w = 0.5, \lambda_v = 0.4 \) and \( \lambda_m = 200 \). Once two vectors, \( w^+_1 \) and \( w^+_2 \) have been recovered, the final morphed image is given by:

\[
x_{\text{morph}} = G\left(\frac{w^+_1 + w^+_2}{2}\right)
\]

(3)

In the middle row of Figure 3 we demonstrate the effect of reverting the method to that used in [1] by removing the perceptual loss term and the regularisation of \( w^+ \) from equation (1) during latent recovery. The reconstructed images as well the midpoint morph become more blurred, lacking in high-frequency detail. This result motivates our use of the full, perceptual loss function in our experiments. Results showing the level of robustness of FR to morphing attacks using the full midpoint method are given in Section 5.1.

4.2. The dual biometric method

Although the latent space of StyleGAN is disentangled with respect to some scale-dependent features, identity features are not necessarily disentangled. This means that the equality

\[
B(x_{\text{morph}}) = \frac{1}{2} B(G(w^+_1)) + \frac{1}{2} B(G(w^+_2))
\]

(4)

where \( B \) is a biometric network producing an identity feature vector, does not necessarily hold; i.e. the identity of the midpoint morph does not necessarily lie between the identities of the two reconstructed images in a biometric feature space. A more reliable method of ensuring that the morphed identity remains close to each of the original identities could be to explicitly minimise those distances in the feature space. This motivates our dual biometric method in which the following cost function is minimised:

\[
\mathcal{L}_{w^+} = ||B(G(w^+)) - B(x_1)||_2^2 + ||B(G(w^+)) - B(x_2)||_2^2 + \lambda_w ||w^+ - \bar{w}||_1
\]

(5)

For \( B \) we used a Keras implementation of the VGGFace2 “SENet” network [3] taken from [20]. We have also included the same L1 regularisation of the latent vector as was used in the midpoint method. Since the biometric loss terms are robust to (i.e. ignore) all image features except for the identity, the L1 regularisation is important for maintaining a realistic looking image. \( \lambda_w \) was tuned by hand based on the appearance of a handful of morphed images and set to a value of 3. Results showing the level of robustness of FR to morphing attacks using this second method are given in Section 5.2.

5. Results

We evaluate robustness of FR to morphing attacks using the Labeled Faces in the Wild (LFW) dataset [14]. To simulate realistic morphing attacks we first select the highest quality image for each of the 5478 identities. We then assign fifty random “friends” to each identity and select the strongest identity match to be the accomplice, as judged by a biometric matching algorithm. Morphed images were produced for each of these image pairs using both the midpoint method and our dual biometric method. The original, bona fide images were then matched against their mated morphs. Note that we do not compare morphs with independent images of the mated subjects. Comparisons are made with the
Figure 6. Distributions of matching scores for Algo. 2017 (left) and Algo. 2019 (right). Morphed imposters were produced using the midpoint method. Dashed lines represent thresholds of FAR=$1 \times 10^{-5}$ for bona fide imposters.

**5.1. Results - The midpoint method**

**bona fide** images used to create the morphs meaning that matching scores are likely to be at a maximum, thus giving conservative estimates of FR system vulnerability. We present results for two matching algorithms, the first based on DeepVisage [13] that we will refer to as “Algo. 2017” and the second based on ArcFace [6] that we will refer to as “Algo. 2019”.

Figures 4 and 5 give examples of face-morphs generated from pairs from LWF using the midpoint method. In Figure 6 we plot distributions of matching scores produced for this type of morph by the 2017 and 2019 algorithms. The green, “Morphed imposters” curves show the distributions of the minimum mated morph similarity scores (MMMSS), i.e. the minimum of either the accomplice-morph or morph-imposter matching score. The minimum score is interesting since it is the strength of the weakest similarity that determines whether the attack as a whole succeeds. The blue, “Genuines” curves show the distribution of mated matching scores for sets of **bona fide** images from LFW sharing the same identity, and the orange, “Bona fide imposters” curves show non-mated matching scores. In each figure we have drawn a threshold at the score corresponding to a False Acceptance Rate (FAR) of $1 \times 10^{-5}$ based on the distribution of **bona fide** imposters. Values of Mated Morph Presentation Match Rate (MMPMR) [24] at this threshold are presented in Table 1 and correspond to the proportions of points lying in the top-right quadrant of the scatter plots.

In typical circumstances, both algorithms are able to well separate the distributions of mated and non-mated matching scores. However, inclusion of minimum mated morph similarity scores (MMMSSs) blurs this separation and at FAR=$1 \times 10^{-5}$ the success rate of simulated morphing attacks, the MMPMR, is 1.99% for Algo. 2017 and 2.96% for Algo. 2019, i.e. the MMPMR is three orders of magnitude larger than the FAR. What is more, despite the Genuine and Imposter curves clearly being better separated by
Table 1. MMPMRs and FRR at a False Acceptance Rate of $1 \times 10^{-5}$ for two different face-recognition algorithms.

| Morphing method       | Algo. 2017 | Algo. 2019 |
|-----------------------|------------|------------|
| Genuines (FRR)        | 0.73%      | 0.25%      |
| Midpoint Morphs (MMPMR) | 1.99%     | 2.96%     |
| Biometric Morphs (MMPMR) | 3.88%     | 2.34%     |

Table 2. MMPMRs and FAR at a False Rejection Rate of 0.73% for two different face-recognition algorithms.

| Morphing method       | Algo. 2017 | Algo. 2019 |
|-----------------------|------------|------------|
| Bone fide imposters (FAR) | $1 \times 10^{-5}$ | $1.81 \times 10^{-6}$ |
| Midpoint Morphs (MMPMR) | 1.99%     | 0.07%     |
| Biometric Morphs (MMPMR) | 3.88%     | 0.00%     |

Figure 7. ROC curves showing the trade-off between MMPMR and FRR.

Figure 8. Comparison of morphs generated using the midpoint and dual biometric methods.

Algo. 2019, the value of MMPMR@FAR=$1 \times 10^{-5}$ increases. This is not because MMMSSs become less distinguishable from bona fide mated matching scores; in fact, from Figure 6 we also see an improvement in separation of the Genuine and Morphed imposter curves. The issue arises from the fact that the improvement in separation of the bona fide mated and non-mated matching scores is larger than for the MMMSSs. This acts to shift the threshold of FAR=$10^{-5}$ to a lower score that “overtakes” the improvements in MMMSS. This means that we cannot assume that improvements to FR systems will lead directly to increased robustness to morphing attacks. Instead, the response of the FR system to datasets of morphed images should be considered when setting operational thresholds.

Table 2 shows values of MMPMR, and also FAR, at a threshold corresponding to FRR=0.73% for the bona fide mated pairs of LFW. We see that this corresponds to the original threshold of FAR=$1 \times 10^{-5}$ for Algo. 2017 but that for Algo. 2019 it corresponds to FAR=$1.81 \times 10^{-6}$. At this much more stringent threshold, MMPMR drops to 0.07% for Algo. 2019 (and drops to 0% for the morphs produced by the dual biometric method). This means that, by compromising on improvements to FRR, essentially all face-morphing attacks of the type presented here can be prevented. [24] suggests reporting Relative Morph Match Rate (RMMR) as a measure of FR system vulnerability where $RMMR = MMPMR + FRR$. This measure varies with threshold, however, and implicitly weights robustness to morphs and low FRR as being equal in priority, which is not necessarily the case. We find it preferable to observe the compromise between MMPMR and FRR by plotting the relevant ROC curve, as has been done in Figure 7. Here we see that the ROC curves for Algo. 2019 are significantly steeper than for Algo. 2017 indicating that accepting only a small increase in FRR can cause the success rates of morphing attacks to plummet relative to those measured against Algo. 2017.

5.2. Results - The dual biometric method

Figure 8 gives a direct comparison of face-morphs generated using the dual biometric method (“BioMorph”) with those generated by the midpoint method (“MidMorph”). We see that the biometrically morphed identities are plausible and that they are distinct from the midpoint morphs. We also notice that the image-quality of the bio-morphs is higher than that of the midpoint morphs. This is because the images of LFW are of a lower quality than the images of FFHQ used to train StyleGAN. Image artefacts from LFW therefore seep into the midpoint morphs via the image-reconstructions. During generation of the bio-morphs, the original images are never reconstructed. The only constraint
is that similar identity-related features be generated.

Figure 9 shows the distributions of matching scores for the biometrically morphed images. From the scatter plots, we see that the matching scores are less balanced between accomplices and imposters, i.e. a large proportion of bio morphs were found to match one identity much more strongly than the other. This contrasts with the midpoint method where a larger proportion of morphs were found to give weak matching scores for both original images. From Table 1 we see that despite the imbalanced matching scores, MMPMR@FAR=$1 \times 10^{-5}$ is larger for biometric morphs than for midpoint morphs as measured by Algo. 2017. This situation reverses, however, for Algo. 2019 which succeeds in reducing the number of successful simulated attacks without modification to the threshold of FAR=$1 \times 10^{-5}$. Table 2 shows that by sacrificing improvements to FRR and modifying the acceptance threshold of Algo. 2019 to FAR=$1.81 \times 10^{-6}$, all simulated biometric morphing attacks can be prevented. Figure 11 shows examples of bio-morphs that remain to be problematic for the 2019 algorithm with a threshold at FAR=$1 \times 10^{-5}$. Those shown in Figure 10 were previously problematic for Algo. 2017 but are correctly rejected by Algo. 2019.

By evaluating the dual biometric method on an in-the-wild dataset, we have inadvertently disguised the fact that desirable (for the attacker), non-identity image characteristics are lost. For example, Figure 12 (top) demonstrates the result of applying the biometric morphing method to the passport-style photographs of Figure 1. The generated morph resembles an in-the-wild image from FFHQ and would likely not be accepted for use on an identity document. To avoid this problem, a pixel-wise reconstruction loss can be applied to background regions. Figure 12 (bottom) shows an example of a biometric morph produced in this way. An alternative approach for an attacker to overcome this issue could be to train a GAN using solely passport-style images.
6. Conclusions

In this work we evaluated the robustness of two facial recognition algorithms to face-morphing attacks using a recent, StyleGAN-based morphing method. We also proposed and evaluated a second, related morphing method in which distances of morphed faces from the contributing identities in a biometric feature space are minimised explicitly. Both morphing methods were found to be of potential threat with their relative success rates depending on the particular FR algorithm under attack. Assuming that we have been able to simulate realistic attack scenarios, it is likely that fewer than $3\%$ of StyleGAN-based morphing attacks would succeed against a state-of-the-art facial recognition algorithm with a matching threshold set at $\text{FAR}=1 \times 10^{-5}$. We also observed that improvements to FR algorithms do not necessarily translate directly to increased robustness to face-morphing attacks and recommend that matching scores for datasets of morphed images be considered when setting operational acceptance thresholds.

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