Unsupervised Eyeglasses Removal in the Wild

Bingwen Hu, Zhedong Zheng, Ping Liu, Member, IEEE, Wankou Yang, and Mingwu Ren

Abstract—Eyeglasses removal is challenging in removing different kinds of eyeglasses, e.g., rimless glasses, full-rim glasses, and sunglasses, and recovering appropriate eyes. Due to the significant visual variants, the conventional methods lack scalability. Most existing works focus on the frontal face images in the controlled environment, such as the laboratory, and need to design specific systems for different eyeglass types. To address the limitation, we propose a unified eyeglass removal model called the eyeglasses removal generative adversarial network (ERGAN), which could handle different types of glasses in the wild. The proposed method does not depend on the dense annotation of eyeglasses location but benefits from the large-scale face images with weak annotations. Specifically, we study the two relevant tasks simultaneously, that is, removing eyeglasses and wearing eyeglasses. Given two face images with and without eyeglasses, the proposed model learns to swap the eye area in two faces. The generation mechanism focuses on the eye area and invades the difficulty of generating a new face. In the experiment, we show the proposed method achieves a competitive removal quality in terms of realism and diversity. Furthermore, we evaluate ERGBAN on several subsequent tasks, such as face verification and facial expression recognition. The experiment shows that our method could serve as a preprocessing method for these tasks.

Index Terms—Eyeglasses removal, generative adversarial network (GAN), image manipulation.

I. INTRODUCTION

The eye is viewed as “a window to the soul” [1], containing rich biometric information, e.g., identity, gender, and age. In recent years, there are increasing interests in face-related applications. Among these applications, eyeglasses are usually considered as one kind of occlusion in the face images. As a result, the occlusion compromises downstream tasks, such as face verification [2]–[8] and expression recognition [9]–[11]. One way to address occlusion is by ignoring the occluded area, which is successfully applied in the field of person reidentification [12]–[16]. Different from the human body, the face is rich in identity information, and the eye area is the most discriminative facial field. The retained information is insufficient to support us making an accurate decision while the occluded area is ignored. Therefore, we propose an eyeglasses removal method to transform the occlusion area into a nonocclusion area. Despite significant advances in image manipulation, eyeglasses removal in the unconstrained environment, as known as in the wild, has not been well studied.

In this article, we intend to fill this gap.

The previous eyeglasses removal works mainly focus on the cases in a controlled environment. Most works [17]–[21] require pairwise training samples. Every pair of images contains two frontal faces of the same identity with and without glasses. When testing, given one frontal testing image, the framework first detects the eye area and then replaces the original eye area with the reconstructed eye. The crafted eye area fuses the no-glasses training samples by principal component analysis (PCA) [22]. These lines of works adopt a strong assumption that faces are in a frontal pose, and the types of eyeglasses are limited. In the realistic scenario, however, there are three main drawbacks: 1) it is hard to collect a large number of pairwise training data of the same people with and without eyeglasses; 2) eyeglasses are usually made of different materials with significant visual variants, such as color, style, and transparency [see Fig. 1(a)]. It is infeasible to train dedicated removal systems for different eyeglasses types; and 3) existing works could not be applied to the face images in different poses. The model trained in the laboratory environment usually lacks scalability to significant visual variants.

This article addresses these three challenges. First, the previous methods [17]–[21] focused on the data collected in a controlled environment. More than that, they need the collected training images to be pairedwise, that is, two frontal faces of the same identity with and without glasses. Other than that, some works [17]–[19] require an extra detector to locate the eyeglasses. Benefiting from the advancement of unsupervised learning [23], [24], we propose an unsupervised eyeglasses removal method. The only information that we need is whether the training image contains eyeglasses on the face. For training the proposed model in this article, we have collected 202,599 training images from the public dataset CelebA [25]. Those collected images are divided into two sets, that is, face images with glasses and face images without glasses, respectively.

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code, respectively. Then, one decoder is learned to combine the
image into a face appearance code and an eye-area attribute
we first utilize two different encoders to decompose the face
captures the semantic pattern in the eye area. In more detail,
metric structure of the face, while the eye-area attribute code
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learning. We learn two representations of the input face image, that
unified ERGAN, which only needs weak annotations for train-
robust to the various pose variants.
proposed method does not need complicated alignment and is
user, however, may upload nonfrontal face images, and
algorithms, the center of the face. Compared with previous works, the
method does not need alignment densely. The only prepro-
alignment calibration to generate frontal faces, which might
 proposes method not only removes the eyeglasses but also has the capa-
bility to generate the eyeglasses, which further enforces the
model to learn the local patterns of different eyeglasses [see
Fig. 1(b)].
Third, the problem of eyeglasses removal from arbitrary face
poses is common and challenging in a realistic scenario. The
previous works mostly assume that we could obtain frontal
face images and accurately align the eye area. In real scenar-
ios, the user, however, may upload nonfrontal face images, and
the eye area is not well aligned. One solution is to resort to
alignment calibration to generate frontal faces, which might be
complicated and time consuming. In contrast, the proposed
method does not need alignment densely. The only prepro-
processing required is to rotate the face images according to
the center of the face. Compared with previous works, the
proposed method does not need complicated alignment and is
robust to the various pose variants.
To address the above-mentioned challenges, we propose a
unified ERGAN, which only needs weak annotations for train-
ing. We learn two representations of the input face image, that
is, the face appearance code and the eye-area attribute code.
The face appearance code mainly contains the low-level geo-
metric structure of the face, while the eye-area attribute code
captures the semantic pattern in the eye area. In more detail,
we first utilize two different encoders to decompose the face
image into a face appearance code and an eye-area attribute
code, respectively. Then, one decoder is learned to combine the
face appearance code with the eye-area attribute code to recon-
struct the face image. The self-reconstruction loss is applied
to ensure that the two latent codes complement each other and
preserve the information of the original image. To enforce the
model focuses on the eye area of the input image, we intro-
duce the eye-area reconstruction loss. Furthermore, the face
appearance reconstruction loss and the cycle consistency loss
are adopted to encourage that the mapping function is invert-
ible between the reconstructed face image and the two latent
codes. When testing, we could combine the face appearance
code of the target face with the eye-area attribute code to
remove or wear any specific eyeglasses.
To evaluate the generation quality, we adopt the Fréchet
inception distance (FID) [26] and learned perceptual image
patch similarity (LPIPS) [27] as an indicator to test the real-
ism and diversity of the generated face images, respectively.
Extensive qualitative and quantitative experiments show that
our method achieves superior performance to several exist-
ing approaches [28]–[30] and could serve as a preprocessing
 tool for subsequent tasks, such as face verification and facial
expression recognition.
In summary, the main contributions of this article are as
follows.
1) We propose a unified framework called ERGAN that
enables different types of eyeglasses removal from faces in the wild. Compared with previous works, the
proposed method does not need densely aligned faces
nor pairwise training samples. The only weak annota-
tion that we need is whether the training data contain
eyeglasses or not.
2) Due to the large visual variants of the eyeglasses, includ-
ing shape and color, eyeglasses removal demands to
learn a robust model. In this article, we propose a dual
learning scheme to simultaneously learn two inverse
manipulations, that is, removing eyeglasses and wearing
eyeglasses. Specifically, we utilize the eye-area recon-
struction loss to explicitly make the model pay more
attention to the eye area. The ablation study verifies the
effectiveness of both the dual learning scheme and the
eye-area reconstruction loss.
3) The qualitative and quantitative experiments show that
our method outperforms other competitive approaches
in terms of realism and diversity. Furthermore, we eval-
uate the proposed method on other face-related tasks.
Attribute to the high-fidelity eyeglass removal, the gen-
erated results benefit the subsequent tasks, such as face
verification and facial expression recognition.
II. RELATED WORK
A. Statistical Learning
Most pioneering works on eyeglasses removal are based on
statistical learning [17], [18], [20], [21], [31]. One line of
works adopts the assumption that the target faces could be
reconstructed from other faces without eyeglasses. Based on
this assumption, previous methods widely adopt PCA [22] to
learn the shared components among the face images. In one
of the early works, Wu et al. [17] proposed a find-and-replace

Fig. 1. (a) Examples of different types of eyeglasses in the wild. Different
types of eyeglasses have significant visual variants, such as color, style, and
transparency. Besides, the faces in the wild are usually in arbitrary poses
with various lighting and backgrounds. (b) Brief pipeline of the proposed
method. The proposed ERGAN simultaneously takes the two relevant tasks,
i.e., wearing and removing glasses, into consideration.
approach to remove eyeglasses from frontal face images. This method first finds the location of eyeglasses by an eye-region detector and then replaces it with a synthesized glasses-free image. The synthesized glass-free image is inferred by combining the original eye area and different weighted glasses-free faces in the training data. Furthermore, Park et al. [18] applied the recursive process of PCA reconstruction and error compensation to generate facial images without glasses. Due to the different temperatures between glasses and human faces, another line of works takes advantage of thermal images to remove the eyeglasses. Wong and Zhao [21] proposed a non-linear eyeglasses removing algorithm for thermal images based on kernel PCA (KPCA) [32]. This method performs KPCA to transfer the visible reconstruction information from the visible feature space to the thermal feature space, and then apply the image reconstruction to remove eyeglasses from the thermal face image. Different from the method based on PCA mentioned above, some researchers resort to sparse coding and expectation-maximization to reconstruct faces. Yi and Li [20] deployed the sparse representation technique in local feature space to deal with the issue of eyeglasses occlusion. De Smet et al. [31] proposed a generalized expectation-maximization approach, which applies the visibility map to inpaint the occluded areas of the face image.

However, these methods [17], [18], [20], [21], [31] are usually designed for frontal faces and specific eyeglasses in a controlled environment. Different from the existing work, our method focuses on face images collected from the realistic scenario, and is scalable to visual variants, such as pose, illumination, and different types of glasses.

B. Generative Adversarial Network

Recent advance in facial manipulation is due to two factors: 1) large-scale public face datasets with attribute annotations, for example, CelebA [25] and 2) the high-fidelity images generated by the generative adversarial network (GAN). GAN is one kind of the generative model benefiting from the competition between the generator and the discriminator [33]–[38]. The facial image manipulation algorithms based on GANs have taken significant steps [28]–[30], [39]–[41]. One line of previous work directly learns the image-to-image translation between different facial attributes. Shen and Liu [39] presented a GAN-based method using residual image learning and dual learning to manipulate the attribute-specific face area. Liu et al. [41] presented a unified selective transfer network for arbitrary image attribute editing (STGAN), by combining difference attribute vector and selective transfer unit (STU) in the autoencoder network. Another line of works first learn the embedding of the face attributes and then decode the learned feature to generate images. Liu et al. [29] proposed an unsupervised image-to-image translation (UNIT) framework, which combines the spirit of both GANs and variational autoencoders (VAEs) [42]. UNIT adopts the assumption that a pair of images in different domains share the same content space but the style space. Sampling different style codes could produce diverse and multimodal outputs while preserving the principle content.

Compared with previous GAN-based approaches [28]–[30], the proposed ERGAN has significant differences listed as follows.

1) To the introduced eye-area loss and invertible eye generation, the proposed ERGAN explicitly focuses on the manipulation of the eye region. The conventional generation mechanism inevitably introduces the noise to other areas of the original face when removing glasses.

2) We adopt the instance generation mechanism, which could swap the eye area of any two facial images. Compared with the CycleGAN-based methods, the proposed method could generate more diverse images.

3) Different from the previous works treating the face with different attributes as two or multiple domains, we view the face images as one domain with two codes, that is, the face appearance code and the eye-area attribute code. By utilizing this fine-grained latent representation decomposition, we could manipulate the code to generate conditional outputs to meet user demands.

III. METHODOLOGY

We first formulate the problem of eyeglasses removal and provide an overview of the proposed ERGAN in Section III-A. In Section III-B, we describe the details of each component in ERGAN, followed by the full objective function in Section III-C.

A. Formulation

In this article, we assume each face image could be decomposed into a face appearance code and an eye-area attribute code. Based on the assumption, we combine a face appearance code with an eye-area attribute code from an example face image to remove or wear eyeglasses. In this case, we could handle two inverse manipulations at the same time, that is, eyeglasses removal and eyeglasses wearing. The architecture of the proposed unified ERGAN is presented in Fig. 2(a). We denote face images with glasses and without glasses as $X$ and $Y$, respectively. The goal of the proposed method is to learn two mappings: 1) $X \rightarrow Y$ and 2) $Y \rightarrow X$ that could transfer an image $x \in X$ to another image $y \in Y$, and vice versa.

Generator: As illustrated in Fig. 2(a), the generator of the proposed method adopts a similar framework of autoencoder [43], [44], which consists of face appearance encoders $(E_X, E_Y)$, eye-area attribute encoders $(E_E^X, E_E^Y)$, and decoders $(G_X, G_Y)$. Specifically, the role of encoders $(E_X, E_Y^*)$ is to encode a given face image into the face appearance code $f$ and the eye-area attribute code $e$, respectively. Moreover, $f$ and $e$ are combined to generate a new image with the decoder $G$. The decoder $G$ is a deterministic function and has inverse encoders $(E_f, E_e^*) = (G_f)^{-1}$. In particular, $G_X$ generates face images without glasses and $G_Y$ generates face images with glasses, respectively.
Fig. 2. Overview of ERGAN. (a) Proposed method implements two mappings: \( X \rightarrow Y \) and \( Y \rightarrow X \). The input face image is decomposed to a face appearance code \( f \) and an eye-area attribute code \( e \) by encoders \( E_f \) and \( E_e \), respectively. Encoders \( E_f \) and \( E_e \) share weights. The black dashed line denotes that the eye region of the input image to face appearance encoder \( E_f \) is masked. (b) Self-reconstruction process of input image \( x \) to generate \( x_{\text{recon}} \). \( x_{\text{mask}} \) denotes \( x \) after the eye area is masked. (c) Illustration of example-guided eyeglasses removal. \( e_x \) and \( f_x \) are combined to generate \( y \) by \( G_X \). (d) We propose a dual learning scheme to simultaneously learn two inverse manipulations (removing eyeglasses and wearing eyeglasses) by swapping eye-area attribute codes.

**Discriminator:** \((D_X, D_Y)\) are two discriminators for \( X \) and \( Y \), respectively. The discriminator \( D \) aims to distinguish between generated images and real images. For instance, given a pair of images \( x \in X \) and \( y \in Y \), the discriminator \( D_X \) aims to distinguish images generated by decoder \( G_X(E_f(x), E_e(x)) \) from real images in \( X \). In the same way, the discriminator \( D_Y \) aims to distinguish images generated by decoder \( G_Y(E_f(y), E_e(y)) \) from real images in \( Y \). Specifically, the generated image by decoder \( G_X(E_f(x), E_e(x)) \) has the same face appearance code of \( x \) and the same eye-area attribute code of \( y \). In contrast, the generated image by decoder \( G_Y(E_f(y), E_e(y)) \) has the same face appearance code of \( y \) and the same eye-area attribute code of \( x \).

**B. Eyeglasses Removal Generative Adversarial Network**

**Face Image Self-Reconstruction:** As shown in Fig. 2(b), to enforce the generator focuses on the eye area of the input face image \( x \), we first mask out the eye region to generate \( x_{\text{mask}} \) and then encode \( x \) and \( x_{\text{mask}} \) by encoders \((E_f^e, E_e^e)\) to obtain the eye-area attribute code \( e_x \) and the face appearance code \( f_x \). Finally, \( e_x \) and \( f_x \) are combined to generate the self-reconstructed image \( x_{\text{recon}} \) with the decoder \( G_X \), where \( x_{\text{recon}} = G_X(E_f^e(x), E_e^e(x)) \). It is straightforward that the generated result of self-reconstruction approximates the source image. We introduce the face self-reconstruction loss, which is defined as

\[
L_{\text{face recon}}^{\text{face}} = \mathbb{E} \left[ \left\| G_X(E_f^e(x), E_e^e(x)) - x \right\|_1 \right] + \mathbb{E} \left[ \left\| G_Y(E_f^e(y), E_e^e(y)) - y \right\|_1 \right]
\]  

(1)

where \( X \) represents the set of face images without glasses and \( Y \) represents the set of face images with glasses, \( x \in X \) and \( y \in Y \). The pixelwise \( \ell_1 \)-norm \( \left\| \cdot \right\|_1 \) is employed for preserving the sharpness of self-reconstruction images. The face self-reconstruction loss enforces the encoders \((E_f^e, E_e^e)\) to learn two representations of the input face image, that is, the face appearance code and the eye-area attribute code, respectively.

**Eye-Area Reconstruction:** The face image self-reconstruction loss encourages the model to focus on the global features of the input image. For the glasses removal task, employing only the face image self-reconstruction loss misses the specific information of the eye area of the generated image. Therefore, enforcing the model to pay more attention to the eye area, we introduce the eye-area reconstruction loss

\[
L_{\text{eye recon}}^{\text{eye}} = \mathbb{E} \left[ \left\| y_{\text{recon}}^{\text{eye}} - x^{\text{eye}} \right\|_1 \right] + \mathbb{E} \left[ \left\| y_{\text{recon}}^{\text{eye}} - y^{\text{eye}} \right\|_1 \right]
\]  

(2)

where \( x^{\text{eye}} \) and \( y_{\text{recon}}^{\text{eye}} \) are denoted as the eye area of \( x \) and \( y_{\text{recon}} \), respectively. Similarly, \( y^{\text{eye}} \) and \( y_{\text{recon}}^{\text{eye}} \) are denoted as the eye area of \( y \) and \( y_{\text{recon}} \). In practice, since the face images are all center-aligned, the eye area is defined as \( (x_1 = 0.4h, x_2 = 0.2w, y_1 = 0.65h, y_2 = 0.75w) \) area of the input image, where \((h, w)\) is the size of the input face image.

**Dual Learning Scheme:** The proposed method is based on the assumption that the face image could be decomposed into a face appearance code and an eye-area attribute code. In detail, given a face appearance code, the decoder \( G \) could combine the face appearance code with the eye-area attribute code from the target face image to generate an image with or without glasses. Fig. 2(c) shows an example of eyeglasses removal.
The two related tasks of removing glasses and wearing glasses could be regarded as a dual process. Therefore, we apply a dual learning scheme [45] to learn two inverse manipulations simultaneously. The ablation study (in Section IV-F) confirms the effectiveness of the dual learning scheme.

We show the process of dual learning in Fig. 2(d). For given images \( x \) and \( y \), we encode them into \((f_x, e_x)\) and \((f_y, e_y)\), where \((f_x, e_x) = (E_x^f, E_x^e)\) and \((f_y, e_y) = (E_y^f, E_y^e)\). The dual tasks (i.e., removing eyeglasses and wearing eyeglasses) are performed by swapping the eye-area attribute codes. We adopt decoders \( G_X \) and \( G_Y \) to generate the final output images \( u = G_Y(f_x, e_y) \) and \( v = G_X(f_y, e_x) \), respectively. In particular, the decoder \( G_Y \) combines the face appearance code of \( x \) and the eye-area attribute code of \( y \) to generate \( u \). Similarly, the decoder \( G_X \) combines the face appearance code of \( y \) and the eye-area attribute code of \( x \) to generate \( v \).

Based on the assumption that each face image could be decomposed into a face appearance code and an eye-area attribute code, in this article, we learn two representations of the input face image, that is, the face appearance code and the eye-area attribute code. The face appearance code mainly contains the low-level geometric structure of the face. Since the encoder maps the region outside the eye area to the face appearance space is irrelevant to the face image with or without glasses. During the training, therefore, we employ the weights sharing between \( E_x^f \) and \( E_y^f \) to update the model synchronously. In contrast, the eye-area attribute code captures the semantic pattern in the eye area, resulting in the eye-area attributes of face images with glasses or without glasses are significantly different. In this case, we do not share weights between \( E_x^e \) and \( E_y^e \).

Furthermore, the proposed method should be able to reconstruct \((f_x, e_x)\) and \((f_y, e_y)\) after decoding \( u \) and \( v \). As illustrated in Fig. 2(d), we apply encoders \( E_x^f \) and \( E_y^f \) to obtain the face appearance code \( f_x \) and the eye-area attribute code \( e_y \), then \( f_x \) and \( e_y \) are concatenated together to generate \( u \). A similar process is utilized to generate \( v \). Then, we encode \( u \) and \( v \) into \((f_u, e_u)\) and \((f_v, e_v)\). To ensure that generated images \( u \) and \( v \) retain the original information, we define the face appearance reconstruction loss \( L_{\text{recon}}^f \) and the eye-area attribute reconstruction loss \( L_{\text{recon}}^e \). We formulate \( L_{\text{recon}}^f \) and \( L_{\text{recon}}^e \) as follows:

\[
L_{\text{recon}}^f = \mathbb{E}[\|f_u - f_x\|_1] + \mathbb{E}[\|f_f - f_y\|_1] \tag{3}
\]

\[
L_{\text{recon}}^e = \mathbb{E}[\|e_u - e_x\|_1] + \mathbb{E}[\|e_f - e_y\|_1] \tag{4}
\]

where \((f_u, f_v) = (E_x^f(u), E_y^f(v))\) and \((e_u, e_v) = (E_x^e(u), E_y^e(v))\). Notably, we find that the performance of the model is declined by introducing the eye-area attribute reconstruction loss \( L_{\text{recon}}^e \). To achieve the highest performance, we ignore \( L_{\text{recon}}^e \). The detailed discussion in our ablation study (in Section IV-F).

Then, we recombine face appearance codes \((f_u, f_v)\) and eye-area attribute codes \((e_u, e_v)\) to generate \( \hat{x} = G_X(f_u, e_v) = G_X(E^f_x(u), E^e_x(v)) \) and \( \hat{y} = G_Y(f_v, e_u) = G_Y(E^f_y(v), E^e_y(u)) \), respectively. To ensure the generated images \( u \) and \( v \) reconstruct the original images \( x \) and \( y \), we introduce the cycle consistency loss [28]. The cycle consistency loss \( L_{cc} \) is defined as

\[
L_{cc} = \mathbb{E}\left[ \left\| G_X\left( E^f_x(u), E^e_y(v) \right) - x \right\|_1 \right] + \mathbb{E}\left[ \left\| G_Y\left( E^f_y(v), E^e_x(u) \right) - y \right\|_1 \right] \tag{5}
\]

where \( u = G_Y(f_x, e_y) \) and \( v = G_X(f_y, e_x) \).

**Adversarial Loss:** To encourage the generated face image indistinguishable from the real face image, we adopt the adversarial loss [33]. In this case, \( G_X \) and \( G_Y \) attempt to generate high-fidelity face images (e.g., with glasses and without glasses), while \( D_X \) and \( D_Y \) attempt to distinguish real face images from generated face images. The adversarial loss is defined as

\[
L_{\text{adv}} = \mathbb{E}[-\log D_X(x)] + \mathbb{E}[-\log (1 - D_X(G_X(f_x, e_y)))] + \mathbb{E}[-\log D_Y(y)] + \mathbb{E}[-\log (1 - D_Y(G_Y(f_y, e_x)))] \tag{6}
\]

**Discussion:** Different from several image-to-image translation frameworks [28]–[30] to manipulate the whole image, the proposed method focuses on the manipulation of the eye area, which does not change the regions outside the eye area and preserves the information of the original image effectively. Specifically, inspired by image inpainting works [46]–[48], we cover the eye area of the input face image and then apply the encoder \( E^f \) to obtain the face appearance code, which avoids the interference of original eye area information. Moreover, we use the encoder \( E^e \) to obtain the eye-area attribute code of the input face image. In particular, introducing both the face image self-reconstruction loss and the eye-area reconstruction loss enforces the model to learn two representations of the input image, that is, the face appearance code and the eye-area attribute code. Besides, both the face image self-reconstruction loss and the eye-area reconstruction loss enforce the proposed model only to manipulate the eye region while maintaining the rest regions unchanged. Furthermore, we argue that the information feedback mechanism by dual learning could effectively improve the performance of the proposed method. Accordingly, we apply the dual learning scheme to realize the two inverse tasks of wearing glasses and removing glasses. The ablation study (in Section IV-F) demonstrates the effectiveness of the dual learning scheme.

### C. Objective Function

Taking all above loss functions into account, we jointly train the encoders, decoders, and discriminators. We formulate the full objective function as

\[
\min_{E^f, E^e, G_X, G_Y} \max_{D_X, D_Y} L_{\text{total}} \left( E^f, E^e, G_X, G_Y, D_X, D_Y \right) = \lambda_{\text{face}} L_{\text{recon}}^f + \lambda_{\text{eye}} L_{\text{recon}}^e + L_{cc} + L_{\text{adv}} \tag{7}
\]

where the hyperparameters \( \lambda_{\text{face}} \) and \( \lambda_{\text{eye}} \) control the weights of the face self-reconstruction loss and the eye-area reconstruction loss.

### IV. EXPERIMENT

#### A. Datasets

**Celeba:** The Celeba dataset [25] consists of 202,599 aligned face images collected from 10,177 celebrities in
the wild. Each image in CelebA is annotated with 40 face attributes (e.g., with/without eyeglasses and smiling/no-smiling). We split the CelebA dataset into one subset with glasses and another without glasses, based on the annotated attributes. Accordingly, we obtain 13,193 images with glasses and 189,406 images without glasses. All face images are center cropped to $160 \times 160$ and resized to $224 \times 224$ with a probability of 0.5 horizontal flipping.

**LFW:** The LFW dataset [49] contains 13,233 face images of 5,749 identities collected from the uncontrolled surroundings. All images are aligned by deep funneling [50]. We choose 1,600 face images with glasses and 8,000 face images without glasses from the LFW dataset to verify the effectiveness of the proposed method. The preprocessing of the LFW dataset is the same as the CelebA dataset.

**MeGlass:** The MeGlass dataset [51] includes 47,917 face images of 1,710 identities selected and cleaned from the MegaFace dataset [52]. The MeGlass dataset contains 14,832 face images with glasses and 33,087 face images without glasses. Besides, each identity contains at least two face images with glasses and two face images without glasses. We also perform experiments on MeGlass to verify the effectiveness of our method.

### B. Evaluation Metrics

**Fréchet Inception Distance:** Most image generation tasks [53]–[56] adopt the FID metric [26], which is utilized to measure the distance between generated images and real images through feature extracted by the inception network [57]. In this article, we apply the FID metric to measure the realism of the generated face images.

**Learned Perceptual Image Patch Similarity:** The LPIPS [27] distance is used to evaluate the diversity of generated images. Following several state-of-the-art image-to-image translation approaches [30], [55], [58], [59], we employ the LPIPS distance to measure the diversity of manipulated face images. Because the proposed method focuses on the task of eyeglasses removal, we only capture the eye area to measure the LPIPS distance to make a fair comparison. We denote the modified LPIPS metric as eLPIPS.

### C. Implementation Details

Here, we provide details about the network architecture of ERGAN.

1) The eye-area attribute encoder $E_e$ consists of several convolutional layers and residual blocks [60] as well as a global average pooling layer and a fully connected layer.

2) For the face appearance encoder $E_f$, it only consists of several convolutional layers and residual blocks.

3) The decoder $G$ combines $E_e$ and $E_f$ through four residual blocks followed by several convolutional layers and upsampling layers. In particular, we finally append a refine block which consists of a convolutional layer and a fully connected layer. The refine block is used to concatenate the reconstructed image with the input image to produce a higher quality generated image. In addition, all convolutional layers are followed by instance normalization [61]. Similar to MUNIT [30], each residual block contains two adaptive instance normalization layers [62].

4) For the discriminator $D$, we apply the multiscale discriminator (PatchGAN) proposes by Wang et al. [63]. Moreover, we adopt the Leaky ReLU with slope 0.2 in both generator and discriminator. In particular, we show detailed network architectures of $E_e$, $E_f$, and $G$ in Tables I–III.

During the training, we adopt Adam optimizer [64] to optimize the generator and the discriminators. In addition, we set the initial learning rate to 0.0001, weight decay 0.0005, and exponential decay rates $\beta_1, \beta_2 = (0, 0.999)$. Following several typical image-to-image translations [29], [30], [59], we set hyperparameters $\lambda_{\text{face}} = 10$ for the face self-reconstruction loss. To encourage the model to focus on the eye region, we set a large weight of $\lambda_{\text{eye}} = 10$ for the eye-area reconstruction loss. For the adversarial loss $\lambda_{\text{adv}}$, we employ the LSGAN objective proposed by Mao et al. [65]. Moreover, the gradient punishment strategy [66] is also adopted to stabilize our model training procedure.
Fig. 3. Results of eyeglasses removal from face images on the CelebA dataset. From top to bottom: real images, CycleGAN [28], UNIT [29], MUNIT [30], and our method.

Table III
Network Architecture of the Decoder $G$.

| Layer        | Parameters | Output Size |
|--------------|------------|-------------|
| Input        | -          | $256 \times 56 \times 56$ |
| ResBlocks    | $3 \times 3$, 256 \times 3 \times 256 \times 4$ | $256 \times 56 \times 56$ |
| Unsamp Conv1 | -          | $256 \times 112 \times 112$ |
| Unsamp Conv2 | $3 \times 3$, 128 \times 3 \times 128 \times 64$ | $128 \times 112 \times 112$ |
| Conv3        | $3 \times 3$, 64 \times 3 \times 64 \times 64$ | $64 \times 224 \times 224$ |
| Conv4        | $3 \times 3$, 3 \times 3 \times 3 \times 3 \times 1$ | $3 \times 224 \times 224$ |

D. Competitive Methods

We compare the proposed method with several two-domain image-to-image translation frameworks, including CycleGAN [28], UNIT [29], and MUNIT [30]. To make a fair comparison, we train our method and [28]–[30] under the same setting.

CycleGAN [28]: CycleGAN combines adversarial loss and cycle consistency loss to train two GANs for image-to-image translation.

UNIT [29]: The UNIT model assumes that images of different domains could be mapped to the same latent representation, and the images generated by the model could be associated with input images of different domains by VAEs [42], respectively.

MUNIT [30]: The MUNIT model is a multimodal UNIT framework. It assumes that images from different domains could be decomposed into a shared content space and a style specific space. Therefore, an image could be translated to the target domain by recombining the content code of the image with a random style code in the target style space.

These competitive methods usually treat the face with different attributes as two or multiple domains. In contrast, we view the face images as one domain with two codes, that is, the face appearance code and the eye-area attribute code. Besides, these three competitive methods manipulate the whole image to remove glasses, while our method only operates the eye area and other regions remain unchanged.

E. Evaluations

Qualitative Evaluation: We first qualitatively compare our method with three generative approaches above mentioned. As shown in Figs. 3 and 4, we evaluate the generated results quality after eyeglasses removal from face images on the CelebA dataset and the LFW dataset, respectively. We reimplement the competitive methods, that is, CycleGAN [28], UNIT [29], and MUNIT [30] by the open-source code. As shown in Figs. 3 and 4, CycleGAN, UNIT, and MUNIT still have limitations in the manipulation of eyeglasses removal. These competitive methods are prone to generate blurry or oversmoothing results and remove glasses insufficiently. In comparison, our generated images are natural and realistic, suggesting that the proposed method is effective in removing eyeglasses from face images. In particular, as illustrated in Fig. 5, the manipulation of eyeglasses removal by three competitive methods also change rest regions outside the eye area, which dramatically reduces the quality of the generated image. In contrast, our method only manipulates the eye region while keeping the rest regions unchanged.

We show example-guided eye-area attribute manipulation results in Fig. 6. We observe that our method achieves high-quality results in two inverse operations, that is, removing glasses and wearing glasses. Moreover, the eye-area feature from the target image maintains faithfully. We further perform linear interpolation between two eye-area attribute codes.
to generate the corresponding face images, as shown in Fig. 7. The linear interpolation results demonstrate that the eye-area attribute of face images change smoothly with latent codes.

**Quantitative Evaluation:** Here, we report the results of quantitative evaluations based on FID and eLPIPS metrics aiming to measure the realism and the diversity of our generated face images. As shown in Table IV, our method obtains the minimum FID and the maximum eLPIPS on the CelebA dataset, suggesting that generated face images by our method have a close distribution of real face images. We proceed to perform our method on the LFW dataset. As shown in Table V, our method also achieves the minimum FID and the maximum eLPIPS. The result indicates that the proposed method has scalability compared to three competitive methods. Moreover, the quantitative evaluation verifies the authenticity of qualitative evaluation, and our method is significantly superior to three competitive methods on both realism and diversity.

**F. Ablation Study**

To study the contribution of each component in the proposed method, we perform several variants of ERGAN and evaluate them on the CelebA dataset. Specifically, we evaluate six variants, that is, 1) *Ours w/o $L_{\text{face recon}}$*: our method without the face self-reconstruction loss term; 2) *Ours w/o $L_{\text{eye}}$*: our method without the eye-area reconstruction loss term; 3) *Ours w/o $L_{\text{rec}}$*: our method without the face appearance reconstruction loss term; 4) *Ours w/o $L_{\text{cc}}$*: our method without the cycle consistency loss term; 5) *Ours (half)*: our method without the dual learning scheme and only implementing the task of eyeglasses removal; and 6) *Ours w/ $L_{\text{eye recon}}$*: our method with the eye-area attribute reconstruction loss term.

We show the qualitative results of six variants in Fig. 8. Without using the face self-reconstruction loss, our method can still generate plausible results. However, some noise is introduced into the generated results, suggesting that the face self-reconstruction loss is a critical factor in keeping the rest regions except the eye area remains unchanged. Without adopting the face appearance reconstruction loss and the cycle consistency loss, our method generates slightly distorted results. The results cannot preserve the consistency of the input image. Without employing the dual learning scheme and only implementing the task of eyeglasses removal, the model produces much lower quality results, demonstrating that the dual learning scheme is effective in learning features. We also evaluate the variant of our method with the eye-area attribute reconstruction loss. The results show that adopting the eye attribute reconstruction loss cannot improve the quality of generated images. We suspect that this constraint is too strong, increasing the interferences in such a small region of the eye area. To achieve the best performance of our method, we remove the eye attribute reconstruction loss.

We report the quantitative ablation study results of six variants in Table IV. It can be observed that the full method obtains a lower FID score than six variants, suggesting that the proposed method can generate more realistic images on two tasks. For diversity, the scores drop dramatically without applying the face self-reconstruction loss, which indicates that this constraint is the key component to generate diversity outputs. In comparison to the variant which only implements the single task of eyeglasses removal, our method achieves lower FID scores and higher eLPIPS scores. It demonstrates that adopting the dual learning scheme can generate higher quality
Fig. 6. Examples of our generated images by swapping eye-area attribute codes on the CelebA dataset.

Fig. 7. Linear interpolation. Image generation results with linear interpolation between two eye-area attribute codes.

### TABLE IV
**QUANTITATIVE RESULTS. COMPARISON OF FID (LOWER IS BETTER) AND eLPIPS (HIGHER IS BETTER) TO EVALUATE REALISM AND DIVERSITY OF GENERATED FACE IMAGES AND THE REAL DATA ON THE CELEB A DATASET**

| Method          | FID ↓ | eLPIPS ↑ |
|-----------------|-------|----------|
|                 | Wearing | Removal | Wearing | Removal |
| Real data       | 6.02    | 5.62     |         |         |
| CycleGAN [28]   | 15.65   | 20.67    | -       | -       |
| UNIT [29]       | 18.80   | 18.86    | 0.114   | 0.074   |
| MUNIT [30]      | 29.42   | 18.85    | 0.283   | 0.144   |
| Ours w/o $L_{\text{face}}^{\text{recon}}$ | 14.12   | 16.60    | 0.005   | 0.002   |
| Ours w/o $L_{\text{eye}}^{\text{recon}}$  | 12.79   | 16.50    | 0.384   | 0.162   |
| Ours w/o $L_{\text{CC}}^{\text{recon}}$  | 14.42   | 15.68    | 0.432   | 0.208   |
| Ours w/o $L_{\text{CC}}^{\text{w/half}}$ | 12.46   | 16.27    | 0.426   | 0.234   |
| Ours (full)     | 11.96   | 15.07    | 0.428   | 0.240   |

### TABLE V
**QUANTITATIVE RESULTS. COMPARISON OF FID (LOWER IS BETTER) AND eLPIPS (HIGHER IS BETTER) TO EVALUATE REALISM AND DIVERSITY OF GENERATED FACE IMAGES AND THE REAL DATA ON THE LFW DATASET**

| Method          | FID ↓ | eLPIPS ↑ |
|-----------------|-------|----------|
|                 | Wearing | Removal | Wearing | Removal |
| Real data       | 24.17   | 6.96     |         |         |
| CycleGAN [28]   | 40.37   | 23.33    | -       | -       |
| UNIT [29]       | 40.30   | 35.31    | 0.132   | 0.076   |
| MUNIT [30]      | 51.74   | 42.83    | 0.201   | 0.141   |
| Ours (full)     | 26.58   | 19.87    | 0.367   | 0.260   |

G. Further Analysis and Discussion

**Limitation:** We notice that the proposed method tends to produce low-fidelity results when the input face image pairs have large pose changes. As shown in Fig. 9, given two face images with a similar pose, our method could generate high-quality results. In contrast, the quality of generated images is
degraded when the input images have significant pose changes (e.g., one front face and one profile face). There are two main reasons for the limitation. One is the limited amount of training data. Therefore, it is hard for our method to learn the two representations, that is, the face appearance code and the eye-area attribute code, to cover all the variations introduced by poses. Another reason is that the profile face usually contains noises, such as background and hairs, compromising the eye-area attribute code learning. As a result, the generated face is hard to simulate the target eye.

Face Verification: To further evaluate the performance of the proposed method, we first test whether it is beneficial to the face verification task. We apply the off-the-shelf face verification model FaceNet\(^1\) [2]. Three test subsets of the LFW dataset are taken into consideration, that is, original test images \(P_1\), selected images with eyeglasses \(P_2\), and selected images removed glasses by the proposed method \(P_2^r\). \(P_1\) is the standard test set of the LFW dataset. Due to the limited number of face images with eyeglasses in LFW, we further sample a subset \(P_2\) from the original test set, which contains both matched pairs (with the same identity, one face image with glasses and another without glasses) and mismatched pairs (with different identities, both face images with glasses). The subset \(P_2^r\) contains the same images as \(P_2\), while those images are manipulated with glasses removal by our method.

We report quantitative face verification results on LFW in Table VI. Comparing the face verification results obtained on \(P_1\) and \(P_2\), we observe that the accuracy obtained on the test set \(P_2\) is lower than that obtained on \(P_1\). This result shows that the occlusion of glasses compromises the accuracy of the face verification model. However, this result does not indicate that the occlusion of glasses is the only factor that reduces accuracy. Other factors, including illumination, resolution, and viewpoint, still account for the reduced accuracy of face verification. Moreover, comparing the results between \(P_2\) and \(P_2^r\), we find that the performance of face verification improved after eyeglasses removal by the proposed method. Notably, it is reasonable to obtain a gain of 0.32% for face verification. Our method can alleviate the impact of glasses occlusion on face verification. Although other factors, such as illumination, resolution, and viewpoint exist and affect the accuracy of face verification, our method can improve the accuracy to a sensible extent.

For face verification, we also perform experiments on three subsets of the MeGlass dataset, that is, \(M_1\) that contains face images without glasses, \(M_2\) that contains face images with glasses, and \(M_2^r\) that includes the same samples as \(M_2\), \(M_2^r\) includes all images that have been manipulated with eyeglasses removal by our method. We report quantitative face verification results on MeGlass in Table VII. We find that the face verification accuracy obtained on the test set \(M_2^r\) is higher than the accuracy on \(M_2\). The result is consistent with our statement that eyeglass removal could help face verification. Therefore, the proposed method could improve the accuracy of face verification on the large-scale dataset.

We show the qualitative face verification results on LFW in Fig. 10(a). We observe that the Euclidean distance decreases between matched images and the generated image by our method. Moreover, we present results of the average Euclidean distance in Fig. 10(b). The blue bar denotes the average Euclidean distance of the same person with and without eyeglasses, and the orange bar denotes the average Euclidean distance of the same person without glasses and removing glasses by ERGAN. We observe that on both LFW and MeGlass, the average Euclidean distance decrease between the same person without glasses and glasses removed by ERGAN. The result indicates that the proposed method could effectively alleviate the interference of glasses occlusion on face verification while preserving identification information well. Quantitative and qualitative results demonstrate that the proposed method is beneficial to the face verification task.

Facial Expression Recognition: Besides, we demonstrate that the proposed method benefits the facial expression recognition. To evaluate our method, we adopt a facial expression recognition algorithm,\(^2\) which effectively classifies the emotion into six adjectives (i.e., angry, scared, happy, sad, surprised, and neutral). We perform experiments on the

\(^1\)https://github.com/davidsandberg/facenet
\(^2\)https://github.com/opconty/keras-shufflenetV2
Fig. 10. Comparison of the Euclidean distance (lower is better) to evaluate the effectiveness of eyeglasses removal by our method. (a) Left image is one input face image with eyeglasses. The middle images are other face images of the same identity. The right image is the generated image which is removed glasses by our method. The number on the line denotes the Euclidean distance between two images. (b) Blue bar denotes the average Euclidean distance of the same person with and without eyeglasses, and the orange bar denotes the average Euclidean distance of the same person without glasses and removing glasses by ERGAN.

Fig. 11. Qualitative facial expression recognition results. The red word in the upper left corner of each image indicates the result of facial expression recognition. First row: expression recognition results of original images. Second row: expression recognition results of generated images by glasses removal.

CelebA dataset. Notably, the CelebA dataset only labels the attribute of smiling or not. Accordingly, we view that smiling represents the emotion of happy, and no-smiling represents other emotions. During the test, three sets are taken into consideration. $S_1$ denotes that the set contains face images with attributes of smiling and no-glasses, and $S_2$ indicates that the set contains face images with attributes of smiling and glasses. $S_2^r$ includes the same samples as $S_2$, while all images are manipulated with eyeglasses removal by our method.

We show qualitative results of facial expression recognition in Fig. 11. We observe that face images with glasses in the first row are all misidentified as other expressions. In contrast, after the manipulation of eyeglasses removal by our method, all images are recognized as the happy expression in the second row.

We present quantitative results in Table VIII. Comparing the facial expression recognition results between $S_1$ and $S_2$, we find that the accuracy drops by 6.9%. This result indicates that facial expression recognition is affected by the occlusion of glasses. Besides, comparing the results between $S_2$ and $S_2^r$, the accuracy of expression recognition gains by 4.9%. The performance is close to the result on $S_1$, which demonstrates the benefit of eyeglasses removal for facial expression recognition.

V. Conclusion
In this article, we have proposed a GAN-based framework for eyeglasses removal in the wild. We adopt a dual learning scheme simultaneously to learn two inverse manipulations (removing glasses and wearing glasses), which enforces the model to generate high-quality results. Extensive qualitative and quantitative experiments demonstrate that our method outperforms previous state-of-the-art methods in terms of realism and diversity. Furthermore, we remark that the proposed method has the potential to serve as a preprocessing tool for other face-related tasks, e.g., face verification and facial expression recognition.
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