DVG-Face: Dual Variational Generation for Heterogeneous Face Recognition

Chaoyou Fu, Xiang Wu, Yibo Hu, Huaibo Huang, and Ran He*, Senior Member, IEEE

Abstract—Heterogeneous Face Recognition (HFR) refers to matching cross-domain faces, playing a crucial role in public security. Nevertheless, HFR is confronted with the challenges from large domain discrepancy and insufficient heterogeneous data. In this paper, we formulate HFR as a dual generation problem, and tackle it via a novel Dual Variational Generation (DVG-Face) framework. Specifically, a dual variational generator is elaborately designed to learn the joint distribution of paired heterogeneous images. However, the small-scale paired heterogeneous training data may limit the identity diversity of sampling. With this in mind, we propose to integrate abundant identity information of large-scale VIS images into the joint distribution. Furthermore, a pairwise identity preserving loss is imposed on the generated paired heterogeneous images to ensure their identity consistency. As a consequence, massive new diverse paired heterogeneous images with the same identity can be generated from noises. The identity consistency and diversity properties allow us to employ these generated images to train the HFR network via a contrastive learning mechanism, yielding both domain invariant and discriminative embedding features. Concretely, the generated paired heterogeneous images are regarded as positive pairs, and the images obtained from different samplings are considered as negative pairs. Our method achieves superior performances over state-of-the-art methods on seven databases belonging to five HFR tasks, including NIR-VIS, Sketch-Photo, Profile-Frontal Photo, Thermal-VIS, and ID-Camera. The related code will be released at [https://github.com/BradyFU].

Index Terms—Heterogeneous face recognition, cross-domain, dual generation, contrastive learning.

1 INTRODUCTION

In the last decades, face recognition for visible (VIS) images has made a great breakthrough with Deep Convolutional Neural Networks [1], [2]. Nevertheless, in some practical security applications, face recognition systems often need to match cross-domain face images rather than merely VIS, raising the problem of Heterogeneous Face Recognition (HFR). For example, a near infrared (NIR) imaging sensor has been integrated into most mobile devices because it offers an inexpensive and effective solution to obtain clear face images in extreme lightings. At the same time, the enrollment of face templates is usually VIS images. In this situation, a face recognition system is asked to match heterogeneous NIR-VIS data. Unfortunately, due to the large domain discrepancy, the performance of the recognition network trained on VIS images often degrades dramatically in such a heterogeneous case [3]. Other HFR tasks also include Sketch-Photo [4], Profile-Frontal Photo [5], Thermal-VIS [6], and ID-Camera [7]. In order to bridge the domain discrepancy between heterogeneous data, researchers have put substantial efforts to match cross-domain features. However, the difficulty of data acquisition often makes the collection of large-scale heterogeneous database unavailable. Over-fitting often occurs when the recognition network is trained on such insufficient data [3].

With the rapid development of deep generative models, “recognition via generation” has been one of the hot topics in the computer vision community [9]. Deep generative models are good at learning the mapping among different domains, and thereby usually employed to reduce the domain discrepancy [10]. For example, [8] proposes to transfer NIR images to VIS ones via a two-path generative model. [11] introduces a multi-stream feature fusion manner with Generative Adversarial Networks (GANs) [12] to synthesize photo-realistic VIS images from polarimetric thermal faces. However, there are two challenging issues for these conditional image-to-image translation based methods: (1) Diversity. Since these methods adopt a “one-to-one” translation manner, the generator can only synthesize one new image of the target domain when one image of the source domain is fed. Therefore, these methods can only generate a limited amount of new data to reduce the domain discrepancy. At the same time, as exemplified in the left part of Fig. 1, the generated new images have the same attributes as the inputs except for the spectrum. This limits the intra-class diversity of the generated data. (2) Consistency. These methods require that the generated images still belong to the same classes of the inputs. Nevertheless, it is hard to meet this requirement, because the widely adopted identity preserving loss [9], [13] only constrains the feature distance between the generated images and the targets, while ignores both the intra-class and the inter-class distances. The above two issues make deep generative models rather difficult to effectively boost the performance of HFR.

In order to tackle the above challenges, we propose an unconditional Dual Variational Generation (DVG-Face) framework, which can generate large-scale new diverse paired heterogeneous images. Different from the aforementioned conditional generation in HFR, unconditional gen-
conditional Dual Variational Generation (DVG-Face) framework, which samples large-scale new diverse paired heterogeneous data from noises to boost the performance of HFR.

- Abundant identity information is integrated into the joint distribution to enrich the identity diversity of the generated data. Meanwhile, a pairwise identity preserving loss is imposed on the generated paired images to ensure their identity consistency. These two properties allow us to make better use of the generated unlabeled data to train the HFR network.

- By regarding the generated paired images as positive pairs and the images obtained from different samplings as negative pairs, the HFR network is optimized via contrastive learning to learn both domain invariant and discriminative embedding features.

- Extensive experiments on seven HFR databases demonstrate that our method gains remarkable improvements over state-of-the-art methods. Particularly, on the challenging low-shot Oulu-CASIA NIR-VIS database, we improve the best TPR@FPR=10−5 by 29.2%. Besides, compared with the baseline trained on the Tufts Face database, VR@FAR=1% is advanced by 26.1% after adding the generated data.

This paper is an extension of our previous conference version [20], and there are three major improvements over the preliminary one: (1) The generated images have richer identity diversity. For the preliminary version, the generator can only be trained with the small-scale paired heterogeneous data, which thereby limits the identity diversity of the generated images. In the current version, the architecture and the training manner of the generator are redesigned, making it can be trained with both paired heterogeneous data and large-scale unpaired VIS data. The introduction of the latter greatly enriches the identity diversity of the generated images. (2) The generated images are leveraged more efficiently. The preliminary version trains the HFR network with the generated paired data via a pairwise distance loss, resorting to the identity consistency property. On this basis, benefiting from the aforementioned identity diversity property, the current version further regards the images obtained from different samplings as negative pairs, formulating a contrastive learning mechanism. Hence, the
preliminary version can only leverage the generated images to reduce the domain discrepancy, while the current version utilizes the generated images to learn both domain invariant and discriminative embedding features. (3) More insightful analyses and more experiments are added. Except for NIR-VIS and Sketch-Photo, we further explore Profile-Frontal Photo, Thermal-VIS, and ID-Camera HFR tasks. Meanwhile, the current version gains remarkable improvements over the preliminary one on all the databases.

2 RELATED WORK

2.1 Heterogeneous Face Recognition

HFR has attracted increasing attention of researchers for its crucial practical value. In this subsection, we review the development of HFR from the perspectives of feature-level learning and image-level learning.

Feature-level learning based methods aim at seeking discriminative feature representations. Some methods try to capture a common latent space between heterogeneous data for relevance measurement. [21] employs a prototype random subspace to improve HFR performance. [22] introduces a generalized transfer subspace with a low-rank constraint. There are also some methods that focus on learning domain invariant features. Traditional works mainly use handcrafted features. For example, [23] extracts Histograms of Oriented Gradients (HOG) features with sparse representations to obtain cross-domain semantics. [24] proposes a common encoding model to obtain discriminant information for HFR. Recently, the thriving deep learning has powerful feature extraction capability, and thus has been widely applied in HFR. [25] explores multiple different metric learning methods to reduce domain gaps. [16] designs a residual compensation framework that learns different modalities in separate branches.

Image-level learning based methods mainly operate on the pixel space to improve the performance of HFR. [26] translates a photo image to a sketch one, thus reducing the domain gap. [27] improves recognition performance by using coupled dictionary learning for cross-domain image synthesis. [28] proposes to composite facial parts, such as eyes, to augment the small database to a larger one. [29] uses a CNN to perform a cross-spectral hallucination, reducing the domain gap at pixel space. Recently, the rapid developed GANs [12] provide a solution to the problem of HFR. [30] utilizes image-to-image translation methods to synthesize new data, and then incorporates the synthesized data into the training set to augment the intra-class scale and reduce inter-class diversity. [31] proposes a cascaded face sketch synthesis model to deal with the illumination problem.

2.2 Generative Model

As a hot topic in machine learning and computer vision communities, generative model has made gratifying progress in recent years [12, 14, 33, 34]. Usually, it can be divided into two types: unconditional generative model and conditional generative model.

Unconditional generative model synthesizes data from noises. The most prominent models include Variational AutoEncoders (VAEs) [14] and Generative Adversarial Networks (GANs) [12]. VAEs adopt a variational inference manner to learn data distribution, consisting of an encoder network \( q_\theta(z|x) \) and a decoder network \( p_\theta(x|z) \). The Evidence Lower Bound Objective (ELBO) is derived for an approximate optimization:

\[
\log p_\theta(x) \geq E_{q_\theta(z|x)} \log p_\theta(x|z) - D_{KL}(q_\theta(z|x)||p(z)),
\]

where the first term is a reconstruction loss and the second term is a Kullback-Leibler divergence. \( p(z) \) is usually set to a standard Gaussian distribution. Recently, some variants are proposed to improve the synthesis quality. IntroVAE [35] generates high-resolution images via an introspective manner. VQ-VAE [36] gets high-quality images via learning discrete representations with an autoregressive prior.

Differently, GANs propose an adversarial manner to learn data distribution implicitly. In general, GANs consist of two networks: a generator \( G \) and a discriminator \( D \). \( G \) generates data from a prior \( p(z) \) to confuse \( D \), while \( D \) is trained to distinguish the generated data and the real data. Such an adversarial manner is formulated as:

\[
\min_G \max_D \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p(z)} [\log (1 - D(G(z)))].
\]

GANs are good at generating high-quality images. PGGAN [15] significantly improves the resolution of the synthesized images to 1024 \( \times \) 1024. SinGAN [37] generates realistic images with merely a single training image. CoGAN [38] tackles the similar problem of our method. It adopts a weight-sharing manner to generate paired data from two domains. However, due to the lacking of explicit identity constrains, it is rather challenging for such a weight-sharing manner of CoGAN to generate paired data with the same identity, as discussed in Section 4.3.1.

Conditional generative model synthesizes data according to the given conditions. pix2pix [10] realizes photo-realistic paired image-to-image translation with a conditional generative adversarial loss. CycleGAN [39] employs a cycle-consistent network to tackle the unpaired image translation problem. MUNIT [40] decomposes image representations into a content code and a style code, realizing example based image synthesis. BigGAN [41] is the pioneer work for high-resolution natural image synthesis. StarGAN [42] devotes to unpaired multi-domain image-to-image translation. StyleGAN [43] proposes a style-based generator that separates high-level attributes automatically. SPADE [44] synthesizes high-quality images with the guidance of semantic layouts. InterFaceGAN [45] edits face images according to the interpretable latent semantics learned by GANs.

3 Method

The goal of our method is to generate a large amount of paired heterogeneous data from noises to boost the performance of HFR. Correspondingly, our method is divided into two parts to tackle: (1) how to generate diverse paired heterogeneous data and (2) how to effectively take advantage of these generated data. The two parts are introduced in the following two subsections, respectively. We take NIR-VIS as an example for presentation. Other heterogeneous face images are also applicable.
Meaning Attribute encoder for NIR/VIS Identity representation sampled from Pre-trained face recognition network Identity representation of
Identity representation of Pre-trained identity sampler Attribute distribution of
Identity representation of Reconstructed NIR/VIS image Generated NIR/VIS image with

3.1 Dual Generation

As stated in Section 1, we expect the generated paired images to have two properties: identity diversity and identity consistency. On the one hand, in order to promote identity diversity, we employ an unconditional generative manner, since it has the ability to generate new samples from noises since it has the ability to generate new samples from noises. On the other hand, in order to constrain the identity consistency property, we impose a pairwise identity preserving loss on the generated paired images, minimizing their feature distances in the embedding space.

Meanwhile, considering that the small number of paired heterogeneous training data may limit the identity diversity of sampling, we introduce abundant identity information of large-scale VIS data into the generated images. On the other hand, in order to constrain the identity consistency property, we impose a pairwise identity preserving loss on the generated paired images, minimizing their feature distances in the embedding space.

The above ideas are implemented by a dual variational generator, whose framework is shown in Fig. 2 (a) and (b). It contains two domain-specific attribute encoders $E_N$ and $E_V$, a decoder $G$, a pre-trained face recognition network $F$, and an identity sampler $F_s$. Among them, $E_N$ and $E_V$ are utilized to learn domain-specific attribute distributions of NIR and VIS data, respectively. $F$ is employed to extract identity representations. $F_s$ can flexibly sample abundant identity representations from noises. The joint distribution of the paired heterogeneous data consists of the identity representations and the attribute distributions. $G$ maps the joint distribution to the pixel space. The parameters of $F$ and $F_s$ are fixed, while those of the other networks are updated during the training with both paired heterogeneous data.
and unpaired VIS data. Table 1 summarizes the meaning of the employed symbols in our method.

### 3.1.1 Training with Paired Heterogeneous Data

Given a pair of NIR-VIS data $I_N$ and $I_V$ with the same identity, the dual variational generator learns disentangled joint distribution in the latent space. To be specific, a face recognition network pre-trained on MS-Celeb-1M [22] is adopted as a feature extractor $F$. The compact embedding features extracted by $F$ are thought to be only identity related [46]. Meanwhile, considering that $F$ is better at extracting the features of VIS images than those of NIR images, we employ $f = F(I_V)$ as the identity representation of both $I_N$ and $I_V$. Then, the encoders $E_N$ and $E_V$ are leveraged to learn domain-specific attribute distributions $z_N = q_{\phi_N}(z_N|I_N)$ and $z_V = q_{\phi_V}(z_V|I_V)$, respectively. $\phi_N$ and $\phi_V$ are the parameters of the encoders. According to the reparameterization trick [14], $z_N = u_N + \sigma_N \odot \epsilon$ and $z_V = u_V + \sigma_V \odot \epsilon$, where $u$ denotes mean and $\sigma$ denotes standard deviation. $\odot$ denotes Hadamard product and $\epsilon$ is a noise sampled from a multi-variate standard Gaussian distribution. Subsequently, in order to ensure that $z_N$ and $z_V$ are merely attribute related, we impose an angular orthogonal loss between the attribute and the identity representations. Finally, the disentangled identity and attribute representations constitute the joint distribution of paired NIR-VIS data, and then are fed to the decoder $G$ to reconstruct the inputs $I_N$ and $I_V$.

Three loss functions are involved in the above process, including an angular orthogonal loss, a distribution learning loss, and a pairwise identity preserving loss. The details of these losses are as follows.

**Angular Orthogonal Loss.** The angular orthogonal loss is imposed between $z_N$ and $f$ as well as $z_V$ and $f$. For the $L_2$ normalized $z_V$ and $f$, the cosine similarity is defined as:

$$\cos(z_V, f) = \langle z_V, f \rangle$$

where $\langle \cdot, \cdot \rangle$ denotes inner product. When the two representations are orthogonal, Eq. (3) is equal to zero. Minimizing the absolute value of Eq. (3) will force $z_V$ and $f$ to be orthogonal, and thus they are disentangled. Ultimately, the angular orthogonal loss that considers both normalized $z_N$ and $z_V$ is formulated as:

$$L_{ort} = |\langle z_V, f \rangle| + |\langle z_N, f \rangle|$$

In the following parts, $z_N$, $z_V$, and the output of $F(\cdot)$ (such as $f = F(I_V)$) all denote the normalized ones.

**Distribution Learning Loss.** Inspired by VAEs [14], the posterior distributions $q_{\phi_N}(z_N|I_N)$ and $q_{\phi_V}(z_V|I_V)$ are constrained by a Kullback-Leibler divergence:

$$L_{kl} = D_{KL}(q_{\phi_N}(z_N|I_N)||p(z_N)) + D_{KL}(q_{\phi_V}(z_V|I_V)||p(z_V))$$

where both the priors $p(z_N)$ and $p(z_V)$ are multi-variate standard Gaussian distributions. After obtaining the identity representation $f$ as well as the domain-specific attribute representations $z_N$ and $z_V$, the decoder network is required to reconstruct the inputs $I_N$ and $I_V$:

$$L_{rec} = -E_{q_{\phi_N}(z_N|I_N)\cup q_{\phi_V}(z_V|I_V)} \log p_{\theta}(I_N, I_V|f, z_N, z_V)$$

Concretely, $L_{rec}$ is implemented as:

$$L_{rec} = ||\hat{I}_N - I_N||_1 + ||\hat{I}_V - I_V||_1,$$

where $\hat{I}_N = G(f, z_N)$ and $\hat{I}_V = G(f, z_V)$.

In general, according to [14], the distribution learning loss is the combination of $L_{kl}$ and $L_{rec}$:

$$L_{dis} = L_{kl} + L_{rec}.$$ (8)

**Pairwise Identity Preserving Loss.** In order to preserve the identity of the generated data, previous conditional image-to-image translation based methods usually adopt an identity preserving loss [9], [13], [47]. It utilizes a pre-trained face recognition network to extract the embedding features of the generated data and those of the target real data respectively, and then forces the two features as close as possible. However, since there are neither intra-class nor inter-class constraints, it is challenging to ensure that the generated images belong to the same class as the targets.

As discussed in Section 1, different from the previous methods, we only concern about the identity consistency of the generated paired images, rather than whom the generated images belong to. Therefore, we propose a pairwise identity preserving loss, which constrains the feature distance between $f_N = F(I_N)$ and $f_V = F(I_V)$:

$$L_{ip-pair} = 1 - f_N \cdot f_V.$$ (9)

Minimizing Eq. (9) will increase the cosine similarity between $f_N$ and $f_V$. Furthermore, in order to stabilize the training process, we also constrain the feature distance between $f_N$ and $f$ as well as $f_V$ and $f$:

$$L_{ip-rec} = (1 - f_N \cdot f_V) + (1 - f_V \cdot f).$$ (10)

The pairwise identity preserving loss that considers both $L_{ip-pair}$ and $L_{ip-rec}$ is formulated as:

$$L_{ip} = L_{ip-pair} + L_{ip-rec}.$$ (11)

**Overall Loss.** The overall loss for the training with paired data is the weighted sum of the above distribution learning, angular orthogonal, and identity preserving losses.

$$L_{overall} = \alpha L_{dis} + \beta L_{ort} + \gamma L_{ip}.$$ (12)
learning loss $L_{\text{dis}}$, the angular orthogonal loss $L_{\text{ort}}$, and the pairwise identity preserving loss $L_{\text{ip}}$. Furthermore, same as [48], an extra adversarial loss $L_{\text{adv}}$ is also introduced to increase the sharpness of the generated data:

$$L_{\text{pair}} = L_{\text{dis}} + \lambda_1 L_{\text{ort}} + \lambda_2 L_{\text{ip}} + \lambda_3 L_{\text{adv}},$$

where $\lambda_1$, $\lambda_2$, and $\lambda_3$ are trade-off parameters. Among them, $\lambda_3$ is fixed as 0.1, according to [48].

### 3.1.2 Training with Unpaired VIS Data

The number of the paired heterogeneous training data is limited, which may affect the identity diversity of the generated images. Hence, we further introduce abundant identity information of large-scale VIS data into the generated images. For the acquisition of the identity information, a straightforward manner is employing a pre-trained face recognition network to extract from the VIS data, as shown in Fig. 2 (b). However, in this situation, if we desire to generate large-scale new paired data at the testing phase, we must have the same number of VIS data with different identities. It makes our framework become a conditional generative model, leading to the diversity problem as mentioned in Section 1. In order to overcome this obstacle, inspired by [49], we introduce an identity sampler to substitute the recognition network. Specifically, we first adopt the recognition network to extract the embedding features of MS-Celeb-1M [32], and then leverage these embedding features to train a VAE model [14]. After the training, the decoder of VAE is used as the identity sampler, which can map the points in a standard Gaussian noise to identity representations, as shown in the lower right corner of Fig. 2 (b). Equipped with the identity sampler, our framework becomes an unconditional generative model. The required identity representations can be flexibly sampled from noises. The detailed discussion about the face recognition network and the identity sampler is reported in Section 3.3.4.

Since these sampled identity representations do not have corresponding ground truth paired heterogeneous data, we propose an unpaired training manner. To begin with, we obtain an identity representation $\tilde{f}$ after sampling from the identity sampler $F_s$. Then, $\tilde{f}$ as well as the attribute representations $z_N$ and $z_V$ in Eq. 4 are fed into the decoder $G$. Finally, a new pair of heterogeneous images, i.e. $\hat{I}_N = G(\tilde{f}, z_N)$ and $\hat{I}_V = G(\tilde{f}, z_V)$, that does not belong to the heterogeneous database is generated. We constrain $\hat{I}_N$ and $\hat{I}_V$ from the aspects of appearance and semantic. For appearance, we introduce a small-weight reconstruction loss [46] to force the appearance of the generated images to be in line with that of the inputs $I_N$ and $I_V$:

$$L_{\text{rec}}^u = \eta \left( ||\hat{I}_N - I_N||_1 + ||\hat{I}_V - I_V||_1 \right),$$

where $\eta$ is set to 0.1 according to [46]. For semantic, same as the aforementioned pairwise identity preserving manner in Eq. (11), we constrain $f_N = F(\hat{I}_N)$ and $\tilde{f}_V = F(\hat{I}_V)$ via:

$$L_{\text{ip}} = (1 - \langle \hat{f}_N, \tilde{f}_V \rangle) + (1 - \langle \tilde{f}_N, \hat{f}_V \rangle) + (1 - \langle \hat{f}_V, \hat{f}_V \rangle).$$

(14)

Consequently, the overall loss for the training with unpaired VIS data is the weighted sum of $L_{\text{rec}}^u$ and $L_{\text{ip}}^u$ as well as an extra adversarial loss $L_{\text{adv}}$ as Eq. (12):

$$L_{\text{unpair}} = L_{\text{rec}}^u + \lambda_2 L_{\text{ip}}^u + \lambda_3 L_{\text{adv}},$$

where $\lambda_2$ and $\lambda_3$ are the same as those in Eq. (12). Algorithm 1 shows the training process with both paired heterogeneous data and unpaired VIS data.

### 3.2 Heterogeneous Face Recognition

After the training of the dual variational generator, we first employ it to generate large-scale paired heterogeneous images, and then leverage these images to facilitate the training of the HFR network. For HFR, we use a face recognition network pre-trained on MS-Celeb-1M as the backbone, which is further trained with both the limited number of real heterogeneous data $I_i \ (i \in \{N, V\})$ and the great deal of generated heterogeneous data $\hat{I}_i \ (i \in \{N, V\})$.

For the real heterogeneous data, we employ a softmax loss to optimize the HFR network:

$$L_{\text{cls}} = \sum_{i \in \{N, V\}} \text{softmax}(f_i, y),$$

where $y$ is the class label of the input $I_i$, and $f_i = F(I_i)$. Here $F$ denotes the pre-trained face recognition network, same as the feature extractor in Section 3.1. The difference is that the parameters of the former are updated while those of the latter are fixed.

For the generated data, since there is no specific class label, the above softmax loss is inapplicable. However, benefiting from the properties of identity consistency and identity diversity, we propose to take advantage of these generated data via a contrastive learning mechanism [50]. To be specific, as shown in Fig. 2 (c), we first randomly sample two paired heterogeneous images ($\hat{I}_N, \hat{I}_V$) and ($\hat{I}_N, \hat{I}_V$) from the generated database. Based on the identity consistency property, the paired heterogeneous images ($\hat{I}_N, \hat{I}_V$) and ($\hat{I}_N, \hat{I}_V$) are set as positive pairs. Meanwhile, thanks to the identity diversity property, the images obtained from different samplings, i.e. ($\hat{I}_N, \hat{I}_V$) and ($\hat{I}_N, \hat{I}_V$), are regarded as negative pairs. Note that we do not set ($\hat{I}_N, \hat{I}_V$) and ($\hat{I}_N, \hat{I}_V$) as negative pairs, since HFR is dedicated to cross-domain matching.

Formally, the contrastive loss for the generated data is:

$$L_{\text{cont}} = \sum_{j \neq k} \left( 1 - \langle \hat{f}_N, \hat{f}_V \rangle \right) + \left( 1 - \langle \hat{f}_N, \hat{f}_V \rangle \right) + \max(0, \langle \hat{f}_N, \hat{f}_V \rangle - m) + \max(0, \langle \hat{f}_N, \hat{f}_V \rangle - m),$$

where $\hat{f}_N = F(\hat{I}_N)$, $\hat{f}_V = F(\hat{I}_V)$, and $m$ is a margin value. Minimizing Eq. (17), the first two terms assist in reducing domain discrepancy, while the last two terms facilitate the learning of discriminative embedding features.

Considering both the softmax loss $L_{\text{cls}}$ and the contrastive loss $L_{\text{cont}}$, the overall loss for the HFR network is:

$$L_{\text{HFR}} = L_{\text{cls}} + \alpha L_{\text{cont}},$$

where $\alpha$ is a trade-off parameter.
set and the corresponding NIR images are used as the probe set. Evaluation indicators include Rank-1 accuracy, VR@FAR=1%, and VR@FAR=0.1%.

**BUAA-VisNir Face Database** [54] is a popular heterogeneous face database that is usually utilized to evaluate domain adaption. It consists of 150 identities, and each identity includes multiple NIR and VIS images. The training set has about 1,200 images from 50 identities, while the testing set contains about 1,300 images from the rest of 100 identities. For testing, only one VIS image per identity is selected as the gallery set and the NIR images constitute the probe set. We report Rank-1 accuracy, VR@FAR=1%, and VR@FAR=0.1% for comparisons.

**IIIT-D Sketch Viewed Database** [4] is developed for Sketch-VIS recognition, containing 238 image pairs. Among them, 67 pairs are from the FG-NET aging database, 99 pairs are from the Labeled Faces in Wild (LFW) database, and 72 pairs are from the IIIT-D student & staff database. Since the IIIT-D Sketch Viewed database only has a small number of images, following [17], we use it as the testing set, and adopt CUHK Face Sketch FERET (CUFSF) [55] as the training set. CUFSF is also a Sketch-VIS face database that contains 1,194 image pairs. Rank-1 accuracy is reported.

**Multi-PIE Database** [5] is often employed for multi-pose evaluation. There are 4 sessions with 337 identities, and each identity has abundant illuminations, poses, and expressions. According to Setting 2 of [55], we only use the face images with the neutral expression under 20 illuminations. The first 200 identities are used for training and the rest of 137 identities are used for testing. For testing, the gallery set has one frontal face image per identity, and the probe set contains ±90° face images. Rank-1 accuracy is reported.

**Tufts Face Database** [6] is collected for the study of imaging systems, providing Thermal-VIS face images. There are a total of 113 identities with 74 females and 39 males, from more than 15 countries. Each identity has multiple cross-domain face images with different poses. We randomly select 50 identities as the training set, including 1,490 VIS images and 450 thermal images. The remaining 63 identities are used as the testing set with 1,916 VIS images and 530 thermal images. For testing, the thermal and the VIS images constitute the probe and the gallery sets, respectively. We report Rank-1 accuracy, VR@FAR=1%, and VR@FAR=0.1%.

**NJU-ID Database** [7] is built to study ID-Camera face verification. This database has a total of 256 identities, and each identity contains one ID card image with 102 × 126 resolution and one camera image with 640 × 480 resolution. Considering the NJU-ID database only has a limited number of images, we merely use it as the testing set, and collect a new ID-Camera database as the training set that has 1,190 image pairs. For testing, the camera images are used as the probe set, and the ID card images are used as the gallery set. Rank-1 accuracy, VR@FAR=1%, and VR@FAR=0.1% are reported for comparisons.

### 4.2 Experimental Settings

For the dual generation, we employ LightCNN [57] pretrained on MS-Celeb-1M [32] as the feature extractor $F$. The network architectures of the encoder $E_V/E_N$ and the decoder $G$ are reported in Table 2. 'Fc' denotes a fully
TABLE 2: Network architectures of the encoder $E_N/E_V$ and the decoder $G$. K/S/P denotes kernel size/stride/padding.

(a) Encoder architecture.

| LAYER | K/S/P | OUTPUT |
|-------|-------|--------|
| Conv1 | 5/1/2 | $32 \times 128^2$ |
| Conv2 | 3/2/1 | $64 \times 128^2$ |
| Conv3 | 3/2/1 | $128 \times 128^2$ |
| Conv4 | 3/2/1 | $256 \times 256^2$ |
| Conv5 | 3/2/1 | $256 \times 128^2$ |
| Conv6 | 3/2/1 | $256 \times 64^2$ |
| FCl   | -     | 512     |

(b) Decoder architecture.

| LAYER | K/S/P | OUTPUT |
|-------|-------|--------|
| FC2   | -     | 2048   |
| Deconv1 | 2/2/0 | $128 \times 8^2$ |
| Deconv2 | 2/2/0 | $128 \times 16^2$ |
| Deconv3 | 2/2/0 | $64 \times 32^2$ |
| Deconv4 | 2/2/0 | $64 \times 64^2$ |
| Deconv5 | 2/2/0 | $32 \times 128^2$ |
| Out   | 1/1/0 | $3 \times 128^2$ |

TABLE 3: Experimental analyses on Tufts Face. MS (Mean Similarity, higher is better) denotes the mean cosine similarity between the generated paired NIR-VIS data. MIS (Mean Instance Similarity, lower is better) presents the mean cosine similarity between two randomly sampled data, including VIS-VIS and NIR-VIS. FID (Fréchet Inception Distance, lower is better) measures the distribution distance between the generated data and the real data. VR@FAR=1% displays the recognition performance after employing these generated data to train the HFR network via contrastive learning.

| Method       | MS  | MIS (VIS-VIS) | MIS (NIR-VIS) | FID   | VR@FAR=1% |
|--------------|-----|---------------|---------------|-------|-----------|
| CoGAN        | 0.53| 0.32          | 0.16          | 0.77  | 22.1      |
| DVG          | 0.52| 0.45          | 0.41          | 0.65  | 39.3      |
| DVG-Face     | 0.53| 0.14          | 0.14          | 0.57  | 68.5      |

Identity diversity plays a crucial role in our method. The more diverse the generated data, the more valuable it will be for the HFR network. In order to promote the identity diversity, we introduce abundant identity information of large-scale VIS data into the generated data. Furthermore, inspired by the instance discrimination criterion [18], [19] that regards each image as an independent class, we propose a Mean Instance Similarity (MIS) to measure the identity diversity property. Intuitively, if the generated images have abundant identity diversity, the images obtained from different samplings can be seen as different classes.

Identity diversity plays a crucial role in our method. The more diverse the generated data, the more valuable it will be for the HFR network. In order to promote the identity diversity, we introduce abundant identity information of large-scale VIS data into the generated data. Furthermore, inspired by the instance discrimination criterion [18], [19] that regards each image as an independent class, we propose a Mean Instance Similarity (MIS) to measure the identity diversity property. Intuitively, if the generated images have abundant identity diversity, the images obtained from different samplings can be seen as different classes.
in the sampled images of CoGAN and DVG. We also observe that CoGAN gains a low MIS (NIR-VIS) value due to the identity inconsistency of the generated paired NIR-VIS data. The lowest MIS (VIS-VIS) and MIS (NIR-VIS) values of DVG-Face prove that it can really generate more diverse data. In addition, when using the generated data to train the HFR network via the contrastive loss in Eq. (17), we observe that CoGAN and DVG get much worse VR@FAR=1% than DVG-Face. This is because that the validity of the contrastive loss is based on the identity consistency and the identity diversity properties, while CoGAN and DVG do not satisfy both of them.

4.3.3 Distribution Consistency

The distribution of the generated data and that of the real data should be consistent, otherwise it will be hard to boost the recognition performance with the generated data. Fréchet Inception Distance (FID) is employed to measure the distance between two distributions in the feature space. In addition, considering the advantage of the face recognition network in extracting facial features, we use LightCNN rather than the conventional Inception model as the feature extractor. Concretely, we first generate 50K paired NIR-VIS data, and then calculate the FID value between the generated NIR data and the real NIR data, as well as the FID value between the generated VIS data and the real VIS data. Then, the two FID values are averaged to get the final result. Table 3 shows that both DVG and DVG-Face gain much lower FID value than CoGAN, proving that our method can indeed learn the data distribution.

Furthermore, Fig. 4 shows the visualization comparisons of CoGAN, DVG, and DVG-Face. We can see that the generated results of CoGAN are full of artifacts. It seems difficult for CoGAN to generate good results under such a large domain discrepancy case. Besides, we also observe that the generated paired Thermal-VIS images of CoGAN are not that similar, which is in line with the quantitative MS value in Table 3. In contrast, both DVG and DVG-Face generate photo-realistic results, further demonstrating the distribution consistency property of our method.

4.3.4 Identity Sampling

As stated in Section 3.1.2, the identity representation can be obtained from the pre-trained face recognition network (LightCNN) or the identity sampler. Correspondingly, there are three potential identity sampling manners: (1) Using LightCNN in both the training and the testing stages of dual generation. In this case, DVG-Face becomes a conditional generative model. At the testing stage, if we desire to generate large-scale paired data, we must have the same number of VIS data with different identities to provide the required identity representations. Therefore, the sampling diversity is limited by the size of the available VIS data. (2) Using LightCNN in the training stage and employing the identity sampler in the testing stage. By this means, we no longer need large-scale available VIS data in the testing stage. The required rich identity representations can be easily sampled from noises. However, the identity representations generated by the identity sampler conform to the Gaussian distribution, while those of LightCNN do not satisfy the Gaussian distribution hypothesis. Thus, there is a distribution gap between the two types of identity representations. (3) Using the identity sampler in both the training and the testing stages. In this way, it is flexible to obtain massive identity representations in both stages.

The performances of the above three manners are shown in Table 4. We observe that the second manner gets the worst results because of the aforementioned distribution gap. Furthermore, the third manner gains better results than the first manner, although the identity sampler is trained on the extracted identity representations of LightCNN. It indicates that the identity sampler may produce new diverse identity representations, based on the property of VAEs.

4.3.5 The Number of Generated Data

We further investigate the effect of the number of the generated data on the recognition performance. In particular, we employ 0, 10K, 30K, 50K, 80K, 100K, 130K, 150K, 180K, and 200K generated paired heterogeneous images to train the HFR network, respectively. Fig. 5 exhibits the results under different amounts of generated images on the Tufts Face database. It is obvious that from 0 to 100K, as the number of the generated images increases, so does the performance of the recognition. Compared with only using the real data (0 generated data), VR@FAR=1% is significantly improved by 26.1% when 100K paired generated images are added. These phenomena demonstrate that the generated images really contain abundant useful information that is helpful for recognition. Besides, as the number of the generated paired images exceeds 100K, there is no obvious improvements, indicating that the generated images have been saturated.

4.3.6 The Usage of Large-Scale VIS Data

Generally, the large-scale VIS database, such as MS-Celeb-1M, is only used to pre-train the HFR network.
The intuition behind this manner is that training the large-scale VIS data together with the small-scale heterogeneous data will lead to serious domain biases, which may degrade the performance of HFR. In order to verify this point, four experiments are elaborately designed: (A) directly trains LightCNN on the large-scale VIS database MS-Celeb-1M. (B) fine-tunes the pre-trained LightCNN with the Tufts Face database. (C) fine-tunes with both Tufts Face and MS-Celeb-1M. (D) is our method. It introduces the identity information of MS-Celeb-1M to enrich the identity diversity of the generated data, and fine-tunes with both Tufts Face and the generated data.

Table 5 shows that the results of (C) are only slightly better than those of the (A), and much worse than those of the (B), revealing that the domain biases actually affect the performance of HFR. Moreover, (D) defeats others by a large margin. It demonstrates the effectiveness of our method that introduces the identity representations of MS-Celeb-1M to enrich the identity diversity of the generated data. In this case, the domain biases are eliminated because the generated images still belong to the same domain of the heterogeneous database.

4.3.7 Ablation Study

For the Dual Generation. The angular orthogonal loss $\mathcal{L}_{ort}$ in Eq. (4) and the pairwise identity preserving loss $\mathcal{L}_{ip}$ in

$$\text{Table 5: Results under different usages of large-scale VIS data on Tufts Face. (A) directly trains LightCNN on the large-scale VIS database MS-Celeb-1M. (B) fine-tunes the pre-trained LightCNN with the Tufts Face database. (C) fine-tunes with both Tufts Face and MS-Celeb-1M. (D) is our method. It introduces the identity information of MS-Celeb-1M to enrich the identity diversity of the generated data, and fine-tunes with both Tufts Face and the generated data.}

| Method | Rank-1 | VR@FAR=1% | VR@FAR=0.1% |
|--------|--------|-----------|-------------|
| (A)    | 29.4   | 23.0      | 5.3         |
| (B)    | 54.5   | 42.4      | 15.6        |
| (C)    | 33.9   | 24.7      | 7.9         |
| (D)    | 75.7   | 68.5      | 36.5        |

The intuition behind this manner is that training the large-scale VIS data together with the small-scale heterogeneous data will lead to serious domain biases, which may degrade the performance of HFR. In order to verify this point, four experiments are elaborately designed: (A) directly trains LightCNN on the large-scale VIS database MS-Celeb-1M. (B) fine-tunes the pre-trained LightCNN with the Tufts Face database. (C) fine-tunes with both Tufts Face and MS-Celeb-1M. (D) is our method. It introduces the identity information of MS-Celeb-1M to enrich the identity diversity of the generated data, and fine-tunes with both Tufts Face and the generated data.

Table 5 shows that the results of (C) are only slightly better than those of the (A), and much worse than those of the (B), revealing that the domain biases actually affect the performance of HFR. Moreover, (D) defeats others by a large margin. It demonstrates the effectiveness of our method that introduces the identity representations of MS-Celeb-1M to enrich the identity diversity of the generated data. In this case, the domain biases are eliminated because the generated images still belong to the same domain of the heterogeneous database.

4.3.7 Ablation Study

For the Dual Generation. The angular orthogonal loss $\mathcal{L}_{ort}$ in Eq. (4) and the pairwise identity preserving loss $\mathcal{L}_{ip}$ in

$$\text{Eq. (11) (including $\mathcal{L}_{ort}$ in Eq. (14)) are studied to analyze their respective roles. Both quantitative and qualitative results are given for a comprehensive comparison.}

Fig. 6 shows the qualitative comparisons between our method and its two variants. Without $\mathcal{L}_{ort}$, the generated images are almost unchanged when the identity representation is varied. It means we cannot enrich the identity diversity of the generated data via injecting more identity information. When omitting $\mathcal{L}_{ip}$, the generated paired images look inconsistent in identities, suggesting the effectiveness of $\mathcal{L}_{ip}$.

In addition, Table 6 displays the quantitative comparison results. We observe that the recognition performance drops significantly if one of the losses is discarded. For instance, VR@FAR=0.1% decreases 19.8% when omitting $\mathcal{L}_{ort}$. The quantitative results further demonstrate the crucial role of each loss.

For the HFR. We design four experiments to study the usage of the generated data: (I) only uses the real data to train the HFR network. (II) merely employs the generated data. (III) leverages both the real data and the generated data, and the latter is utilized via a pairwise distance loss. (IV) is our method, which replaces the pairwise distance loss with a contrastive loss.

$$\text{Table 6: Quantitative ablation study of the angular orthogonal loss $\mathcal{L}_{ort}$ and the pairwise identity preserving loss $\mathcal{L}_{ip}$ on Tufts Face.}

| Method | Rank-1 | VR@FAR=1% | VR@FAR=0.1% |
|--------|--------|-----------|-------------|
| w/o $\mathcal{L}_{ort}$ | 55.9   | 43.6      | 16.7        |
| w/o $\mathcal{L}_{ip}$ | 62.4   | 57.6      | 22.1        |
| Ours   | 75.7   | 68.5      | 36.5        |

$$\text{Table 7: Results under different usages of the generated data on Tufts Face. (I) only uses the real data to train the HFR network, while (II) merely employs the generated data. (III) leverages both the real data and the generated data, and the latter is utilized via a pairwise distance loss. (IV) is our method, which replaces the pairwise distance loss with a contrastive loss.}

| Method | Rank-1 | VR@FAR=1% | VR@FAR=0.1% |
|--------|--------|-----------|-------------|
| (I)    | 54.5   | 42.4      | 15.6        |
| (II)   | 36.6   | 24.7      | 7.2         |
| (III)  | 70.3   | 60.8      | 29.6        |
| (IV)   | 75.7   | 68.5      | 36.5        |
TABLE 8: Verification rates on Tufts Face under different parameter values.

| λ₁ in Eq. (12) | λ₂ in Eq. (13) | α in Eq. (18) |
|----------------|----------------|----------------|
| λ₁ FAR=1%      | λ₂ FAR=1%      | α FAR=1%       |
| 10             | 0.10           | 2e-4           |
| 25             | 0.25           | 5e-4           |
| 50             | 0.50           | 1e-3           |
| 75             | 0.75           | 2e-3           |
| 100            | 1.00           | 3e-3           |

TABLE 9: The study of the margin value m in Eq. (17) on Tufts Face.

| margin m | VR@FAR=1% |
|----------|-----------|
| 0.2      | 67.0      |
| 0.3      | 67.5      |
| 0.4      | 68.1      |
| 0.5      | 68.5      |
| 0.6      | 68.2      |
| 0.7      | 67.4      |

of the current DVG-Face, as discussed in Section 4.3.2, (IV) gains better results than the third one, which verifies the effectiveness of the contrastive loss. It optimizes both the intra-class and the inter-class distances, facilitating the learning of both domain invariant and discriminative embedding features. By contrast, the pairwise distance loss of DVG can only assist in reducing domain discrepancy. Note that the effectiveness of the contrastive loss is based on the identity consistency and the identity diversity properties of the generated data, as stated in Section 4.3.2.

Table 8 lists the results of sensitivity study for the parameters λ₁ and λ₂ in Eq. (12) as well as α in Eq. (18). Specifically, the initial values of the three parameters are set to 50, 0.5, and 1e-3 respectively to balance the magnitude of each loss function. We can see that our method is not sensitive to these trade-off parameters in a large range. For example, when the value of λ₁ is varied from 10 to 100, verification rates only change from 67.4% to 68.5%. Finally, we further explore the setting of the margin parameter m in Eq. (17). Table 9 reveals that the best margin value is 0.5.

4.4 Comparisons with State-of-the-art Methods

4.4.1 Results on the CASIA NIR-VIS 2.0 Database

In order to verify the effectiveness of our DVG-Face, we compare it with 16 state-of-the-art methods, including 6 traditional methods and 10 deep learning based methods. The traditional methods contain H2(LBP3) [53], DSIFT+PCA+LDA [61], CDL [62], Gabor+RBM [63], Recons.+UDP [64], and CEFD [24]. The deep learning based methods consist of IDNet [55], HFR-CNN [25], Hallucination [29], DLFace [66], TRIVET [67], W-CNN [8], PACH [13], RCN [16], MC-CNN [68], and DVR [69]. The reported results of these methods are from their respective published papers.

Table 10 lists the results of Rank-1 accuracy and verification rates of the above methods. We can see that most of the deep learning based methods outperform the traditional methods. Nevertheless, the deep learning based method HFR-CNN performs worse than the traditional method Gabor+RBM. It indicates that training on the small-scale heterogeneous data is challenging for the deep learning based methods. The methods, such as W-CNN, MC-CNN, and DVR, which are devoted to tackling the over-fitting caused by the limited training data, get higher performance. Moreover, our method gains best results than all the competitors. Particularly, regarding Rank-1 accuracy and VR@FAR=0.1%, DVR-Face exceeds the conditional generation based method PACH by 1.0% and 1.6% respectively, suggesting the superiority of our unconditional generation manner. Compared with the state-of-the-art method DVR, we improve VR@FAR=0.01% from 98.6% to 99.2%. More importantly, the ROC curves in Fig. 8 show that we improve the harder indicator True Positive Rate (TPR)@False Positive Rate (FPR)=10⁻⁵ by 3.0% over DVR. In addition, compared with our preliminary version DVG [20], we further improve TPR@FPR=10⁻⁵ from 97.8% to 98.6%. The improvement highlights the importance of the abundant identity diversity and the consequent contrastive loss. The generated paired NIR-VIS images of DVR-Face are displayed in Fig. 7(a).

4.4.2 Results on the Oulu-CASIA NIR-VIS Database

Different from the CASIA NIR-VIS 2.0 database, the training set of the Oulu-CASIA NIR-VIS database only contains 20 identities. Such a low-shot database brings huge challenges for the training of the HFR network. We evaluate our method against 5 traditional methods and 4 deep learning based methods. The compared traditional methods include MPL3 [52], KCSR [70], KPS [21], KD서 [71], and H2(LBP3) [53]. The results of these methods are from [53]. The compared deep learning based methods contain TRIVET [67], W-CNN [8], PACH [13], and DVR [69]. The reported results are from their respective published papers.

In Table 11 we find that the deep learning based methods significantly outperform the traditional methods in terms of Rank-1 accuracy. Meanwhile, we also notice that compared with Rank-1 accuracy, verification rates of all methods are not that high. This may be caused by the testing protocol. There are only 20 identities in the testing set, and each identity contains up to 48 VIS images as the galleries and 48 NIR images as the probes. As a consequence, it is relatively easy to retrieve the right image according to the highest similarity score, leading to generally higher Rank-1 results. However, due to the large domain discrepancy and
The dual generation results on (a) CASIA NIR-VIS 2.0 [51], (b) Oulu-CASIA NIR-VIS [52], (c) BUAA Vis-Nir [54], (d) CUFSF [55], (e) MultiPIE [5], and (f) Tufts Face [6]. More results are shown in the supplementary material.

4.4.3 Results on the BUAA VisNir Database

A total of 5 traditional methods and 4 deep learning based methods are compared on the BUAA VisNir database. The former includes MPL3 [52], KCSR [70], KPS [21], KDSR [71], and H2(LBP3) [53], and the latter contains TRIVET [67], W-CNN [3], PACH [13], and DVR [69]. The reported results of MPL3, KCSR, KPS, KDSR, and H2(LBP3) are from [53], and those of the remaining methods are from their respective published papers.

We can also observe that the deep learning based methods are always superior to the traditional methods. In addition, the improvements over the conditional generation based method PACH are significant. VR@FAR=0.1% is advanced from 93.5% to 99.1%. Besides, although the state-of-the-art DVR has achieved very high results, DVG-Face still exceeds it by 2.2% in VR@FAR=0.1%. The ROC curves in Fig. 8 further show the advantages of our method. Regarding TPR@FPR=10−5, DVG-Face leads DVR by 5.4% and our preliminary version DVG by 5.1%. The generated paired images of DVG-Face on the BUAA VisNir database are exhibited in Fig. 7 (b).

4.4.4 Results on the IIIT-D Sketch Viewed Database

Considering the crucial role of the Sketch-Photo recognition in criminal investigation, we further evaluate our method on the IIIT-D Sketch Viewed database. The compared methods include 5 traditional methods: Original WLD [72], SIFT [73], EUCLBP [74], LFDA [23], MCWLD [4], as well as 4 deep learning based methods: LightCNN [57], CDL [17], RCN [16], and MC-CNN [68]. The reported results of Original WLD, SIFT, EUCLBP, and LFDA are from [4], and the remaining results are from their respective published papers.

From Table 13 we can see that on such a Sketch-Photo database, the overall performance discrepancy between the

| Method       | Rank-1 | VR@FAR=1% | VR@FAR=0.1% |
|--------------|--------|-----------|-------------|
| MPL3 [52]    | 48.9   | 41.9      | 11.4        |
| KCSR [70]    | 66.0   | 49.7      | 26.1        |
| KPS [21]     | 62.2   | 48.3      | 22.2        |
| KDSR [71]    | 66.9   | 56.1      | 31.9        |
| H2(LBP3) [53]| 70.8   | 62.0      | 33.6        |
| TRIVET [67]  | 92.2   | 67.9      | 33.6        |
| W-CNN [3]    | 98.0   | 81.5      | 54.6        |
| PACH [13]    | 100.0  | 97.9      | 88.2        |
| DVR [69]     | 100.0  | 97.2      | 84.9        |
| DVG [20]     | 100.0  | 98.5      | 92.9        |
| DVG-Face     | 100.0  | 99.2      | 97.3        |

4.4.5 Evaluation on Other Databases

The performance of our method is also evaluated on other databases, including the MultiPIE and Tufts Face datasets. The results are shown in Table 12. The method can achieve state-of-the-art performance on these datasets.

| Method       | Rank-1 | VR@FAR=1% | VR@FAR=0.1% |
|--------------|--------|-----------|-------------|
| MPL3 [52]    | 53.2   | 58.1      | 33.3        |
| KCSR [70]    | 81.4   | 83.8      | 66.7        |
| KPS [21]     | 66.6   | 60.2      | 41.7        |
| KDSR [71]    | 83.0   | 86.8      | 69.5        |
| H2(LBP3) [53]| 88.8   | 88.8      | 73.4        |
| TRIVET [67]  | 93.9   | 93.0      | 80.9        |
| W-CNN [3]    | 97.4   | 96.0      | 91.9        |
| PACH [13]    | 98.6   | 98.0      | 93.5        |
| DVR [69]     | 99.2   | 98.5      | 96.9        |
| DVG [20]     | 99.3   | 98.5      | 97.3        |
| DVG-Face     | 99.9   | 99.7      | 99.1        |
Fig. 8: The ROC curves of different methods on (a) CASIA NIR-VIS 2.0, (b) Oulu-CASIA NIR-VIS, and (c) BUAA-VisNir.

TABLE 13: Experimental results on IIIT-D Sketch Viewed.

| Method     | Rank-1 |
|------------|--------|
| Original WLD [72] | 74.34  |
| SIFT [73]    | 76.28  |
| EUCLBP [74]  | 79.36  |
| LFDA [23]    | 81.43  |
| MCWLD [4]    | 84.24  |
| LightCNN [57] | 83.24  |
| CDL [17]     | 85.35  |
| MC-CNN [68]  | 87.40  |
| RCN [16]     | 90.34  |
| DVG [20]     | 96.99  |
| DVG-Face     | 97.21  |

4.4.5 Results on the MultiPIE Database

Since the recognition under the extreme pose is still a challenging problem, here we further evaluate our method on the representative MultiPIE database. The compared methods include 6 state-of-the-art methods: GridFace [75], FF-GAN [76], TPGAN [9], CAPG-GAN [47], PIM [77], and Rotate-and-Render [78]. All of these methods except for GridFace are based on conditional generation. The reported results are from the corresponding published papers.

Table 14 shows that our method gains more prominent performance than the compared methods. The best Rank-1 accuracy under the most challenging $\pm 90^\circ$ is improved from 94.4% [78] to 97.6%. Fig. 7(d) presents the dual generation results of Sketch-Photo.

TABLE 14: Experimental results under $\pm 90^\circ$ on MultiPIE.

| Method              | Rank-1 |
|---------------------|--------|
| GridFace [75]       | 75.4   |
| FF-GAN [76]         | 61.2   |
| TPGAN [9]           | 64.6   |
| CAPG-GAN [47]       | 66.1   |
| PIM [77]            | 86.5   |
| Rotate-and-Render [78]| 94.4  |
| DVG [20]            | 83.9   |
| DVG-Face            | 97.6   |

4.4.6 Results on the Tufts Face Database

As tabulated in Table 5, the face recognition network pre-trained on MS-Celeb-1M only obtains 29.4% Rank-1 accuracy on the Tufts Face database, reflecting the large domain discrepancy between the Thermal data and the VIS data. Meanwhile, we also find that after fine-tuning on the training set of Tufts Face, Rank-1 accuracy only increases to 54.5%, which is still unsatisfactory. This phenomenon is caused by the limited number of available Thermal-VIS data. Obviously, data augmentation is a straightforward idea. Both of our preliminary version DVG and the current DVG-Face aim to generate more data to facilitate the training of the HFR network. The comparisons of DVG, DVG-Face, and the baseline LightCNN are reported in Table 15. We can see that compared with the baseline, DVG boosts Rank-1 accuracy from 29.4% to 56.1%, and VR@FAR=0.1 from 5.3% to 17.1%. On this basis, DVG-Face further improves Rank-1 accuracy by 19.6%, and VR@FAR=0.1 by 19.4%. We show the dual generation results on the Tufts Face database in Fig. 7(f).

4.4.7 Results on the NJU-ID Database

With the popularization of face authentication systems, the importance of ID-Camera recognition is increasingly prominent. Therefore, we further evaluate our method on the representative ID-Camera database NJU-ID. The results of our method and the baseline LightCNN are reported in Table 16. It suggests that when using the augmented data,
either the data generated by DVG or DVG-Face, we can observe significant improvements. This presents the value of our generated data. In addition, DVG-Face shows obvious superiority than the preliminary version DVG in terms of Rank-1 accuracy, VR@FAR=1%, and VR@FAR=0.1%. Particularly, VR@FAR=0.1% is improved by 8.2%. We do not display the generated data since it may violate privacy.

5 Conclusion
This paper has proposed a novel unconditional DVG-Face framework. It generates large-scale new paired heterogeneous images from noises to boost the performance of HFR. To begin with, a dual variational generator is elaborately designed to train with both paired heterogeneous data and unpaired VIS data. The introduction of the latter greatly promotes the identity diversity of the generated images. Subsequently, a pairwise identity preserving loss is imposed on the generated paired images to guarantee their identity consistency. Finally, benefiting from the identity consistency and diversity properties, the generated unlabeled images can be employed to train the HFR network via contrastive learning. Our method gets the best results on seven databases, exposing a new way to the HFR problem.

References

[1] Y. Wen, K. Zhang, Z. Li, and Y. Qiao, “A discriminative feature learning approach for deep face recognition,” in European Conference on Computer Vision, 2016.

[2] J. Deng, J. Gao, N. Xue, and S. Zachariou, “Arcaface: Additive angular margin loss for deep face recognition,” in IEEE Conference on Computer Vision and Pattern Recognition, 2019.

[3] R. He, X. Wu, Z. Sun, and T. Tan, “Wasserstein cnn: Learning invariant features for nir-viis face recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 41, no. 7, pp. 1761–1773, 2018.

[4] H. S. Bhatt, S. Bharadwaj, R. Singh, and M. Vatsa, “Mimetic approach for matching sketches with digital face images,” Tech. Rep., 2012.

[5] R. Gross, I. Matthews, J. Cohn, T. Kanade, and S. Baker, “Multipie,” Image and Vision Computing, vol. 28, no. 5, pp. 807–813, 2010.

[6] K. Panetta, Q. Wan, S. Agaian, S. Rajev, S. Kamath, R. Rajendran, S. Rao, A. Kaszowska, H. Taylor, A. Samani, and Y. Xin, “A comprehensive database for benchmarking imaging systems,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 3, pp. 509–520, 2018.

[7] J. Huo, Y. Gao, Y. Shi, W. Yang, and H. Yin, “Heterogeneous face recognition by margin-based cross-modality metric learning,” IEEE Transactions on Cybernetics, vol. 48, no. 6, pp. 1814–1826, 2017.

[8] L. Song, M. Zhang, X. Wu, and R. He, “Adversarial discriminative heterogeneous face recognition,” in AAAI Conference on Artificial Intelligence, 2018.

TABLE 15: Experimental results on Tufts Face.

| Method   | Rank-1 | VR@FAR=1% | VR@FAR=0.1% |
|----------|--------|-----------|-------------|
| LightCNN | 29.4   | 23.0      | 5.3         |
| DVG      | 56.1   | 44.3      | 17.1        |
| DVG-Face | 75.7   | 68.5      | 36.5        |

TABLE 16: Experimental results on NJU-ID.

| Method   | Rank-1 | VR@FAR=1% | VR@FAR=0.1% |
|----------|--------|-----------|-------------|
| LightCNN | 91.3   | 90.5      | 80.4        |
| DVG      | 96.8   | 96.7      | 83.0        |
| DVG-Face | 98.4   | 98.1      | 91.2        |

[9] R. Huang, S. Zhang, T. Li, and R. He, “Beyond face rotation: Global and local perception gain for photorealistic and identity preserving frontal view synthesis,” in IEEE International Conference on Computer Vision, 2017.

[10] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, “Image-to-image translation with conditional adversarial networks,” in IEEE Conference on Computer Vision and Pattern Recognition, 2017.

[11] H. Zhang, B. S. Riggan, S. Hu, N. J. Short, and V. M. Patel, “Synthesis of high-quality visible faces from polarimetric thermal faces using generative adversarial networks,” International Journal of Computer Vision, vol. 127, no. 6–7, pp. 845–862, 2019.

[12] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in Neural Information Processing Systems, 2014.

[13] B. Duan, C. Fu, Y. Li, X. Song, and R. He, “Pose agnostic cross-spectral hallucination via disentangling independent factors,” in IEEE Conference on Computer Vision and Pattern Recognition, 2020.

[14] D. P. Kingma and M. Welling, “Auto-encoding variational bayes,” in International Conference on Learning Representations, 2014.

[15] T. Karras, T. Aila, S. Laine, and J. Lehtinen, “Progressive growing of gans for improved quality, stability, and variation,” in International Conference on Learning Representations, 2018.

[16] Z. Deng, X. Peng, and Y. Qiao, “Residual compensation networks for heterogeneous face recognition,” in AAAI Conference on Artificial Intelligence, 2019.

[17] X. Wu, L. Song, R. He, and T. Tan, “Coupled deep learning for heterogeneous face recognition,” in AAAI Conference on Artificial Intelligence, 2018.

[18] Z. Wu, Y. Xiong, S. X. Yu, and D. Lin, “Unsupervised feature learning via non-parametric instance discrimination,” in IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[19] P. Bachman, R. D. Hjelm, and W. Buchwalter, “Learning representations by maximizing mutual information across views,” in Advances in Neural Information Processing Systems, 2019.

[20] C. Fu, X. Wu, Y. Hu, H. Huang, and R. He, “Dual variational generation for low shot heterogeneous face recognition,” in Advances in Neural Information Processing Systems, 2019.

[21] B. F. Klare and A. K. Jain, “Heterogeneous face recognition using kernel prototype similarities,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 6, pp. 1410–1422, 2012.

[22] M. Shao, D. Kit, and Y. Fu, “Generalized transfer subspace learning through low-rank constraint,” International Journal of Computer Vision, vol. 109, no. 1–2, pp. 97–114, 2015.

[23] B. Klare, Z. Li, and A. K. Jain, “Matching forensic sketches to mug shot photos,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 3, pp. 639–646, 2010.

[24] R. Huang, S. Zhang, T. Li, and R. He, “Beyond face rotation: Global and local perception gain for photorealistic and identity preserving frontal view synthesis,” in IEEE International Conference on Computer Vision, 2017.

[25] D. A. Huang and Y.-C. Frank Wang, “Coupled dictionary and feature space learning with applications to cross-domain image synthesis and recognition,” in IEEE International Conference on Computer Vision, 2013.

[26] M. Zhang, Y. Li, N. Wang, Y. Chi, and X. Gao, “Cascaded face sketch synthesis under various illuminations,” IEEE Transactions on Image Processing, vol. 29, pp. 1507–1521, 2020.

[27] Y. Guo, L. Zhang, Y. Hu, X. He, and J. Gao, “Ms-celeb-Im: A dataset and benchmark for large-scale face recognition,” in European Conference on Computer Vision, 2016.
