Asymmetric GANs for Image-to-Image Translation

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Existing models for unsupervised image translation with Generative Adversarial Networks (GANs) can learn the mapping from the source domain to the target domain using a cycle-consistency loss. However, these methods always adopt a symmetric network architecture to learn both forward and backward cycles. Because of the task complexity and cycle input difference between the source and target domains, the inequality in bidirectional forward-backward cycle translations is significant and the amount of information between two domains is different. In this paper, we analyze the limitation of existing symmetric GANs in asymmetric translation tasks, and propose an AsymmetricGAN model with both translation and reconstruction generators of unequal sizes and different parameter-sharing strategy to adapt to the asymmetric need in both unsupervised and supervised image translation tasks. Moreover, the training stage of existing methods has the common problem of model collapse that degrades the quality of the generated images, thus we explore different optimization losses for better training of AsymmetricGAN, making image translation with higher consistency and better stability. Extensive experiments on both supervised and unsupervised generative tasks with 8 datasets show that AsymmetricGAN achieves superior model capacity and better generation performance compared with existing GANs. To the best of our knowledge, we are the first to investigate the asymmetric GAN structure on both unsupervised and supervised image translation tasks.

Additional Key Words and Phrases: GANs; Asymmetric Networks; Image-to-Image Translation

ACM Reference Format:
Hao Tang and Nicu Sebe. 2018. Asymmetric GANs for Image-to-Image Translation. In Woodstock ’18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY. ACM, New York, NY, USA, 20 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

Recently, Generative Adversarial Networks (GANs) [4] have received considerable attention in computer vision community. GANs are generative models which are particularly designed for generation tasks. Recent works have been able to yield promising image translation performance, such as Pix2pix [7], in a supervised setting given carefully annotated image pairs. However, pairing the training data is usually difficult and costly. To tackle this problem, several GAN approaches, such as CycleGAN [36], DualGAN [34] and ComboGAN [1], target to effectively learn a mapping from the source domain to the target domain without paired training data. However, these are not efficient for multi-domain image-to-images translation tasks.

To fix the limitation, Choi et al. propose StarGAN [3], which performs multi-domain image translation using only one generator/discriminator pair and an extra domain classifier [18]. Mathematically, we assume X and Y represent the source and target domains, and $x \in X$ and $y \in Y$ denote images in domain X and domain Y, respectively; we define $z_x$ and $z_y$ denote category labels of domain X and Y, respectively. StarGAN utilizes a symmetric GAN model and uses the same generator $G$ twice to translate X into Y with the target label $z_y$, i.e., $G(x, z_y) \approx y$, and then reconstruct the
input image $x$ from the translated output $G(x, z_y)$ and the label $z_x$, i.e., $G(G(x, z_y), z_x) = x$. In this way, the generator $G$ shares a common mapping and data structures for two different tasks, i.e., image translation and image reconstruction. Moreover, StarGAN cannot handle with some specific image translation tasks such as person image generation [11, 22] and hand gesture translation [25] since both tasks have infinite image domain $m$ as indicated in [25].

To solve the limitations, Tang et al. propose GestureGAN [25], which produces hand gestures with different poses, sizes and locations by using hand skeletons $l_x$ and $l_y$. Note that GestureGAN also uses a symmetric structure, i.e., GestureGAN utilizes the same generator $G$ twice for both image translation and image reconstruction, which can be defined as $G(x, l_y) = y$ and $G(G(x, l_y), l_x) = x$, respectively. In summary, both StarGAN and GestureGAN use a symmetric structure of generators for both image translation and image reconstruction tasks. We argue that since each task has unique information and distinct targets, it is harder to optimize the generator and to make it gain a good generalization ability on both tasks.

In this paper, we analyze the limitation of both StarGAN and GestureGAN, and observe that it is their symmetric generator that hinders the improvement of model performance. To fix this limitation, we propose a novel asymmetric-structured generator in our Asymmetric Generative Adversarial Network (AsymmetricGAN) for both unsupervised and supervised image translation tasks. Unlike StarGAN and GestureGAN, AsymmetricGAN consists of two different asymmetric generators of unequal sizes to adapt to the asymmetric need in both image translation and image construction.

There are three reasons for designing the asymmetric-structured generators. Firstly, the translation generator $G_t$ transforms images from $X$ to $Y$, and the reconstruction generator $G_r$ uses the translated images from $G_t$ and the original domain guidance $z_x/l_x$ to reconstruct the original $x$. Generators $G_t$ and $G_r$ cope with different tasks. Image translation is our main task and image reconstruction is an auxiliary task which aims to provide supervision information to the main task. Moreover, during testing time, generating a new image from the input image is more difficult than reconstructing the input image since the image reconstruction process has itself as the reference. Thus we need a stronger generator for image translation and a weaker generator for image reconstruction in our framework.

Secondly, the input data distribution for them is different. The inputs of the translation generator $G_t$ are a real image and a target domain guidance. The goal of $G_t$ is to generate the target domain image. While $G_r$ accepts a translated image and an original domain guidance as input, and tries to reconstructs the original input image. For generator $G_t$ and $G_r$, the input images are a real image and a generated image respectively, and thus the data distribution is different between them.

Thirdly, because of the complexity difference between the source and target image domains, the complexity inequality in a bidirectional image-to-image translation is significant. Therefore, it is intuitive to design different network structures for the two different generators, i.e, the powerful network for the complex image translation process and the simple network is used for the simple image reconstruction process. These two generators are allowed to use different network architecture designs and different levels of parameter sharing strategy according to the diverse difficulty of the tasks. By doing so, each generator can have its own network parts which usually helps to learn better each task-specific mapping in a multi-task setting [20].

We also investigate how the distinct network designs and different network sharing schemes for the asymmetric generators dealing with different sub-tasks could balance the generation performance and network complexity. Moreover, to avoid the model collapse issue in training AsymmetricGAN for both unsupervised and supervised image-to-image translation tasks, we further explore different objective functions for better optimization. 1) The color cycle-consistency loss which targets solving the ‘channel pollution’ problem proposed in [25] by separately generating red, green and blue
color channels instead of generating all three at one time. 2) The multi-scale SSIM loss, which preserves the information of luminance, contrast and structure between reconstructed images and input images across different scales. 3) The conditional identity preserving loss, which helps retaining the identity information of the input images. These loss functions are jointly embedded in AsymmetricGAN for training and help to generate results with higher consistency and better stability.

In summary, the main contributions of this paper are: 1) We study an interesting problem in both unsupervised and supervised image-to-image translation tasks with a novel Asymmetric Generative Adversarial Network (Asymmetric-GAN). From architecture to loss functions, we present reasonable and useful solutions. 2) We propose the asymmetric dual generators, allowing different network structures and different-level parameter sharing, to specifically cope with image translation and image reconstruction tasks, which facilitates obtaining a better generalization ability of the proposed model to improve the generation performance. More importantly, we provide a new direction in designing a good GAN model for both unsupervised and supervised image-to-image translation tasks. 3) We explore jointly utilizing different objectives for a better optimization of the proposed AsymmetricGAN, and thus obtaining both unsupervised and supervised image-to-image translation with higher consistency and better stability. 4) We extensively evaluate AsymmetricGAN on both multi-domain image translation and hand gesture translation tasks with eight different datasets, demonstrating its superiority in model capacity and its better generation performance compared with state-of-the-art methods.

A preliminary version of this paper appeared as [27]. Compared with [27], extensions are made on five aspects. 1) A more detailed analysis is presented in ‘Introduction’ section by giving a deeper analysis on the motivation and the difference from relevant works. 2) A more detailed discussion is presented in ‘Related Work’ section by including recently published works dealing with both unsupervised and supervised image-to-image translation. 3) We extend the model proposed in [27] to a unified GAN framework for handling both unsupervised and supervised image-to-image translation tasks. 4) We present an in-depth description of the proposed approach, providing all the architectural and implementation details of the method, with special emphasis on guaranteeing the reproducibility of the experiments. 5) We extend the experimental evaluation provided in [27] in several directions. First, we discuss the generation performance and network complexity of our AsymmetricGAN with different network designs and parameter-sharing strategies on multi-domain image-to-image translation tasks. Second, we conduct extensive experiments on the challenging hand gesture-to-gesture translation task with two different datasets, demonstrating the wide application scope of our GAN framework on both unsupervised and supervised image-to-image translation tasks.

2 RELATED WORK

Generative Adversarial Networks (GANs) [4] are generative models, which have achieved promising results on different generative tasks such as image generation. Moreover, to generate images controlled by users, Mirza et al. [16] propose Conditional GANs (CGANs), which use a conditional information to guide the image generation process. Extra guidance information can be category labels [3, 32], human skeletons [22] and semantic maps [29]. In this paper, we mainly focus on image-to-image translation tasks.

Image-to-Image Translation. CGANs learn a mapping between image inputs and image outputs using convolutional neural networks. For example, Isola et al. propose Pix2pix [7], which is a conditional framework using a CGAN to learn the mapping function. Similar ideas have also been applied to many other tasks, e.g., person image generation [11]. However, all of these models require paired training data, which are usually costly to obtain. To alleviate the issue of pairing training data, Zhu et al. introduce CycleGAN [36], which learns the mappings between two unpaired image
domains without supervision with the aid of a cycle-consistency loss. However, these models are only suitable to cross-domain translation tasks.

**Multi-Domain Image-to-Image Translation.** There are only very few recent methods attempting to implement multi-domain image-to-image translation in an efficient way. Anoosheh et al. propose ComboGAN [1], which only requires to train $m$ generator/discriminator pairs for $m$ different image domains. Choi et al. present StarGAN [3], which equips a single symmetric-structured generator to handle the task. Although the model complexity is low, jointly learning both image translation and image reconstruction with the same generator require the sharing of all parameters, which increases the optimization complexity and reduces the generalization ability, thus leading to unsatisfactory generation performance. The proposed method targets at obtaining a good balance between the network capacity and image generation quality. Along with this research line, we propose a novel AsymmetricGAN, which achieves this target via using two task-specific and asymmetric generators. Moreover, we explore various optimization objectives to train better the model to produce more consistent and more stable results.

3 ASYMMETRICGAN

This paper studies an asymmetric problem in GANs with a new model. From architecture to loss functions, we present reasonable and useful solutions. In this section, we first start with the network architecture of unsupervised AsymmetricGAN for multi-domain image-to-image translation tasks, and then introduce the network architecture of supervised AsymmetricGAN for hand gesture-to-gesture translation tasks. Finally, we introduce the network optimization for both frameworks.

3.1 Network Architecture of Unsupervised Framework

We focus on multi-domain image-to-image translation tasks with unpaired training data. The overview of the proposed AsymmetricGAN is illustrated in Fig. 1. Existing cross-domain generation models, such as CycleGAN [36], DiscoGAN [9] and DualGAN [34], which need to separately train $\frac{m(m-1)}{2}$ models for $m$ different image domains. However, the proposed AsymmetricGAN is specifically designed for tackling multi-domain image translation problems with significant advantages in the model complexity and in the training overhead, which only needs to train a single model. To directly compare with StarGAN [3], which simply adopts the same generator for both image reconstruction and image translation tasks. We argue that the training of a single generator model for multiple domains is a challenging
problem as mentioned in the introduction section, thus we propose a more effective asymmetric generator network structure and more robust optimization objectives to stabilize the training process. In summary, our work focuses on exploring different strategies to improve the optimization of multi-domain translation models, which we aim to give useful insights into the design of more effective multi-domain translation generators. These aspects are not covered and considered in the multi-domain model StarGAN [3].

The proposed AsymmetricGAN consists of an asymmetric dual-generator and a discriminator as shown in Fig. 1. The asymmetric dual generators are designed to specifically deal with different tasks in GANs, i.e., the translation and the reconstruction tasks, which have different targets for training the network. We can design different network structures for the different generators to make them learn better task-specific objectives, which allows us to share parameters
Fig. 2. Supervised framework of our AsymmetricGAN for hand gesture-to-gesture translation. \( l_x \) and \( l_y \) indicate the hand skeletons of images \( x \) and \( y \), respectively. \( G^t \) and \( G^r \) are task-specific asymmetric generators. The translation generator \( G^t \) converts images from domain \( X \) into domain \( Y \) and the construction generator \( G^r \) receives the generated image \( G^t(x, l_y) \) and the original hand skeleton \( l_x \) and attempts to reconstruct the original image \( x \) during the optimization with the proposed different objective losses. We have two cycles, i.e., \( x \mapsto y \mapsto \tilde{x} \mapsto x \) and \( x \mapsto x^\prime \mapsto \tilde{y} \mapsto y \), but we only show one here, i.e., \( x \mapsto y^\prime \mapsto \tilde{x} \approx x \).

between the generators to further reduce the model capacity since the shallow image representations are shareable for both generators. The parameter sharing facilitates the achievement of good balance between the model complexity and the generation quality.

To achieve this goal, we design three different combination settings (i.e., S1, S2, S3) with three different generator architectures ranging from light-weight to heavy-weight: 1) Architecture I has the simplest network structure, only consisting of 7 non-linear transformation operations with each using a convolution and a ReLU layer. The number of parameters of this architecture is 2.9K. 2) Architecture II uses an encoder-decoder network with a symmetric structure, which has 1.3M parameters. 3) Architecture III employs the same encoder-decoder network as architecture II while adding extra 6 residual blocks. It has the largest network capability (8.4M parameters) in the considered three. The detailed structures are shown in Tables 1, 2, 3.

In multi-domain image translation, the final target is to make the network have a good generation ability. Thus the translation generator \( G^t \) is expected to use a more powerful architecture, while the reconstruction generator \( G^r \) can employ a lighter structure. We consider the following combinations for the translation and the reconstruction generators: 1) In S1, \( G^t \) uses the generator architecture III, and \( G^r \) uses the generator architecture I. 2) In S2, \( G^t \) uses the architecture III, and \( G^r \) uses the generator architecture II. 3) In S3, \( G^t \) and \( G^r \) use the same generator architecture III. Note that the proposed model generalizes the state-of-the-art model StarGAN [3]. When the parameters are fully shared with the usage of the same network structure for both generators, our framework becomes a StarGAN.

For each combination, the translation generator \( G^t \) is learned to translate an input image \( x \) into an output image \( y \) which is conditioned on the target domain label \( z_y \), this process can be expressed as \( G^t(x, z_y) \rightarrow y \). Then the reconstruction generator \( G^r \) receives the translated image \( G^t(x, z_y) \) and the original domain label \( z_x \) as input, and learns to recover the input image \( x \), this process can be formulated as \( G^r(G^t(x, z_y), z_x) \rightarrow x \). We represent the class labels \( z_x \) and \( z_y \) using a one-hot vector, and then the vector is passed through a linear layer to obtain a label embedding with 64 dimensions. This embedding is replicated to form feature maps that are further concatenated with the image feature maps for follow-up convolution operations with residual blocks and several deconvolution layers to obtain the target images. The discriminator \( D \) tries to distinguish between the real image \( y \) and the generated image \( G^t(x, z_y) \), and also to classify the translated image \( G^t(x, z_y) \) to the corresponding domain label \( z_y \) via the proposed domain classification loss. We adopt PatchGAN [3, 36] as the architecture of discriminator \( D \).
3.2 Network Architecture of Supervised Framework

In this part, we start to introduce the supervised framework of the proposed AsymmetricGAN for hand gesture-to-gesture. The framework of the proposed AsymmetricGAN is shown in Fig. 2, which consists of asymmetric dual generators (i.e., \(G^t\) and \(G^r\)) and a discriminator \(D\). Specifically, we concatenate the input image \(x\) and the target hand skeleton \(l_y\), and input them into the translation generator \(G^t\) and synthesize the target image \(y' = G^t(x, l_y)\). Different from GestureGAN [25], which adopts the same generator to reconstruct the original input image, we propose an asymmetric reconstruction generator \(G^r\) to benefit more from the image translation process. The conditional hand skeleton \(l_x\) together with the generated image \(y'\) are input into the reconstruction generator \(G^r\), and reconstruct the original input image \(\hat{x}\). We formalize the process as \(\hat{x} = G^r(y', l_x) = G^r(G^t(x, l_y), l_x)\). Then the optimization objective is to make \(\hat{x}\) as close as possible to \(x\).

We adopt the architecture from [8] as our generators \(G^t\) and \(G^r\). Since our main task is the image translation, it means that \(G^t\) should be more powerful than \(G^r\). Therefore we use a deeper network for \(G^t\) and a shallow network for \(G^r\) to adapt to the asymmetric translations. Specifically, we use nine residual blocks for both generators. However, the filters in first convolutional layer of \(G^t\) and \(G^r\) are 64 and 4, respectively. The network of \(G^t\) consists of: \(c7s1_64, d128, d256, R256, R256, R256, R256, R256, R256, R256, d128, u64, c7s1_3\), where \(c7s1\_k\) denote a 7×7 Convolution-InstanceNormReLU layer with \(k\) filters and stride 1; \(dk\) denotes a 3×3 Convolution-InstanceNormReLU layer with \(k\) filters and stride 2; \(Rk\) denotes a residual block that consists of two 3×3 convolutional layers with the same number of filters on both layer; \(uk\) denotes a 3×3 fractionally-strided-ConvolutionInstanceNorm-ReLU layer with \(k\) filters and stride 1/2. The network of \(G^r\) consists of: \(c7s1_4, d8, d16, R16, R16, R16, R16, R16, R16, R16, u8, u4, c7s1_3\).

Thus, the total parameter of \(G^t\) and \(G^r\) is 11.388 M and 0.046 M, respectively. For the discriminator \(D\), we adopt 70×70 PatchGAN proposed in [7].

3.3 Network Optimization

In this section, we first introduce the same optimization functions between unsupervised and supervised frameworks of AsymmetricGAN, then we separately introduce different optimization functions of the two frameworks. These optimization losses are jointly embedded into the proposed AsymmetricGAN during the training stage.

**Optimization Functions of Both Frameworks.** The same optimization functions between unsupervised and supervised frameworks are the color cycle-consistency loss and conditional identity preserving loss.

**Color Cycle-Consistency Loss.** The cycle-consistency loss can be regarded as ‘pseudo’ pairs in training data even though we do not have corresponding samples in the target domain. This loss function can be defined as,

\[
L_{ycle}(x) = \mathbb{E}_{x \sim p_{data}(x)} \left[ \left\| G^r(G^t(x, g_y), g_x) - x \right\|_1 \right],
\]

(1)

where \((g_x, g_y)\) can be one of \((z_x, z_y)\) and \((l_x, l_y)\) according to the tasks, i.e. \((z_x, z_y)\) for unsupervised tasks and \((l_x, l_y)\) for supervised tasks. The goal of this loss is to make the reconstructed image \(G^r(G^t(x, g_y), g_x)\) as close as possible to the input image \(x\). However, the generation of a whole image at one time makes the different color channels influence each other, thus leading to artifacts in the generation results [25]. To overcome this limitation, we propose a novel color cycle-consistency loss, which constructs the consistency loss for each channel, separately. Thus, this loss can be expressed as,

\[
L_{colycle} = \sum_{i \in \{r,g,b\}} L_{ycle}(x^i),
\]

(2)
where $x^b, x^g, x^r$ denote the blue, green and red channels of the image $x$. We calculate the pixel loss for the red, green, blue channel separately and then sum up these three color losses as the final loss.

**Conditional Identity Preserving Loss.** To reinforce the identity information during the translation process, we use a conditional identity preserving loss [36]. This loss encourages the mapping to preserve identity information such as color information between the input images and the output images,

$$L_{\text{id}} = \mathbb{E}_{x \sim \mathcal{P}_{\text{data}}(x)} [||G^i(x, g_x) - x||_1] + \mathbb{E}_{y \sim \mathcal{P}_{\text{data}}(y)} [||G^f(y, g_y) - y||_1].$$

(3)

where $(g_x, g_y)$ can be one of $(z_x, z_y)$ and $(l_x, l_y)$ according to the tasks.

**Optimization Functions of Unsupervised Framework.** Other optimization objects for the unsupervised framework are the conditional least square loss, the multi-scale SSIM loss and the domain classification loss.

**Conditional Least Square Loss.** We use a least square loss [13, 36] to stabilize our model during the training stage, which is more stable than the negative log likelihood objective. This loss can be expressed as:

$$L_{\text{lsun}} = \mathbb{E}_{y \sim \mathcal{P}_{\text{data}}(y)} [(D_y(y) - 1)^2] + \mathbb{E}_{x \sim \mathcal{P}_{\text{data}}(x)} [D_y(G^f(x, z_y))^2],$$

(4)

where $z_y$ are the category label of $y$, $D_y$ is the probability distribution over sources produced by discriminator $D$. The target of $G^f$ is to generate an image $G^f(x, z_y)$ that is expected to be similar to the images from domain $Y$, while $D$ aims to distinguish the generated image $G^f(x, z_y)$ from the real $y$.

**Multi-Scale SSIM Loss.** The structural similarity index (SSIM) has been originally proposed in [30] to measure the similarity of two images. We introduce it here to help to preserve the information of luminance, contrast and structure across scales. For the reconstructed image $\hat{x} = G^f(G^i(x, z_y), z_y)$ and the input image $x$, the SSIM loss is written as:

$$L_{\text{ssim}}(\hat{x}, x) = [I(\hat{x}, x)]^{2\alpha} [c(\hat{x}, x)]^{2\beta} [s(\hat{x}, x)]^{2\gamma},$$

(5)

where $I(\hat{x}, x) = \frac{2\mu_x \mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$, $c(\hat{x}, x) = \frac{2\sigma_x \sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$ and $s(\hat{x}, x) = \frac{2\sigma_x \sigma_y + C_3}{\sigma_x^2 + \sigma_y^2 + C_3}$. These three terms compare the luminance, contrast and structure information between $\hat{x}$ and $x$. $\alpha$, $\beta$ and $\gamma$ are hyper-parameters to control the relative weight of $I(\hat{x}, x)$, $c(\hat{x}, x)$ and $s(\hat{x}, x)$, respectively; $\mu_\hat{x}$ and $\mu_x$ are the means of $\hat{x}$ and $x$; $\sigma_\hat{x}$ and $\sigma_x$ are the standard deviations of $\hat{x}$ and $x$; $\sigma_{\hat{x}x}$ is the covariance of $\hat{x}$ and $x$; $C_1$, $C_2$ and $C_3$ are predefined parameters. To make the model benefit from multi-scale deep information, we refer to a multi-scale implementation of SSIM [31] which constrains SSIM over $M$ scales,

$$L_{\text{msssim}}(\hat{x}, x) = [I_M(\hat{x}, x)]^{2\alpha_M} \prod_{j=1}^{M} |c_j(\hat{x}, x)|^{2\beta_j} |s_j(\hat{x}, x)|^{2\gamma_j}.$$

(6)

**Domain Classification Loss.** To perform multi-domain image translation with a single discriminator, we employ an auxiliary classifier [3, 18] on the top of the discriminator, and impose the domain classification loss when updating both the generator and discriminator.

$$L_{\text{class}} = \mathbb{E}_{x \sim \mathcal{P}_{\text{data}}(x)} \left\{ - \log D_c(z_x|x) + \log D_c(z_y|G^f(x, z_y)) \right\},$$

(7)

where $D_c(z_x|x)$ represents the probability distribution over the domain labels given by discriminator $D$. $D_c(z_y|G^f(x, z_y))$ denotes the domain classification for fake images. We minimize the domain classification loss to produce the image $G^f(x, z_y)$ that can be classified to the corresponding domain $z_y$.
Full Objective of Unsupervised Framework. Given the loss functions presented above, the complete optimization objective of Unsupervised AsymmetricGAN for multi-domain image-to-image translation can be written as:

$$\mathcal{L} = \mathcal{L}_{cgan} + \lambda_c \mathcal{L}_{class} + \lambda_{yc} \mathcal{L}_{color_{yc}} + \lambda_m \mathcal{L}_{msssim} + \lambda_{id} \mathcal{L}_{id}.$$  \hfill (8)

where $\lambda_c$, $\lambda_{yc}$, $\lambda_m$ and $\lambda_{id}$ are parameters controlling the relative importance of the corresponding objective. All objectives are jointly optimized in an end-to-end fashion. We follow previous works [7, 25] and empirically set $\lambda_c=1$, $\lambda_{yc}=10$, $\lambda_m=1$, $\lambda_{id}=0.5$ in our experiments.

Optimization Functions of Supervised Framework. Other optimization objects for the supervised framework are the conditional adversarial loss, the improved pixel loss, the perceptual loss, and the total variation loss.

Conditional Adversarial Loss. The goal of CGANs try to learn the mapping from a conditional image $x$ to the target image $y$. The generator $G^t$ tries to generate image $y' = G^t(x)$ which cannot be distinguished from the real image $y$, while the discriminator $D$ tries to detect the fake images produced by $G^t$.

$$\mathcal{L}_{cgan}(G^t, D) = \mathbb{E}_{y \sim p_{data}(y)} \left[ \log D(x, y) \right] + \mathbb{E}_{x \sim p_{data}(x)} \left[ \log (1 - D(x, G^t(x), y)) \right].$$ \hfill (9)

where $D$ tries to distinguish the fake image pair $(x, G^t(x), y)$ from the real image pair $(x, y)$. To jointly learn the images and the hand skeletons, we make a modification base on Eq. (9),

$$\mathcal{L}_{cgan}(G^t, D) = \mathbb{E}_{y \sim p_{data}(y)} \left[ \log D(x, y, y') \right] + \mathbb{E}_{x \sim p_{data}(x)} \left[ \log (1 - D(x, l_y, G^t(x), l_y)) \right].$$ \hfill (10)

where $D$ tries to distinguish the fake image triplet $(x, l_y, G^t(x), l_y)$ from the real image triplet $(x, l_y, y)$. In this way, $D$ takes consideration of both images and hand skeletons during optimization.

Improved Pixel Loss. We also adopt an improved pixel loss between generated images and ground truths, i.e., channel-wise color loss, to reduce the ‘channel pollution’ issue [25]. The loss can be expressed as,

$$\mathcal{L}_{color} = \sum_{i \in \{r, g, b\}} \mathbb{E}_{x \sim p_{data}(x)} \left[ ||G^t(x^i, l_y) - y'^i||_1 \right].$$ \hfill (11)

where $y'$, $g^i$ and $b^i$ denote the red, green and blue color channels of image $y$. By calculating the loss of each channel independently, the error from each channel will not influence other channels.

Perceptual Loss and Total Variation Loss. We also use a perceptual loss and a total variation loss between the generated image $y'$ and the real image $y$ to better optimize our model. Both losses have been shown to be useful in Pix2pixHD [29] and SelectionGAN [26], respectively.

Full Objective of Supervised Framework. The final objective of AsymmetricGAN for hand gesture-to-gesture translation can be expressed as,

$$\mathcal{L} = \mathcal{L}_{cgan} + \lambda_c \mathcal{L}_{color} + \lambda_{yc} \mathcal{L}_{color_{yc}} + \lambda_{id} \mathcal{L}_{id} + \lambda_{agg} \mathcal{L}_{agg} + \lambda_{tv} \mathcal{L}_{tv},$$ \hfill (12)

where hyper-parameters $\lambda_c$, $\lambda_{yc}$, $\lambda_{id}$, $\lambda_{agg}$ and $\lambda_{tv}$ are controlling the relative importance of each loss. In our experiments, we follow previous works [7, 25] and empirically set $\lambda_c=800$, $\lambda_{yc}=0.1$, $\lambda_{id}=0.01$, $\lambda_{agg}=1000$ and $\lambda_{tv}=1e^-6$.

4 EXPERIMENTS

We conduct experiments on two challenging tasks to evaluate the effectiveness of our AsymmetricGAN, i.e., multi-domain image-to-image translation and hand gesture-to-gesture translation.
**Table 4. Description of datasets used in multi-domain image-to-image translation.**

| Dataset       | Type             | #Domain | #Mapping | Resolution | Unpaired/ Paired | #Train | #Test | #Total |
|---------------|------------------|---------|----------|------------|------------------|--------|-------|--------|
| Facades [28]  | Architectures    | 2       | 2        | 256×256    | Paired           | 800    | 212   | 1,012  |
| AR Face [14]  | Faces            | 4       | 12       | 768×576    | Paired           | 920    | 100   | 1,020  |
| Bu3dfe [35]   | Faces            | 7       | 42       | 512×512    | Paired           | 2,520  | 280   | 2,800  |
| Alps [1]      | Natural Seasons  | 4       | 12       |            | Unpaired         | 6,033  | 400   | 6,433  |
| RaFD [10]     | Faces            | 8       | 56       | 1024×681   | Unpaired         | 5,360  | 2,680 | 8,040  |
| Collection Style [36] | Painting Style | 5       | 20       | 256×256    | Unpaired         | 7,837  | 1,593 | 9,430  |

Fig. 3. Different methods for label→photo translation on Facades. From left to right: Input, Ground Truth (GT), CycleGAN [36], DualGAN [34], ComboGAN [1], DistanceGAN [2], DistanceGAN+Cycle Loss [2], DistanceGAN+Self Distance [2], StarGAN [3], Pix2pix [7], BicycleGAN [37], and AsymmetricGAN (Ours).

### 4.1 Multi-Domain Image-to-Image Translation

#### 4.1.1 Experimental Setup. Datasets and Parameter Settings.

We employ 6 datasets to validate our AsymmetricGAN on multi-domain image-to-image translation tasks. Table 4 shows the details of these datasets. The batch size is set to 1 for all the experiments and all the models are trained with 200 epochs.

**Competing Baselines.** We employ several models as our baselines, i.e., CycleGAN [36], DualGAN [34], ComboGAN [1], DistanceGAN [2], Dist.+Cycle [2], Self Dist. [2], BicycleGAN [37], Pix2pix [7], and StarGAN [3].

#### 4.1.2 Comparison Against State-of-the-Arts.

**Task 1: Label→Photo Translation.** We use Facades to perform label→photo translation, which we aim to show that AsymmetricGAN is also applicable on the translation on two domains only and could produce competitive performance. Results are shown in Fig. 3. We can see that Dist.+Cycle, Self Dist., ComboGAN fail to generate reasonable results on the photo→label task. For the opposite mapping, i.e., label→photo, Dist.+Cycle, Self Dist., DualGAN, StarGAN and Pix2pix suffer from model collapse, leading reasonable but blurry results. However, the proposed AsymmetricGAN achieves compelling results in both directions compared with baselines.

**Task 2: Facial Expression Synthesis.** We employ three face datasets, i.e., AR Face, Bu3dfe and RaFD, to evaluate facial expression synthesis tasks. Results of AR Face are shown in Fig. 4, we can see that Dist.+Cycle and Self Dist. fail to produce faces similar to the target domain. DualGAN generates reasonable but blurry faces. DistanceGAN, StarGAN, BicycleGAN and Pix2pix produce much sharper results, but still contain some artifacts in the translated faces, e.g., twisted mouths on StarGAN, Pix2pix and BicycleGAN in the ‘neutral2fear’ direction. ComboGAN, CycleGAN and the proposed AsymmetricGAN work better than other baselines. Similar results can be seen on Bu3dfe as shown in Fig. 5. We also present results on RaFD compared with the most related two works, i.e., CycleGAN and StarGAN, in Fig. 6. We see that our method achieves visually better results than both.
Fig. 4. Different methods for multi-domain facial expression translation on AR Face. From left to right: Input, Ground Truth (GT), CycleGAN [36], DualGAN [34], ComboGAN [1], DistanceGAN [2], DistanceGAN+Cycle Loss [2], DistanceGAN+Self Distance [2], StarGAN [3], Pix2pix [7], BicycleGAN [37], and AsymmetricGAN (Ours).

Fig. 5. Different methods for multi-domain facial expression translation on Bu3df. From left to right: Input, Ground Truth (GT), CycleGAN [36], DualGAN [34], ComboGAN [1], DistanceGAN [2], DistanceGAN+Cycle Loss [2], DistanceGAN+Self Distance [2], StarGAN [3], Pix2pix [7], BicycleGAN [37], and AsymmetricGAN (Ours).

Task 3: Season Translation. Fig. 7 shows the season translation results. Clearly, DistanceGAN, Dist.+Cycle, Self Dist., DualGAN fail to produce reasonable results. StarGAN can generate reasonable but blurry results, and there are some visual artifacts in the translated results. ComboGAN, CycleGAN and the proposed AsymmetricGAN are able to produce better results than other methods. However, ComboGAN yields some visual artifacts in some cases, such as in the ‘summer2autumn’ direction. We also show three failure case of the proposed method on this dataset as shown in Fig. 7. Our method generates images similar to the input domain, while existing methods such as CycleGAN and DualGAN generate visually better results compared with the proposed AsymmetricGAN in the ‘winter2spring’, ‘spring2winter’ and ‘autumn2spring’ directions. However, both DualGAN and CycleGAN require to train 12 generators for this task on
the dataset, while the proposed AsymmetricGAN only needs to train 2 generators, and thus our model complexity is significantly lower.

**Task 4: Painting Style Transfer.** Comparison results on painting style transfer tasks compared with the most related two methods, i.e., CycleGAN and StarGAN, are shown in Fig. 8. We see that StarGAN generates less diverse generations crossing different styles compared with CycleGAN and AsymmetricGAN. The proposed AsymmetricGAN
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Fig. 8. Different methods for multi-domain painting style transfer on Collection Style. From top to bottom: CycleGAN [36], StarGAN [3], and AsymmetricGAN (ours). Our method achieves significantly better results than StarGAN.

Table 5. AMT of multi-domain image translation on Facades, AR Face, Alps and Bu3dfe.

| AMT ↑ | label→photo | photo→label | AR Face | Alps | Bu3dfe |
|-------|-------------|-------------|---------|------|--------|
| CycleGAN [36] | 8.8±1.5 | 4.8±0.8 | 24.3±1.7 | 39.6±1.4 | 16.9±1.2 |
| DualGAN [34] | 0.6±0.2 | 0.8±0.3 | 1.9±0.6 | 18.2±1.8 | 3.2±0.4 |
| ComboGAN [1] | 4.1±0.5 | 0.2±0.1 | 4.7±0.9 | 34.3±2.2 | 25.3±1.6 |
| DistanceGAN [2] | 5.7±1.1 | 1.2±0.5 | 2.7±0.7 | 4.4±0.3 | 6.5±0.7 |
| Dist.+Cycle [2] | 0.3±0.2 | 0.2±0.1 | 1.3±0.5 | 3.8±0.6 | 0.3±0.1 |
| Self Dist. [2] | 0.3±0.1 | 0.1±0.1 | 0.1±0.1 | 5.7±0.5 | 1.1±0.3 |
| StarGAN [3] | 3.5±0.7 | 1.3±0.3 | 4.1±1.3 | 8.6±0.7 | 9.3±0.9 |
| Pix2pix [7] | 4.6±0.3 | 1.5±0.4 | 2.8±0.6 | - | 3.6±0.5 |
| BicycleGAN [37] | 5.4±0.6 | 1.1±0.3 | 2.4±0.5 | - | 2.7±0.4 |
| Ours, Fully-Sharing | 4.6±0.9 | 2.4±0.4 | 6.8±0.6 | 15.4±1.9 | 13.1±1.3 |
| Ours, Partially-Sharing | 8.2±1.2 | 3.6±0.7 | 16.8±1.2 | 36.7±2.3 | 18.9±1.1 |
| Ours, No-Sharing | 10.3±1.6 | 5.6±0.9 | 22.8±1.9 | 47.7±2.8 | 23.6±1.7 |

has comparable performance with CycleGAN, requiring only one single model for all the styles, and thus the network complexity is remarkably lower compared with CycleGAN which trains an individual model for each pair of styles.

Quantitative Comparison on All Tasks. We follow both CycleGAN and StarGAN, and use the same perceptual study protocol to evaluate the generated images, which is a perceptual metric to assess the realism from a holistic level. As we can see from Tables 5, 6 and 7, AsymmetricGAN achieves very competitive results compared with baselines. Moreover, we observe that AsymmetricGAN significantly outperforms StarGAN trained using one generator on most of the metrics and on all the datasets. We also note that supervised Pix2pix shows worse results than unpaired methods in Table 5, which can be also observed in [34].

We then adopt IS [21] to measure the quality of synthesized images. IS tries to capture two properties of generated images, i.e., image quality and diversity. Results compared with the most related two works (i.e., CycleGAN and StarGAN) are shown in Table 7. We see that our method achieves better IS than both CycleGAN and StarGAN. Moreover, we employ FID [6] to evaluate the performance on both RaFD and painting style datasets. Results compared with CycleGAN and StarGAN are shown in Tables 6 and 7, we observe that AsymmetricGAN achieves the best results.
Table 6. AMT, FID and CA of multi-domain image translation on Collection Style.

| Model              | AMT ↑ | FID ↓ | CA (%) ↑ |
|--------------------|-------|-------|----------|
| CycleGAN [36]      | 16.8±1.9 | 47.4823 | 73.72    |
| StarGAN [3]        | 13.9±1.4 | 58.1562 | 44.63    |
| AsymmetricGAN      | 19.8±2.4 | 43.7473 | 78.84    |
| Real Data          | -     | -     | 91.34    |

Table 7. AMT, IS and FID of multi-domain image translation on RaFD.

| Model              | AMT ↑ | IS ↑ | FID ↓ |
|--------------------|-------|------|-------|
| CycleGAN [36]      | 19.5  | 1.6942 | 52.8230 |
| StarGAN [3]        | 24.7  | 1.6695 | 51.6929 |
| AsymmetricGAN      | 29.1  | 1.7187 | 51.2765 |

Table 8. Comparison results with different generator settings of AsymmetricGAN on Bu3dfe. StarGAN++ uses the same optimization objectives as our method.

| Model                                                                 | #Time   | #Parameters | AMT ↑ | IS ↑ | FID ↓ |
|-----------------------------------------------------------------------|---------|-------------|-------|------|-------|
| StarGAN [3]                                                          | 2m23s   | 8.4M        | 9.3±0.9 | 1.5640 | @1:52.704, @5:94.898 |
| StarGAN++ [3]                                                        | 2m26s   | 8.4M        | 12.4±1.2 | 1.6532 | @1:53.765, @5:95.125 |
| S1: G t (Architecture III), G r (Architecture I)                      | 2m27s   | 8.4M±2.9K   | 18.9±1.4 | 1.8790 | @1:55.575, @5:96.014 |
| S2: G t (Architecture III), G r (Architecture II)                     | 2m29s   | 8.4M±1.3M   | 20.1±1.4 | 1.9293 | @1:56.173, @5:97.112 |
| S3: G t (Architecture III), G r (Architecture III)                    | 2m33s   | 8.4M±4.4M   | 23.6±1.7 | 1.8714 | @1:55.625, @5:96.250 |

compared with StarGAN and CycleGAN. We finally compute Classification Accuracy (CA) on the generated images as in [3]. Table 6 shows the results on style transfer task. We see that AsymmetricGAN significantly outperforms both CycleGAN and StarGAN.

4.1.3 Model Analysis. Importance of Distinct Network Designs for Different Generators. We first report the results of the running-time for training one epoch, the total number of generator parameters and the quantitative performance on Bu3dfe. The network architectures of different generator combinations (i.e., S1, S2, S3) are described in Sec. 3 and results are compared with the most related model StarGAN as shown in Table 8. Note that we also tried increasing the depth and channel number of the generator in StarGAN in our preliminary experiments, but did not observe improved performance. Thus, we intuitively replaced the symmetric generator in StarGAN with the proposed asymmetric dual-generator, and the performance has improved significantly. Specifically, we observe in Table 8 that AsymmetricGAN achieves much better performance than StarGAN on all metrics when we consider only a light-weight generator structure for the reconstruction generator (S1). By so doing, the number of parameters for ours is only 2.9k more than StarGAN, while the performance is significantly boosted, which shows that the distinct network designs for different generators are very important for learning better both the generators, demonstrating our initial motivation.

Moreover, to study the effectiveness of the proposed asymmetric structure and remove the impact of the proposed optimization functions, we conduct experiments with StarGAN using the same optimization objectives as our method. Results are shown in Table 8, we observe that the proposed method still achieves much better results than StarGAN++, which further validates our design motivation.
Table 9. Ablation study of AsymmetricGAN on Facades, AR Face and Bu3dfe for multi-domain image translation. All: AsymmetricGAN, I: Identity preserving loss, S: multi-scale SSIM loss, C: Color cycle-consistency loss, D: Double discriminators strategy.

| Model           | Label→Photo | Photo→Label | AR Face          | Bu3dfe          |
|-----------------|-------------|-------------|------------------|-----------------|
|                 | AMT ↑       | AMT ↑       | CA (%) ↑         | AMT ↑           | CA (%) ↑       | FID ↓           |
| All             | 10.3 ± 1.6  | 5.6 ± 0.9   | 22.8 ± 1.9       | 23.6 ± 1.7      | 23.6 ± 1.7    |
| All - I         | 2.6 ± 0.4   | 4.2 ± 1.1   | 4.7 ± 0.8        | 16.3 ± 1.1      | 16.3 ± 1.1    |
| All - S - C     | 4.4 ± 0.6   | 4.8 ± 1.3   | 8.7 ± 0.6        | 14.4 ± 1.2      | 14.4 ± 1.2    |
| All - S - C - I | 2.2 ± 0.3   | 3.9 ± 0.8   | 2.1 ± 0.4        | 13.6 ± 1.2      | 13.6 ± 1.2    |
| All - D         | 9.0 ± 1.5   | 5.3 ± 1.1   | 21.7 ± 1.7       | 22.3 ± 1.6      | 22.3 ± 1.6    |
| All - D - S     | 3.3 ± 0.7   | 4.5 ± 1.1   | 14.7 ± 1.7       | 20.1 ± 1.4      | 20.1 ± 1.4    |
| All - D - C     | 8.7 ± 1.3   | 5.1 ± 0.9   | 19.4 ± 1.5       | 21.6 ± 1.4      | 21.6 ± 1.4    |
| All - D         | 9.0 ± 1.5   | 5.3 ± 1.1   | 21.7 ± 1.7       | 22.3 ± 1.6      | 22.3 ± 1.6    |
| All - D - S     | 3.3 ± 0.7   | 4.5 ± 1.1   | 14.7 ± 1.7       | 20.1 ± 1.4      | 20.1 ± 1.4    |
| All - D - C     | 8.7 ± 1.3   | 5.1 ± 0.9   | 19.4 ± 1.5       | 21.6 ± 1.4      | 21.6 ± 1.4    |

Table 10. Comparison of the overall model capacity of different models with the number of image domain $m=7$ for multi-domain image-to-image translation tasks.

| Model             | #Models | #Parameters |
|-------------------|---------|-------------|
| Pix2pix [7]       |         | 57.2M×42    |
| BicycleGAN [37]   |         | 64.3M×42    |
| CycleGAN [36]     | $A_m^2 = m(m-1)$ | 52.6M×21    |
| DiscoGAN [9]      | $C_m^2 = m(m-1)/2$ | 16.6M×21    |
| DualGAN [34]      |         | 178.7M×21   |
| DistanceGAN [2]   |         | 52.6M×21    |
| ComboGAN [1]      | m       | 14.4M×7     |
| StarGAN [3]       | 1       | 53.2M×1     |
| Ours, Fully-Sharing | 1       | 53.2M×1     |
| Ours, Partial-Sharing | 1       | 53.8M×1     |
| Ours, No-Sharing  | 1       | 61.6M×1     |

Generation Performance v.s. Network Complexity. Through a comparison of the performance among the setting S1, S2, S3 in Table 8, we also observe that using a more complex generator indeed improves the generation performance, while the network capacity is consequently increased. Specifically, from S2 to S3, the number of parameter changes from 8.4M+1.3M to 8.4M+8.4M. Although the parameters remarkably increase, the generation performance has slight improvement (IS and CA metrics are even worse), meaning that the balance between the network complexity and the generation performance should be also considered in designing a good GAN.

Efficiency. Table 8 provides the running-time of one epoch on different methods. We see that our proposed method is only slightly slower than StarGAN++ [3]. Specifically, StarGAN++ needs 2m26s to finish one epoch, while the proposed baseline S2 only needs 2m29s for training one epoch. However, our baseline S2 achieves remarkably better results than StarGAN on all three evaluation metrics. Moreover, since the introduction of the proposed asymmetric structure, we observe that our model converges more easily and quickly, thus making image translation with higher consistency and better stability. Therefore, in order to balance performance and efficiency, we adopt baseline S2 in our unsupervised image-to-image translation experiments.

Model Component Analysis. We conduct an ablation study of the proposed AsymmetricGAN on several datasets, i.e., Facades, AR Face and Bu3dfe. We report the generation performance without using the conditional identity preserving loss (I), multi-scale SSIM loss (S), color cycle-consistency loss (C) and double discriminators strategy (D), respectively. We also employ two different discriminators as in [17, 25] to further improve our generation performance. In order to investigate the parameter-sharing strategy of the asymmetric generator, we perform experiments on different schemes
Table 11. Comparison between SymmetricGAN and AsymmetricGAN for hand gesture-to-gesture translation tasks on NTU Hand Digit.

| Model            | PSNR ↑ | AMT ↑ | FID ↓ | FRD ↓ | #Parameters       |
|------------------|--------|-------|-------|-------|-------------------|
| SymmetricGAN     | 32.5740| 27.9  | 6.8711| 1.7519| 11.388M*2         |
| AsymmetricGAN    | 32.6686| 29.7  | 6.7132| 1.7341| 31.5624           |

Table 12. Comparison with different models for hand gesture translation.

| Model          | NTU Hand Digit | Senz3D |
|----------------|----------------|--------|
|                | PSNR ↑ | AMT ↑ | FID ↓ | FRD ↓ | PSNR ↑ | AMT ↑ | FID ↓ | FRD ↓ |
| PG² [11]       | 28.2403| 3.5   | 24.2093| 2.6319| 26.5138| 2.8   | 31.7333| 3.0933|
| SAMG [33]      | 28.0185| 2.6   | 31.2841| 2.7453| 26.9545| 2.3   | 38.1758| 3.1006|
| DPIG [12]      | 30.6487| 7.1   | 6.7661 | 2.6184| 26.9451| 6.9   | 26.2713| 3.0846|
| PoseGAN [22]   | 29.5471| 9.3   | 9.6725 | 2.5846| 27.3014| 8.6   | 24.6712| 3.0467|
| GestureGAN [25]| 32.0691| 26.1  | 7.5860 | 2.5223| 27.9749| 22.6  | 18.4595| 2.9836|
| AsymmetricGAN  | 32.6686| 29.7  | 6.7132 | 1.7341| 31.5624| 28.1  | 12.4326| 2.2011|

including: 1) Fully-sharing, i.e., the two generators share the same parameters. 2) Partially-sharing, i.e., only the encoder part shares the same parameters. 3) No-sharing, i.e., two independent generators. The basic generator structure follows StarGAN [3].

Quantitative results of both AMT score and CA are reported in Table 9. We observe that without using double discriminators slightly degrades performance, meaning that the proposed model can achieve good results trained using the proposed asymmetric dual generators and one discriminator. However, removing the conditional identity preserving loss, multi-scale SSIM loss and color cycle-consistency loss substantially degrades the performance, meaning that the proposed joint optimization objectives are particularly important to stabilize the training process and thus produce much better generation performance. Results of different parameter-sharing strategies are shown in Tables 5 and 10, we observe that different-level parameter sharing influences both the generation performance and the model capacity, demonstrating our initial motivation.

Overall Model Capacity Analysis. We also compare the overall model capacity with several state-of-the-art methods. The number of trained models and the number of model parameters on Bu3df3e for $m$ domains are presented in Table 10. We note that both StarGAN and AsymmetricGAN only need to train one model to learn all the mappings of $m$ domains. We also report the number of parameters on Bu3df3e in Table 10. This dataset contains 7 different facial expressions, which means $m=7$. The proposed AsymmetricGAN uses fewer parameters compared with the other baselines except for StarGAN, but we achieve significantly better generation results in most metrics as shown in Tables 5, 6 and 7. When we adopt a parameter-sharing strategy, our generation performance is only slightly lower (but still outperforming StarGAN) while the number of parameters is comparable with StarGAN.

4.2 Hand Gesture-to-Gesture Translation

Besides unsupervised image translation tasks, we also conduct experiments on supervised image translation, i.e., hand gesture-to-gesture translation, to validate the effectiveness of the proposed AsymmetricGAN.

Datasets and Parameter Settings. We follow GestureGAN [25] and employ the NTU Hand Digit [19] and Creative Senz3D [15] datasets to evaluate the proposed AsymmetricGAN. The batch size is set to 4 for both datasets and all the
models are trained with 20 epochs. Moreover, we follow [11, 25] and employ OpenPose [23] to extract hand skeletons as training data.

**Evaluation Metric.** We follow GestureGAN [25] and employ PSNR, FID [6], FRD [25] and AMT user study to evaluate the quality of generated images. PSNR evaluates generated images and real images from a pixel-level similarity. Both FID and FRD evaluate generated images and real images from a high-level feature space. Specifically, FID is a measure of similarity between generated images and real images, and FRD is a measure of distance between each generated image and the corresponding real image.

**Ablation Study.** We conduct ablation studies between SymmetricGAN (i.e., GestureGAN) and AsymmetricGAN on NTU Hand Digit to validate our motivation of the asymmetric network design. 1) SymmetricGAN has two separate generators with the identity structure for both generators $G^t$ and $G^r$, which has $11.388M^2 \times 2 = 22.776M$ parameters totally. 2) AsymmetricGAN also has two separate generators for both generators $G^t$ and $G^r$. However, the filters in first convolutional layer of $G^t$ and $G^r$ are 64 and 4, respectively. It means $G^t$ has 11.388M and 0.046M parameters, respectively.
Both network architectures are described in Sec. 3 and comparison results of both generation performance and network parameters are reported in Table 11. We see that although the total number of parameters of AsymmetricGAN is much less than SymmetricGAN, AsymmetricGAN still achieves better results than SymmetricGAN on all metrics, which validate our motivation of the asymmetric generator design.

**State-of-the-Art Comparisons.** We compare the proposed AsymmetricGAN with the most related five works, i.e., GestureGAN [25], PG2 [11], DPIG [12], PoseGAN [22] and SAMG [33]. Quantitative Results of PSNR, FID and FRD are shown in Table 12. We see that our performance are significantly much better than existing models on all metrics. Moreover, we visually compare the proposed method with the most related work GestureGAN in Fig. 9. We see that AsymmetricGAN produces much more photo-realistic results with convincing details compared with GestureGAN, validating our motivation. We also provide arbitrary hand gesture translation results on both datasets in Fig. 10, we observe that the proposed method generates different hand gestures according to the target skeletons.

**User Study.** Similar to GestureGAN [25], we also conduct a user study. The results compared with existing methods are shown in Table 12. We note that AsymmetricGAN consistently achieves better results than other baselines on both datasets.

**Data Augmentation.** We use the generated images to improve the performance of a hand gesture classifier as in GestureGAN [25]. Specifically, we employ a pre-trained ResNet50 [5] as the classifier. For both datasets, we make a split of 70%/30% between training and testing sets. Results compared with existing methods are shown in Table 13. The term ‘real/real’ in Table 13 represents the result without data augmentation. We observe that the performance improves significantly after adding the generated images by different methods. Moreover, we can see that AsymmetricGAN achieves the best result compared with other methods, meaning the generated images produced by our method are more photo-realistic.
5 CONCLUSION

We present a novel AsymmetricGAN, a robust and efficient model that can perform both supervised and unsupervised image-to-image translations. The proposed asymmetric dual generators, allowing for different network architectures and different-level parameter sharing strategy, are designed for the image translation and image reconstruction tasks. Moreover, we explore jointly using different objective functions to optimize AsymmetricGAN, and thus generating images with better fidelity and high quality. Extensive experimental results on different scenarios demonstrate that AsymmetricGAN achieves more photo-realistic results and more modeling capacity than existing methods for both unsupervised and supervised image translation tasks. Finally, the proposed model and training skills can be easily applied to other GAN frameworks. In the future, we will focus on the face aging task [24], which aims to generate facial image with different ages in a continuum.

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