Dual Variational Generation for Low Shot Heterogeneous Face Recognition

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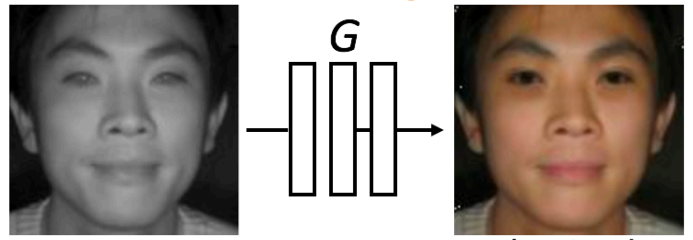
Background

- Heterogeneous Face Recognition is a challenging issue because of the large domain discrepancy and a lack of heterogeneous data
- Previous image-to-image translation based methods face two challenges
  - **Diversity**

    Given one image, a generator only synthesizes one new image of the target domain, resulting in **limited number of images**. Moreover, two images before and after translation have same attributes except for the spectral information, leading to **limited intra-class diversity**
  - **Consistency**

    When generating large-scale samples, it is challenging to guarantee that the synthesized face images belong to the **same identity** of the input images

Conditional Synthesis

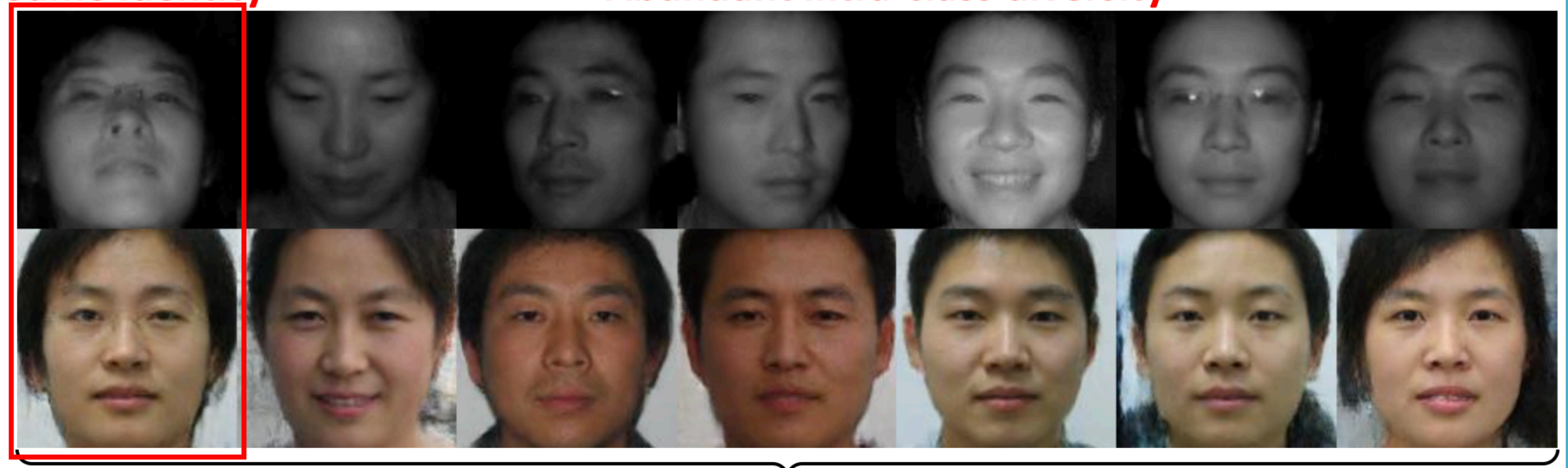


Input NIR — Synthesized VIS

Dual Variational Generation

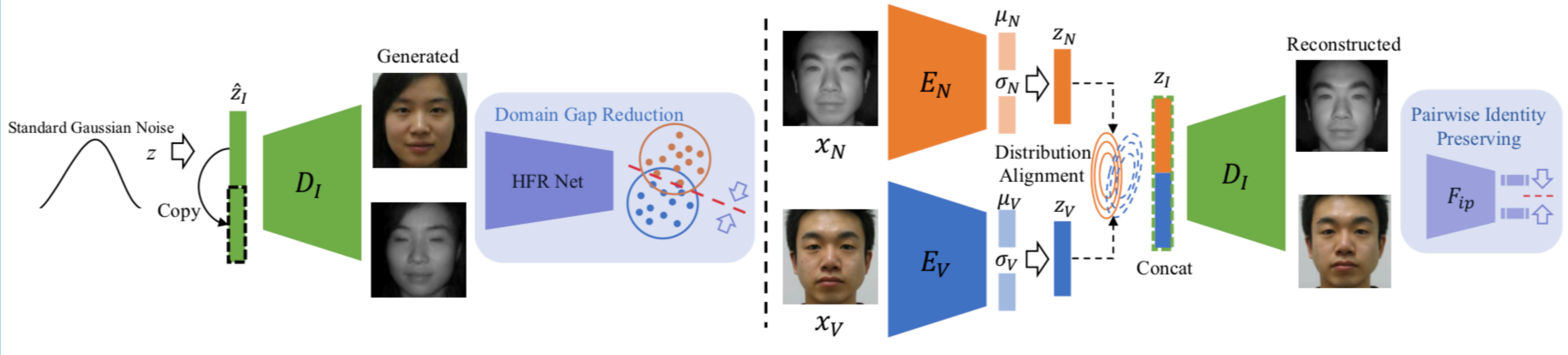
- Generate **paired** new heterogeneous data from **noise**
  - Sample large-scale new images with abundant intra-class diversity
  - Ensure the identity consistency of the generated paired images

Same identity — **Abundant intra-class diversity**



Large-scale new images

Framework



The purpose (left part) and training model (right part). It generates large-scale new paired heterogeneous images with the same identity from standard Gaussian noise, aiming at reducing the domain discrepancy for HFR. A **distribution alignment** in the latent space and a **pairwise identity preserving** in the image space are imposed to guarantee the identity consistency of the generated paired images

Objective

- Lean the joint distribution

$$\mathcal{L}_{\text{rec}} = -\mathbb{E}_{q_{\phi_N}(z_N|x_N)\cup q_{\phi_V}(z_V|x_V)} \log p_\theta(x_N, x_V|z_I)$$

$$\mathcal{L}_{\text{kl}} = D_{\text{KL}}(q_{\phi_N}(z_N|x_N)||p(z_N)) + D_{\text{KL}}(q_{\phi_V}(z_V|x_V)||p(z_V))$$

- Align the distributions

$$\mathcal{L}_{\text{dist}} = \frac{1}{2}\left[||u_N^{(i)} - u_V^{(i)}||_2^2 + ||\sigma_N^{(i)} - \sigma_V^{(i)}||_2^2\right]$$

- Pairwise Identity Preserving

$$\mathcal{L}_{\text{ip-pair}} = ||F_{ip}(\hat{x}_N) - F_{ip}(\hat{x}_V)||_2^2$$

$$\mathcal{L}_{\text{ip-rec}} = ||F_{ip}(\hat{x}_N) - F_{ip}(x_N)||_2^2 + ||F_{ip}(\hat{x}_V) - F_{ip}(x_V)||_2^2$$

Visual Results

CASIS NIR-VIS 2.0 — Oulu — BUAA

More Experiments

Thermal-VIS

- Tufts Face database

  Baseline: Rank-1 = 37.5%

  DVG: Rank-1 = 53%

  Improving 15.5%

Sketch-Photo

- IIIT-D Viewed Sketch database

  Baseline: VR@FAR=1% = 81.04%

  DVG: VR@FAR=1% = 97.86%

  Improving 16.82%

Profile-Frontal Face

- Multi-PIE database

  Baseline: Rank-1 = 65.4%

  DVG: Rank-1 = 83.9%

  Improving 18.5%

Quantitative Results

Method	CASIA NIR-VIS 2.0		Oulu-CASIA NIR-VIS			BUAA-VisNir		
	Rank-1	FAR=0.1%	Rank-1	FAR=1%	FAR=0.1%	Rank-1	FAR=1%	FAR=0.1%
IDNet [29]	87.1 ± 0.9	74.5	-	-	-	-	-	-
HFR-CNN [30]	85.9 ± 0.9	78.0	-	-	-	-	-	-
Hallucination [23]	89.6 ± 0.9	-	-	-	-	-	-	-
DLFace [28]	98.68	-	-	-	-	-	-	-
TRIVET [26]	95.7 ± 0.5	91.0 ± 1.3	92.2	67.9	33.6	93.9	93.0	80.9
IDR [10]	97.3 ± 0.4	95.7 ± 0.7	94.3	73.4	46.2	94.3	93.4	84.7
W-CNN [11]	98.7 ± 0.3	98.4 ± 0.4	98.0	81.5	54.6	97.4	96.0	91.9
DVR [35]	99.7 ± 0.1	99.6 ± 0.3	100.0	97.2	84.9	99.2	**98.5**	96.9
RCN [4]	99.3 ± 0.2	98.7 ± 0.2	-	-	-	-	-	-
MC-CNN [3]	99.4 ± 0.1	99.3 ± 0.1	-	-	-	-	-	-
LightCNN-9	97.1 ± 0.7	93.7 ± 0.8	93.8	80.4	43.8	94.8	94.3	83.5
LightCNN-9 + DVG	99.2 ± 0.3	98.8 ± 0.3	100.0	97.6	89.5	98.0	97.1	93.1
LightCNN-29	98.1 ± 0.4	97.4 ± 0.5	99.0	93.1	68.3	96.8	97.0	89.4
LightCNN-29 + DVG	**99.8 ± 0.1**	**99.8 ± 0.1**	**100.0**	**98.5**	**92.9**	**99.3**	**98.5**	**97.3**

Contributions

- We provide a new insight into the problems of HFR. That is, we consider HFR as a dual generation problem, and propose a novel dual variational generation framework. This framework generates new paired heterogeneous images with abundant intra-class diversity
- We can sample large-scale diverse paired heterogeneous images from noise. By constraining the pairwise feature distances of the generated paired images in the HFR network, the domain discrepancy is effectively reduced